

ABSTRACT

Title of Dissertation: VALUING CLIMATE AMENITIES
IN BRAZIL USING A HEDONIC
PRICING FRAMEWORK

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In this dissertation, I measure the amenity value of climate in Brazil. The value is useful for the measurement of one consequence of greenhouse gas emissions, climate change. A basic hedonic framework shows that "good" climate is of value to workers and consumers of housing. Workers accept lower wages and pay greater housing rents (all else equal) to work and live in a city with better climate. To measure the impact of reducing emissions, I estimate the variations in wage and rents attributable to cross-sectional differences in climate.

Studies typically evaluate the effect of variations in climate on housing prices or income. They do not account for the effect of climate on firms' costs, however. If climate affects production, then the value of a marginal change in the climate amenity is the difference between the effects on housing price and wages.

In Chapter 2, I describe this result from the Roback model (1982).

Empirical results from hedonic studies suggest that there is still no consensus on the impact of climate change. One potential cause of the discord is the correlation between climate and amenities omitted from models. Estimates suffer from bias due to data limitations and incomplete information on preferences. A second cause is the correlation of amenities included in the model. Consequences of multicollinearity are implausible and imprecise parameter estimates. The severity of the impact of multicollinearity will depend on the model and dataset. In Chapters 5 and 6, I perform sensitivity analyses on the rent and wage models and show the unreliability of climate parameter estimates.

Hedonic studies also ignore the potential correlation between unobservables in the rent and wage equations. By contrast, I estimate the equations as a system of seemingly unrelated regression equations. In Chapter 7, I compare the results from the single-equation and system methods. I find that the values of climate amenities obtained from the single-equation method are larger in magnitude. The overestimation of amenity values has implications for evaluating the benefits of an improvement in environmental quality.

VALUING CLIMATE AMENITIES
IN BRAZIL USING A HEDONIC
PRICING FRAMEWORK

by

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DEDICATION

To My Family

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Chapter 1

Introduction

Since the Intergovernmental Panel on Climate Change (IPCC) discussions, many countries are considering policies to reduce carbon emissions. Determining the benefits of emission reductions will be useful for designing the optimal emission-reducing policy and even determining whether such policies should be instituted at all. A major point of contention in weighing the costs and benefits of emission reductions, though, is how to measure the economic benefits.

The approach adopted in this dissertation is to focus on a single consequence of greenhouse gas emissions, climate change. A basic economic model shows that workers are attracted to jobs in cities with amenities, such as “good” climate. The influx of workers to a city with greater levels of amenities increases the labor supply, depressing wages. Since these individuals require housing, demand for housing in the city shifts upward causing housing prices and rents to rise. “Good” climate is of value to workers and consumers of housing. Workers accept lower wages and/or pay greater housing rents (all else equal) to work and live in a city with better climate. To measure the impact of reducing greenhouse gas emissions, I estimate the cross-sectional variations in wages and housing prices attributable to differences in climate.

Climate is multidimensional. In this dissertation, I focus on just two climate factors: temperature and rainfall. I estimate the impacts of marginal changes in temperature and rainfall averages on Brazilian housing prices and wages.

Brazil is an important case study for several reasons. Several studies have attempted to measure how changes in annual averages of climate variables, such as temperature and rainfall, affect agricultural land values, residential land values, wages, and household welfare in the U.S. (see Chapter 3). Because the U.S. has a more temperate climate, it is no surprise that one observes welfare gains from increases in temperature, contrary to what might be anticipated in countries with tropical climates. What is the value of climate for countries that already experience warm weather conditions? The definition of “good” weather perhaps will greatly differ from that in the U.S.

In addition, the measure used to value climate amenities in U.S. cities is typically based on a model of consumer decision-making. In fact, climate may also affect firms’ production in cities. To maintain a given level of profit, an increase in temperature could cause firms’ electricity bills to increase. In another example, construction workers may become less productive in warmer temperatures, increasing the contractors’ costs. Firms in developing countries are even more vulnerable to these changes. They have fewer resources to overcome the effect of climate change on production. If climate affects production, then the effect of climate change on housing prices and wages will depend on consumers preferences for climate *and* how climate affects production. Under these circumstances, the effect of climate change on housing prices or wages is ambiguous (Roback, 1982). An empirical model can provide insight on how climate change

may affect production costs, as well as allow one to quantify the value of the change in climate.

Lastly, Brazil is an international leader in climate change policy, because of the impact of Amazon deforestation on global carbon emissions. Brazil is also involved in designing incentive schemes for developing countries to develop more sustainably, e.g. Clean Development Mechanisms. I focus on the 15 major counties of Brazil, where approximately 21 percent of the population resides. If Brazilians are not experiencing the damages firsthand, then all else equal, it may be more difficult to implement national and international policies aimed at reducing emissions.

In the next section, Section 1.1, I briefly describe Brazilian climate and the anticipated long-term changes in Brazilian climate. In Section 1.2, I present the structure of the dissertation.

1.1 Brazilian Climate

Though 90 percent of Brazil is tropical, over 60 percent of Brazilians lives in areas where altitude, sea winds, or polar fronts moderate the temperature (Embassy of Brazil in London, 2004). Brazilian climate has four distinct regions: the Amazon Basin, the Brazilian Plateau, the East Coast within the Tropics, and the Southern States outside of the Tropics (BBC, 2004). Temperatures in the Amazon Basin are consistently hot, but rarely exceed 90° F (32° C) (Brazil INFONET, 2002). The Plateau cities have a mild climate, and warm temperatures in the eastern coastal cities are offset by periodic winds. The southern cities outside of the tropics are generally cooler and experience winter temperatures comparable to those in the U.S. and Europe, occasionally with temperatures

below freezing (Brazil INFONET, 2002). Of all major cities, the southern cities experience greater variation in seasonal temperatures.

Rainfall levels vary widely by region. Rainfall is greatest in the mouth of the Amazon, where there is no real dry season (BBC, 2004). The Northeast of Brazil tends to be the driest region.

Most areas in Brazil experience the greatest levels of rainfall in the summer (Brazil INFONET, 2002), though there is quite a bit of variation in the season of greatest rainfall among the eastern tropical cities (BBC, 2004). In the south, the inland cities experience the wettest months during the summer. The opposite is true in the southern coastal district.

1.1.1 The Impact of Climate Change on the Welfare of Brazilians

Before measuring the impact of climate change on welfare, it is important to resolve two questions. First, why should climate have any effect on welfare at all? Second, do the climate data included in a model, such as temperature and rainfall, faithfully capture information on climate that affects human welfare?

Addressing the first issue, climate can affect individual welfare in three ways. First, people “consume” it directly. That is to say, living in an area with a pleasant climate makes them happy. Second, climate can affect individual welfare as a complementary input in leisure activities. For example, individuals may enjoy spending their leisure time hiking, fishing, sunbathing, or engaging in other activities that depend on climate. Third, climate could potentially affect the welfare of producers. As mentioned earlier, increases in temperature could potentially make the production of goods more expensive. In the dissertation, I

measure the combined impact of these effects of climate change.

With respect to the second question, climate variables have been incorporated in several hedonic studies (see Chapter 3). Despite the numerous studies on climate, there is still no consensus on the signs and magnitudes of their effects on welfare.

There are many reasons for this result. One reason is that climate variables are often correlated with other amenities valued by individuals. For example, rainfall is correlated with forest coverage, proximity to national parks, and the number of mosquitoes. Due to data limitations and our incomplete knowledge of preferences, estimates on the values of climate amenities often suffer from omitted variable bias.

A second reason for the inconsistencies in values across studies is that climate variables are often highly correlated. The severity of the correlation will depend on the data used. One possible consequence of multicollinearity is implausible magnitudes of parameter estimates. In the empirical chapters of the dissertation, I perform robustness checks to provoke more discussion on the interpretation and reliability of parameter estimates on climate amenity variables in hedonic models.

1.1.2 Climate Change Predictions in Brazil

I focus on two commonly examined components of climate: temperature and precipitation. There is still considerable scientific uncertainty regarding the level of change in these variables that will be caused by greenhouse gas emissions.

Based on historical data, Hulme and Sheard (1999) claim that warming will be greatest during the period of June-August (Brazilian winter) at 0.2°C-

0.6°C/decade. During the wetter season, December-February, warming will be 0.1°C-0.4°C/decade. Temperature changes may incur minimal costs on Brazilians' welfare since the expected changes are small.

Greenhouse gas-induced changes in rainfall are anticipated to be more substantive than changes in temperature. According to Hulme and Sheard, precipitation will increase in the rainy season (March-May) in southern states. In many of the densely-populated coastal cities, however, the models predict as much as a 27 percent reduction in rainfall by 2050. These predictions suggest that the impacts of increased greenhouse gas emissions on Brazilian welfare could be minimal in urban areas, unless slight changes in temperature are valued dearly and rainfall has a significant impact on welfare.

1.2 Organization of the Dissertation

To measure the values of climate amenities, I apply the location equilibrium model in Roback (1982). Estimates from the hedonic wage and rent regressions allow for the measurement of the value of a marginal change in a given climate amenity. The values of climate amenities can be used to measure the economic implications of greenhouse gas-induced climate change on Brazil.

Chapter 2 reviews the hedonic theory. Roback derives analytically the value of a marginal change in an amenity common to housing and labor markets. She uses the inter-city variation in amenities to explain the variation in housing prices and wages. The hedonic approach is used to impute the value of an amenity without knowledge of the explicit structures of individual preferences and the production of goods, and using data that are readily available.

Chapter 3 reviews hedonic studies measuring the values of climate ameni-

ties. Studies measuring the values of climate amenities focus on a single market, such as agricultural land, housing, or labor, in an industrialized country. These studies have three common features. First, they often assume national markets in order to have enough variation in climate characteristics to capture their values. At the national level, however, choice of location depends on job opportunities and the perceived desirability of a residential area. Thus, it may be more appropriate to measure the value of climate implicit in both housing prices and wages. Second, many of the studies concentrate on industrialized countries with temperate climates. The values of climate amenities probably differ for developing countries because of the different climate and economic conditions. Third, the models typically assume that the production of goods is independent of climate. The production of goods in cities of developing countries may be more vulnerable to changes in climate, because they lack the resources to overcome the change and are primarily in tropical regions.

Chapter 4 describes the data sources: the 1995 Brazilian household survey (PNAD), an online database on health and other demographic information (DATASUS), the 1998 database on county statistics (BIM), an agricultural database (EMBRAPA), and the 1995 Brazilian statistical yearbook. I present a detailed discussion of the data issues that arise in the analysis.

Four major concerns relate to the Brazilian household survey, climate, and non-climate amenity data. First, a number of households do not report housing prices and others report incomplete measures of housing prices. This missing information raises questions on how to treat these households in the hedonic housing model.

Second, I focus on the 15 major municípios (counties) in Brazil. This

approach has the advantage of encompassing areas where there is a fair amount of mobility. It does, however, create some potential problems. In restricting the analysis to these municipios, I do not account for climate variation throughout the country. Moreover, the preferences of only a large fraction of the members of society are represented.

Third, many of the climate and non-climate variables are highly correlated. I discuss the Pearson correlation coefficients of these variables to emphasize the difficulty in isolating a significant effect of a given climate amenity on housing prices and wages due to the multicollinearity inherent between climate and non-climate variables.

Fourth, many of the climate and non-climate amenity variables may be measured with error. I discuss the implications of these possible errors on the empirical results.

In Chapters 5 and 6, I estimate the housing price and wage equations separately. I estimate several models that assume different functional forms, include different combinations of climate amenity variables, and impose different assumptions on the error terms. The emphasis being that the climate parameters and standard errors in the rent and wage equations are sensitive to model specification.

Chapter 7 expands on the previous research in this area by estimating the hedonic rent and wage equations as a system of seemingly unrelated regression equations (SURE). Unobserved characteristics of individuals are likely to influence decisions of both where to work and where they live. If the disturbances in each equation are in fact correlated and the correlation coefficient is known, then the system will yield more efficient parameter estimates. In essence, the esti-

mated variances of the climate amenity parameters will be smaller, and therefore the parameter estimates are more precise. I also anticipate that the point estimates from the system will differ from the single-equation method (Zellner, 1962). I compare the values of climate amenities accounting for the correlation in the error terms in the wage and rent equations to the values obtained using single-equation estimation of the rent and wage models (from Chapters 5 and 6). I conclude the chapter with a demonstration of how these climate amenity values can be used to predict the impact of climate change in Brazil. I also use the example to show how the results from the single-equation and SURE models may lead to distinct policy recommendations.

In Chapter 8, I conclude the dissertation by summarizing the findings in the analysis. I also delineate ideas for future research.

Chapter 2

Hedonic Price Models

Rosen's (1974) seminal paper outlined the theory of hedonic markets, products differentiated by bundles of attributes. For this dissertation, there are two reasons why this approach is appealing. First, the technique is particularly useful in measuring the value of an environmental good. Since markets for environmental goods do not exist, one can draw from their roles in implicit markets. Next, observation of buyers' and sellers' preferences is not necessary in measuring the value of a product's characteristic. The approach simply calls for product price data and characteristics thought to contribute to prices.

In Section 2.1, I describe the Rosen model, and list the assumptions inherent in the hedonic housing price and labor models to evaluate the price of environmental quality. Additional assumptions required for the estimation of individual willingness to pay for a market good's attribute are listed in Section 2.2. Sections 2.1 and 2.2 provide a basis for the Roback model (1982) underlying this analysis. In section 2.3, I derive a measure for the values of location amenities implicit in both real estate and labor markets that follows from Roback's theoretical model.

2.1 Hedonic Theory

In this section, I describe the market of a product differentiated by a bundle of attributes. In modeling the product, I show how one can obtain a value for the product's attribute—price or willingness to pay (Section 2.1.1). Next, I review the assumptions of the hedonic housing (Section 2.1.2) and labor (Section 2.1.3) models. Housing price and wage information are commonly used to measure the values of location amenities, such as the value of environmental quality, by applying the theory of a differentiated product.

2.1.1 Decision-Making and Market Equilibrium

In this section, I describe the behavior of consumers and producers of a product differentiated by a bundle of attributes \mathbf{z} . Market equilibrium of the differentiated product is defined using the results from the consumers' and producers' optimization problems.

The consumer's problem is to choose the quantities of a composite good x and the vector of characteristics of a differentiated product $\mathbf{z} \equiv (z_1, z_2, \dots, z_n)$ that maximizes his utility subject to his budget constraint:

$$\max_{x, \mathbf{z}} U(x, \mathbf{z}) \text{ s.t. } w = x + p(\mathbf{z}). \quad (2.1)$$

The budget constraint is the sum of the expenditures on all goods which is exactly equal to income w , $w = x + p(\mathbf{z})$.¹ For simplicity, the price of the composite good is normalized to one.

¹The budget constraint is binding since the consumer does not receive any utility from saving money.

Since the budget constraint is binding at the optimum, (2.1) can be rewritten as an unconstrained optimization problem:

$$\max_{\mathbf{z}} U(w - p(\mathbf{z}), \mathbf{z}). \quad (2.2)$$

The results from the first order conditions of the unconstrained optimization problem reveal that at the optimum:

$$\frac{\frac{\partial U}{\partial z_i}}{\frac{\partial U}{\partial x}} = \frac{\partial p}{\partial z_i}. \quad (2.3)$$

The marginal rate of substitution is equal to the marginal price of the good's characteristic z_i at the optimum.

From the maximization process, a consumer achieves a given level of utility u . If the consumer has income level w and attribute vector \mathbf{z} , let $\theta(\mathbf{z}, u, w)$ denote the amount of money taken away from the consumer to leave him with utility level u :

$$U(y - \theta(\mathbf{z}, u, w), \mathbf{z}) = u. \quad (2.4)$$

Totally differentiating equation (2.4) yields:

$$-\frac{\partial U}{\partial x} \partial \theta + \frac{\partial U}{\partial z_i} \partial z_i = 0. \quad (2.5)$$

Rearranging the terms in equation (2.5) produces the condition that the marginal bid for characteristic z_i equals the marginal rate of substitution at the optimum:

$$\frac{\partial \theta}{\partial z_i} = \frac{\frac{\partial U}{\partial z_i}}{\frac{\partial U}{\partial x}}. \quad (2.6)$$

Using expressions (2.3) and (2.6), the equilibrium condition indicates that the marginal bid for characteristic z_i equals the marginal price for characteristic z_i at the optimum,

$$\frac{\partial \theta}{\partial z_i} = \frac{\partial p}{\partial z_i}. \quad (2.7)$$

In other words, the optimum quantity of a good's characteristic is consumed where the bid and the price function are tangent.

The producer chooses the number of goods produced M and the characteristics offered in the good \mathbf{z} that maximizes his profit:

$$\max_{M, \mathbf{z}} Mp(\mathbf{z}) - C(M, \mathbf{z}). \quad (2.8)$$

The first order conditions from the profit maximization problem are:

$$M : p(\mathbf{z}) - \frac{\partial C}{\partial M} = 0, \quad (2.9)$$

$$z_i : M \frac{\partial p}{\partial z_i} - \frac{\partial C}{\partial z_i} = 0, \forall i. \quad (2.10)$$

First order conditions (2.9) and (2.10) produce condition (2.11). Condition (2.11) requires that the producer choose product type and quantity such that the marginal price of characteristic z_i equals the marginal cost of increasing a unit of the characteristic:

$$\frac{\partial p}{\partial z_i} = \frac{\frac{\partial C}{\partial z_i}}{M}. \quad (2.11)$$

Analogous to the bid function in the consumer problem, Rosen defines an offer function $\phi(\mathbf{z}, \pi)$. The offer function represents the unit price a producer accepts given a product with characteristics \mathbf{z} and specific profit level π :

$$M\phi(\mathbf{z}, \pi) - C(M, \mathbf{z}) = \pi. \quad (2.12)$$

Differentiating (2.12) with respect to z_i and rearranging terms yields:

$$\frac{\partial \phi}{\partial z_i} = \frac{\frac{\partial C}{\partial z_i}}{M}. \quad (2.13)$$

Using expressions (2.11) and (2.13), the equilibrium condition indicates that the marginal offer for characteristic z_i equals the marginal price for characteristic z_i

at the optimum,

$$\frac{\partial \phi}{\partial z_i} = \frac{\partial p}{\partial z_i}. \quad (2.14)$$

Equilibrium conditions (2.7) and (2.14), indicate that the optimum quantity of a good's characteristic is consumed where the bid, offer, and price functions are tangent.

Thus, market equilibrium is determined by the producers and consumers bidding and offering prices for a bundle \mathbf{z} . The price $p(\mathbf{z})$ of a differentiated product is determined by market clearing conditions, where the number of products offered is equal to the number of products demanded at a given attribute vector \mathbf{z} . Each buyer and seller chooses to produce or consume a certain quantity of the good based on preferences and optimizing behavior. The market is assumed to be competitive, with an individual buyer or seller being unable to influence the price schedule $p(\mathbf{z})$.

Figure 2.1 displays how the interaction of consumers and producers determines the price schedule of a characteristic. I simplify the illustration by assuming that the product has only one characteristic z . Variable θ^1 and θ^2 are the bid functions of two consumers with different tastes or incomes. Variables ϕ^1 and ϕ^2 represent the offer functions of two producers with different technologies.

Drawing from Figure 2.1, the equilibrium price schedule $p(z)$ is determined by the tangencies of the sellers' offer and buyers' bid curves, where $\frac{\partial \phi}{\partial z} = \frac{\partial \theta}{\partial z} = \frac{\partial p}{\partial z}$. Here, the marginal price $\frac{\partial p}{\partial z}$ is the value of an additional unit of z . The slope of the offer curve $\frac{\partial \phi}{\partial z}$ measures the increase in price necessary to compensate the producer for producing one more unit of z . The slope of the bid curve $\frac{\partial \theta}{\partial z}$ represents the additional amount the consumer is willing to pay for one more unit of z .

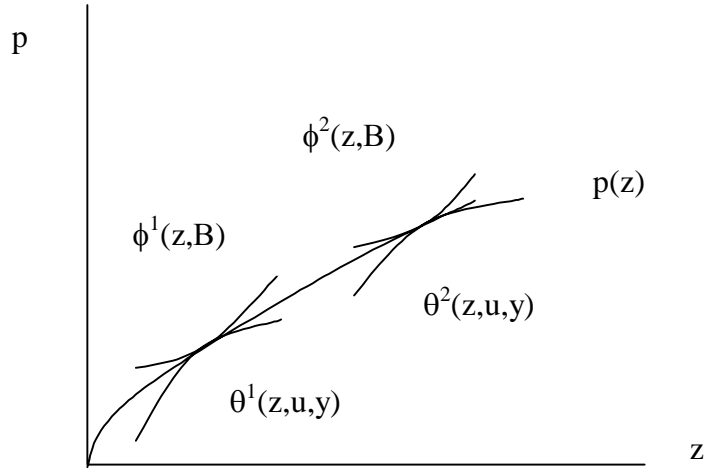


Figure 2.1: Hedonic Equilibrium

The equilibrium price schedule has received particular attention in measuring the marginal price of an environmental good. The marginal price of an environmental good can be extrapolated from an estimated hedonic price function $p(\mathbf{z})$ as long as $\frac{\partial \phi}{\partial z} = \frac{\partial \theta}{\partial z} = \frac{\partial p}{\partial z}$ holds. The hedonic approach is appealing since the price for a marginal change in the environmental good can be retrieved without explicitly identifying consumer and producer preferences. In the next section (2.1.2), I discuss how several studies exploit the equilibrium condition to obtain the marginal price of environmental quality implicit in the housing market. I also present the limitations of the approach, by presenting a few cases where the equilibrium condition may not be satisfied.

2.1.2 The Value of Environmental Quality Implicit in the Housing Market

Since housing prices are readily available, several studies apply the hedonic model to housing to obtain a value of environmental quality. In this section, I review the assumptions imposed for this purpose.²

The hedonic housing price model hinges on the assumption of housing market equilibrium. Buyers and sellers of homes bid and offer prices for housing units given exogenous levels of environmental quality. The tangencies of the bid and offer curves formed by the transactions of buyers and sellers of housing formulate a price schedule $p(\mathbf{z})$ that can be estimated using housing price data. The housing price differential for environmental quality $\frac{\partial p}{\partial z_i}$ is equal to the marginal willingness to pay for environmental quality $\frac{\partial \theta}{\partial z_i}$.

Auxiliary assumptions establish the use of housing price differentials for the measurement of a household's benefit from a marginal improvement in environmental quality. Households have complete information on variation in housing prices and levels of environmental quality. The price vector adjusts immediately to changes in demand or supply. Transaction and moving costs are zero. If moving or transaction costs do exist, then adjustment may only be an issue if the costs exceed the utility gain of moving in response to a change in environmental quality. Relatively high moving and transaction costs can result in imperfect or lagged adjustment. In both cases, the marginal implicit price and marginal willingness to pay of a housing attribute may not be equal. This could lead to an

²This section draws from Freeman (1979). Freeman presents an exhaustive description of the issues involved in using hedonic property value models to measure environmental benefits.

overstatement or understatement of marginal willingness to pay.³ A way of overcoming this condition is to use housing sales prices from individuals who recently entered the market. Recent homeowners have overcome the transaction costs.⁴

The hedonic function is assumed to be smooth and continuous. A smooth function is possible if there is a large number of housing units and substantial variation in prices and characteristics. A discontinuous hedonic function results from the lack of particular combinations of housing characteristics. If a continuum of housing attribute combinations is absent, then some households are unable to satisfy the first order conditions in their optimization problem. Under these circumstances, there may be a corner solution. The marginal implicit price will not represent equilibrium marginal willingness to pay.

The final assumption is that housing markets are unified and there are no barriers to entry. If submarkets do exist and are unaccounted for, estimates for the implicit prices of housing attributes will be biased.

³Consider the case where lag adjustment takes place because of high transaction costs. Under these circumstances, housing prices change, but households lag in their adjustment to the change because of high transaction costs. A possible consequence of the lag in adjustment is that the observed marginal implicit price schedule diverges from household willingness to pay. If housing prices increase due to an improvement in environmental quality, for example, *and* the marginal implicit price schedule consistently moves in one direction, then the marginal willingness to pay will be overstated. Households that prefer cheaper housing to improved environmental quality are not able to relocate speedily because it is too costly. Thus, their true willingness to pay is no longer reflected by the marginal price (Freeman, 1979).

⁴One potential shortcoming of this approach is by restricting the sample to recent homeowners one may further need to address issues of sample selection.

2.1.3 The Value of Environmental Quality Implicit in the Labor Market

The assumptions of the hedonic wage model are similar to the housing price model. To avoid repetition, I briefly discuss equilibrium in this context and any additional assumptions imposed in the hedonic wage model.

In the labor market, workers seek jobs in locations with desirable amenities, such as environmental quality. Each worker chooses a job with location attributes that maximizes his welfare with respect to wages. All else equal workers require higher wages to live in an area with poor environmental quality. Thus, the firm must offer workers compensating differentials in wages to attract workers to live in less desirable areas.

To measure the value of environmental quality, researchers typically assume a national labor market. If labor markets differ for each city, the firm cannot offer workers a premium for living in an area with poor environmental quality. Even though environmental quality, like air pollution, may greatly vary within a city, firms are unable to offer wages that account for distinctions in amenities by residential site. At equilibrium, a given vector of wages clears the labor market given the supply of labor and distribution of environmental quality across locations.

Cropper (1981) shows that the values of amenities implicit in the housing market are also embedded in wages. The mobility of workers requires that the prices of housing and other local goods adjust to account for inter-city differences in amenities. Because of this adjustment, firms must offer workers additional wages to account for the higher costs of living associated with highly desirable locations. Thus, the marginal prices obtained from hedonic models overstate the

compensation required for living in areas with less desirable amenities. They also include adjustments made on wages to account for differences in locations' costs of living.

The interdependence of the labor and land markets inspired economists, e.g., Roback (1982) and Blomquist, Berger, and Hoehn (1988), to reframe the hedonic model, so that land and labor markets are modeled concurrently. I adopt this approach in the dissertation. Before describing the model, I briefly discuss issues with identifying consumer preferences from the hedonic regression.

2.2 Identification of Consumer Preferences

In section 2.1, I demonstrated how a marginal change in environmental quality affects a market good's price using hedonic theory. If the measure of interest is instead how large changes in the environmental good affect welfare, then one needs the demand function for the environmental good.

The purpose of this section is to establish the issues involved in the identification of consumer preferences. Although I do not attempt to identify the demands for climate amenities in this dissertation, I present the material to reveal the strengths and weakness of using the marginal values of amenities as measures of welfare.

2.2.1 Estimating the Demand for Environmental Quality

The hedonic price schedule contains the points where the values of the marginal willingness to pay and marginal prices are equal for given levels of environmental quality z . However, estimating the demand function for each individ-

ual involves recovering each individual bid function. Since the tangencies of the bid and offer curves at market equilibrium are observed, only one point is known on each representative demand function. This means that one cannot deduce how much the consumer is willing to pay for other levels of z , unless it is assumed that all consumers are alike— with identical incomes and utility functions.

Figure 2.2 illustrates the distinction between marginal willingness to pay and marginal price. Two marginal willingness to pay curves are displayed for individuals 1 and 2, each representing the values of the slope of bid curves 1 and 2 at different levels of environmental quality z , $\frac{\partial \theta^1}{\partial z}$ and $\frac{\partial \theta^2}{\partial z}$. The marginal price curve $\frac{\partial p}{\partial z}$ (depicted as p_z in the figure) represents the slope of the hedonic function for various levels of environmental quality z . Each marginal willingness to pay curve intersects the marginal price curve at a point, which is what is observed when the hedonic price schedule is estimated. In order to obtain the marginal willingness to pay or marginal bid functions, additional assumptions on the hedonic model are imposed.

Rosen (1974) suggested two ways of estimating the marginal bid function for a good's characteristic. The first method involves imposing structure on the theoretical model to obtain a closed-form solution of the marginal bid function. The second method was less restrictive in its assumptions. Because a family of bid and offer curves are tangent to the price schedule due to differences in buyers' tastes and sellers' technologies, one can exploit the variation in marginal prices to estimate the actual bid and offer curves.

In practice, Rosen's second method involved three stages. First, the hedonic model is estimated regressing the price of the differentiated good on the goods' attributes. Second, the implicit marginal prices are computed. Third, two

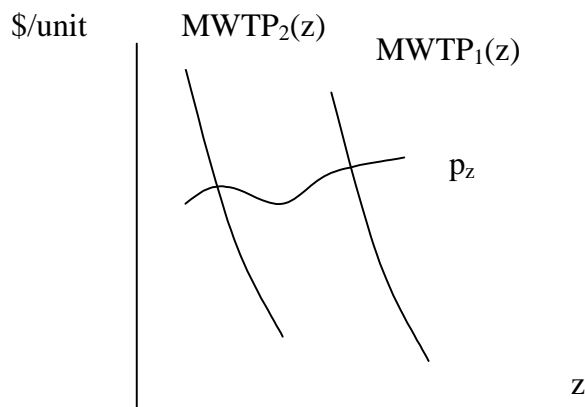


Figure 2.2: Marginal Willingness to Pay Versus Marginal Price

regressions are estimated as demand and supply functions where the marginal price is used as the endogenous variable in each regression, and the demand (i.e., quantity, income and other variables reflecting tastes), and supply (i.e. quantity and other variables reflecting industry costs) shift variables are included in each equation respectively.

Rosen's methodology is problematic. First, the methodology leads to inaccurate representations of the demand and supply functions. Because the demand function comes from the utility-maximization problem, the demand function must contain parameters relating to preferences. Taste parameters, however, cannot be identified from the hedonic price schedule. The inability to recover the true demand and supply functions using Rosen's procedure is commonly referred to as the identification problem.

Next, the estimation of the regressions proposed in the second-stage required further investigation. The feasibility of the estimation urged researchers to apply his technique. They found that there were additional endogeneity issues involved in the second-stage estimation. I discuss the issues of identification and

endogeneity in the ensuing sections.

2.2.2 Identification

To facilitate the explanation of the identification problem, it is important to review the definition of the bid function. Recall that the bid function is the amount of money necessary to take away from the consumer given his income w and bundle of attributes \mathbf{z} that leaves him with utility level u . The function itself is implicitly derived from the utility function as shown in expression (2.4). Therefore, the bid function includes preference parameters, which cannot be extracted from the hedonic price equation.

Also, conditions (2.6), (2.7), (2.13), (2.14) are equal to each other at market equilibrium. Thus, the marginal price depends on both the marginal rate of substitution and the marginal cost of producing the differentiated good. In order to estimate the demand and supply functions as Rosen suggested, one would need additional data on preferences and production technologies or to impose structure on the decision-making behavior in the model.

Brown and Rosen (1982) show that for the special case of a quadratic hedonic equation and linear demand and supply equations, the parameters in the demand and supply functions are not identifiable. They demonstrate how the structural parameters estimated in the second-stage are functions of the marginal price and the good's characteristics, and, therefore, do not add any new information to the model. The intuition behind this result is that the only variation in the marginal prices in the second-stage comes from the differences of quantities consumed by each buyer in the single market, which is not enough information to distinguish the marginal price function from the marginal bid function. They

suggest imposing structure on the system of equations or looking at multiple markets. In estimating the demand and supply functions assuming multiple markets, one must assume that the structural demand and supply parameters are identical across markets.

A recent example of imposing structure on a model to identify consumer preferences is in Bajari and Kahn (2003). They demonstrate a three-stage procedure used to recover willingness to pay for housing attributes. The technique is feasible under the following assumptions: i) utility is a function of the consumption of housing attributes and a composite commodity and is represented by a linear-logarithmic function, and ii) taste parameters are random and functions of demographic characteristics and a household-specific residual. The three-stage procedure involves, first, using local polynomial modeling to estimate the hedonic function and to compute the set of implicit prices for each metropolitan area.⁵ Next, they use the first order conditions from the theoretical model and the implicit prices from the hedonic regression to derive the individual preference parameters for each housing attribute. In the third stage, they regress the taste parameters on a vector of demographic characteristics using ordinary least

⁵In the first stage, Bajari and Kahn (2003) also recover an estimate for a housing characteristic unobservable to the economist but observable to the consumer. The unobserved housing characteristic is defined as the residual to the hedonic regression. Bajari and Kahn include this unobserved product attribute in the regression as a way of reducing potential omitted variable bias in the parameter estimates. From the onset, Bajari and Kahn note that applying this method hinges on the assumption that the unobserved housing characteristic is independent of the observed housing characteristics. An additional assumption is that the sample did not experience any housing or city shocks, which may be unobservable to the consumer yet still affect housing prices.

squares (OLS) to estimate the population distribution of tastes and demographics. The Bajari and Kahn method is one way of identifying consumer preferences for a good's attribute without having to assume multiple markets.

2.2.3 Endogeneity

The nature of the implicit market for a good's characteristic is such that the marginal price and quantity of a good's characteristics are simultaneously determined. By choosing the characteristic of a differentiated good, the individual is also choosing the price. This poses a problem in estimating the demand function in the second stage.⁶

Consider two regression equations. The first equation (2.15) represents the hedonic regression, where β is the vector of regression parameters. The second equation (2.16) represents the regression characterizing the demand for environmental quality z_i . It is a function of variables that might affect tastes α , and a vector of marginal prices \mathbf{p}_z for housing attributes (including environmental quality) estimated from the first regression.⁷

$$p = f(\mathbf{z}; \beta) + \varepsilon_1, \tag{2.15}$$

$$z_i = g(\mathbf{p}_z; \alpha) + \varepsilon_2 \tag{2.16}$$

The problem arises because the hedonic function in (2.15) may be non-linear. Marginal prices may then vary with \mathbf{z} . The assumption that each explanatory variable in (2.16) is independent of the error term is violated, i.e.

⁶The supply side need not be considered as long as the researcher uses disaggregate data and it is assumed that the individual does not have any influence in the determination of supply.

⁷Equation (2.16) is called the inverse marginal bid function. As I will show, Bartik (1987a) proposes the same problem exists with the estimation of the marginal bid function.

$E[p_{z_i} | \varepsilon_2] \neq 0$. The parameters estimated in the second regression using OLS will thus be inconsistent.

In addressing this issue, Palmquist (1984) suggests using an instrumental variables (IV) approach. Before estimating the demand function, he regressed the endogenous variables (the marginal characteristic prices) on linear and quadratic terms of exogenous socioeconomic and urban dummy variables.⁸ He then included the predicted values for the marginal prices of housing attributes as instruments in the final estimation of the demand for a particular housing characteristic.

Bartik (1987b) noted the perfect instruments for estimating the marginal bid function are those that exogenously shift the budget constraint and remain uncorrelated with unobserved tastes. He estimates the marginal bid function for neighborhood physical condition using a sample of households subject to an experimental treatment: some receiving subsidies for rent and others receiving income transfers.⁹ He interprets external income sources as instruments for the quantity of physical condition and non-housing expenditures. The idea is that given additional wealth, individuals will buy greater quantities of most goods. Thus, the instruments reflect the influence of wealth on the consumption of these goods, not taste differences independent of wealth. He finds that the OLS parameter estimates on physical condition and non-housing expenditures were positively biased in comparison to the 2SLS parameter estimates.¹⁰

⁸The socioeconomic characteristics must be uncorrelated with the unobserved variables implicit in the error term (ε_2 in expression (2.16)).

⁹In the experiment, households were randomly assigned to one of the two treatment groups.

¹⁰Bartik describes why one might expect the OLS estimates to be positively biased. Suppose two consumers are identical in all characteristics except for their consumption of z . The fact that the consumer that obtains greater quantities of z reflects that she has greater tastes for

In another study, Bartik (1987a) reveals how the instruments applied in most hedonic studies using single market data are in fact correlated with unobserved tastes. He concludes that unbiased estimates of parameters in the marginal bid function are obtainable only when using multi-market data. In using multi-market data, individuals with similar tastes and demographic characteristics have different marginal prices which are attributed to different supply conditions across markets.

Recent studies explore the implications of estimating demand functions for public goods when location amenities are endogenous. Households may choose the optimal level of a given amenity by selectively sorting themselves in a given location where that level of the public good is provided.¹¹ If households do selectively sort themselves in locations with desirable amenities, then again the level of the amenities are endogenous and the parameter estimates on these quantities in the marginal bid function are also biased.

Since dealing with the issue of sorting can be problematic and data intensive, researchers have tried to first test if residential sorting in fact exists. Hoyt and Rosenthal (1997) test for sorting using housing prices from the American Housing Survey. They exploit the condition that the marginal benefits of location amenities for families living in the same location are equal if sorting exists. To test their hypothesis, Hoyt and Rosenthal estimate two model specifications.

the good. This suggests that there are unobservable variables that capture tastes in the error term which are positively correlated with z . Failure to account for this endogeneity will lead to a positive bias on the OLS estimate for the coefficient on z .

¹¹The urban economics literature refers to this phenomenon as Tiebout sorting. In Tiebout sorting, individual households are freely mobile and choose the optimal value of a public good by sorting themselves in communities offering that level of the good, "voting with their feet".

The first specification is a location-difference model. A regression is estimated for each time period. The second specification consists of a double-fixed effect model where spatial and time-specific effects are differenced. Hoyt and Rosenthal propose that both model specifications will yield consistent estimates if sorting exists. If sorting is inefficient or does not exist, then only the double fixed-effect model will produce consistent estimates of the housing structural parameters.

The first phase of the analysis consists of estimating the following regression for each time period t and $t - 1$:

$$P_{is,t} - \bar{P}_t = \alpha_H(H_{i,t} - \bar{H}_{s,t}) + \alpha_B(B_{is,t} - \bar{B}_{s,t}) + \varepsilon_{is,t}, \quad (2.17)$$

where P refers to housing price; B refers to location amenities; i , s , and t are indices signifying household, spatial cluster, and time respectively; and $\bar{H}_{s,t}$ and $\bar{B}_{s,t}$ refer to the averages of housing structural characteristics and location amenities within a spatial cluster and for a particular year. Hoyt and Rosenthal note that $B_{is,t} - \bar{B}_{s,t}$ is zero if sorting exists. Excluding the term from the regression, therefore, should not affect the remaining parameters of the model.

In the second phase, Hoyt and Rosenthal estimate the following regression:

$$\begin{aligned} (P_{is,t} - \bar{P}_t) - (P_{is,t-1} - \bar{P}_{t-1}) &= \alpha_H[(H_{i,t} - \bar{H}_{s,t}) - (H_{i,t-1} - \bar{H}_{s,t-1})] \quad (2.18) \\ &+ \alpha_B[(B_{is,t} - \bar{B}_{s,t}) - (B_{is,t-1} - \bar{B}_{s,t-1})] + [\varepsilon_{is,t} - \varepsilon_{is,t-1}]. \end{aligned}$$

The model in (2.18) provides consistent estimates irrespective of the absence of sorting because the location amenities and averages of the location amenities for a spatial cluster do not change over time, i.e. $[(B_{is,t} - \bar{B}_{s,t}) - (B_{is,t-1} - \bar{B}_{s,t-1})] = 0$. If Hoyt and Rosenthal's hypothesis is true then the estimated value of α_H will be similar in both models. The results from both model specifications suggest

that households may sort themselves efficiently among locations based on their preferences of location amenities.¹²

2.2.4 Limitations of Using the Hedonic Approach to Measure Welfare Effects

The abovementioned discussions of identification and endogeneity issues illustrate why studies usually refrain from estimating the demand for environmental quality. Estimating the marginal values of amenities is useful particularly when there are doubts regarding the impact of environmental quality on prices of differentiated goods. The focus of this study is on the hedonic techniques used to impute the marginal values of climate amenities. Much of the dissertation is dedicated to determining the robustness of the marginal values, as well as the plausibility that climate amenities affect housing prices and wages in Brazil. Because this study focuses on estimating the marginal values of climate, I briefly mention the limitations of using these values to measure the effect of changes in environmental quality on welfare.

First, I measure the effect of a marginal change in climate amenities on housing prices and wages. The marginal value of an amenity may be useful to gauge whether improvement of environmental quality is desirable (Freeman,

¹²Hoyt and Rosenthal (1997) recognize that if the marginal benefits from location-specific amenities differ for families in a given location then the parameters on the housing structural characteristics in both models may still be consistent if these differences are not correlated with the housing structural characteristics. Because inefficient sorting may exist, they recognize that the conclusion to their test is “a necessary but not sufficient condition for Tiebout sorting” (Hoyt and Rosenthal, 1997).

1993). If the basis of a study is to obtain the value of a specific change in environmental quality, however, it may be more useful to evaluate a non-marginal change in the amenity. For example, one may be interested in the values of non-marginal changes in amenities to evaluate the benefits of a particular environmental policy. As mentioned, the identification of preferences and issues of endogeneity preclude such efforts.

Next, the value of a non-marginal change in a given amenity is accurately reflected by the change in the marginal price evaluated at the original hedonic function, if a few households are affected by the amenity change. The value of a non-marginal change in the amenity under these circumstances does not represent individual willingness to pay, however. Suppose an improvement in environmental quality occurs within a localized area causing prices of an asset to increase to the price level of assets with similar characteristics in other areas. In this case, the hedonic price schedule remains the same. Assuming transaction costs are equal to zero, consumers of assets with the improvement will opt to consume assets without the improvement, maintaining their original level of utility. The welfare effect, thus, is the gain to the owners of the assets affected by the improvement in environmental quality (Palmquist, 1991).

If the amenity change is substantive, as may be the case for changes in climate, the welfare of both consumers and producers is affected. Thus, the hedonic price schedule itself changes. By not accounting for the adjustment processes, the measure of a non-marginal change in the amenity calculated using the original hedonic function is an upper bound to the true benefits of the change in environmental quality (Kanemoto, 1988; Bartik, 1988).¹³ In this dissertation, I

¹³In their survey, Bartik and Smith (1987) derive an exact measure of the individual benefit

calculate the upper bound of the welfare effect from a change in climate amenities throughout Brazil.

In the remaining section, I describe the Roback model applied in this dissertation. Roback derives an analytical expression for the marginal value of an amenity, when land is fixed and the amenity jointly affects the production and consumption of goods. The important artifact of this model is that the marginal values of amenities depend on both changes in housing rents and wages. This finding is exploited in the dissertation to impute the marginal values of climate amenities.

2.3 The Roback Model

Roback (1982) expressed two major criticisms of using hedonic models to measure the value of a location amenity. First, hedonic models typically exclude the role of firm behavior. Studies usually focus on how amenities affect workers. For example, the focus is on measuring the payment necessary to compensate a

 from an improvement in environmental quality:

$$\int_{q_j^0}^{q_j^1} \frac{\partial p}{\partial q_j} [q_j, \mathbf{a}] dq_j \quad (2.19)$$

where q_j represents environmental quality at location j , \mathbf{a} is a vector of amenities left unchanged, and $\frac{\partial p}{\partial q_j}$ describes the change in the hedonic price function from the improvement. The advantages of using (2.19) as a measure of benefits is that it accounts for the relocation of households in response to a change in environmental quality and housing prices, and knowledge of the marginal bid function is not required (Freeman, 1993). In practice, expression (2.19) is not readily calculated because it involves knowing the equilibrium hedonic price function for all distributions of amenities.

worker for accepting an additional unit of a disamenity. These studies, however, ignore firms' choices in locating to a given area and how firms are able to pay for the wage premium provided to workers (Palmquist, 1991).¹⁴

Second, hedonic models look at only one aspect of the location problem: property values or wages. Location choice depends on both. Because land is fixed, hedonic equilibrium depends on labor and land markets to clear simultaneously. Thus, it is not enough to observe how amenities affect wages or property values separately. One must understand through the interconnectedness of labor and land markets how amenities affect both markets. In her paper, Roback develops a general model of interurban equilibrium to elicit the interrelation between land and labor markets in equilibrium, and decompose the factors that influence the full implicit prices of amenities.¹⁵

In what follows, I describe the interurban equilibrium model.¹⁶ Using the equilibrium conditions from the model, I derive the expression for the marginal value of an amenity. Using diagrammatic illustrations, I show how the use of data can help economists determine the signs of the marginal values without imposing restrictive assumptions on production technologies or preferences.

¹⁴The marginal price at equilibrium is not only dependent on the marginal valuation of the consumer but the marginal cost of the producer.

¹⁵Roback (1982) ignores intra-city variation in amenities and assumes that city boundaries are fixed. Berger, Blomquist, and Hoehn (1988) extend the Roback model to account for within-city variation of amenities and flexible city boundaries.

¹⁶Roback (1982) revealed the expression for imputing the full implicit price of an amenity accounting for how housing prices and wages are influenced by marginal changes in location amenities, but did not describe the underlying model explicitly.

2.3.1 Interurban Equilibrium

I assume that each head of household chooses to work and live in city so that he maximizes his utility $U(x, \mathbf{z})$ subject to his budget constraint $w(\mathbf{z}) - p(\mathbf{z}) - x$.¹⁷ His utility depends on the consumption of a composite commodity x , and city amenities \mathbf{z} . Amenities are obtained indirectly in the purchase of housing and employment in the city. Each head of household is endowed with one unit of labor.¹⁸ Earnings are received from local firms in exchange for labor, and spent on housing and the composite commodity.¹⁹ The head of household's indirect utility function is expressed as a function of wages, rents, and the available amenities: $V(w, p; \mathbf{z}) = k$.

There are two industries represented in this economy: producers of x and housing h . Firms minimize costs in producing x and h in a city using labor and land. The commodities are produced under constant returns to scale. The unit

¹⁷It is assumed that each head of household lives in one residence and the return to land is included in the price of housing.

¹⁸Roback (1982) also assumes labor is homogeneous and tastes are identical among workers. Because the variation in housing price and wage data most likely reflects individual taste differences, Roback further assumes that individuals can be divided into groups with strong and weak preferences for amenities. Those with strong preferences are willing to accept a lower wage than individuals with weak preferences for an additional unit of the amenity. A similar argument can be made for the rent gradient. The implications of this assumption are that the price for a marginal change in the amenity is an average of the true prices for various groups. For example, the wage differential will underestimate (overestimate) of the true differential for individuals with strong (weak) preferences (Roback, 1982). The problem can be overcome with the use of household level data.

¹⁹Roback (1982) assumes that heads of households work and live within the same city, so that transportation costs are negligible and therefore not included in household expenditures.

cost functions of the composite commodity and housing are: $C(w, r; \mathbf{z}) = 1$ and $G(w, r; \mathbf{z}) = p$, which depend on workers' wages w , the price of land r , and the level of amenities in the city \mathbf{z} .

Interurban equilibrium is achieved when the unit production costs are equal to the unit product price, households across all cities obtain utility level k , and the total output of traded and non-traded goods is equal to their total consumption. Equilibrium conditions (2.20), (2.21), and (2.22) determine the wage, price of land, and housing price as functions of amenities in a particular city.

$$V(w, p; \mathbf{z}) = k \tag{2.20}$$

$$C(w, r; \mathbf{z}) = 1 \tag{2.21}$$

$$G(w, r; \mathbf{z}) = p \tag{2.22}$$

Using the equilibrium conditions, the expression for the willingness to pay for a marginal change in the amenity is recovered. Totally differentiating (2.20) and rearranging terms yields:

$$\frac{\frac{\partial V}{\partial z_i}}{\frac{\partial V}{\partial w}} = -\frac{\partial w}{\partial z_i} - \frac{\frac{\partial V}{\partial p}}{\frac{\partial V}{\partial w}} \frac{\partial p}{\partial z_i}. \tag{2.23}$$

Roy's identity implies $\frac{\frac{\partial V}{\partial z_i}}{\frac{\partial V}{\partial w}} = -h$. Substituting this expression in (2.23) gives an expression for the amount of income necessary to compensate the individual for a small change in amenity z_i :

$$\frac{\frac{\partial V}{\partial z_i}}{\frac{\partial V}{\partial w}} = h \frac{dp}{dz_i} - \frac{dw}{dz_i}. \tag{2.24}$$

The expression for marginal willingness to pay has two parts: the willingness to spend more for a house in a desirable area, and the willingness to forgo income to work in the desirable area. The expression illustrates that the willingness to

pay for a small improvement in an amenity depends on how the amenity affects housing prices and wages directly.²⁰

The estimates of $\frac{\partial p}{\partial z_i}$ and $\frac{\partial w}{\partial z_i}$ are obtained from the empirical rent and wage regressions:

$$P_{ij} = f(S_{ij}, N_j, Z_j; \beta) + \varepsilon_{ij} \quad (2.25)$$

$$w_{ij} = g(D_{ij}, N_j, Z_j; \gamma) + \eta_{ij}, \quad (2.26)$$

where i represents the individual, and j the location; P is the monthly price of the residence; w is the head of household's monthly wage; S_{ij} is a vector of structural characteristics of the house or apartment; D_{ij} is a vector of demographic characteristics; N_j is a vector of neighborhood characteristics; Z_j is a vector of public goods or environmental attributes; β and γ are vectors of parameters specifying the functional relationship between P , S , N , and Z , and w , S , N , and Z ; and ε_{ij} and η_{ij} are the idiosyncratic error terms, capturing characteristics unobservable to the researcher. Having estimated (2.25) and (2.26), the implicit price of an environmental good z_i is computed using the estimated coefficients from (2.25) and (2.26).²¹

Typically, researchers estimate (2.25) or (2.26) to measure the value of a marginal change in a given amenity. In doing so, they are assuming that the amenity does not affect the production of goods. To illustrate the restrictiveness of the assumption, I compare the effects of amenity variations on real estate

²⁰Since each head of household lives in one residence, h is assumed equal to 1.

²¹If the hedonic regressions were linear in the amenities, one could simply use the coefficients on the amenity variables in the housing price and wage regressions in calculating (2.24). Because most hedonic regressions are non-linear, the housing price and wage differentials are non-linear functions of the coefficients.

values and wages when the amenities i) do not affect production, ii) adversely affect production, and iii) enhance production.²²

Consider two cities with amenity levels z_i^1 and z_i^0 , $z_i^1 > z_i^0$, as shown in Figure 2.3. Since migration is costless, individuals obtain the same level of utility across locations at equilibrium, $V(w^0, p^0, z_i^0) = V(w^1, p^1, z_i^1)$. For this condition to hold, it must be true that (all else equal) consumers in the city with greater units of the amenity z_i^1 pay greater real estate prices and earn lower wages than consumers in the city with less units of the amenity z_i^0 . This is why the indifference curve $V(w^1, p^1, z_i^1)$ lies above $V(w^0, p^0, z_i^0)$.

Assume the amenity does not affect the production of goods. Production costs do not depend on amenity quantities. They are also equal across locations $C(w^0, p^0, z_i^0) = C(w^1, p^1, z_i^1)$. For this case, a unit increase in a given amenity leads to an unequivocal positive differential on real estate values $\frac{\partial p}{\partial z_i}$, and negative differential on wages $\frac{\partial w}{\partial z_i}$.

Now, assume the amenity adversely affects production (Figure 2.4). For firms to be indifferent in producing x and h between cities, the factor prices must also be lower in the city with greater units of the amenity, since the presence of the amenity incurs additional costs to production. As a result, greater housing prices and lower wages prevent an excess of workers from migrating to cities with greater levels of amenities. Similarly, higher real estate values prevent an excess of firms from migrating to cities with greater levels of amenities. These confounding factors cause the wage differential to be negative and the housing price differential

²²The model distinguishes between housing prices and land values. For clarity of illustration, I focus on one value for residential and commercial real estate p that affects utility and costs. The price of residential and commercial real estate depends on the value of land r , but is not discussed here explicitly.

to be ambiguous.

Now assume the amenity enhances production (Figure 2.5). For firms to be indifferent to producing x between cities, the factor prices must be lower in the city with less units of the amenity z . Lower housing prices and greater wages attract some workers to cities with less amenities. Lower real estate values attract some firms to cities with less amenities. Under these conditions, the wage differential is ambiguous and the housing price differential is positive.

Equations (2.20), (2.21), and (2.22) are used to show explicitly the effect of a change in a given amenity on housing prices, wages, and rents. The equilibrium wage, housing price, and land rent differentials are solved for using the total differential of equation system:²³

$$\begin{bmatrix} V_w & V_p & 0 \\ C_w & 0 & C_r \\ G_w & -1 & G_r \end{bmatrix} \begin{bmatrix} \frac{dw}{dz_i} \\ \frac{dp}{dz_i} \\ \frac{dr}{dz_i} \end{bmatrix} = \begin{bmatrix} -V_{z_i} \\ -C_{z_i} \\ -G_{z_i} \end{bmatrix}. \quad (2.27)$$

The housing price, land price, and wage differentials are equal to respectively:

$$\frac{dp}{dz_i} = \frac{1}{\Delta} \{V_{z_i} [G_r C_w - G_w C_r] - C_{z_i} [V_w G_r] + G_{z_i} [V_w C_r]\}, \quad (2.28)$$

$$\frac{dr}{dz_i} = \frac{1}{\Delta} \{-V_w C_{z_i} - V_p [C_{z_i} G_w - G_{z_i} C_w] + V_{z_i} C_w\}, \quad (2.29)$$

$$\frac{dw}{dz_i} = \frac{1}{\Delta} \{-V_{z_i} C_r - V_p [G_{z_i} C_r - C_{z_i} G_r]\}, \quad (2.30)$$

where $\Delta = V_w C_r - V_p (C_w G_r - C_r G_w) > 0$.²⁴

²³For simplicity, the following comparative statics show the effect of an increase in a unit of a single amenity z_i on wages, housing prices, and land rental prices.

²⁴Using the definitions of the factor shares in each industry and the fact that the sum of the factor shares are equal to one, Roback (1980) shows that $\Delta > 0$.

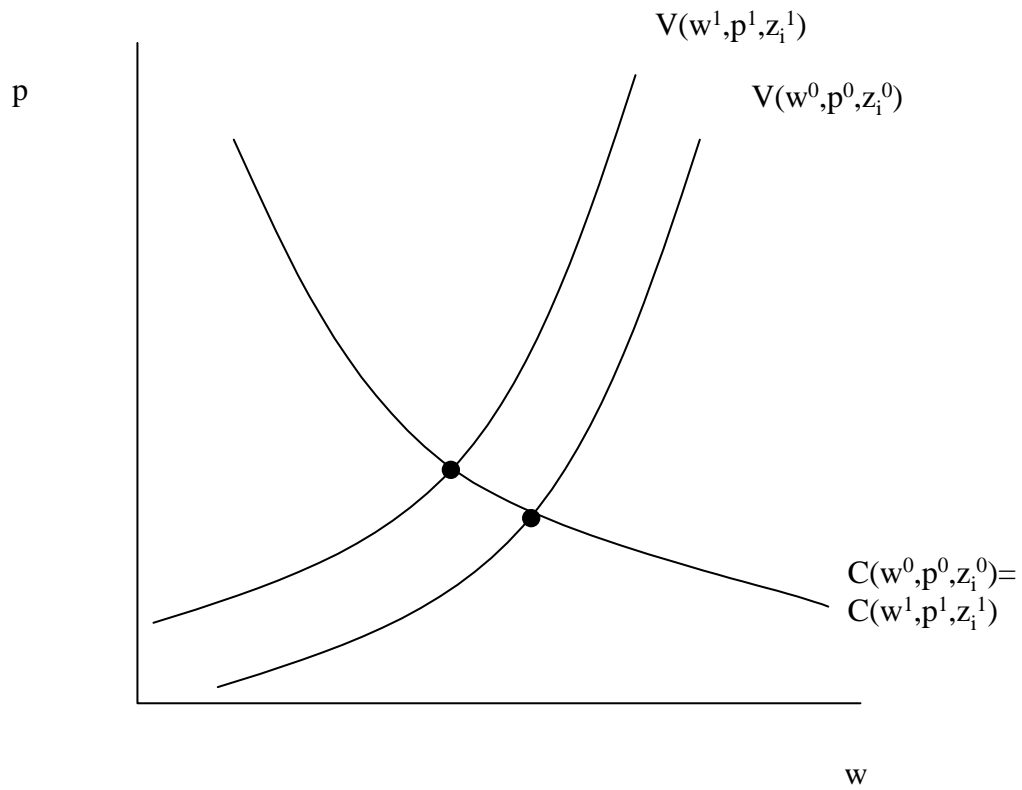


Figure 2.3: Effects On Real Estate Prices And Wages When The Amenity Does
Not Affect Production

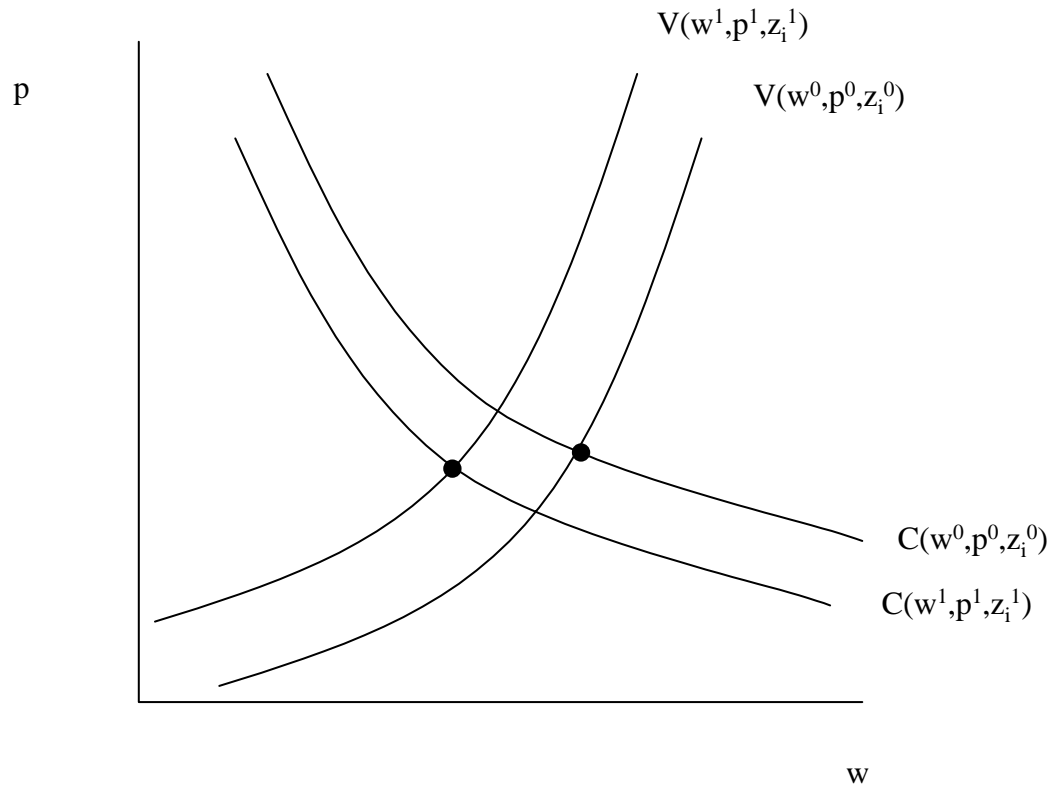


Figure 2.4: Effects On Real Estate Prices And Wages When The Amenity Adversely Affects Production

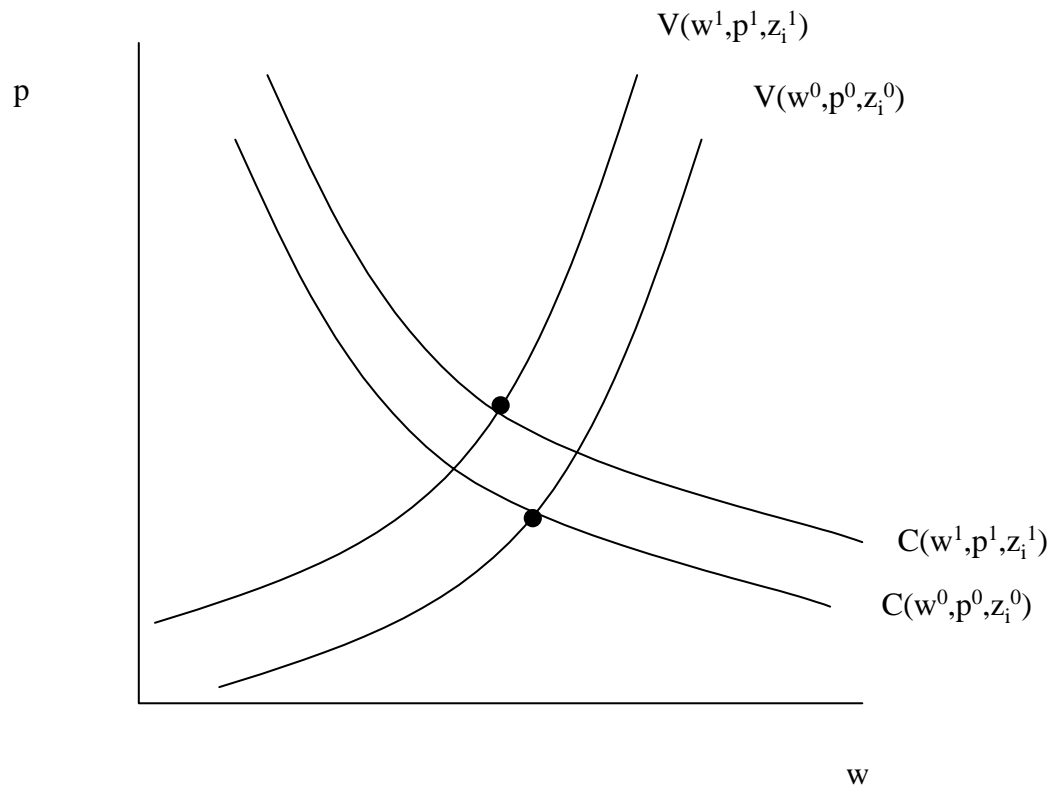


Figure 2.5: Effects On Real Estate Prices And Wages When The Amenity
Enhances Production

In determining the sign of (2.24), the signs of (2.28) and (2.30) are essential. The housing price differential (2.28) depends on the effect of an increase of the amenity on welfare (the first term),²⁵ the effect on the production costs of the composite commodity (the second term), and the effect on the production costs of housing (the third term). The wage differential (2.30) also depends on how the amenity affects welfare in terms of the effect it has on wages, and on the costs of production. Based on (2.28) and (2.30), it is evident that only for the case of the amenity being neutral to production will an increase in the amenity lead to a positive differential on housing prices and a negative differential on wages (Figure 2.3).²⁶

Roback (1982) uses this model to demonstrate the difficulty in obtaining the value of an amenity compared to a model that looks at the variation in land

²⁵It can be shown that the first term can also be expressed as the effect of an increase in a given amenity on welfare in terms of how the change affects income and the prices of goods consumed. Totally differentiating (2.21) yields: $V_w \frac{dw}{dp} \frac{dp}{dz} + V_p \frac{dp}{dz} + V_z = 0$. Rearranging terms, $\frac{dp}{dz} = \frac{-V_z}{V_w \frac{dw}{dp} + V_p}$.

Solving for $\frac{dw}{dp}$ by totally differentiating (2.21) and (2.22), and plugging in $\frac{dw}{dp}$ in the expression above yields the following after the simplification of terms: $\frac{dp}{dz} = \frac{V_z[G_r C_w - G_w C_r]}{\Delta}$.

²⁶If the amenity is neutral to the production of x and h (i.e. $C_z = G_z = 0$), the wage differential will be unambiguously negative. The housing price differential is unambiguously positive if the production of housing is land intensive. This can be shown by applying Shephard's Lemma to (2.28). In doing so, the housing price differential can be expressed in terms of the factors of production of the composite commodity and housing,

$\frac{dp}{dz}|_{C_z=G_z=0} = \frac{1}{\Delta} \left\{ \frac{V_z}{h} \left[\frac{A^h}{A^x} - \frac{L^h}{L^x} \right] \right\}$, where A_h and A_x are the units of land used in the production of housing and the composite commodity, and L_h and L_x are the units of labor used in the production of housing and the composite commodity. Thus, implicitly, I assume that the production of housing is land intensive.

prices and/or within city amenity variation. Models of intra-city price differences do not face the issues discussed for two reasons. First, the productivity of the housing industry within cities is likely to be similar. Next, wages are independent of location for identical individuals because jobs are obtained anywhere in the city. Thus, housing prices rise with an increase in the amenity. To show the effect of an amenity on housing price in the intra-city context, I refer to the following expression obtained by totally differentiating (2.22):

$$\frac{dp}{dz} = G_w \frac{dw}{dz} + G_r \frac{dr}{dz} + G_z. \quad (2.31)$$

For the case of intra-city amenity differences, housing price is directly related to the effect of an increase in an amenity on land rents, which is unambiguously positive.

In the interurban equilibrium context, the theoretical ambiguity of the value of a given amenity can be resolved through the use of empirical work. Here, I apply the interurban equilibrium theoretical framework. Estimation of equations (2.25) and (2.26) allows for the calculation of the housing price and wage differentials. The housing price and wage differentials are then used to compute the marginal values of climate amenities in Brazil.

Chapter 3

A Review of Hedonic Studies Measuring Climate Amenity Values

In this chapter, I review the relevant literature on using hedonic models to measure the values of climate amenities. Most hedonic models include climate to capture the appeal of a city as it affects housing prices and wages. Workers are attracted to jobs in a city that has favorable climate conditions. The influx of people will increase the labor supply, depressing wages. Since these individuals require housing in the city, demand for housing shifts upward, causing housing prices and rents to rise.

Given the growing interest in the economic consequences of climate change, several recent studies have examined the value of climate. In the context of climate change, the scope of the effect is often large. In such cases, general equilibrium models are appropriate to measure the effect of climate change at the national level.

Additionally, climate may affect both production and utility. Typically, hedonic studies assume climate has minimal influence on nonfarm output. The model applied in this dissertation relaxes this assumption. A change in climate

could affect firm costs in metropolitan areas, however. For example, firms' energy costs may rise due to the enhanced need for air conditioning when summer temperatures increase. The costs may be even more devastating in a developing tropical country like Brazil that may lack resources for mitigation.

In chapter 2, I showed how the effect of a change in an amenity on land rents, housing prices, and wages is ambiguous when the amenity influences firm costs. The total value of a change in climate cannot be explained by the wage or housing price gradients alone (Roback, 1982).

In what follows, I first review the literature which uses a single market to evaluate the impact of changes in climate amenities on urban markets.¹ Next, I discuss the studies that evaluate the effect of climate change on both housing prices and wages. These studies are based on an interurban equilibrium model, monitoring the effects of climate change on both national housing and labor markets. In reviewing this literature, I distinguish between two candidate empirical models: continuous versus discrete choice models. The continuous choice model that I use is the empirical derivative of the interurban equilibrium model discussed in Chapter 2. I also review recent studies using discrete choice models to measure the values of climate amenities. The distinction between the two empirical models is discussed in the context of the papers reviewed.

¹I do not cover studies such as Mendelsohn, Nordhaus, Shaw (1994), and Schlenker, Hanemann, and Fisher (2005) that concentrate on agricultural property values.

3.1 Values of Climate Amenities Implicit in a Single Market

One type of application of the hedonic model estimates the effect of a marginal change in an amenity on housing prices. In an intra-city framework, it may be possible to obtain the complete value of a change in climate from housing prices if there is enough variation in the amenity in one metropolitan market. By assuming a national labor market, another approach estimates the values of changes in climate amenities reflected by variations in wages. Since firms adjust wages for standard of living differences (also affected by amenities), the amenity values obtained using the hedonic wage gradient overstate willingness to pay for marginal changes in amenities (see Section 2.1.3). In the next two sections, I review studies that measured the impact of climate amenities on housing prices (Section 3.1.1) or wages (Section 3.1.2).

3.1.1 Housing Price Studies

Englin (1996) measures the value of changes in average rainfall and of changes in rainfall variation. By regressing housing sale prices on a set of real estate and rainfall characteristics in the Olympic Peninsula of Washington state. The rainfall variables vary by house, which is advantageous for the purpose of identifying the effect of weather when the housing market is concentrated in a single county. He interpolates average and standard deviation of rainfall data for each household based on the information from the two closest weather-reporting stations.

Studies that measure the value of rainfall nationwide require calibrating

the impact on both housing prices and wages. A drawback of national data is that it becomes difficult to obtain the data to capture accurately the value of rainfall within two markets. By reducing the region of analysis to a micro-climate with rainfall variation, Englin can justify confining the analysis to the housing market. One limitation in his analysis is the exclusion of other amenity variables relevant to housing sales. In this case, it would require more spatially diverse amenity data, which may or may not be relevant.

3.1.2 Wage Studies

Hoch and Drake (1974) were among the first to measure the effect of changes in climate amenities for the purpose of predicting the damage from climate change. They estimate a wage regression for each occupation group in the U.S., using climate variables to explain wage differentials.² They use the ratio of predicted wages given the changes in climate and predicted wages under the status quo to estimate the effect on wages. They compute this index with various changes in temperature and precipitation variables. The paper explores the use of different climate-related variables, as well as potential nonlinear effects of climate on wages by including higher order terms. The authors conclude that i) climate variables do significantly influence wages (especially the negative impact of greater summer temperature) which affects standardized wages negatively; and ii) climate factors affect wages in a nonlinear fashion.

Nordhaus (1996) estimates a hedonic wage equation to obtain the value of climate change in the U.S. as predicted by general circulation climate models.

²Wages are standardized for each occupational group by dividing the wages of each individual by her occupation's average wage and multiplying by 100.

In the analysis, he addresses two issues. First, he allows labor supply to be endogenous. To obtain consistent estimates of climate parameters, he includes employment in export industries (in a county per unit area) as an instrument in the wage equation for labor supply.³ He shows that simultaneous equation bias is a serious problem: the OLS estimate of the temperature coefficient is twice as large as the IV estimate. Second, he uses a specification bootstrap test to show how results are sensitive to model specification. He concludes that there is a large degree of uncertainty in the values of changes in climate. He estimates a 0.35 percent impact on wages from climate change with a standard error of 5 percent. He attributes the error largely to the complexity of labor markets and noisy wage-temperature relationship.

Maddison and Bigano (2003) evaluate the marginal impact of changes in climate amenities in Italy using a hedonic net income model. Net income is classified as a province's average annual income deducting taxes and housing costs. The measured effect of a change in a climate amenity is similar in spirit to that calculated in (2.24). Because data on dwelling characteristics was unavailable, the authors estimated the effect of climate change on the net difference rather than attempting to disentangle the effect in two markets.

Maddison and Bigano is one of the first studies that assesses the value of climate amenities outside of the U.S. The geography and topography of Italy varies greatly throughout the country making it particularly suitable for this purpose.

³Nordhaus argues that broad export employment is independent of climate and other omitted labor-supply variables. Broad exports comprise mining, fisheries, and other industries dependent more on natural resources and geographical characteristics than labor supply variables.

Maddison and Bigano acknowledge that some of the climate parameters may capture household preferences' for amenities correlated with climate, such as fauna and flora. It may be difficult to measure household preferences' for precipitation for this reason, as factors like lush environment, national parks, and natural beauty are correlated with precipitation levels.

3.2 Values of Climate Amenities Implicit in Two Markets

3.2.1 Interurban Equilibrium Models of Continuous Location Choice

In Chapter 2, I described the Roback model(1982) and showed how to calculate the values of changes in amenities using property value and wage data. In her empirical analysis, Roback includes heating degree days, total snowfall, number of cloudy days, and number of clear days in her wage and land price regressions. With the exception of the number of clear days, all of the climate variables had a positive sign in the wage regression.⁴ Many of the parameter es-

⁴One drawback of the analysis was that all climate variables were not at once included in the same regression. She estimates four wage and residential site value regressions, each including a different climate variable. The combined effect of climate variables may be more important than the individual effect on wages and site prices. For example, temperature may affect wages but the magnitude of the effect will greatly depend on the location's altitude and rainfall. Omitting variables relevant to the wage and regression models results in biasing the remaining regression parameters if the excluded and included variables are correlated. From her results, it is clear the coefficients on the variables held constant across models vary by model specification.

timates from the property value regression were insignificant, however. The data source used in the analysis overrepresented low-income households, restricting the variation in land prices. Recognizing the limitations of the analysis, Roback shows as an illustration how one could compute the value of an amenity change using the results from hedonic wage and property value regressions.

Blomquist, Berger, and Hoehn (1988) adapt the Roback model to measure the values of amenities in the U.S. In their model, they allow for within-city amenity variation as well as across-city amenity variation. Two notable features of their model differ from the Roback model. Production depends on city size which is treated as endogenous to the system. City size is determined by the population of a given county, which also is a function of wages, housing prices, and amenities.⁵

The Blomquist, Berger, and Hoehn model produces an analytical expression for the value of an amenity similar to the expression derived in Roback. The amenity value is the difference in the housing price and wage differentials by county, in their case. These wage and housing price differentials are estimated using housing price and wage regressions as shown in Roback.⁶ Unlike Roback, they use a more comprehensive and extensive dataset, which includes individual wages and housing price data from 253 counties in the U.S.

⁵By assuming firms' production depends on city size, the authors are essentially accounting for agglomeration effects. A given amenity in one county causes a change in the county's size, in turn, affecting the cost of firms in adjacent counties. This ultimately also influences the wages and housing prices in adjacent counties.

⁶They also point out that biases may surface in calculating the value of a given amenity due to the correlation of amenities across counties in a given urban area. In their paper, they show analytically that the biases cancel out.

Of the numerous county-level variables, Blomquist et al. include six climate variables: precipitation, humidity, heating degree days, cooling degree days, wind speed, and sunshine. There are two interesting features of their empirical findings. First, only two variables consistently have alternative signs in both wage and housing price regressions: humidity and sunshine. Humidity is considered a disamenity, and sunshine an amenity in both markets. These findings imply that production of housing and other commodities in U.S. urban areas may be independent or less affected by humidity and sunshine (see Figure 2.3). This is not too surprising given the type of goods produced in U.S. cities (i.e., manufactured, industrial, and services). Second, the signs of the coefficients on rainfall, heating and cooling degree days, and wind speed indicate that these variables may in fact affect the production of goods. It is difficult to interpret the meaning of the coefficients without modeling the consumer and producer behavior explicitly, and obtaining additional information on preferences and technology. Nevertheless, the findings from the study provide support for the argument that accurate measurement of the economic impact of climate amenity changes requires data from more than one market.

Rehdanz and Maddison (2004) calculate the implicit price of summer and winter temperature and rainfall to German households. Rather than assume nationally unified German labor and housing markets, they account for housing and labor submarkets. The authors find that climate amenities strongly influence the housing market, and less so the labor market. Many of the climate parameters are insignificant in the wage regression. These findings may be consistent with the assumption that the climate amenity enhances production (Figure 2.5). Rehdanz and Maddison (2004) report the 5th and 95th percentiles for the implicit prices

of climate amenities for three German regions to show the uncertainty of the sign and magnitude of the welfare value.

3.2.2 Interurban Equilibrium Models of Discrete Location Choice

In Section 3.2.1, I discussed three empirical applications of the interurban equilibrium model. The aforementioned studies estimate hedonic models to obtain the wage and housing price differentials necessary to compute the value of an amenity. In applying hedonic models, each individual has the opportunity to choose a housing (or job) bundle with any quantity of an amenity. There are several cases where such an assumption is violated. For example, housing markets may be segmented. Perfect mobility may not exist. Some cities may offer amenities unavailable in other cities, but are off limits to some due to financial, racial, or cultural discrimination. Under these circumstances, a model of discrete choice based on the Random Utility Model (RUM) is better suited for the discrete nature of location choice (Freeman, 1993).

The RUM serves as the theoretical construct in motivating a household's decision to live in a particular location. It is assumed that the head of household h maximizes his utility by choosing an area of residence i and consumption C_{ih} :

$$\max_{i, C_{ih}} U(Z_i, C_{ih} | X_h) + \varepsilon_{ih}, \quad (3.1)$$

where utility depends on the amenities available in the location Z_i , private consumption C_{ih} , individual household characteristics X_h , and a stochastic component ε_{ih} indicative of unobserved taste preferences and location amenities.

The solution to the above problem yields the indirect utility function.

The random utility framework assumes that each possible alternative location in the individual's choice set is associated with an indirect utility V_{ik} , which is broken down into a deterministic component and an error term. The error term captures determinants of choice that are known to the individual or household but are unobservable to the researcher: $V_{ih} = \bar{V}_{ih} + \varepsilon_{ih}$.

The household chooses the location i that gives the highest utility level. In other words, i is selected over j ($i \neq j$) if:

$$\bar{V}_{ih} + \bar{V}_{jh} > \varepsilon_{jh} - \varepsilon_{ih} \quad \forall i. \quad (3.2)$$

If the error terms are *i.i.d.* and follow the type I extreme value distribution, it can be shown that the probability that household h selects location i is:

$$\Pr(\text{household } h \text{ chooses location } i) = \frac{\exp(\bar{V}_{ih})}{\sum_{k=1}^K \exp(\bar{V}_{kh})}, \quad (3.3)$$

where \bar{V} is a function of observable variables, such as rent, the wage rate, household characteristics and location attributes, via a set of unknown parameters. Expression (3.3) is a conditional logit model, which can be estimated once the functional form is specified for \bar{V} .

From the RUM, calculation of willingness to pay for a non-marginal change in climate is straightforward.⁷ The ease of calculating welfare measures comes from the functional form assumed for utility and distribution of the error term in the empirical model. In this sense, the RUM application is as restricted as a hedonic model that assumes an explicit functional form for the demand of

⁷Haab and McConnell (2002) provide several examples of how to calculate willingness to pay for a change in environmental quality using a RUM.

a location's attribute in the second-stage of the estimation process (Bartik and Smith, 1987). Both approaches are potentially very sensitive to specification, and it would seem prudent to perform sensitivity.

Cragg and Kahn (1997) adopt a RUM and a conditional logit empirical model to estimate the willingness to pay for climate amenities in the U.S. They argue that there are additional opportunity costs of relocation implicit in wage and rent changes. Their model allows wages and rental payments to vary across both individuals and locations to capture regional idiosyncrasies (e.g. unemployment, returns to education, and location desirability) that otherwise are lost in the usual applications of RUM.⁸ Cragg and Kahn find that the individuals in their sample are willing to pay positive amounts for moderate climate.

Timmins (2003) applies the RUM to evaluate the welfare effect from a change in Brazilian climate when housing price data is unavailable, where the location choice set consists of 495 microregions in Brazil.⁹ He uses this framework for two reasons. First, he uses a geographically comprehensive dataset to incorporate the broader variation in climate. In covering the country extensively, Timmins argues that some of the individuals represented in the dataset are likely immobile, violating the free mobility assumption of traditional hedonic models.¹⁰

⁸From the price gradients (wages and rent), Cragg and Kahn (1997) are able to gauge the extent that individuals pay for both public and private goods in the form of reduced wages and higher rents. The additional utility an individual attains from living in a region with a desirable climate or having the finest schools, is measured from willingness to pay measures deduced from the indirect utility function. They use both the measures from the price gradients and the indirect utility function to compare the benefits capitalized in wages and rents with those implicit in indirect utility.

⁹Microregions consist of 6 to 12 contiguous municipios (Timmins, 2003).

¹⁰To relax the assumption of costless migration, Timmins adds migration as an argument

Second, the RUM also provides a construct for the evaluation of non-marginal changes in climate. Timmins uses predictions from general circulation models (GCM) to define climate change. In these models, climate change is posed in the form of temperature and rainfall scenarios. In order to measure the welfare effect of these scenario changes, one needs a welfare measure that can account for the effect of non-marginal changes in amenities.

There are three interesting features of the Timmins model that are atypical of most RUM applications. In order to explain these features with clarity, I refer to the indirect utility function assumed in his paper:

$$\ln V_{i,j,k} = A_{0,k} + (\alpha_{Q,k} + \alpha_{h,k}) \ln W_{i,j,k} - \alpha_{h,k} \ln P_{j,k}^h + f(M_{i,j,k}; \bar{\alpha}_{M,k}) + \quad (3.4)$$

$$\alpha_{C1,k} \ln C_j + \alpha_{C2,k} C_j \ln C_j + \alpha_{X,k} X_j + \alpha_{\Delta,k} \ln \Delta_j + \varphi_{j,k} + \nu_{i,j,k}.$$

In (3.4), the indexes i , j , and k represent individual, location, and type respectively. The arguments in the indirect utility function and what they represent are the following: A_0 characterizes the type of each individual (educational attainment);¹¹ W is individual wage; P_h is the price of housing (which is not observed in the data); M is migration a function of the distance between the birth location and current location of the individual; C is climate which is expressed

in the utility function. Migration is a function of the distance between the current state of residence and state the individual migrated from last. One limitation in this approach is that only 10 percent of the sample responded to the migration questions.

¹¹Specifically, $A_0 = \ln \alpha_{0,k} + \alpha_{Q,k} \ln \frac{\alpha_{Q,k}}{\alpha_{Q,k} + \alpha_{h,k}} + \alpha_{h,k} \ln \frac{\alpha_{h,k}}{\alpha_{Q,k} + \alpha_{h,k}}$, where $\alpha_{0,k}$, $\alpha_{Q,k}$, and $\alpha_{h,k}$ are the parameter in the utility function expressing the relationship between individual utility and individual type (a function of individual attributes that define the individual to be of type k), and the consumption of a traded numeraire commodity Q , and housing h .

as a non-monotonic function of climate variables, $\alpha_{C1,k} \ln C_j + \alpha_{C2,k} C_j \ln C_j$; X is a vector of non-climate local attributes; Δ is population density, ϕ is a local attribute unobserved to the econometrician, and v is an idiosyncratic stochastic term. The parameters $\alpha_{Q,k}$, $\alpha_{h,k}$, $\alpha_{X,k}$, and $\alpha_{\Delta,k}$ relate the effect of the consumption of a traded numeraire commodity Q , housing h , local non-climate local attributes X , and population density Δ on utility.

First, Timmins includes migration as an argument in the utility function. Migration is a non-linear function of distance from birthplace and individual education level. Migration varies by individual type to account for the possibility that individuals' adaptive capacities to global warming differ. Including migration in the utility function first acknowledges potential costs of migration. Second, it recognizes the possibility for individuals to adapt to a substantial change in climate by altering their migration distance or substituting migration for other goods.

Second, Timmins resolves the issue of missing housing price data. He assumes an inverse supply relationship for all commodities (except Q) consumed by the individuals that varies with climate and non-climate amenities, and population density by location:

$$\ln P_{j,k}^h = \delta_{0,k} + \delta_{X,k} \ln X_j + \delta_{C1,k} \ln C_j + \delta_{C2,k} C_j \ln C_j + \delta_{\Delta,k} \ln \Delta_j + \varepsilon_{j,k}^h, \quad (3.5)$$

Equation (3.5) is substituted back into the indirect utility function, which is now a function of the determinants of the housing supply.

Third, Timmins accounts for the endogeneity of location size via population density. The procedure used to estimate the model is performed in two stages.

In the first stage, a conditional logit regression is estimated by individual

type to obtain the coefficients on wages, the migration dummy variables, and the location-specific constant. In order to obtain the location-type constants, Timmins solves a system of simultaneous $J \times K$ population-share equations represented below, where type k is distinguished by education level:

$$\frac{pop_j}{M_k} = \frac{\exp(f(\widehat{W}_{j,s}, d_{i,j,k}^{M1}, d_{i,j,k}^{M2}, \theta_{j,k}, \zeta_{j,k}; \pi))}{\sum_{i=1}^J \exp(f(\widehat{W}_{l,s}, d_{i,l,k}^{M1}, d_{i,l,k}^{M2}, \theta_{l,k}, \zeta_{l,k}; \pi))}. \quad (3.6)$$

In (3.6), M_k is the number of type- k individuals and pop_j is the number of people living in location j . $\widehat{W}_{i,j}$ is a type-specific component of wages earned by an individual with a subset of attributes s in location j . Dummy variables $d_{i,j,k}^{M1}$ and $d_{i,j,k}^{M2}$ take the value one if the migration distance from the individual's birth state to the state of location j is greater than (i) 764 km, and (ii) 1380km respectively. A location and type-specific component (also a function of X , C , and Δ) is represented by $\theta_{j,k}$ for simplification of notation and computation. The final argument in (3.6) is an unobservable attribute distributed independently of climate and non-climate amenities for each type of individual and used to reduce the omitted variable bias problem often burdening hedonic regressions.

In the second stage, Timmins disentangles the type and location-specific fixed effect parameters. He regresses the location-type specific fixed effect parameters $\theta_{j,k}$ on a function of climate amenities, non-climate amenities, and population density by individual type. Four regressions are estimated, one for each educational group. Since population density is endogenous, Timmins corrects for simultaneous equation bias by constructing a set of instruments for population density.

Having specified the parameters in the indirect utility function, he uses the following simulation procedure to evaluate the consequences of climate change.

For each climate change scenario, he accounts for an individual's new choice of location and the effect it has on utility. The first step involves calculating the new population densities. In the second stage, he uses the predicted population densities to calculate the change in utility caused by wage and housing price equilibrium changes per location. Post climate change wage and housing price predictions are substituted in the indirect utility function. These price changes in turn affect the location choice of an individual post climate change, the migration costs involved (if applicable), and the new level of utility achieved.

In the final stage, he measures the welfare change caused by a given climate change scenario. His measure comprises the difference in individual utility from the best choice of location under the status quo and post-climate change scenarios, normalized by the marginal utility of wages in the status quo. His second approximation of welfare takes the difference in utilities explained above, but normalizes the difference by the marginal utility of wages after climate change.

3.3 Concluding Remarks

In this dissertation, I measure the value of a change in climate by applying the Roback model (1982). The dissertation varies from the previous literature in three aspects. First, this is the first application of the continuous choice location equilibrium model for measuring the values of climate amenities in Brazil.

Second, although Timmins and I both focus on Brazil, the source of the data used in the analysis as well as the geographical focus is different. In his empirical work, Timmins uses data on households included in the 1991 Brazilian Demographic Census, which does not contain housing price data. He further restricts the sample to include those households in which report migration activity

(10 percent of the sample). By contrast, I use the 1995 Pesquisa Nacional de Amostra Domicilio (PNAD), a Brazilian household survey, which includes data on monthly mortgage and rental payments. I restrict the analysis to households living in cities because the design and collection of the survey is geared toward urban residents. Since households in metropolitan areas are more mobile than households living in rural areas, application of the continuous choice interurban equilibrium model is permissible. I further restrict the sample to 15 major counties in Brazil. These are chosen to reflect the largest cities of Brazil with a complete representation of the housing market including *favelas*, or shantytowns (Gilbert, 1996).

One limitation of my work is that I do not account for the climate variation throughout the country as in Timmins. The 15 municipios represent approximately 21 percent of the population. If a substantial portion of the population is not affected by changes in climate, then all else equal, it may be more difficult to implement national policies aimed at reducing emissions as they are not experiencing the damages firsthand.

Finally, I estimate the rent and wage regressions as part of a system of seemingly unrelated regression equations (SURE). I assume that unobserved characteristics of individuals influence both the decision of where to work and where to live. The SURE model is consistent with this assumption in allowing the error terms to be correlated across equations.

Estimating the rent and wage equations separately provides consistent estimates of the parameters in the models. In other words, as long as the sample size is large, the estimate produced from the single equations will be close to the true parameter value with high probability (Judge et al., 1988). By esti-

mating the rent and wage equations simultaneously, however, I can also obtain efficient estimates of the parameters. This is true as long as the disturbances in both equations are correlated and the explanatory variables in each equation differ. By definition, an efficient estimator indicates that the asymptotic covariance matrix is no larger than the covariance matrix of another consistent estimator (Greene, 1997). In practice, this usually means that the standard errors of efficient parameters are smaller. In result, the efficient parameter estimates are more precise and inferences based on hypothesis tests may change.

I also expect the point estimates of the single-equation and SURE models to differ because one method is more efficient and the estimation process of both models involves minimizing quadratic forms (Zellner, 1962). The covariance matrix is used to estimate the parameters of the regression model. Since the estimator of the covariance matrix differs for the SURE model and also is more efficient, then it is natural to expect differences in the point estimates across models. In the dissertation, I compare the values of climate amenities calculated using estimates from the SURE model to those values calculated using estimates from the single rent and wage regressions.

Chapter 4

Data

The dataset is compiled from five main sources: (i) the Pesquisa Nacional por Amostra de Domicilios (PNAD), a national survey of sample households administered by the Brazilian government; (ii) DATASUS, a Brazilian government statistical database (online); (iii) the Base de Informacoes Municipais (BIM) 1998 CD ROM; (iv) EMBRAPA, a Brazilian government agricultural statistics database (online); and (v) the Anuario Estatistico do Brasil, the annual Brazilian statistical yearbook.

I use the 1995 PNAD survey covering 85,270 households from 808 municipios. There are approximately 5,000 municipios in Brazil.¹ Households from the northern states of Brazil are underrepresented. Only households living in urban areas are surveyed in the northern states, although these states predominantly consist of rural areas. Households are sampled according to two groups. The first group of households are sampled from municipios that comprise Brazilian metropolitan areas. The second group of households are from the remaining municipios and are selected by stratification, with probability of selection pro-

¹Municipios are similar to U.S. counties.

portional to the resident population in the census district.²

I eliminate households that were not in one of the 15 major municípios in Brazil, to confine my sample to urban areas. I further exclude households from this sample that were either living in a home provided at no charge by their employer or someone else, or had some other unidentifiable type of residential arrangement. Finally, due to my interest in wages and rents, the sample is restricted to heads of single-family households between the ages of 18 and 65 who lived in residences they owned (paid or in the process of paying) or rented.³ The final sample is comprised of 14,861 individuals.

Table 4.1 reports the number of heads of households in the final sample by município and region and the number of heads of households between the ages of 18 and 65 living in each município in 1996.⁴ From the table, it is clear that the household samples are roughly proportional to the population of households in each município. Figure 4.1 shows the five regions of Brazil, following the notation of the Brazilian government: the North, Northeast, Southeast, South, and Midwest.⁵

²Details of the PNAD sampling process and how to address the stratification in statistical analyses can be found in Do Nascimento Silva, Pessoa, and Lila (2002).

³The individuals in this age group most likely earn wages. As of 1999, the statutory retirement age is 65 for men, and 60 for women (United Nations, 2002).

⁴These data were taken from the IBGE website (www.ibge.gov.br). As the data are presented according to 5-year age groups, I approximated the number of heads of households that are 18 and 19 years of age by multiplying the figure from the 15-19 year age group by 0.4. I also approximated the number of heads of households that are 65 years of age by multiplying the figure from the 65-69 age group by 0.2.

⁵The map was taken from the Ande Tur Brazilian Travel Club website: <http://www.andetur.com/us/statesof.htm> created by Santos (1995). Brazil's federal dis-

Table 4.1: Number of Households and Cities in each Region

Município	Heads (Sample)	Heads (Population)	Region
Manaus	474	235,387	N
Belem	776	223,098	N
Sao Luis	154	154,745	NE
Fortaleza	1,410	406,619	NE
Recife	889	290,420	NE
Salvador	1,764	497,266	NE
Belo Horizonte	1,352	481,083	SE
Rio de Janeiro	1,658	1,396,604	SE
Campinas	191	225,646	SE
Santos	82	102,250	SE
Sao Paulo	2,027	2,383,950	SE
Curitiba	1,040	376,320	S
Porto Alegre	1,224	345,154	S
Goiania	524	248,531	MW
Brasilia	1,296	428,317	MW
Total Brazilian Population		155,822,296 ⁶	

Source: Contagem da População 1996

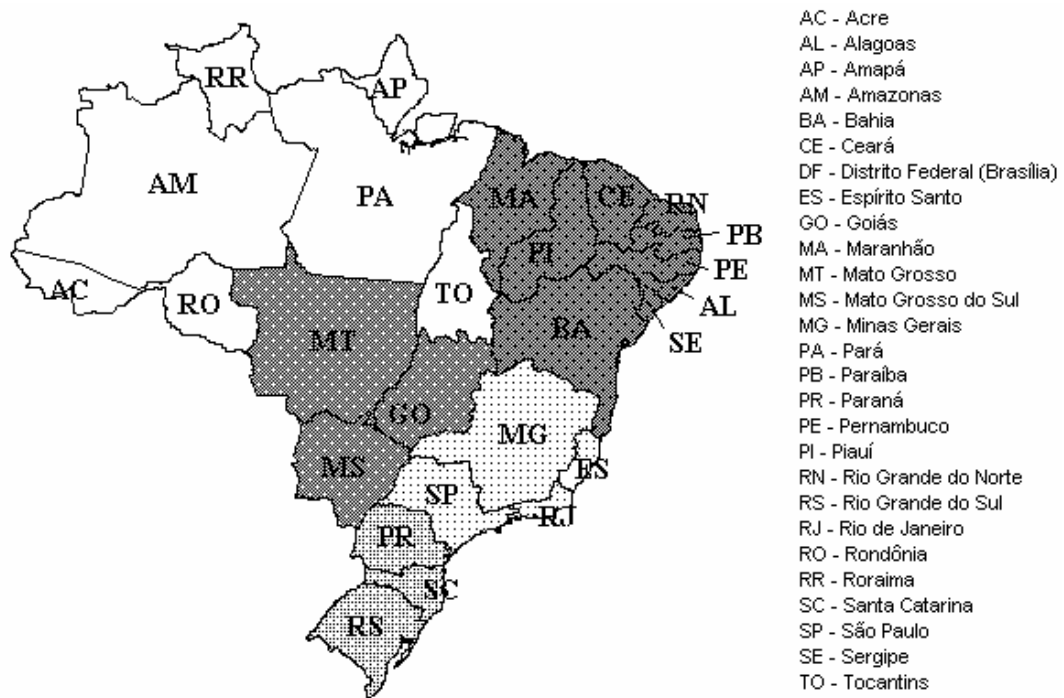


Figure 4.1: Regions of Brazil

The PNAD questionnaire collected a variety of information about demographics, rents, wages, and housing, to be used to estimate the hedonic housing rent and wage models.

Demographic variables consist of the number of people living in a household, the number of household members 10 years or older, and the age of the head of household. Socioeconomic characteristics are the number of years of education, race, job specification, monthly wages, and monthly rent or mortgage payments. Jobs are defined according to the International Standard Classification of Occupations 1988:⁷ legislators, senior officials and managers; professionals, technicians, and associate professionals; clerks; service workers, and shop markets and sales workers; skilled agricultural and fishery workers; craft and related trade workers; plant and machine operators and assemblers; elementary occupations, and the armed forces.⁸ Real monthly rent/mortgage payments and wages are calculated by dividing the corresponding nominal variables by an interregional cost of living index. The details of how the cost of living index is constructed are included in Appendix A.1.

One problem with using the PNAD data for the purpose of estimating a hedonic housing price model is that a substantial portion of the sample (64 percent, or 9,937 households) did not report housing price values, because they

trict (DF) is located within the boundaries of Goias (GO).

⁷The description of this classification can be found on the Interational Labor Organization webiste (www.ilo.org).

⁸Two tables taken from a Brazilian government website (CONCLA) are used to codify the 927 job codes presented in the PNAD survey into these 10 occupation groups. The tables labeled *Codigos e Descrições* and *IBGE X CBO 94* can be found at www.ibge.gov.br/concla/download.shtm.

already paid for their houses or apartments. Those who report a form of housing price, report monthly mortgage payments without providing the details or conditions of the location (1,909 households).

The survey asks two questions about housing prices: 1) What is your monthly rental payment? 2) What is your monthly mortgage payment? If the individual already paid for his house, than he did not answer either of these two questions. The survey does not require individuals who have completed their housing payments to calculate what their payments would have been had mortgage payments been pending. Due to this limitation, I focus on the rental housing market (35 percent of the sample), but include all consumers of housing (renters and owners) in the sample of workers for purposes of estimating the wage equation.

The housing characteristics reported in the PNAD data are type of housing (house, apartment, or room),⁹ material of external walls and roof material (durable, such as stone and tile and non-durable, such as straw and zinc), number of rooms and number of rooms used as bedrooms. Infrastructure characteristics are expressed in terms of water distribution, sewage, and sanitation variables. Water distribution variables include whether the residence has running water in at least one room, and whether the residence has some form of filtered water. Sanitation variables consist of whether the house has a bathroom or toilet, and toilet type. The type of toilet is categorized as follows: toilet connected to a sewerage or pluvial system, septic cavity connected to a sewerage or pluvial system, septic cavity not connected to sewerage or pluvial system, rudimentary cavity,

⁹I exclude 237 individuals that reported renting or owning a room because there is an insufficient number of observations to capture this submarket in the hedonic rent equation.

ditch/trench, directly in river/lake/sea, or other. For simplicity, in my empirical work I regard the household as having a flush toilet if the toilet or septic cavity is connected to a sewerage or pluvial system. Waste management is described based on the destination of a resident's refuse: (a) directly collected, (b) indirectly collected, (c) burned or buried on property, (d) thrown in vacant lot or wasteland, (e) thrown in river/lake/sea, or (f) other. In my analysis, I simply consider the household to have some form of trash collection if their trash is directly or indirectly collected (modes (a) and (b)).

The DATASUS and BIM data primarily contain variables reflecting the community or neighborhood environment at the municipio level. Data from DATASUS include population, and number of hospitals. Population is used to convert the location attribute variables to per capita terms. The number of hospitals is included to reflect availability of medical care in a given municipio.

I obtain data regarding the number of banks, violent deaths, schools in each municipio and the area of a municipio (in square kilometers) from the BIM dataset. I use the area of each municipio to calculate population density. Population density is a proxy for the congestion of a municipio, but also the degree of urbanization of the municipio, which may be considered desirable or undesirable depending on the individual.

I convert the number of banks, violent deaths, and schools to the number of attributes per 100,000 people using the population variable. The banks variable proxies the level of economic activity in a municipio. Violent deaths per 100,000 population is an indicator of municipio crime. High crime rates may be undesirable, but are often unavoidable in large cities. Thus, crime may or may not be an effective determinant of housing prices and wages for this particular

sample. Finally, schools may attract families to locate in a particular municipio. The number of schools includes private and public pre-school, primary, and secondary schools (e.g., pre-escolar, ensino fundamental, and ensino medio).

All of the amenities mentioned likely vary dramatically within a municipio. The intra-municipio variation in amenities will also influence housing prices and wages. Unfortunately, the data precludes accounting for such variation.

Climate data and other geographical descriptors are taken from EMBRAPA and the Anuario Estatístico do Brasil 1971-1990. EMBRAPA contains monthly temperatures, precipitation, evapotranspiration potential rates, and altitude levels for all of the municipios. The climate data are based on monthly averages over a 1961-1990 time frame, except for Sao Paulo and Santos (1941-1970), Brasilia (1963-1990), Sao Luis (1971-1990), Belem (1972-1990), and Rio de Janeiro (1973-1990). I use available annual Brazilian statistical yearbooks to construct the climate data for Sao Paulo (1970-1990), and supplement the existing data for Sao Luis (1970), Belem (1970-1971), and Rio de Janeiro (1970-1972).¹⁰ Unfortunately, data are not readily available to supplement the Santos climate data.¹¹

Temperature and rainfall variables are included in the analysis to measure the values of marginal changes in climate. As mentioned, climate may directly affect utility. Temperature and rainfall levels may also affect the ability to consume leisure and recreational activities. Temperature and rainfall are included to capture the effect of climate change on the consumption of non-market goods,

¹⁰The annual statistical yearbooks of Brazil publish climate data for all Brazilian capitals. Two of the municipios included in the dataset are not state capitals, Campinas and Santos.

¹¹Only 82 heads of households in the sample are from Santos (0.6 percent of the sample).

particularly climate and climate-dependent recreational activities.¹²

Evapotranspiration potential is included to control for a feature of climate that may affect housing prices and wages and may be correlated with temperature and rainfall, aridity.¹³ I use the evapotranspiration potential data to construct an aridity index. Typically, the aridity index is the ratio of the annual average precipitation to annual average evapotranspiration potential (P/PET) of a given area. The aridity index was first applied by UNESCO (UNESCO, 1977). Following Leemans and Kleidon (2002), I use the index to make five environmental classifications hyper-arid zone ($P/PET \leq 0.03$), arid zone ($0.03 < P/PET \leq 0.2$), semi-arid zone ($0.2 < P/PET \leq 0.5$), and subhumid zone ($0.5 < P/PET \leq 0.75$). Index values larger than 0.75 indicate that the area is humid, and is generally representative of forest and woodland areas. Thus, municipios with large values for the aridity index will be indicative of areas with forest and woodlands, which also have amenity values. This is one attempt to control for the correlation between rainfall and prevalence of flora and fauna.

I construct monthly aridity indexes for the analysis. An aridity index that includes the annual average precipitation and evapotranspiration rates would be

¹²Since running water is readily available in most homes in Brazilian cities, I do not believe that the rainfall variables are capturing the effect of water supply on housing prices and wages.

¹³According to the IBGE, the evapotranspiration potential is the quantity of water that evaporates in a given area during a period of time (Anuario Estatístico do Brasil, 1975). The IBGE further describes that it theoretically corresponds to the loss of water height in the reservoir (Anuario Estatístico do Brasil, 1975).

The effect of evapotranspiration potential is particularly important in combination with precipitation (Thornthwaite, 1948). For example, if precipitation increases and the evapotranspiration rate remains the same, the environment will generally become wetter. Alternatively, if the evapotranspiration exceeds precipitation, then severe droughts could occur.

informative if one were interested in comparing moisture levels worldwide, or illustrating trends of desertification across countries. Since Brazil is a tropical country, an index that uses annual average precipitation and evapotranspiration levels is not particularly informative (i.e., all index values exceed 0.75). Instead, I use a monthly or seasonal index to elicit the variation in seasonal moisture levels.

The altitude variable is also included in the analysis, as it characterizes the elevation of the municipio. The altitude of a municipio could potentially capture the picturesque beauty of a mountainous county. I include altitude in the analysis to also gauge the effect of adjusting the impact of temperature by elevation of the municipio on housing prices and wages. Since many of the municipios included in the analysis are close to sea level, this effect may only be considerable for Sao Paulo, Campinas, Curitiba, Belo Horizonte, Brasilia, and Goiania.

4.1 Descriptive Statistics

Table 4.2 provides statistics describing the composition of household and head of household demographics in the sample, i.e., mean, standard deviation, minimum and maximum value observed. The household characteristics include household size, and the number of individuals living in the household that are greater than ten years old. Head of household demographic variables are: gender, age, education level, race,¹⁴ job type,¹⁵ number of years worked on

¹⁴I use a dummy variable indicating whether the head of household is black. The survey has five categories relating to one's skin color: indigenous, white, black, yellow, and mulatto. In my analysis, black includes individuals classified as black and mulatto.

¹⁵The survey questionnaire also included another category for those who could not find their occupation code on the survey. The percent of the sample that indicated the other job type

the job, real monthly rental payments, real monthly mortgage payments, and real monthly wages. Table 4.3 describes the housing structural characteristics of the sample residences. Housing structural characteristics include number of bedrooms, durable walls and roofs, access to trash collection, possession of bathroom exclusive to the residence, flush toilet, running water, and water filter, and whether the residence is an apartment.

Table 4.4 shows the mean, standard deviation, minimum and maximum values for each non-climate amenity variable. These are population density (individuals per square kilometer divided by 100), number of banks, hospitals, schools, and violent deaths per 100,000 people to establish the average level of amenities, and thus, desirability of a municipio. Altitude (meters) is presented in Table 4.4 to reflect the geographical location of each municipio.

Table 4.5 displays the mean, standard deviation, minimum and maximum values for each climate variable. The climate variables included are monthly average temperatures ($^{\circ}\text{C}$), precipitation (mm), and the aridity index.

4.2 Data Issues

In the next section, I discuss three issues posed by the data. First, several heads of households either do not report a form of housing price or report an incomplete measure of housing price. Due to this data limitation, I focus on the rental market for housing. I compare descriptive statistics across ownership groups to see if there are any fundamental differences between heads of households across groups.

category was 2.17.

Table 4.2: Descriptive Statistics of Heads of Households

Variable	Mean	Std Dev	Min	Max
Household size	3.94	1.85	1.00	18.00
Members of household less than 10 years old	3.18	1.58	1.00	15.00
Male	0.81	0.39	0.00	1.00
Age	40.58	10.34	18.00	65.00
Years of Education	9.02	4.61	1.00	16.00
Black	0.44	0.50	0.00	1.00
Occupation:				
Legislators, senior officials, and managers	0.13	0.33	0.00	1.00
Professionals	0.13	0.33	0.00	1.00
Technicians and associate professionals	0.10	0.31	0.00	1.00
Clerks	0.03	0.18	0.00	1.00
Service workers, and shop and market sales workers	0.16	0.37	0.00	1.00
Skilled agricultural and fishery workers	0.02	0.12	0.00	1.00
Craft and related trades workers	0.20	0.40	0.00	1.00
Plant and machine operators and assemblers	0.08	0.27	0.00	1.00
Elementary occupations	0.11	0.32	0.00	1.00
Armed Forces	0.02	0.14	0.00	1.00
On job experience (years)	8.60	8.38	0.00	59.00
Real monthly rent	256.44	228.92	6.65	2513.46
Real monthly mortgage payments	175.39	269.54	0.98	2693.00
Real monthly wages	875.51	1288.06	5.10	31088.08

Table 4.3: Descriptive Statistics of Housing Structural Characteristics

Variable	Percent of Sample
Number of Bedrooms:	
1	28.75
2	44.55
3	22.00
4	3.88
>4	0.82
Durable Walls	98.89
Durable Roofs	99.02
Trash Collection	95.29
Non-shared bathroom	97.26
Flush Toilets	67.74
Running Water	94.57
Water Filter	70.27
Apartment	26.94

Table 4.4: Descriptive Statistics of Non-Climate Amenity Variables

Variable	Mean	Std Dev	Min	Max
Altitude (meters)	392.13	429.87	5.00	1159.00
Population density (population/km ² /100)	39.12	22.30	0.98	66.36
Banks (per 100,000 population)	12.96	4.05	6.03	21.32
Violent deaths (per 100,000 population)	98.03	38.26	32.94	208.73
Hospitals (per 100,000 population)	2.54	1.29	0.92	7.38
Schools (per 100,000 population)	77.08	30.95	41.02	186.04

Table 4.5: Descriptive Statistics of Climate Variables

Variable	Mean	Std Dev	Min	Max
Monthly temperature (season):				
January (Summer)	24.65	2.34	19.60	28.00
February (Summer)	24.74	2.14	19.90	28.30
March (Summer/Fall)	24.37	2.27	19.00	27.50
April (Fall)	23.00	2.91	16.70	26.80
May (Fall)	21.80	3.76	14.60	26.80
June (Fall/Winter)	20.66	4.41	12.20	26.70
July (Winter)	20.39	4.20	12.80	26.50
August (Winter)	21.10	3.85	14.00	27.00
September (Winter/Spring)	21.96	3.60	15.00	27.50
October (Spring)	22.81	3.10	16.50	27.60
November (Spring)	23.48	2.62	18.20	27.40
December (Spring/Summer)	24.14	2.44	19.30	28.50
Annual Average	22.76	3.02	16.48	27.03
Monthly precipitation (season):				
January (Summer)	190.85	79.48	100.00	388.00
February (Summer)	197.75	76.19	109.00	410.00
March (Summer/Fall)	196.22	83.26	104.00	378.00
April (Fall)	178.94	114.00	61.00	436.00
May (Fall)	149.35	113.31	28.00	329.00
June (Fall/Winter)	127.34	120.34	9.00	390.00
July (Winter)	101.53	95.52	6.00	386.00
August (Winter)	74.75	56.43	13.00	213.00
September (Winter/Spring)	82.48	39.34	15.00	198.00
October (Spring)	110.80	43.09	16.00	313.00
November (Spring)	134.51	67.15	13.00	301.00
December (Spring/Summer)	165.02	78.93	48.00	378.00
Monthly Aridity Index (season):				
January (Summer)	1.72	0.95	0.72	3.90
February (Summer)	1.96	1.16	0.89	5.89
March (Summer/Fall)	1.81	0.95	0.94	5.28
April (Fall)	1.76	0.85	0.78	3.58
May (Fall)	1.59	0.99	0.42	3.72
June (Fall/Winter)	1.69	1.48	0.14	4.19
July (Winter)	1.38	1.25	0.09	4.01
August (Winter)	1.02	0.99	0.15	3.59
September (Winter/Spring)	1.02	0.75	0.11	2.81
October (Spring)	1.14	0.53	0.11	2.66
November (Spring)	1.31	0.73	0.09	2.67
December (Spring/Summer)	1.50	0.86	0.25	3.14

The second issue is related to the variability of the climate and non-climate amenity data. There is little variation in seasonal temperature across municipios in Brazil, especially for the areas of focus in the analysis. If the climate data lacks variation, the empirical results may indicate that a change in climate will not affect housing price and wage differentials. I include maps and graphs of climate variables to help motivate the discussion of the variability issue. The discussion concludes with the illustration of graphs exhibiting the distribution of non-climate amenity variables in the sample. Here, I am primarily interested in establishing whether there is enough cross-sectional variation disentangle the effects of non-climate amenities on prices from the appeal of favorable climate characteristics.

The third issue is possible multicollinearity between amenity variables. I present the Pearson correlation coefficients of variables included in the analysis and highlight the difficulties that may arise in trying to isolate the effect of a particular amenity.

The fourth issue regards the possibility of stochastic regressors. I discuss why there may be measurement in error in the variables included in the analysis and the implications of such error on the empirical results.

4.2.1 Focusing on the Rental Market

Table 4.6 shows the distribution of households by ownership type for each municipio. The average percentage of renters in each municipio is 23.57. These figures indicate that the percentages of renters, owners with mortgages, and owners who already paid for their homes vary across locations. Percentages of renters are lowest in Manaus, Belem, Sao Luis, Recife, and Salvador, and

highest in Santos and Sao Paulo.

Tables 4.7 and 4.8 provide descriptive statistics of demographic and housing variables by ownership group. Tables 4.9-4.14 include the t-statistics testing if the differences in variable means by ownership group are significantly different from zero. In what follows, I use these tables to observe the discernible differences in demographic and housing structural characteristics of heads of households and their homes by ownership group.

In Table 4.9, the t tests indicate that there are considerable differences in the demographic characteristics between the owners who report mortgage payments and renters. The results in Table 4.7 show that renters tend to be younger (36.82 years old on average compared to 40.15). Renters are less educated on average, however, the variance in years of education is also larger among renters. The educational differences in higher education may be attributed to the differences in ages between the two groups. The t-tests also indicate that there are considerable differences in the types of jobs possessed by these two groups, except for the jobs in the categories of skilled agricultural and fishery workers and the armed forces. The statistics from Table 4.7 show that individuals with mortgage payments tend to have more high-powered and technical positions than renters.

The housing characteristics available to both groups also differ as shown by the t statistics in Table 4.10. However, from the descriptive statistics in Table 4.8, there are no appreciable differences between possession of durable walls, roofs, and trash collection. Many of these figures are close to 100%. The frequencies of availability of flush toilets, running water, water filter, non-shared bathroom, and whether the individual lived in an apartment vary. Individuals with mortgage payments are more likely to own apartments, purchase water fil-

Table 4.6: Distribution of Heads of Households by Ownership

Município	Owners (Paid homes)	Owners (With mortgages)	Renters
Manaus	70.46	18.78	10.76
Belem	78.87	5.93	15.21
Sao Luis	61.69	27.92	10.39
Fortaleza	63.90	14.11	21.99
Recife	74.24	6.97	18.79
Salvador	68.88	14.68	16.44
Belo Horizonte	66.05	6.43	27.51
Rio de Janeiro	63.81	11.28	24.91
Campinas	62.83	11.52	25.65
Santos	48.78	3.66	47.56
Sao Paulo	57.87	8.78	33.35
Curitiba	58.85	20.48	20.67
Porto Alegre	53.02	22.47	24.51
Goiania	60.50	10.50	29.01
Brasilia	58.49	14.74	26.77

ters, and have running water, non-shared-bathrooms, and flush toilets in their residences. In sum, individuals with mortgage payments are considerably different than renters, not only in demographic characteristics but also in their choice of housing characteristics.

The t statistics from Tables 4.11 and 4.12 indicate that owners who have already paid for their homes and renters are statistically different for age, education, race, some occupation choices, monthly wages, and in their choice of housing structural characteristics. The descriptive statistics in Table 4.7, however, indicate that many of these differences may be considered minor. The first difference is that owners tend to be older, which may be why they have already paid for their homes. There are minor educational differences. Specifically, renters on average have 9.51 years of education compared to owners in which have 8.37 years

Table 4.7: Means of Head of Household Characteristics by Ownership

Variable	Owners (housing prices not available)	Owners (housing prices available)	Renters
Household size	4.19 (1.92)	3.73 (1.64)	3.40 (1.62)
Members of household less than 10 years old	3.40 (1.64)	3.01 (1.44)	2.69 (1.33)
Male	0.82 (0.38)	0.80 (0.40)	0.80 (0.40)
Age	42.06 (10.37)	40.15 (9.09)	36.82 (9.89)
Years of Education	8.37 (4.65)	11.36 (4.07)	9.51 (4.30)
Black	0.47 (0.50)	0.38 (0.49)	0.40 (0.49)
Occupation:			
Legislators, senior officials, and managers	0.13 (0.33)	0.16 (0.36)	0.11 (0.31)
Professionals	0.11 (0.31)	0.20 (0.40)	0.13 (0.34)
Technicians and associate professionals	0.09 (0.29)	0.16 (0.37)	0.11 (0.31)
Clerks	0.03 (0.17)	0.05 (0.22)	0.04 (0.18)
Service workers, and shop and market sales workers	0.15 (0.36)	0.14 (0.34)	0.19 (0.39)
Skilled agricultural and fishery workers	0.02 (0.13)	0.01 (0.10)	0.01 (0.10)
Craft and related trades workers	0.23 (0.42)	0.12 (0.33)	0.18 (0.39)
Plant and machine operators and assemblers	0.09 (0.28)	0.06 (0.24)	0.07 (0.26)
Elementary occupations	0.13 (0.33)	0.02 (0.15)	0.11 (0.31)
Armed Forces	0.02 (0.12)	0.02 (0.15)	0.03 (0.16)
On job experience	9.23 (8.80)	8.91 (7.68)	6.74 (7.26)
Real monthly rent/mortgage payments	N/A	175.39 (269.54)	256.44 (228.92)
Real monthly wages	824.15 (1325.55)	1180.55 (1451.20)	847.74 (1046.83)

*The standard deviation of the variable is included in parenthesis below the mean.

Table 4.8: Means of Housing Structural Characteristics by Ownership

Variable	Percent of Owners (housing prices not available)	Percent of Owners (housing prices available)	Percent of Renters
Number of Bedrooms:			
1	24.21	22.52	44.30
2	44.87	49.29	41.11
3	24.94	24.25	12.86
4	4.94	3.30	1.34
>4	1.04	0.64	0.39
Durable Walls	98.48	99.95	99.40
Durable Roofs	98.77	99.58	99.40
Trash Collection	93.19	99.90	98.44
Non-shared bathroom	97.74	99.48	94.77
Flush Toilets	61.22	83.92	76.47
Running Water	93.22	99.69	95.42
Water Filter	28.90	71.97	67.11
Apartment	16.77	62.02	35.16
Observations	9,437	1,909	3,515

Table 4.9: T-statistics for Difference in Demographic Variable Means of Renters
and Individuals with Mortgages

Variable	Variances Assumed Equal	Variances Assumed Unequal
Household size	7.00	6.97
Members of household less than 10 years old	8.36	8.16
Male	0.26	0.26
Age	12.19	12.49
Years of Education	15.48	15.73
Black	-0.99	-0.99
Occupation:		
Legislators, senior officials, and managers	5.05	4.83
Professionals	6.48	6.17
Technicians and associate professionals	6.14	5.82
Clerks	2.59	2.47
Service workers, and shop and market sales workers	-4.92	-5.11
Skilled agricultural and fishery workers	-0.21	-0.21
Craft and related trades workers	-5.99	-6.30
Plant and machine operators and assemblers	-1.98	-2.04
Elementary occupations	-5.69	-6.14
Armed Forces	-0.58	-0.59
On job experience	10.27	10.1
Real monthly wages	9.72	8.85

Table 4.10: T-statistics for Difference in Housing Variable Means of Renters and

Individuals with Mortgages

Variable	Variiances Assumed Equal	Variiances Assumed Unequal
Number of Bedrooms:		
1	-16.27	-17.12
2	5.82	5.79
3	10.81	10.06
4	4.91	4.34
>4	1.17	1.10
Durable Walls	3.02	3.89
Durable Roofs	0.98	1.04
Trash Collection	5.05	6.57
Non-shared bathroom	8.99	11.48
Flush Toilets	6.46	6.74
Running Water	8.75	11.37
Water Filter	3.70	3.75
Apartment	19.67	19.57

Table 4.11: T-statistics for Difference in Demographic Variable Means of
Individuals who Already Paid for their Homes and Renters

Variable	Variiances Assumed Equal	Variiances Assumed Unequal
Household size	21.50	23.20
Members of household less than 10 years old	23.01	25.34
Male	3.21	3.14
Age	25.89	26.45
Years of Education	-12.68	-13.15
Black	7.06	7.12
Occupation:		
Legislators, senior officials, and managers	2.54	2.61
Professionals	-3.67	-3.54
Technicians and associate professionals	-2.32	-2.25
Clerks	-2.00	-1.91
Service workers, and shop and market sales workers	-5.00	-4.81
Skilled agricultural and fishery workers	2.78	3.10
Craft and related trades workers	5.19	5.37
Plant and machine operators and assemblers	2.26	2.34
Elementary occupations	3.18	3.30
Armed Forces	-3.79	-3.39
On job experience	14.98	16.34
Real monthly wages	-0.95	-1.06

Table 4.12: T-statistics for Difference in Housing Variable Means of Individuals
who Already Paid for their Homes and Renters

Variable	Variiances Assumed Equal	Variiances Assumed Unequal
Number of Bedrooms:		
1	-22.69	-21.21
2	3.83	3.85
3	14.97	16.80
4	9.37	12.19
>4	3.50	4.30
Durable Walls	-4.23	-5.17
Durable Roofs	-3.06	-3.56
Trash Collection	-11.83	-15.75
Non-shared bathroom	8.77	7.34
Flush Toilets	-16.39	-17.46
Running Water	-4.63	-5.03
Water Filter	4.41	4.34
Apartment	-23.01	-20.60

Table 4.13: T-statistics for Difference in Demographic Variable Means of

Homeowners

Variable	Variances Assumed Equal	Variances Assumed Unequal
Household size	9.75	10.79
Members of household less than 10 years old	9.54	10.41
Male	2.24	2.18
Age	7.48	8.16
Years of Education	-26.22	-28.65
Black	6.65	6.76
Occupation:		
Legislators, senior officials, and managers	-3.68	-3.46
Professionals	-10.88	-9.27
Technicians and associate professionals	-9.32	-7.94
Clerks	-4.81	-4.04
Service workers, and shop and market sales workers	1.80	1.85
Skilled agricultural and fishery workers	2.34	2.79
Craft and related trades workers	10.31	12.12
Plant and machine operators and assemblers	3.87	4.33
Elementary occupations	8.34	10.38
Armed Forces	-2.31	-2.04
On job experience	1.50	1.64
Real monthly wages	-10.54	-9.93

Table 4.14: T-statistics for Difference in Housing Variable Means of Homeowners

Variable	Variences Assumed Equal	Variences Assumed Unequal
Number of Bedrooms:		
1	1.58	1.60
2	-3.54	-3.53
3	0.64	0.64
4	3.10	3.52
>4	1.67	1.96
Durable Walls	-5.25	-10.83
Durable Roofs	-3.16	-4.45
Trash Collection	-11.61	-24.87
Non-shared bathroom	-4.98	-7.70
Flush Toilets	-19.28	-23.18
Running Water	-11.18	-22.39
Water Filter	-0.77	-0.77
Apartment	-45.68	-38.48

of education. The occupational differences are slight. Renters tend to have more service jobs, and less craft and trade, and elementary occupation jobs than owners. A final demographic difference is in the amount of wages earned. Renters tend to earn more than owners.

The housing characteristic differentials also indicate that owners who have already paid for their homes and renters may choose different housing as well.¹⁶ The t statistics in Table 4.12 deem all of the variable means relating to housing statistically different. Comparing the sample frequencies for these

¹⁶There is no way of identifying the squatters representative in the sample of owners who have already paid for their homes. To gain some insight on whether squatters may appear in the sample, Table 4.15 shows the distribution of the percentage of homes in favelas. Based on this distribution, it is likely that squatters or homes in favelas appear in the sample, especially in the northern Brazilian counties.

characteristics between groups in Table 4.8, I observe that owners tend to have more bedrooms.¹⁷ They also have less trash collection, flush toilets, and purchase less water filters than renters. The quality of housing may be different across ownership type. Based on the housing structural differences, I conclude that I might not be able to treat renters and owners that already paid for their homes as a homogeneous group of people.

To compare the demographic and housing characteristics between individuals with mortgage payments and those who already paid for their homes, I draw on the t statistics in Tables 4.13 and 4.14 and the descriptive statistics in Tables 4.7 and 4.8. The t-statistics show that there are considerable differences in age, education, occupations, and monthly wages. Those who already paid for their homes tend to be older. They also are less educated with 8.37 years of education on average compared to 11.36 years of education among individuals with mortgages. The education discrepancy may also explain why many of the individuals who have paid their home in full tend to have less director, professional, and technical positions than those still paying for their homes. Finally, the individuals that already paid for their homes have substantially lower wages than the other group of owners. Thus, I can speculate whether this particular group could afford the same house as those who currently have mortgage payments.

¹⁷It should be noted that the variable related to bedrooms actually is showing how many rooms are *used* as bedrooms, rather than what rooms are considered bedrooms from a real estate perspective. Thus, the fact that owners tend to have more bedrooms may be a false indication of the type of house chosen. If the individual is affluent, the number of bedrooms may indicate that the home is particularly large. However, if the individual is financially strained, then this may also be picking up that the individual characterizes other rooms, like living or common area rooms, as bedrooms.

The t statistics testing for statistically significant differences in housing characteristics also suggest that the homes purchased by these two groups may be different. Excluding the results on durable walls and roofs for reasons mentioned before, there seem to be differences in trash collection, possession of flush toilets, and availability of running water. It appears that owners who have already paid for their homes tend to have less of these amenities. There is also a general difference in whether the individual tends to live in an apartment or home. For example, owners who have already paid for their homes tend to live in homes whereas a considerable amount of owners with mortgages own apartments.

Based on these observations, there appear to be some slight differences in the housing and demographic characteristics of heads of households that rent, own, and have a mortgage. Thus, care should be taken to extrapolate inferences from the rent regression to the rest of the population.

4.2.2 Variability in Climate and Non-Climate Amenity Variables

Figures 4.2 and 4.3 contain maps of the annual mean temperature and cumulative precipitation in Brazil over a sixty year time-frame. From Figure 4.2, it is evident that there is little variation in annual temperature throughout Brazil. The extreme values in the range of temperatures in Brazil are in few areas in the Northeast and the South. Figure 4.3 illustrates that there is quite a bit more variation in annual precipitation.

In what follows, I present maps of temperature and precipitation distributions for the months that are the warmest, coolest, wettest, and driest in the year. I also use graphs of the monthly aridity index and temperature and rainfall

Table 4.15: Favela households by city in Brazil, 1990

City	Percentage of homes in Favelas
Sao Paulo	5.8
Rio de Janeiro	9.8
Belo Horizonte	10.0
Salvador	3.7
Brasilia	0.1
Porto Alegre	6.5
Fortaleza	13.3
Curitiba	6.7
Recife	42.2
Belem	15.1
Goiania	1.6
Campinas	17.8
Manaus	4.7
Santos	7.1
Sao Luis	3.9
Average of 15 cities	9.9
Average of 7 southern cities	7.2

Source: Gilbert (1996)

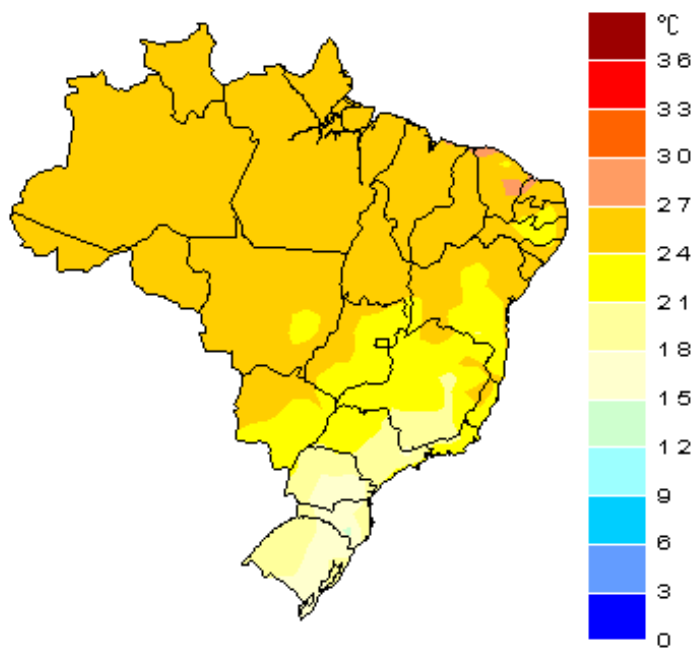


Figure 4.2: Mean Annual Temperature, 1931-1990 (Source: Instituto Nacional De Meteorologia)

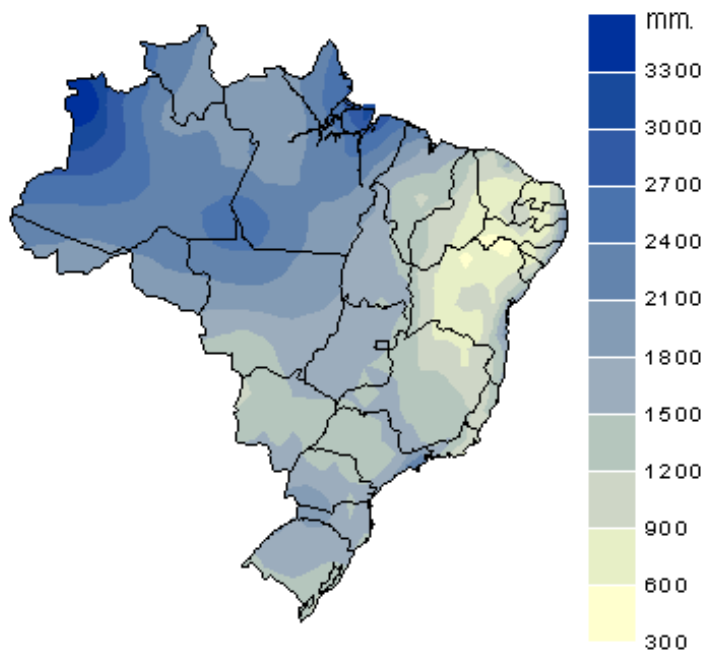


Figure 4.3: Mean Annual Cumulative Precipitation, 1931-1990 (Source: Instituto Nacional De Meteorologia)

variables by municipio to exhibit the cross-sectional variation in the climate variables. In these graphs, it will also become clear if the variation of the variables may be attributable to a municipio outlier.

Figures 4.4-4.7 illustrate that, of the warmest months (December-March), the December temperature variable is the warmest month cross-sectionally with the most variation. However, it should be noted that the difference in the range of temperatures and cross-sectional variation among the warmest months is minute. This lack of variation foreshadows the difficulty that may arise in measuring the value of increasing temperatures in the warmest season of Brazil, which could potentially be the most damaging for the country.

Of the coolest months (June-August), the June temperature variable has the most cross-sectional variation (see Figures 4.8-4.10). As in the case of warm temperature months, little difference exists in the range of temperatures and cross-sectional variation among the cool month variables, yet overall there is more variation among these variables than the warm month variables. It may be difficult to isolate the effect of increasing the temperature of *both* warm and cool months. In Chapters 5 and 6, I compare the results from hedonic regression models that include seasonal versus annual temperature variables to see if it is possible to capture the value of temperature in this context at all.

Figure 4.11 illustrates the geographical distribution of monthly and average temperature variables in the sample. From the Figure, it is clear that little cross-sectional variation exists in the temperature variables. The temperatures in Curitiba are generally lower than the temperatures of the rest of the municipios. While the temperature values for Curitiba may be considered outliers, I anticipate that this will only slightly affect the parameter estimates. Only 7 per-

cent of the total sample consists of households from Curitiba. Nevertheless, I estimate a model in the empirical chapters that includes a variable that interacts temperature and a southern dummy variable to observe if the marginal effect of temperature on rents and wages differs.

The wettest months in Brazil are February and March, where March precipitation clearly has more cross-sectional variation than February precipitation (see Figures 4.12 and 4.13). What is classified as a dry month depends on the interpretation (refer to Figures 4.14-4.17). Figure 4.18 shows the geographical distribution of monthly and average precipitation levels. In our sample, the cross-sectional average precipitation levels are lowest in August and September, where the August precipitation variable has the most cross-sectional variation (Table 4.5). However, some municipios possess precipitation levels in the single digits during the months of June and July, where the month of June has the highest cross-sectional variation of the two. In the analysis, I will use each of these variables (February, March, June, and August precipitation) to see how sensitive the climate parameter estimates are to the use of climate variable.

In terms of the effect of rainfall on preferences, one would expect summer rainfall to have an impact on welfare since it influences beach recreation and leisure activities during one's summer holiday. This may particularly be the case for the sample used in the analysis, since many of the municipios are along the coast of Brazil. However, it remains unclear what impact an increase in dry weather, especially when it occurs in the winter season, will have on preferences. Temperatures rarely reach freezing anywhere in Brazil during the winter. Thus, increases in rainfall may have the same directional effect in the winter as in the summer, except the magnitude of the effect may be smaller. The magnitude of

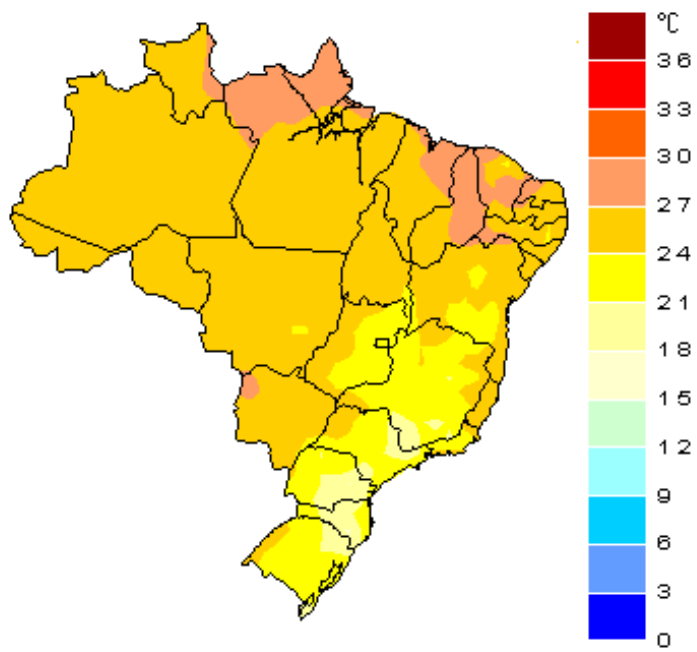


Figure 4.4: Annual Average December Temperature, 1931-1990 (Source: Instituto Nacional De Meteorologia)

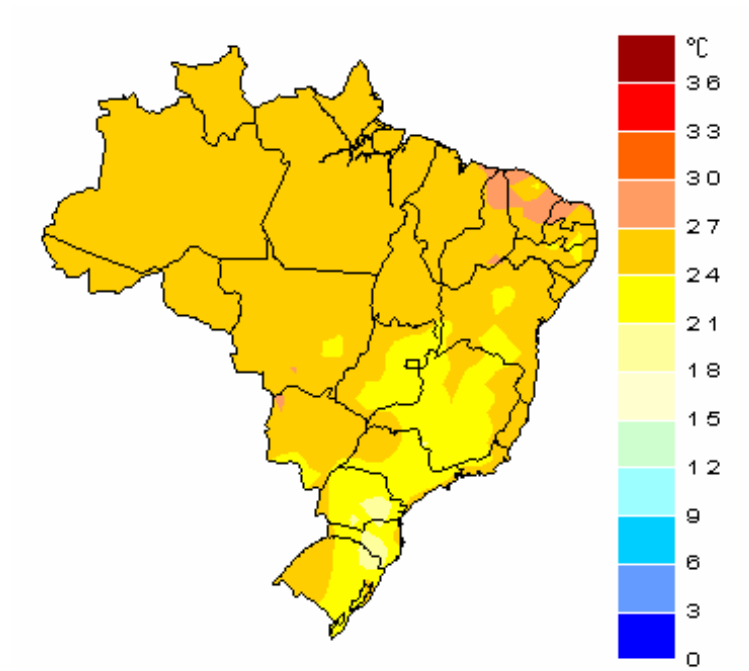


Figure 4.5: Annual Average January Temperature, 1931-1990 (Source: Instituto Nacional De Meteorologia)

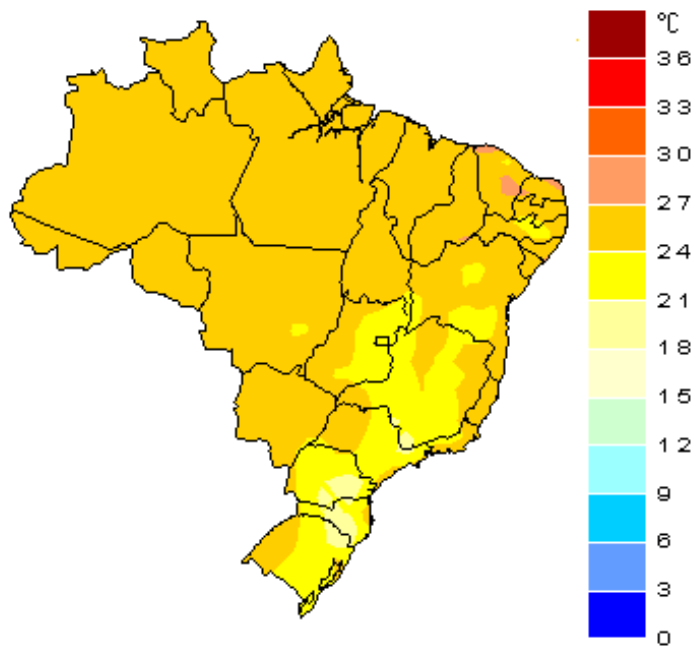


Figure 4.6: Annual Average February Temperature, 1931-1990 (Source: Instituto Nacional De Meteorologia)

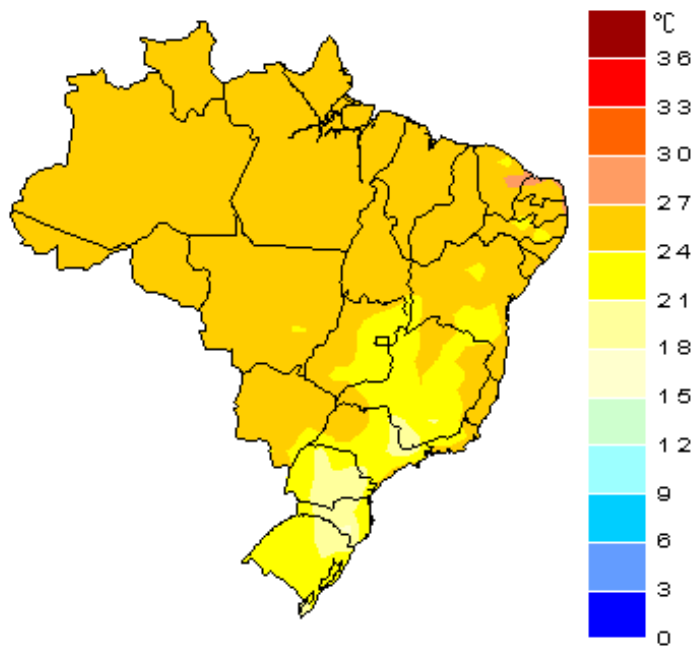


Figure 4.7: Annual Average March Temperature, 1931-1990 (Source: Instituto Nacional De Meteorologia)

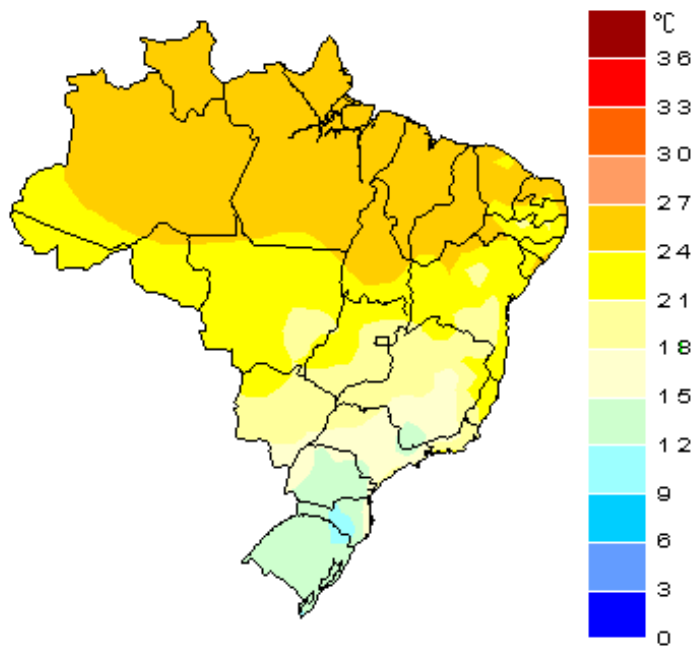


Figure 4.8: Annual Average June Temperature, 1931-1990 (Source: Instituto Nacional De Meteorologia)

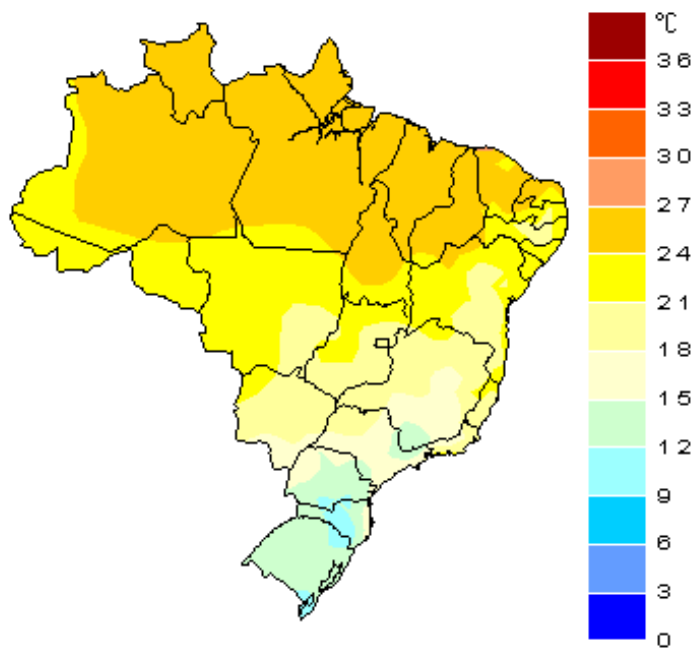


Figure 4.9: Annual Average July Temperature, 1931-1990 (Source: Instituto Nacional De Meteorologia)

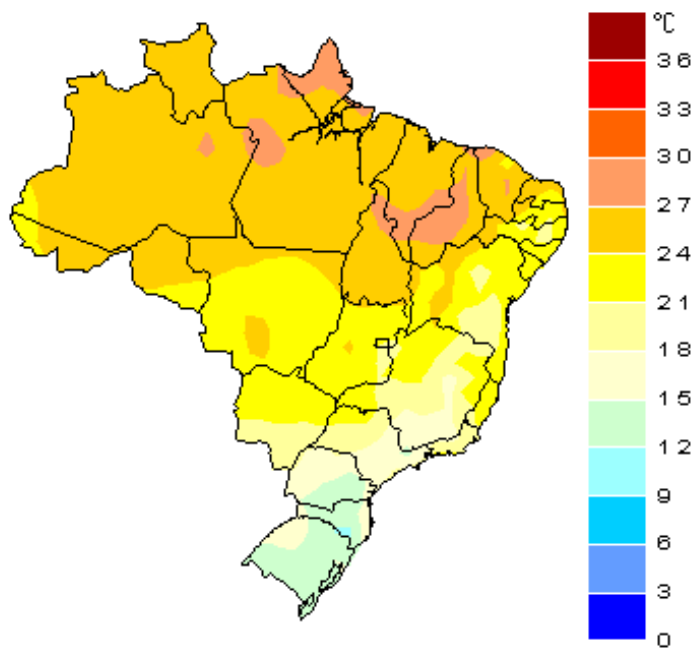


Figure 4.10: Annual Average August Temperature, 1931-1990 (Source: Instituto Nacional De Meteorologia)

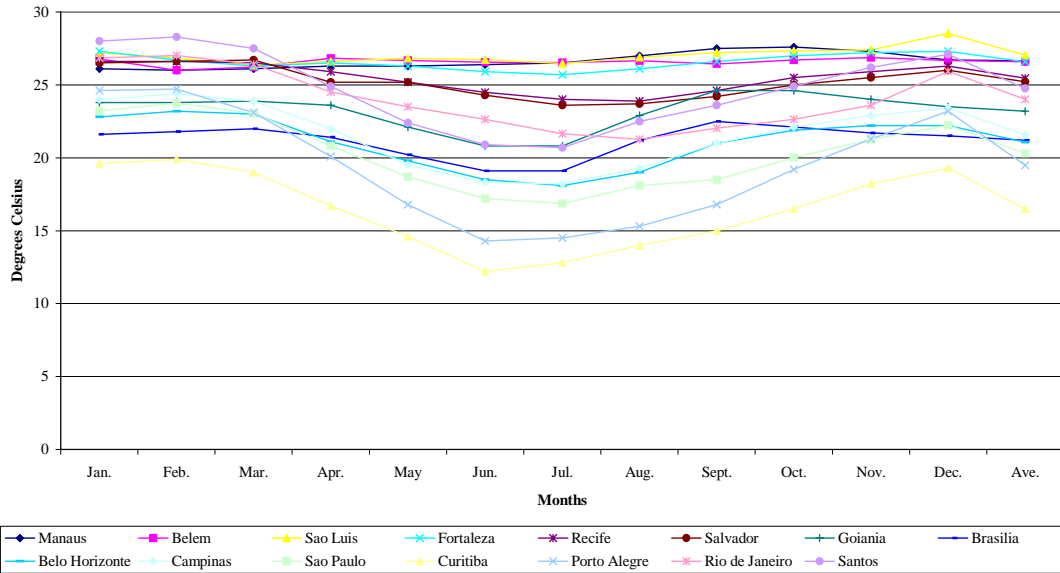


Figure 4.11: Geographical Distribution of Monthly and Average Temperatures

the value of rainfall should also be influenced by which monthly variable is used, particularly since there are significantly low values for rainfall in June and July precipitation variables.

Next, I graph the distribution of the monthly arid indexes to observe whether there is enough variation in the variables. In Figure 4.19, the municipios on the x-axis are organized from left to right by region. From the far left of the graph's x-axis, the municipios are in the northern, northeastern, midwestern, and southern (far right) regions. At the onset, there appears to be quite a bit of variation in the index during the wet and dry months of Brazil.

I am particularly interested in whether a monthly aridity index could potentially isolate the effect of other goods/amenities, e.g., the prevalence of flora, other climate variables, often correlated with rainfall. To determine this possibility, I graph the distribution of candidate monthly precipitation variables with

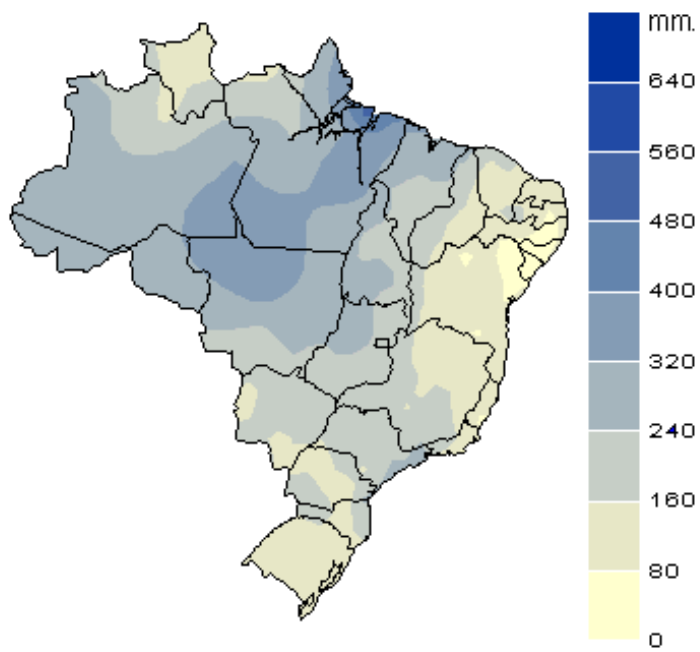


Figure 4.12: Annual Average February Precipitation, 1931-1990 (Source: Instituto Nacional De Meteorologia)

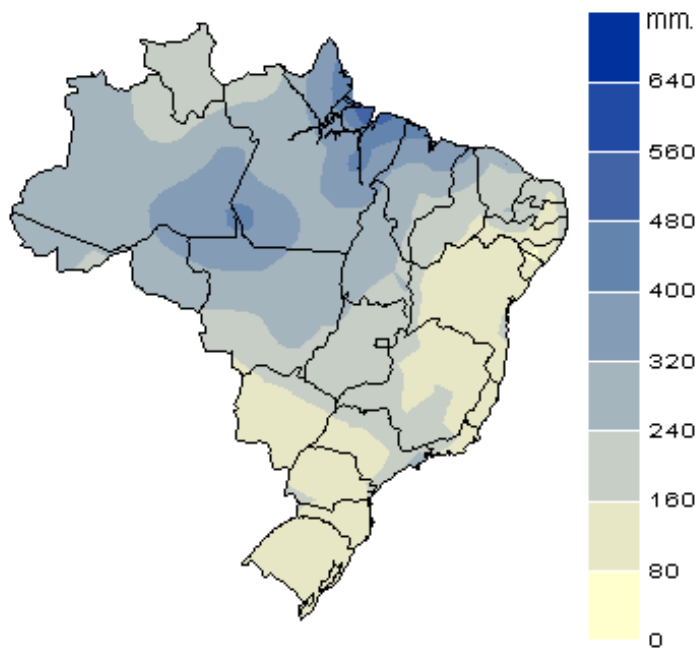


Figure 4.13: Annual Average March Precipitation, 1931-1990 (Source: Instituto Nacional De Meteorologia)

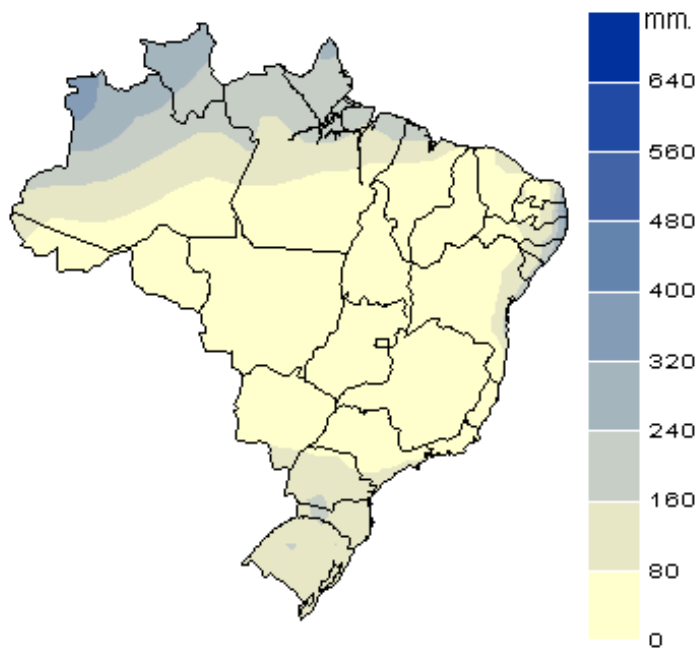


Figure 4.14: Annual Average June Precipitation, 1931-1990 (Source: Instituto Nacional De Meteorologia)

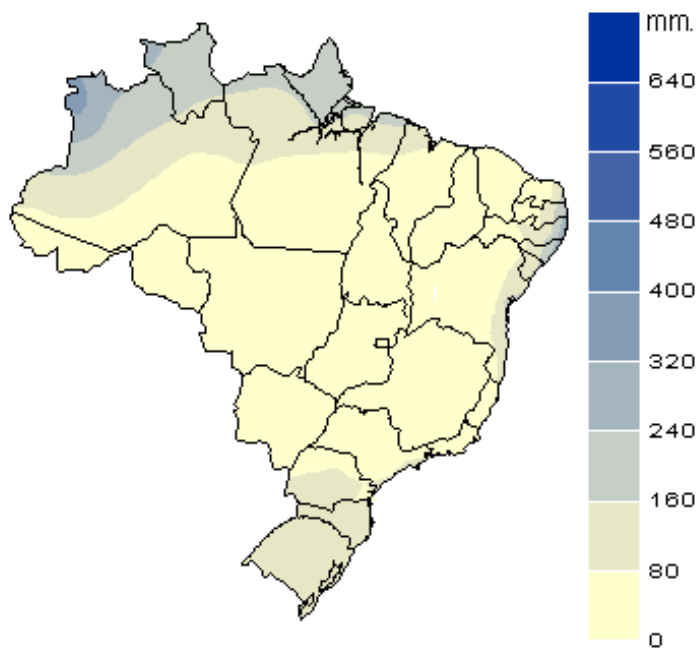


Figure 4.15: Annual Average July Precipitation, 1931-1990 (Source: Instituto Nacional De Meteorologia)

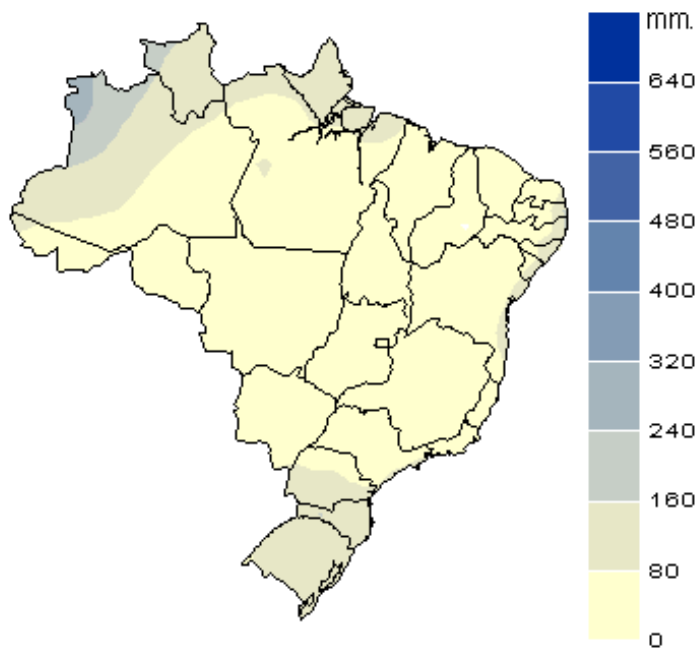


Figure 4.16: Annual Average August Precipitation, 1931-1990 (Source: Instituto Nacional De Meteorologia)

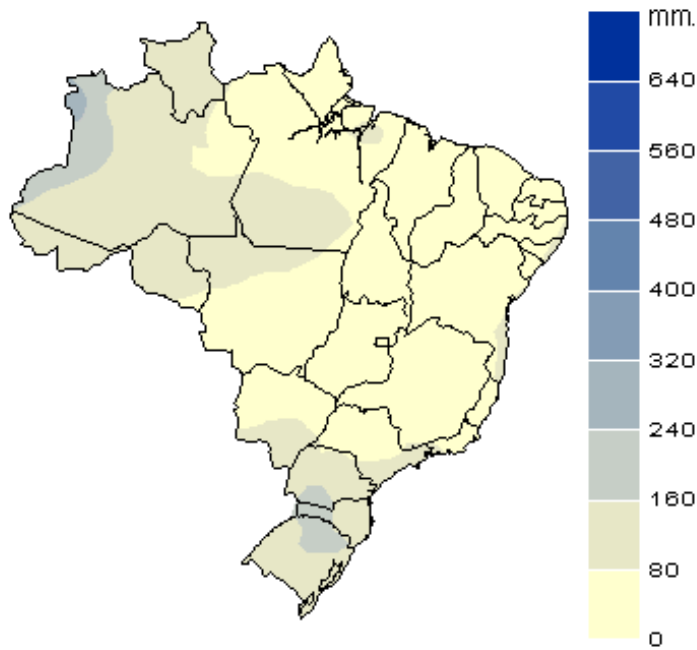


Figure 4.17: Annual Average September Precipitation, 1931-1990 (Source: Instituto Nacional De Meteorologia)

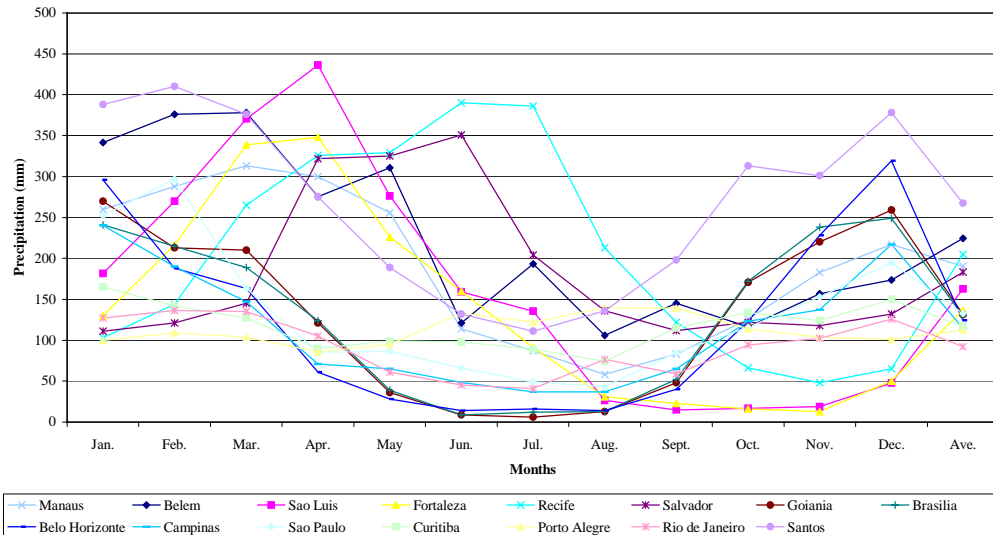


Figure 4.18: Geographical Distribution of Monthly and Average Precipitation

the aridity indexes for the respective months to observe whether the distribution of the variables are distinct. I do not include graphs of the aridity indexes during wet months because all values are close to or greater than one.

From Figures 4.20-4.23, it appears that there may be problems isolating the effect of rainfall and aridity since there exists a strong correlation between the two variables. The graphs demonstrate that many of the regions with arid, semi-arid or savannah type climates, e.g. Sao Luis or Brasilia, have low values for the aridity index indicating that there may be less forests or woodlands in these areas. Also, Porto Alegre, known for having quite a bit of trees relative to its size, obtains the highest value for the aridity index among all the cities in the sample. It is this effect that I would like to isolate from the sheer value of rainfall in the housing price and wage models.

Next, I graph the distribution of non-climate amenity variables to see whether there is enough variation in these variables to disentangle the effects of other valued public goods on housing prices and wages. Figure 4.24 shows the distribution of schools, violent deaths, banks, hospitals per 100,000, population density, and altitude variables. The municipios on the x-axis are organized from left to right by region. From the left to right on each graph's x-axis the municipios are in the northern, northeastern, southeastern, southern, and midwestern regions. I sort the data regionally in order to uncover any regional disparities or similarities in non-climate amenity variables. This also serves as a check of the degree of intra-regional variation in the variables, which will help facilitate estimation of the parameters and interpretation of results.

Figure 4.24 shows that many of the amenity variables differ only by northern and southern locations. With the exception of the number of hospitals

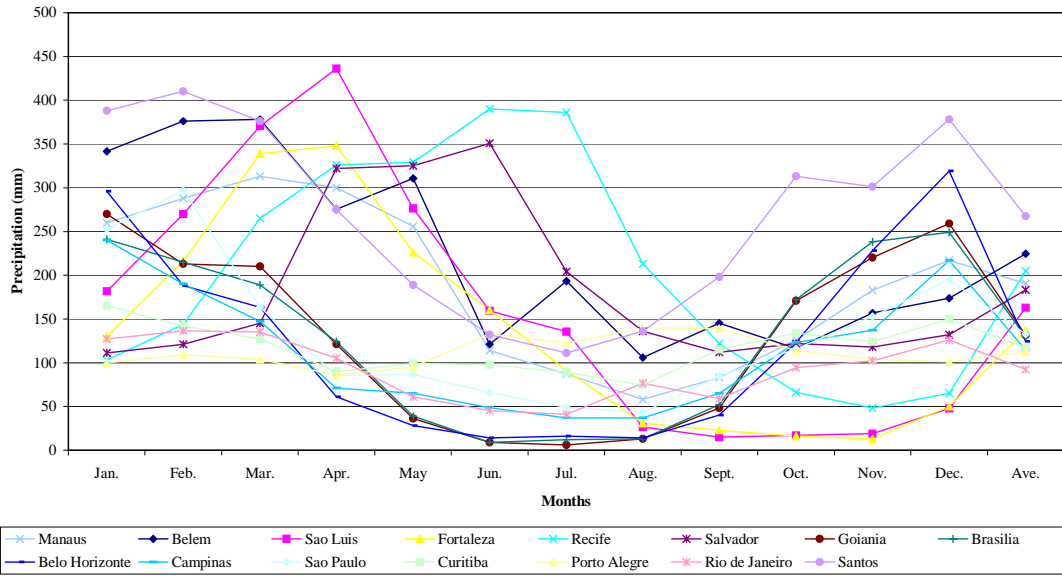


Figure 4.19: Geographical Distribution of Monthly Aridity Indexes

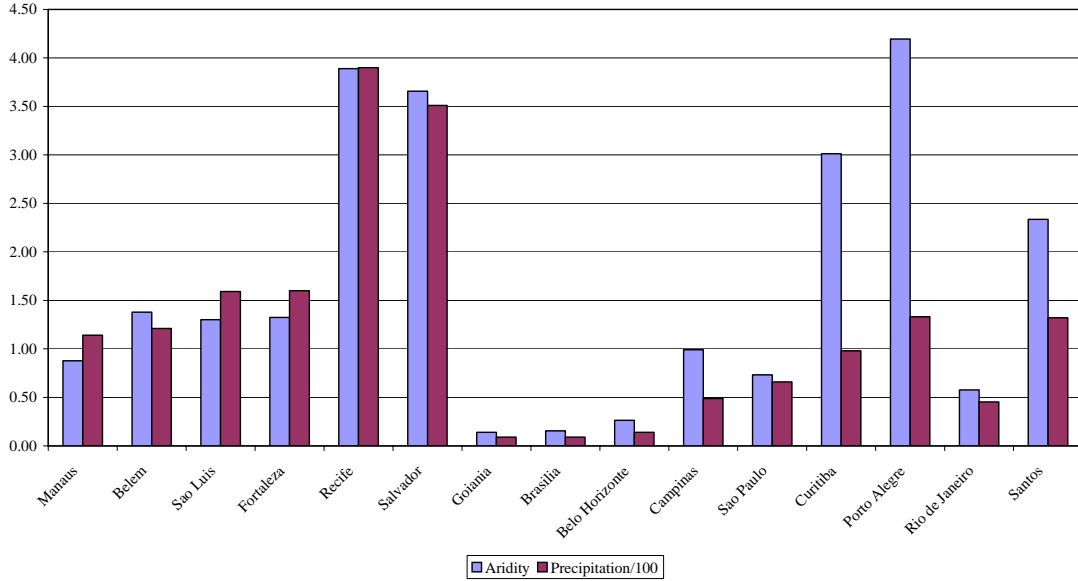


Figure 4.20: Geographical Distribution of the June Precipitation and Aridity Index Variables

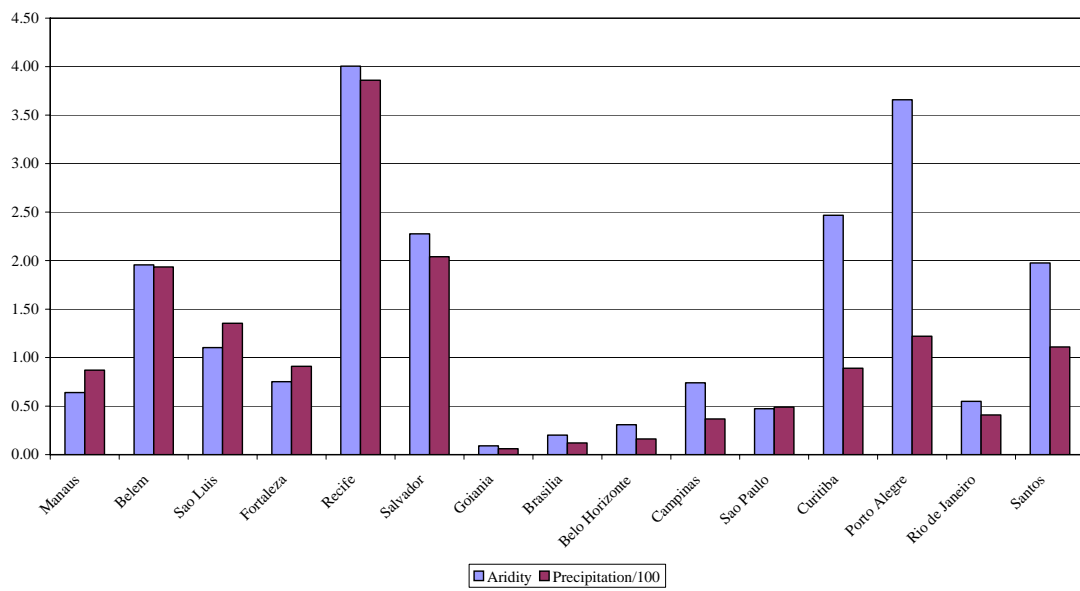


Figure 4.21: Geographical Distribution of the July Precipitation and Aridity Index Variables

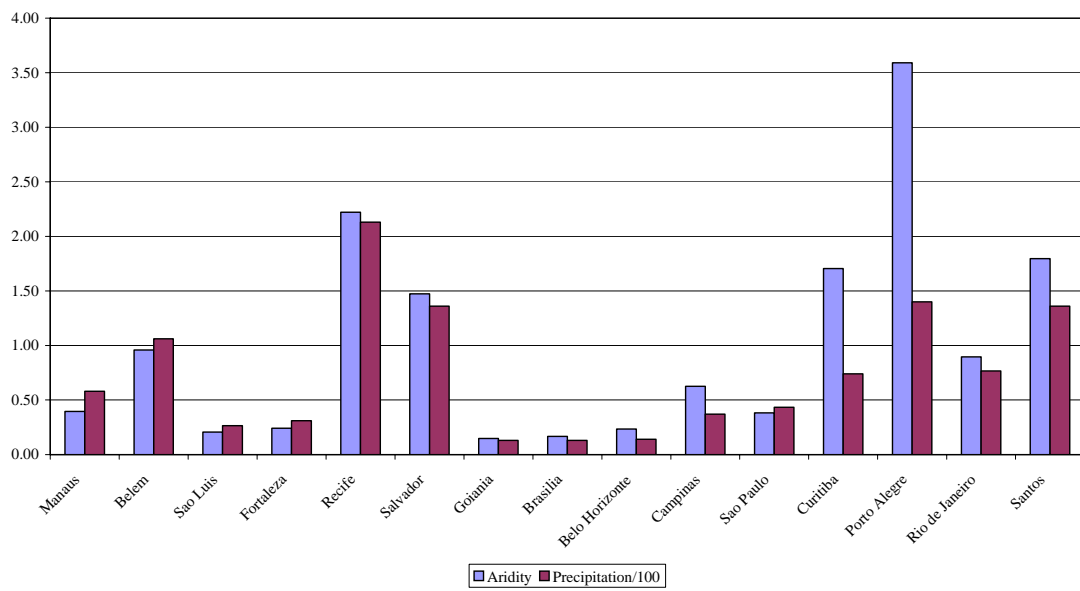


Figure 4.22: Geographical Distribution of the August Precipitation and Aridity Index Variables

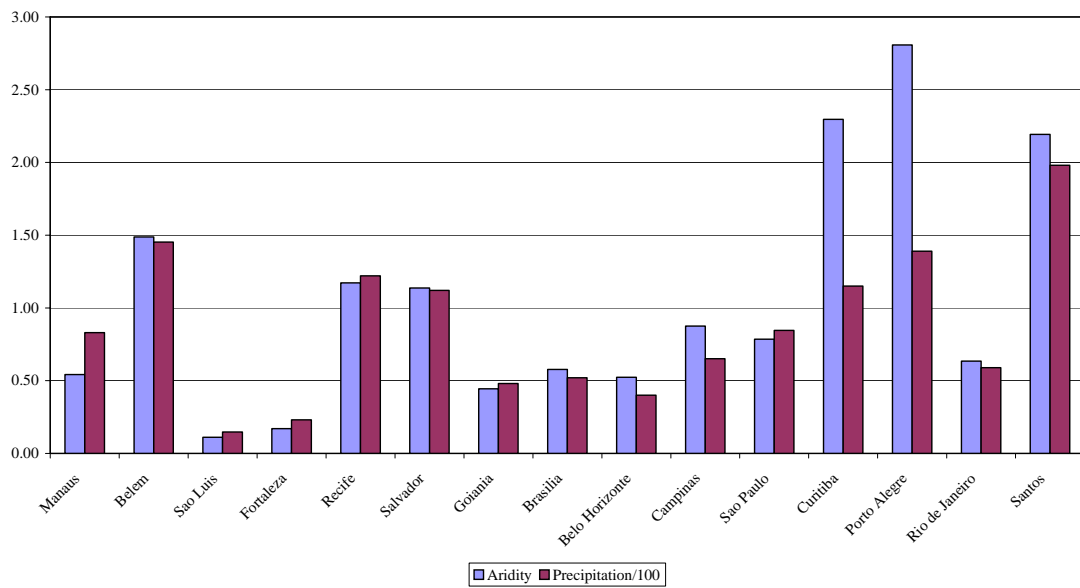


Figure 4.23: Geographical Distribution of the September Precipitation and Aridity Index Variables

variables, all non-climate amenity variables have enough interregional and intra-regional variation to distinguish between a city's appeal and favorable climate conditions. Including the hospital variable in the regression analysis is unlikely to be informative, as there is little cross-sectional variation in the variable.

With the exception of Recife, the North generally has less crime than the other areas. One reason for including the number of violent deaths is that I can capture the tradeoff individuals made in choosing to locate in the South, especially from Rio de Janeiro and Sao Paulo where most Brazilians live. Specifically, the North has less crime and more schools per capita. A disadvantage in using the schools variable is that it does not reflect variations in the quality of education. The quality of schools may be considered more important to the head of household in his choice of where to work and raise his family.

The number of banks serves as a proxy for the economic activity in the municipio. From Figure 4.24, it appears that the number of banks is greater in the South and Midwest than the North. However, there are less banks in the Midwest than the South. Porto Alegre has the most banks in the sample. This is not surprising considering Porto Alegre is known for having a strong economy.

Population density and altitude also vary considerably. The variation in these variables is independent of region. There is enough intra-regional variation in these variables to distinguish the appeal of cities within a region from each other in the model.

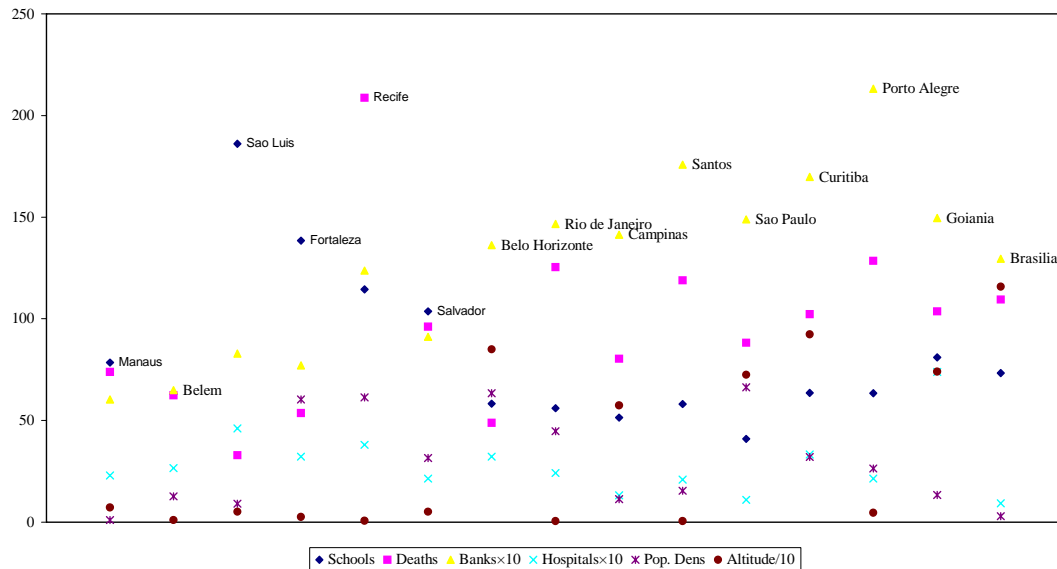


Figure 4.24: Geographical Distribution of the Non-Climate Amenity Variables

4.2.3 Multicollinearity between Climate and Non-Climate Amenity Variables

Tables 4.16-4.20 display the correlation coefficients of the climate and non-climate variables. One of the consequences of multicollinearity in a regression model is that the standard errors of the coefficients may be relatively high and the significance level low even though the variables are jointly significant (Greene, 1997). Often, researchers exclude variables from models when their coefficients have low significance levels. If such a variable is in fact a determinant of the dependent variable but highly correlated with another variable included in the model, then excluding the explanatory variable from a model may result in omitted variable bias. In what follows, I will briefly go over the Pearson correlation coefficients of variables that would be included in the same model.

Table 4.16 displays the correlation coefficients of the temperature variables. The high correlation coefficients are highlighted. Earlier, I noted that it may be difficult to isolate the effect of seasonal temperatures on housing prices and wages due to the lack of variation among those variables. An additional complication in isolating those effects may be attributed to the high collinearity between variables. One remedy of this inherent collinearity between variables is to include average temperature in the regression models instead of seasonal temperature variables.

Table 4.17 displays the correlation coefficients of the temperature and rainfall variables. March rainfall, which is one of the candidate variables for capturing the effect of summer rainfall on prices, is highly correlated with the winter rainfall variables. Although the March rainfall variable has more cross-sectional variation than the February rainfall variable, one pitfall in using the March rainfall variable is that it is highly collinear with the winter temperature variables.

Table 4.18 shows the correlation coefficients of all rainfall variables. Of the variables that would be included in the same model, none have correlation coefficients that exceed 0.65.

Table 4.19 presents the correlation coefficients of the aridity index variables and the rainfall and temperature variables. The highlighted correlation coefficients are of the variables that may pose multicollinearity issues if included in the same regression model. Many of the aridity index variables have strong correlations with the rainfall variables, as expected. Smaller correlation coefficients exist for the September aridity index and rainfall variables.

Table 4.20 displays the correlation coefficients of the non-climate and

climate amenity variables. The correlation coefficients of the non-climate amenity variables suggest that there is less of a risk of multicollinearity in including these variables in the model. The strongest correlation exists between the number of schools and banks, with a correlation coefficient of -0.59. Including altitude in the model may cause symptoms of multicollinearity in the regression models, however, since the variable is strongly correlated with the temperature variables. If included in the model, altitude may cause the coefficients on the variables of interest, seasonal temperatures, to be insignificant. A test on the joint significance of the altitude and temperature coefficients will answer if this factor is an issue.

In Chapters 5 and 6, I use much of the analysis performed in this chapter to determine the specification of the models, and to interpret the results from the hedonic rent and wage regressions. The analysis conducted in this chapter suggests that the major issue will be trying to isolate the effect of a particular climate amenity on housing rents and wages, particularly because of the lack of variation in climate amenity variables and the high collinearity between climate amenity variables.

Table 4.16: Correlation Coefficients of Temperature Variables

	Average	December	January	February	March	June	July	August
Average	1.00	0.95	0.89	0.85	0.93	0.99	0.99	0.96
December	0.95	1.00	0.98	0.95	0.97	0.91	0.90	0.85
January	0.89	0.98	1.00	0.99	0.97	0.84	0.82	0.74
February	0.85	0.95	0.99	1.00	0.98	0.80	0.77	0.69
March	0.93	0.97	0.97	0.98	1.00	0.90	0.87	0.81
June	0.99	0.91	0.84	0.80	0.90	1.00	1.00	0.98
July	0.99	0.90	0.82	0.77	0.87	1.00	1.00	0.99
August	0.96	0.85	0.74	0.69	0.81	0.98	0.99	1.00

Table 4.17: Correlation Coefficients of Temperature and Rainfall Variables

	Temperature							
Rainfall	Average	December	January	February	March	June	July	August
February	0.15	0.02	-0.03	-0.08	-0.01	0.17	0.20	0.28
March	0.69	0.59	0.47	0.37	0.45	0.69	0.74	0.78
June	0.47	0.52	0.51	0.52	0.53	0.44	0.44	0.38
July	0.43	0.48	0.47	0.46	0.46	0.40	0.41	0.35
August	0.22	0.37	0.43	0.45	0.39	0.17	0.16	0.07
September	-0.16	-0.04	0.03	0.03	-0.03	-0.20	-0.19	-0.23

Table 4.18: Correlation Coefficients of Rainfall Variables

	February	March	June	July	August	September
February	1.00	0.60	-0.35	-0.21	-0.42	-0.07
March	0.60	1.00	0.15	0.27	-0.07	-0.16
June	-0.35	0.15	1.00	0.91	0.81	0.48
July	-0.21	0.27	0.91	1.00	0.89	0.61
August	-0.42	-0.07	0.81	0.89	1.00	0.78
September	-0.07	-0.16	0.48	0.61	0.78	1.00

4.2.4 Errors in the Climate and Non-Climate Amenity Variables

The variables included in the analysis are susceptible to the errors in variables issue. First, the climate amenity variables reflect county temperature and rainfall averages. I am unable to capture the level of climate amenities experienced by each individual. Temperature and rainfall can vary even within a small geographic area. Thus, the actual climate variables included in the analysis measure the climate conditions realized by each individual with error.

Many of the non-climate amenities were used to proxy amenities that are typically of value to workers and consumers of housing. Examples include the number of schools and banks variables. While households are likely more

Table 4.19: Correlation Coefficients of Arid, Rainfall, and Temperature

	Variables			
	Jun.arid.	Jul.arid.	Aug.arid.	Sept.arid.
Ave.temp	-0.01	-0.03	-0.21	-0.50
Dec.temp	0.15	0.13	0.00	-0.32
Jan.temp.	0.19	0.17	0.10	-0.24
Feb.temp.	0.19	0.16	0.11	-0.25
Mar.temp	0.11	0.07	-0.03	-0.37
Jun.temp.	-0.08	-0.09	-0.30	-0.56
Jul.temp.	-0.06	-0.08	-0.29	-0.54
Aug.temp	-0.14	-0.15	-0.37	-0.58
Feb.rain.	-0.54	-0.45	-0.56	-0.33
Mar.rain.	-0.18	-0.09	-0.35	-0.38
Jun.rain.	0.79	0.71	0.47	0.21
Jul.rain.	0.76	0.81	0.55	0.32
Aug.rain.	0.86	0.90	0.81	0.58
Sep.rain.	0.74	0.80	0.77	0.83
Jun.arid.	1.00	0.95	0.87	0.74
Jul.arid.	0.95	1.00	0.92	0.79
Aug.arid.	0.87	0.92	1.00	0.89
Sep.arid.	0.74	0.79	0.89	1.00

Table 4.20: Correlation Coefficients of Non-Climate and Climate Variables

	Banks	Deaths	Schools	Pop.Dens.	Altitude
Ave.temp.	-0.81	-0.07	0.65	-0.05	-0.70
Dec.temp.	-0.65	0.02	0.63	0.02	-0.87
Jan.temp.	-0.52	0.08	0.52	0.10	-0.92
Feb.temp.	-0.46	0.12	0.46	0.15	-0.91
Mar.temp.	-0.61	0.08	0.50	0.09	-0.83
Jun.temp.	-0.86	-0.09	0.63	-0.05	-0.63
Jul.temp.	-0.88	-0.11	0.65	-0.09	-0.62
Aug.temp.	-0.90	-0.16	0.66	-0.15	-0.51
Feb.rain.	-0.36	-0.46	-0.21	0.00	0.22
Mar.rain.	-0.73	-0.28	0.55	-0.07	-0.31
Jun.rain.	-0.36	0.38	0.61	0.08	-0.60
Jul.rain.	-0.28	0.53	0.49	0.05	-0.58
Aug.rain.	0.06	0.69	0.21	-0.02	-0.64
Sep.rain.	0.24	0.45	-0.22	-0.25	-0.29
Jun.arid.	0.16	0.47	0.33	-0.07	-0.48
Jul.arid.	0.22	0.58	0.24	-0.09	-0.46
Aug.arid.	0.50	0.59	0.00	-0.14	-0.43
Sep.arid.	0.58	0.37	-0.26	-0.26	-0.12
Banks	1.00	0.40	-0.59	0.08	0.31
Deaths	0.40	1.00	-0.03	-0.05	-0.21
Schools	-0.59	-0.03	1.00	-0.02	-0.45
Pop.Dens.	0.08	-0.05	-0.02	1.00	-0.06
Altitude	0.31	-0.21	-0.45	-0.06	1.00

motivated to locate to an area based on the quality of schools, I did not have access to this variable. Thus, the number of schools in a sense measures the quality of schooling in a given county with error. A similar argument could be made for the number of banks variable used as a proxy for economic activity in a given county.

The implications of including stochastic regressors in the analysis is obtaining a downwardly biased and inconsistent OLS estimator (Judge, 1988). This occurs because the assumption that the regressors are independent of the error term is violated. Because the bias is downward, the effects of climate on wages and housing prices may appear weaker than the true effects.

One way of addressing this issue is to apply an instrumental variables approach. I do not apply this approach because i) finding a suitable instrument for each variable measured with error is quite difficult, ii) the degrees of freedom allowable to the model restricts the number of municipio-level instruments I can use, and iii) the data are not readily available. In future work, I intend to search for climate data at a more disaggregate level, e.g. census district level, to better approximate the individual level of climate amenities consumed and mitigate the errors in variables problem. I also intend to expand the geographical scope of the analysis to include areas surrounding the 15 municipios. This eradicates the degrees of freedom issue and allows the use of an instrumental variables approach. However, the difficulty in discovering suitable instruments for these variables remains.

Chapter 5

The Hedonic Rent Model

In this chapter, I estimate the hedonic rent equation expressed in (2.25) using the sample of renters. The purpose of this chapter is to show how sensitive the housing rent differentials of climate amenities are to the specification of the hedonic rent model. The organization of the chapter is as follows. In Section 5.1, I describe any assumptions implicitly imposed on the empirical models in this chapter. Section 5.2 describes the variables included in a baseline rent model and its results. In Section 5.3, I address the issues raised in the Data chapter. Specifically, I show that the instability of the rent differential estimates can be attributed to the collinearity between climate variables and the specification of climate amenities. Section 5.4 concludes with a summary of the findings of this chapter.

5.1 Model Assumptions

5.1.1 Functional Form

Three commonly estimated functional forms are assumed in each version of the hedonic rent model: semilog, double log, and the Box-Cox transformation of the dependent and independent variables. Using the same notation as in equation (2.25), the log-linear, double-log, and Box-Cox models are respectively:

$$\ln P_{ij} = \beta_0 + \beta_1 S_{ij} + \beta_2 N_j + \beta_3 Z_j + \varepsilon_{ij}, \quad (5.1)$$

$$\ln P_{ij} = \beta_0 + \beta_1 S_{ij} + \beta_2 N_j + \beta_3 \ln Z_j + \varepsilon_{ij}, \quad (5.2)$$

$$\frac{P_{ij}^\lambda - 1}{\lambda} = \beta_0 + \beta_1 S_{ij} + \beta_2 N_j + \beta_3 \frac{Z_j^\lambda - 1}{\lambda} + \varepsilon_{ij}. \quad (5.3)$$

Note for each functional form the housing structural characteristic and non-climate amenity variables remain untransformed.¹

All of the statistical analysis is performed using Intercooled Stata 8.0. I first estimate equations (5.1) and (5.2) using OLS. Assuming the error term ε_{ij} is normally distributed with mean zero and variance σ^2 , the log-likelihood function used to estimate the parameters in equation (5.3) is:

$$-\frac{n}{2} \ln(2\pi) - \frac{n}{2} \ln \sigma^2 + (\lambda - 1) \sum_{i=1}^n \ln P_{ij} - \frac{1}{2\sigma^2} \sum_{i=1}^n \left(\frac{P_{ij}^\lambda - 1}{\lambda} - \beta_0 - \beta_1 S_{ij} - \beta_2 N_j - \beta_3 \frac{Z_j^\lambda - 1}{\lambda} \right)^2.$$

¹I do not transform the housing structural variables since they are dummy variables. I do not transform the non-climate amenity variables in the Box-Cox model due to the inability to estimate more complex versions of the model. I do transform the non-climate amenity variables in the double-log model in order to compare the results across models.

For the Box-Cox procedure, Stata does not report the variance estimates of the coefficients. Thus, estimates for the standard errors of the parameters in the Box-Cox regressions were calculated using Gauss 5.0.

I only estimate the linear version of the Box-Cox model. Due to the relative flatness of the likelihood function, I was unable to successfully estimate the hedonic model with the following functional forms: 1) the Box-Cox transformation of the climate and non-climate amenity variables, 2) distinct Box-Cox transformations of the dependent variable and the climate and non-climate amenity variables, and 3) distinct Box-Cox transformations of the dependent variable and the climate variables.² The lack of variation in the climate data also precludes estimation of more complex versions of the Box-Cox model, like the quadratic Box-Cox model.

Cropper, Deck, and McConnell (1988) conduct a set of Monte Carlo experiments simulating the Baltimore housing market. Their objective was to observe how the assumption of functional form affected the estimation of marginal prices when all attributes were observed and when some attributes were unobserved. Six different scenarios were assessed: each varying specifications on utility, housing attributes, and buyer characteristics. For the case where all attributes were observed, they found that the linear Box-Cox performed best. The criterion for the result was the functional form that yielded the smallest magnitude for the maximum of the ratio of the mean error to true bid. Based on other criteria, both the linear and quadratic Box-Cox models outperformed the models with other functional forms. When actual variables were replaced by proxy variables in the hedonic function, they found that the linear Box-Cox had the

²The model specified in 3) is $\frac{P_{ij}^\lambda - 1}{\lambda} = \beta_0 + \beta_1 S_{ij} + \beta_2 N_j + \beta_3 \frac{Z_i^\theta - 1}{\theta} + \varepsilon_{ij}$.

smallest average value of the standard errors as a fraction of the mean true bid of all functions, and smaller mean errors as a function of the mean true bid than the those from the quadratic Box-Cox model. Based on their results, Cropper, Deck and McConnell suggest using the linear Box-Cox functional form.

5.1.2 Heteroskedasticity

Each model in this chapter is estimated both with and without assuming homoskedasticity since greater variation in housing rents may exist among particular groups of households because of a common characteristic. For example, the variation in rental prices among high-income households may be greater than low-income households due to the greater purchasing power available to these households. In the presence of heteroskedasticity, the OLS estimator of the parameters in the hedonic rent model is unbiased and consistent, but inefficient (Greene, 1997). The standard errors are biased and inconsistent rendering t statistics and confidence intervals based on these standard error estimates invalid (Greene, 1997).

Weighted least squares (WLS) is a common approach used to produce efficient OLS estimators and unbiased and consistent standard errors. In using WLS, the efficiency gains are only possible if the correct assumption is imposed on the conditional variance (Wooldridge, 2002). Applying WLS with improper specifications of the conditional variance leads not only to an inefficient estimator of the parameters, but also incorrect standard errors (Greene, 1997).

When the nature of the heteroskedasticity is uncertain, a heteroskedasticity-robust (HR) estimator is often used to correct potentially biased standard errors.³

³White, Eicker, and Huber are acknowledged for having contributed to the development of

The HR covariance estimator is:

$$\widehat{V}(\widehat{\theta}) = (\mathbf{X}'\mathbf{X})^{-1} \left(\sum_{i=1}^N \widehat{u}_i^2 \mathbf{x}'_i \mathbf{x}_i \right) (\mathbf{X}'\mathbf{X})^{-1}, \quad (5.4)$$

where $\widehat{u}_i = y_i - \mathbf{x}_i \widehat{\boldsymbol{\beta}}$. Standard errors computed using (5.4) are robust to homoskedasticity or heteroskedasticity, however, at the expense of the possible gains in efficiency from using a correctly specified WLS estimator (Wooldridge, 2002).

Expression (5.4) is the OLS estimator for the HR covariance matrix. As mentioned, I will also be estimating a linear Box-Cox model which involves obtaining the maximum likelihood estimator (MLE) of the parameters. The HR estimator of the covariance matrix for this model is:

$$\widehat{V}(\theta_{MLE}) = \widehat{\mathbf{V}} \left(\sum_{i=1}^N \mathbf{u}'_i \mathbf{u}_i \right) \widehat{\mathbf{V}}, \quad (5.5)$$

where $\widehat{\mathbf{V}}$ is the BHHH estimator of the asymptotic covariance matrix, and \mathbf{u}_i is a row vector representing the contribution from the i th observation to the scores $\frac{\partial \ln L}{\partial \theta}$.⁴

For each model, I report the standard errors under the assumption of homoskedasticity and heteroskedasticity. For ease of presentation, the t (for the semilog and double-log models) and Wald (for the Box-Cox models) tests are used to determine whether the coefficient is significantly different from zero and are calculated using the HR standard errors.

An additional concern in using cross-sectional data is the existence of clustered samples, e.g. unobservable shocks affect individuals living in the same

this estimator (see Wooldridge, 2002).

⁴The BHHH estimator of the covariance matrix is the outer product of gradients of the likelihood function (see Greene, 1997).

municipio systematically. I do not allow for clustering of the error term in any of the empirical models. First, Wooldridge notes that the properties of the estimator accounting for clustering is generally satisfactory if the number of clusters is large (Wooldridge, 2002; Wooldridge, 2003). Only 15 clusters are present in the sample. Second, in applying the robust covariance matrix estimator accounting for clustering in preliminary work, the standard errors were suspect. In particular, the standard errors in the model that accounted for clustering by municipio were substantially smaller than the standard errors in the model without clustering. This implies that the residuals are negatively correlated within a cluster. Sribney (2001) notes that, under these circumstances, the specification of the model may be questionable.

Two consequences of ignoring this component of the model, if the cluster effect truly exists, are obtaining inefficient coefficient estimators and obtaining standard errors that are downward biased. In future work, I would like to broaden the scope of the analysis by including areas surrounding the 15 municipios. By expanding the pool of geographic areas in the sample, I will have more confidence in using the HR covariance matrix that accounts for clustering in the sample.

5.2 The Baseline Hedonic Rent Model

The variables considered determinants of real monthly rental prices S_{ij} , N_j , and Z_j are:

- i) Housing structural characteristics: dummy variables interacting resi-

dence size and type of residence⁵ (e.g., for a two-bedroom apartment, $Br2 \times A=1$),⁶ flush toilet ($Flusht=1$), and water filter⁷ ($Filter=1$);⁸

2) Location attributes: number of banks ($Banks$), violent deaths ($Deaths$), schools ($Schools$) per 100,000 residents, population density (population/km²) divided by 100 ($Popdens$), the aridity index for the driest month ($Arid$), and altitude divided by 10 ($Altitude$);

3) Climate: winter ($Junetemp$) and summer ($Febtemp$) temperature, and winter ($Junerain$) and summer ($Febrain$) rainfall; and

4) Region: dummy variables for region—north ($N=1$), northeast ($NE=1$), south ($S=1$), and midwest ($MW=1$).

One of the major limitations in the analysis is the number of parameters that can be identified on variables that vary by municipio. Only 14 parameters of the municipio-level variables can be estimated in the model due to the nature of the data and number of cities included in the sample. Because of this restriction,

⁵The PNAD survey does not identify whether the dwelling is a duplex, a semi-attached house, or a townhouse.

⁶The number of bedrooms reflects the size of the residence. I create bedroom dummy variables, $BR1$, $BR2$, $BR3$, and $BRGT3$, where $BRGT3$ takes a value of 1 when the residence has more than 3 bedrooms. I also create dummy variables for the type of residence, apt ($A=1$) or house ($H=1$). The final model includes all of the interaction dummy variables, with the exception of $BR1 \times H$.

⁷The survey does not ask the individual to specify the type of water filter obtained. Thus, the water filter variable may be capturing a housing characteristic that adds value to the house or also may serve as a proxy for poor water quality.

⁸As seen in chapter 4, most of the households in the sample lived in residences with durable walls and roofs, running water, and trash collection. Thus, these variables are excluded from the model.

the analysis may exclude variables or combination of variables, which contribute to housing rent.

The first version of the baseline rent model assumes the semilog functional form described in equation (5.1). In order to test for the joint significance of parameters, I estimate four models. The first model includes only housing structural characteristic variables (results are displayed in Table 5.1). The second model adds non-climate amenity variables to the first model (see Table 5.2). The third model adds the regional dummy variables to the second model (see Table 5.3). The fourth model is the baseline rent model and assumes a semilog functional form including housing structural characteristic, non-climate amenity, climate amenity, and region dummy variables (see Table 5.4). In each table, I report the estimated coefficients, standard errors, the significance of the parameters, the sum of squared residuals of the model (SSR), and the F-statistic and adjusted R-square as indicators of the model's goodness of fit.

The sum of squared residuals reported in Tables 5.1-5.4 are used to calculate the F statistics testing the joint significance of parameters. The F statistic testing the joint significance of the non-climate amenity parameters is equal to 36.44 which is greater than the critical value at the 1 percent significance level, 2.80. Therefore, I reject the hypothesis that the parameters are jointly equal to zero. Using the same methodology, the regional dummy parameters ($F=28.75 > F_{4,3495}^{0.99}=3.32$) and climate amenity parameters ($F=7.69 > F_{4,3491}^{0.99}=3.32$) are also not jointly equal to zero.

The housing structural parameters are all significant individually and coincide with what one would expect. Rental prices increase with residential size, however, houses tend to be less expensive than apartments. Housing infrastruc-

Table 5.1: Results from the Rent Model Assuming Semilog Functional Form

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	4.2738***	0.0299	0.0300
Flusht	0.5547***	0.0274	0.0290
Filter	0.08569***	0.0243	0.0244
Br1×A	0.8218***	0.0363	0.0364
Br2×A	0.9428***	0.0368	0.0329
Br3×A	1.1969***	0.0504	0.0501
Brgt3×A	1.2829***	0.1721	0.1767
Br2×H	0.2740***	0.0298	0.0292
Br3×H	0.6362***	0.0474	0.0575
Brgt3×H	1.0171***	0.0999	0.1403
SSR	1534.06		
Adj. R-sq	0.38		
F[9,3505]	243.13***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table 5.2: Results from the Rent Model Assuming Semilog Functional Form

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	4.9815***	0.0970	0.0333
Flusht	0.3467***	0.0312	0.0263
Filter	0.1147***	0.0255	0.0366
Br1×A	0.8691***	0.0364	0.0338
Br2×A	1.0065***	0.0368	0.0494
Br3×A	1.2700***	0.0495	0.1496
Brgt3×A	1.3464***	0.1673	0.0286
Br2×H	0.3121***	0.0292	0.0563
Br3×H	0.7087***	0.0464	0.1375
Brgt3×H	1.1235***	0.0974	0.0005
Popdens	-0.0012***	0.0005	0.0050
Banks	-0.0014	0.0048	0.0004
Deaths	-0.0013***	0.0004	0.0006
Schools	-0.0061***	0.0006	0.0116
Arid	0.0121	0.0114	0.0004
Altitude	0.0003	0.0003	0.1102
SSR	1443.85		
Adj. R-sq	0.42		
F[15,3499]	169.3***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table 5.3: Results from the Rent Model Assuming Semilog Functional Form

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	1.9736***	0.3035	0.2876
Flusht	0.3847***	0.0319	0.0334
Filter	0.1494***	0.0257	0.0264
Br1×A	0.8682***	0.0360	0.0365
Br2×A	1.0213***	0.0364	0.0335
Br3×A	1.2850***	0.0491	0.0489
Brgt3×A	1.3728***	0.1649	0.1508
Br2×H	0.3034***	0.0289	0.0282
Br3×H	0.7024***	0.0460	0.0557
Brgt3×H	1.0932***	0.0963	0.1361
Popdens	-0.0185***	0.0023	0.0021
Banks	0.3244***	0.0336	0.0312
Deaths	-0.0008	0.0005	0.0005
Schools	-0.0212***	0.0027	0.0026
Arid	-0.7221***	0.0890	0.0859
Altitude	0.0066***	0.0008	0.0007
N	3.0905***	0.3042	0.2919
NE	4.5642***	0.5367	0.5182
S	0.4658***	0.1347	0.1400
MW	-0.8166***	0.1270	0.1061
SSR	1397.85		
Adj. R-sq	0.44		
F[19,3495]	143.95***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table 5.4: Results from Baseline Rent Model Assuming Semilog Functional

Variable	Form		
	Coeff.	Std. Error	Robust Std. Error
Constant	23.3016***	9.7559	8.1799
Flusht	0.3980***	0.0324	0.0338
Filter	0.1468***	0.0256	0.0264
Br1×A	0.8570***	0.0360	0.0364
Br2×A	1.0143***	0.0364	0.0333
Br3×A	1.2793***	0.0490	0.0489
Brgt3×A	1.3612***	0.1643	0.1507
Br2×H	0.3087***	0.0288	0.0281
Br3×H	0.7025***	0.0459	0.0555
Brgt3×H	1.0817***	0.0960	0.1343
Popdens	0.0075	0.0085	0.0068
Banks	-0.3143**	0.1990	0.1589
Deaths	0.0036***	0.0011	0.0010
Schools	0.0273**	0.0178	0.0137
Arid	0.7124**	0.4259	0.3646
Altitude	-0.0348**	0.0189	0.0157
N	-1.1288	1.4076	1.1140
NE	-3.3703	2.8083	2.1847
S	-3.8287***	1.7371	1.4544
MW	0.6432	0.5340	0.4385
Junetemp	-0.3968***	0.1466	0.1179
Junerain	-0.0039***	0.0017	0.0016
Febtemp	-0.3020	0.2169	0.1936
Febrain	0.0010***	0.0004	0.0004
SSR	1385.64		
Adj. R-sq	0.44		
F[23,3491]	121.17***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

ture captured by the flush toilet and water filter variables also adds value to a rental home.

Table 5.5 includes the average predicted rent values by municipio. In comparing the predicted and actual values, it becomes clear that a substantial portion of the rental values remains unexplained by the variation in housing characteristic variables for the households living in Manaus, Belem, Fortaleza, Recife, Rio de Janeiro, Campinas, and Sao Paulo. Thus, if variation in climate and non-climate amenity variables across municipios does contribute to rental price variation, then the rent model could be improved by including these variables.

The values from Table 5.5 also suggest that rental properties on average may vary by municipio. Thus, the parameter estimates on the housing variables will be influenced by the rental properties in municipios that have a sizeable rental market, such as Santos, Sao Paulo, and Goiania (see Table 4.6).

Many of the climate and non-climate amenity parameters have signs that coincide with what one would expect. However, many are insignificant at the 10 percent critical level. The population density parameter is positive, which likely reflects the effect of other amenities that attract people to a given municipio. The North and Northeast dummy parameters are negative which is indicative of the lack of resources in the Northern regions which also affects rental prices. Summer temperature (represented by the February temperature variable) negatively impacts rental prices, but is deemed insignificant statistically. Referring to Table 4.16, the collinearity between the February and June temperature variables may be rendering one of the parameters insignificant.

Several non-climate amenity parameters are significant at the 10 percent critical level, but the parameter signs do not meet my expectations. I had expected

Table 5.5: Predicted Rent Values from Semilog Model Including Housing

Structural Variables		
Município	Predicted Ln(Rent)	Actual Ln(Rent)
Manaus	4.99	5.27
Belem	4.98	5.33
Sao Luis	5.31	5.31
Fortaleza	4.86	4.68
Recife	5.07	4.81
Salvador	5.17	4.85
Belo Horizonte	5.34	5.29
Rio de Janeiro	5.45	5.31
Campinas	5.23	5.58
Santos	5.53	5.79
Sao Paulo	5.18	5.42
Curitiba	5.22	5.20
Porto Alegre	5.45	5.54
Goiania	5.09	4.94
Brasilia	5.23	5.28

the number of banks and schools to have positive effects on rental prices. However, the bank parameter sign is negative. I would also expect the number of homicides in a municipio to negatively impact rental prices, and yet the estimated parameter on the variable is positive.

I did not have any *a priori* expectations on the signs of the June aridity index and altitude parameters. One possible interpretation of the aridity index is the presence of forest coverage or number of parks in a given municipio. Recall that higher values of the aridity index are indicative of the presence of forest and woodland areas in a municipio. If the aridity index is truly capturing this effect, then the positive sign of the aridity index parameter is consistent with this interpretation.

The June temperature parameter indicates that an increase in winter temperature negatively influences rental prices. This finding may be consistent with the negative impact of increasing temperatures in a tropical country overall. Since there is little cross-sectional variation in temperature in Brazil, I later explore whether the model results change upon including average annual temperature in the model rather than seasonal temperature variables in the model. Additionally, I worry that the sign of this parameter may be an artifact of spurious correlation. I estimate several models in Section 5.3 to see how robust the parameter sign is to model specification.

The rainfall parameters are both significant at the 10 percent critical level, but have opposite signs. An increase in winter rainfall (Junerain) seems to negatively impact monthly housing rents, while the opposite is true for an increase in summer rainfall. One would expect that rainfall would negatively influence housing prices overall. However, summer rainfall may assuage the impact of

summer heat. In Section 5.3, I also compare the rainfall parameter signs of models with diverse specifications.

Tables 5.6 and 5.7 include the results from the estimated regression equations (5.2) and (5.3). $\text{Ln}(\cdot)$ and $\text{BC}(\cdot)$ denote that the variables were transformed logarithmically or using a Box-Cox transformation respectively.

For comparative purposes, I impute the marginal effects of the climate amenity variables on real monthly rental prices from the parameter estimates of regressions (5.1), (5.2), and (5.3). In the semilog case, the marginal effect of climate amenity Z_k on rental prices is calculated for each individual using the expression $\widehat{P}_{ij} \times \widehat{\beta}_{3k}$. The marginal effect of climate amenity Z_k on rental prices is calculated for each individual using expression $\frac{\widehat{P}_{ij}}{Z_{jk}} \times \widehat{\beta}_{3k}$ for the double-log model. Finally, for the linear Box-Cox model, the marginal effect of climate amenity Z_k on rental prices is calculated using expression $\widehat{\beta}_{3k} \times \widehat{P}_{ij}^{1-\widehat{\lambda}} \times Z_{jk}^{\widehat{\lambda}-1}$, where $\widehat{P}_{ij} = \left[\widehat{\lambda} \times \left(\widehat{\beta}_0 + \widehat{\beta}_1 S_{ij} + \widehat{\beta}_2 N_j + \widehat{\beta}_3 \frac{Z_{ij}^{\widehat{\lambda}-1}}{\widehat{\lambda}} \right) + 1 \right]^{1/\widehat{\lambda}}$ (assuming that $\varepsilon = E(\varepsilon) = 0$). The calculation of the marginal effect values require $\widehat{\beta}_{3k}$ which is the estimated coefficient on the climate amenity variable Z_k . The marginal effect values are reported in Table 5.8.

Although the signs of the marginal effect values remain consistent across models, the mean and median values of the marginal effects of climate amenities on rents vary considerably in magnitude. The lowest marginal effect values are obtained from a model that assumes a semi-logarithmic functional form and yet even these values are unreasonably large. For example, the semi-log results evaluated at the mean indicate that a 1°C increase in winter temperature could potentially cause a 85.76 Reais decrease in monthly rents all else equal, which is approximately 33 percent of the mean monthly rent. This effect seems unlikely

Table 5.6: Results from the Baseline Rent Model Assuming Double-Log

Functional Form			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	669.6439***	237.0900	213.9283
Flusht	0.3980***	0.0324	0.0338
Filter	0.1468***	0.0256	0.0264
Br1×A	0.8570***	0.0360	0.0364
Br2×A	1.0143***	0.0364	0.0333
Br3×A	1.2793***	0.0490	0.0489
Brgt3×A	1.3612***	0.1643	0.1507
Br2×H	0.3087***	0.0288	0.0281
Br3×H	0.7025***	0.0459	0.0555
Brgt3×H	1.0817***	0.0960	0.1343
Popdens	0.1828***	0.0678	0.0603
Banks	-5.7408***	2.0200	1.8091
Deaths	0.0489***	0.0159	0.0144
Schools	0.4133***	0.1485	0.1318
Arid	10.0248***	3.6217	3.2370
Altitude	-0.5577***	0.1973	0.1781
N	-24.4178***	9.0347	8.0554
NE	-55.7630***	20.2903	18.0029
S	-57.2210***	20.2134	18.1157
MW	14.6653***	5.3079	4.7442
Ln(Junetemp)	-137.5411***	47.1080	42.3211
Ln(Junerain)	-5.7607***	1.9525	1.7849
Ln(Febtemp)	-54.7298***	21.4630	19.5789
Ln(Febrain)	1.5449***	0.4477	0.4348
SSR	1385.64		
Adj. R-sq	0.44		
F[23,3491]	121.17***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table 5.7: Results from the Baseline Rent Model with Linear Box-Cox

Transformation (Lambda=0.1266)

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	367.6333**	172.4440	172.3890
Flusht	0.7243***	0.0727	0.0624
Filter	0.2859***	0.0517	0.0485
Br1×A	1.6716***	0.1297	0.0690
Br2×A	1.9735***	0.1398	0.0754
Br3×A	2.5467***	0.1865	0.0895
Brgt3×A	2.7178***	0.3564	0.3152
Br2×H	0.5836***	0.0701	0.0594
Br3×H	1.3832***	0.1264	0.0765
Brgt3×H	2.1534***	0.1900	0.1265
Popdens	0.1097*	8.2697	8.2577
Banks	-3.5562*	18.7874	18.7605
Deaths	0.0310**	17.1382	17.1166
Schools	0.2601**	4.6500	4.6448
Arid	6.4590**	25.0296	25.0146
Altitude	-0.3501***	0.8255	0.8238
N	-14.8493*	15.5352	15.5351
NE	-34.7269***	0.1814	0.1806
S	-35.8956*	0.0618	0.0617
MW	8.9653**	1.6726	1.6700
BC(Junetemp)	-58.4830***	0.0107	0.0107
BC(Junerain)	-2.1849**	0.1353	0.1352
BC(Febtemp)	-26.0914**	3.2756	3.2692
BC(Febrain)	0.6639**	0.1638	0.1636
Value of LLF	-21648.06		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The Wald statistics are calculated using the heteroskedasticity-robust standard errors.

Table 5.8: Marginal Effects of Climate Amenities on Monthly Rents

	Semi-log		Double-log		Box-Cox	
	Mean	Median	Mean	Median	Mean	Median
Junetemp	-85.76 (47.21)	-68.95 (75.71)	-1584.43 (1008.43)	-1342.59 (2707.72)	-493.57 (270.42)	-437 (495.46)
Junerain	-0.84 (0.46)	-0.68 (25.74)	-39.47 (54.51)	-17.47 (275.68)	-11.08 (13.27)	-5.76 (68.70)
Febtemp	-65.27† (35.93)	-52.48† (52.81)	-483.72 (273.33)	-395.44 (389.37)	-175.54 (85.31)	-151.19 (129.24)
Febrain	0.22 (0.12)	0.17 (26.80)	1.84 (1.23)	1.37 (208.33)	0.77 (0.45)	0.62 (79.26)
Rent	256.44	196.27	256.44	196.27	256.44	196.27

† The parameter used to compute the marginal effect value was not significant at the 10 percent critical level.

* The values in parentheses are the standard deviations of the marginal effect values among the sample of renters.

in magnitude. These values are probably estimated with error, although the culprit of this error is unknown. In the next section, I estimate several models to hopefully reveal which data problems are at most risk of adding noise to this model.

5.3 Sensitivity Analysis

In this section, I address the data issues raised in Chapter 4. I use these as a guide for estimation to observe how sensitive the predicted marginal effects of climate amenities are to model specification and inherent problems with the dataset.

Issue #1: *All temperature variables are highly correlated and lack variation.*

Measuring the value of future temperature changes is crucial in evaluating the impact of reducing GHG emissions. In the empirical model, I am particularly

concerned that there is not enough variation in seasonal temperatures throughout Brazil to isolate their effects on housing prices. Additionally, the seasonal temperature variables are highly correlated. Including the seasonal temperature variables in the same model may reduce the precision of the parameter estimates, i.e. increase their standard error estimates. To observe the impact of using annual average temperature versus seasonal temperature variables on the models' parameter and standard error estimates, I compare estimates from models that include the average annual temperature variable assuming semilog, log-log, and Box-Cox specifications to the baseline versions of the model. The results from the models that include average annual temperature instead of seasonal temperature variables are displayed in Tables 5.9, 5.10, and 5.11. Also, models that include average annual temperatures are probably best suited for making predictions of the effects of climate change on welfare. Table 5.12 includes the marginal effect values calculated using the parameters from Tables 5.9-5.11.

Comparing the results from Tables 5.4-5.7 and Tables 5.9-5.11, it becomes evident that the symptoms of multicollinearity have been greatly reduced in the models that include the average annual temperature variable. For the Box-Cox model, Febrain is now significant at the 1 percent critical level, as opposed to the 5 percent critical level. The temperature and June rainfall variables however are no longer significant at the 10 percent critical level.

Another noticeable difference is the significant reduction in the magnitudes of the marginal effect values and the standard deviation of the marginal effect values for climate variables. However, the values are still relatively greater than one would expect. Multicollinearity between the climate and non-climate amenity variables likely remains and could be the impetus of the implausible

magnitudes of these values. This is not to say that the parameter estimates are biased. Rather, the standard errors of the parameter estimates are large increasing the likelihood of obtaining an estimate for the parameter at the tails of the parameter distribution. Another plausible explanation is that the climate amenity variables are capturing other amenities unaccounted for in the model that influence housing prices and vary cross-sectionally in a similar fashion to the variables included in the model.

Another feature of this newer model is that the signs and significance of the non-climate amenity parameters have changed. The sign on the Banks parameter has changed from negative to positive in the semilog, double-log, and Box-Cox models. I would expect the number of banks to affect housing prices positively as I believe it serves as a proxy for economic activity in a municipio. Many of the non-climate amenity parameters however have changed from being significant at the 5 percent critical level to insignificant at the 10 percent critical level, such as Schools, Arid, and Altitude (in the semilog model), Deaths and S (in the double-log model), and Deaths, MW, Avetemp, and Junerain (in the Box-Cox model) Conversely, the Population Density, North, Northeast, and South parameters are now significant at the 1 percent critical level in the semilog model, with the North and Northeast parameters having signs that contradict what one would expect.

Based on these results, it seems that the presence of multicollinearity between temperature variables and other non-climate amenity variables has serious consequences on the parameter and standard error estimates of the model. There seems to be enough variation in the annual average temperature variable to capture the effect it has on real monthly rental prices atleast when the functional

form assumed is semi-log or double-log. From here on, I estimate versions of the baseline model substituting annual average temperature for seasonal temperatures. One could argue that in eliminating the seasonal temperature variables from the model the remaining amenity parameter estimates may be biased. I think omitted variable bias is less at risk here for two reasons. First, average annual temperature is almost perfectly correlated with most of the seasonal temperature variables. Thus, seasonal temperature variables may not be adding auxiliary information to the model. In fact, the adjusted R-square values are the same for all models regardless of the temperature variables included in the models. Second, average temperature is highly correlated with more of the amenity variables than are the seasonal temperature variables (see Table 4.20). Thus, there seems to be more of a risk of omitted variable bias on the parameter estimates when excluding the average temperature variable than excluding one of the seasonal temperature variables.

Issue #2: March is the wettest month. The March rainfall variable also has the most variation, but it is highly correlated with the temperature variables.

Changes in rainfall could potentially have more serious consequences on welfare than changes in temperature in some areas of Brazil. Measuring the value of rainfall is problematic because it is correlated with several variables omitted from the model, such as forest coverage, also valued by consumers of housing. The degree of omitted variable bias however will vary with the rainfall variable used.

In addition to the potential correlation with omitted variables, there is quite a bit of correlation between the rainfall variables and variables included in the model, especially temperature. In the baseline model, I used the February

Table 5.9: Results from Semilog Model Including Annual Average Temperature

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	8.5925***	2.1848	1.7839
Flusht	0.3978***	0.0324	0.0338
Filter	0.1455***	0.0256	0.0263
Br1×A	0.8587***	0.0360	0.0364
Br2×A	1.0153***	0.0364	0.0333
Br3×A	1.2799***	0.0490	0.0488
Brgt3×A	1.3588***	0.1643	0.1504
Br2×H	0.3087***	0.0288	0.0282
Br3×H	0.7022***	0.0459	0.0555
Brgt3×H	1.0799***	0.0960	0.1337
Popdens	-0.0084***	0.0033	0.0027
Banks	0.0926*	0.0606	0.0509
Deaths	0.0015*	0.0009	0.0008
Schools	-0.0021	0.0066	0.0049
Arid	0.0865	0.1854	0.1681
Altitude	-0.0047	0.0040	0.0032
N	1.6455***	0.4732	0.4121
NE	1.8903***	0.9561	0.7556
S	-1.3656***	0.5338	0.4516
MW	-0.2780	0.2118	0.1757
Avetemp	-0.2263***	0.0834	0.0672
Junerain	-0.0049***	0.0016	0.0014
Febrain	0.0012***	0.0003	0.0003
SSR	1386.02		
Adj. R-sq	0.44		
F[22,3492]	126.63***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table 5.10: Results from Double-log Model Including Annual Average

Temperature			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	28.4171***	10.9890	10.1455
Flusht	0.3967***	0.0324	0.0338
Filter	0.1451***	0.0257	0.0264
Br1×A	0.8653***	0.0360	0.0364
Br2×A	1.0183***	0.0364	0.0334
Br3×A	1.2827***	0.0490	0.0488
Brgt3×A	1.3600***	0.1645	0.1513
Br2×H	0.3077***	0.0288	0.0282
Br3×H	0.7015***	0.0460	0.0556
Brgt3×H	1.0820***	0.0961	0.1340
Popdens	-0.0188***	0.0042	0.0035
Banks	0.1662***	0.0554	0.0483
Deaths	0.0018	0.0012	0.0012
Schools	-0.0150**	0.0070	0.0051
Arid	-0.3760***	0.1533	0.1259
Altitude	-0.0164**	0.0081	0.0077
N	2.3268***	0.5202	0.4771
NE	4.1663***	1.1541	0.9817
S	-0.6590	0.6617	0.5131
MW	-0.6938***	0.2610	0.2070
Ln(Avetemp)	-8.4743***	3.4542	3.1811
Ln(Junerain)	-0.5708***	0.2222	0.2242
Ln(Febrain)	0.8391***	0.2389	0.2446
SSR	1389.36		
Adj. R-sq	0.44		
F[22,3492]	125.95***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table 5.11: Results from Linear Box-Cox Model Including Annual Average

Temperature(Lambda=0.1285)

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	45.6648**	20.2774	20.1290
Flusht	0.7283***	0.0734	0.0631
Filter	0.2854***	0.0523	0.0491
Br1×A	1.7023***	0.1320	0.0695
Br2×A	2.0006***	0.1418	0.0761
Br3×A	2.5794***	0.1891	0.0906
Brgt3×A	2.7430***	0.3596	0.3177
Br2×H	0.5880***	0.0708	0.0600
Br3×H	1.3962***	0.1276	0.0771
Brgt3×H	2.1750***	0.1925	0.1275
Popdens	-0.0334***	1.1085	1.0912
Banks	0.2746***	2.6930	2.6725
Deaths	0.0039	1.8158	1.8089
Schools	-0.0250**	0.6273	0.6251
Arid	-0.5190**	5.0931	5.0791
Altitude	-0.0315***	0.2427	0.2414
N	4.2212***	0.1984	0.1982
NE	7.4658***	0.0094	0.0093
S	-1.5697**	0.1336	0.1334
MW	-1.2019	0.0025	0.0024
BC(Avetemp)	-11.0773	0.0198	0.0198
BC(Junerain)	-0.7114	0.3902	0.3899
BC(Febrain)	0.8126***	0.0167	0.0165
Value of LLF	-21651.54		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The Wald statistics are calculated using the heteroskedasticity-robust standard errors.

Table 5.12: Marginal Effects of Climate Amenities on Monthly Rents

	Semi-log		Double-log		Box-Cox	
	Mean	Median	Mean	Median	Mean	Median
Avetemp	-49.23 (27.07)	-39.53 (55.44)	-83.88 (49.22)	-70.88 (95.82)	-86.26† (42.96)	-76.39† (94.65)
Junerain	-1.07 (0.59)	-0.86 (0.62)	-3.90 (5.34)	-1.68 (5.78)	-3.77† (4.45)	-1.93† (4.82)
Febrain	0.26 (0.14)	0.21 (1.13)	1.00 (0.66)	0.75 (2.76)	1.00 (0.57)	0.79 (2.99)
Rent	256.44	196.27	256.44	196.27	256.44	196.27

† The parameter used to compute the marginal effect value was not significant at the 10 percent critical level.

* The values in parentheses are the standard deviations of the marginal effect values among the sample of renters.

instead of March rainfall variable because March rainfall was highly correlated with the temperature variables. However, each of these variables could potentially have different effects on housing prices, especially if one is more correlated with variables omitted from the model.

To observe how sensitive the results are to the inclusion of the February and March rainfall variables, I estimate three additional models (assuming semilog, double-log, and linear Box-Cox functional forms) which include average annual temperature, June rainfall, and March rainfall to represent the effect of climate amenities on housing prices. The results from these models are presented in Tables 5.13-5.15. The values of the marginal effect of these climate amenities on housing prices are included in Table 5.16.

Drawing on the results from Tables 5.13-5.15, it appears that substituting March rainfall in the model for February rainfall has changed the significance of some of the climate and non-climate amenity parameters. The effects on parameter significance differ by the functional form assumed, as expected. The

levels of significance changed for the Banks, Deaths, Schools, Altitude, MW, Average temperature, and June rainfall parameters in 2 out of the 3 models.

The marginal effect calculations also changed from the previous example. The March rainfall variable has an overall greater effect on housing prices than the February rainfall variable assuming a semilog functional form, and the opposite is true when assuming the double-log and Box-Cox linear functional forms. Of the models that yielded significant temperature parameters (at the 10 percent critical level), the marginal effects of temperature on housing rents were substantially greater for the Model that includes the March rainfall variable. This greater magnitude is likely attributable to the strong relationship between the March rainfall and temperature variables.

Issue #3: August is the driest month on average, but the minimum rainfall levels are lowest cross-sectionally for the month of June.

In the baseline model, I included June rainfall to capture the effect of a change in rainfall during the dry month on housing prices. While August rainfall is the driest month on average, the minimum rainfall levels were lower in June than in August. In what follows, I estimate six additional models including the August rainfall variable as the driest month variable. Three models include February as the wet month variable, and three models include March as the wet month variable. The results from these models are displayed in Tables 5.17-5.22. The corresponding marginal effect values of the climate amenities on housing rents are presented in Tables 5.23 and 5.24. Because there are differences in the ranges in values in the June and August rainfall variables, I anticipate that the magnitudes on the June and August rainfall parameters will differ.

To observe the effect of including the August rainfall variable on the

Table 5.13: Results from Semilog Model Including March Rainfall

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	11.9676***	2.5132	1.9973
Flusht	0.3976***	0.0324	0.0338
Filter	0.1452***	0.0256	0.0263
Br1×A	0.8591***	0.0360	0.0364
Br2×A	1.0156***	0.0364	0.0333
Br3×A	1.2800***	0.0490	0.0488
Brgt3×A	1.3581***	0.1643	0.1504
Br2×H	0.3087***	0.0288	0.0282
Br3×H	0.7021***	0.0459	0.0555
Brgt3×H	1.0794***	0.0960	0.1336
Popdens	-0.0084***	0.0033	0.0027
Banks	0.0817	0.0625	0.0529
Deaths	-0.0002	0.0009	0.0008
Schools	-0.0006	0.0068	0.0050
Arid	0.0289	0.1812	0.1655
Altitude	-0.0104	0.0046	0.0036
N	1.6092***	0.4843	0.4246
NE	1.5592**	1.0079	0.8014
S	-1.7868***	0.5559	0.4592
MW	-0.0290	0.2422	0.1996
Avetemp	-0.3589***	0.0941	0.0727
Junerain	-0.0033**	0.0017	0.0015
Marrain	0.0016***	0.0004	0.0004
SSR	1386.24		
Adj. R-sq	0.44		
F[22,3492]	126.59***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table 5.14: Results from Double-log Model Including March Rainfall

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	32.8865**	15.7783	15.7090
Flusht	0.3923***	0.0324	0.0338
Filter	0.1466***	0.0257	0.0265
Br1×A	0.8694***	0.0360	0.0364
Br2×A	1.0206***	0.0364	0.0335
Br3×A	1.2855***	0.0491	0.0488
Brgt3×A	1.3661***	0.1647	0.1518
Br2×H	0.3070***	0.0289	0.0282
Br3×H	0.7023***	0.0460	0.0557
Brgt3×H	1.0863***	0.0962	0.1347
Popdens	-0.0150***	0.0040	0.0032
Banks	0.1904***	0.0547	0.0476
Deaths	-0.0023***	0.0007	0.0007
Schools	-0.0095**	0.0068	0.0048
Arid	-0.3443***	0.1573	0.1333
Altitude	-0.0161	0.0108	0.0109
N	2.4179***	0.5554	0.5103
NE	3.1048***	1.0827	0.8972
S	-1.6299*	0.9627	0.8954
MW	-0.1167	0.2750	0.2473
Ln(Avetemp)	-9.9103**	5.0034	4.9774
Ln(Junerain)	-0.2265	0.1849	0.1903
Ln(Marrain)	0.5247**	0.2264	0.2382
SSR	1392.13		
Adj. R-sq	0.44		
F[22,3492]	125.38***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table 5.15: Results from Linear Box-Cox Model Including March Rainfall

Variable (Lambda=0.1300)

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	68.6646***	26.3105	26.0566
Flusht	0.7274***	0.0738	0.0636
Filter	0.2888***	0.0528	0.0495
Br1×A	1.7230***	0.1336	0.0700
Br2×A	2.0206***	0.1434	0.0767
Br3×A	2.6052***	0.1912	0.0914
Brgt3×A	2.7727***	0.3626	0.3199
Br2×H	0.5916***	0.0714	0.0605
Br3×H	1.4086***	0.1288	0.0778
Brgt3×H	2.1977***	0.1945	0.1283
Popdens	-0.0282***	1.1495	1.1305
Banks	0.2965**	2.6054	2.5973
Deaths	-0.0045**	2.2508	2.2249
Schools	-0.0133	0.6448	0.6440
Arid	-0.4266***	6.6263	6.6013
Altitude	-0.0445**	0.1996	0.1990
N	4.6051***	0.1882	0.1880
NE	5.6905***	0.0091	0.0090
S	-4.4212**	0.1343	0.1341
MW	0.0879***	0.0016	0.0016
BC(Avetemp)	-17.0391	0.0200	0.0200
BC(Junerain)	-0.4147	0.4023	0.4019
BC(Marrain)	0.6569**	0.0208	0.0206
Value of LLF	-21654.27		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The Wald statistics are calculated using the heteroskedasticity-robust standard errors.

Table 5.16: Marginal Effects of Climate Amenities on Monthly Rents

	Semi-log		Double-log		Box-Cox	
	Mean	Median	Mean	Median	Mean	Median
Avetemp	-77.43 (42.44)	-61.8 (87.81)	-98.28 (57.67)	-83.01 (113.39)	-128.50† (65.06)	-113.98† (143.08)
Junerain	-0.71 (0.39)	-0.57 (0.42)	-1.55† (2.11)	-0.66† (2.29)	-2.13† (2.53)	-1.08† (2.74)
Marrain	0.35 (0.19)	0.28 (0.93)	0.69 (0.47)	0.55 (1.43)	0.86 (0.50)	0.72 (2.00)
Rent	256.44	196.27	256.44	196.27	256.44	196.27

† The parameter used to compute the marginal effect value was not significant at the 10 percent critical level.

* The values in parentheses are the standard deviations of the marginal effect values among the sample of renters.

models' results, I compare the marginal effect values and the significance of the parameter estimates reported in Tables 5.12 and 5.23 and Tables 5.16 and 5.24. Looking at the first pair of tables, the driest month rainfall parameter is not significant at the 10 percent critical level for the Box-Cox version of the model, as in the previous model, and moreover it is not significant for the semilog model. The double-log model yields a significant parameter estimate for the August rainfall variable, but the marginal effects are substantially greater on most climate parameters. The correlation between the August and February rainfall variables (the Pearson correlation coefficient is equal to -0.42) may be the cause of the wide change in the parameter estimates. In comparison, the June and February rainfall variables have a Pearson correlation coefficient equal to -0.35.

Focusing on the second pair of tables, including the March and August rainfall variables in the same model actually improves the significance of the driest month parameter estimates. The parameter estimate for the driest month variable (Augrain) remains insignificant in the model assuming the semilog func-

tional form but not for the double-log and linear Box-Cox functional forms. One drawback of the model that includes the March and August rainfall variables is that the correlation between the March rainfall and average temperature variables (the Pearson correlation coefficient is 0.69) may be influencing the magnitudes on the marginal effect values. The model that utilizes the June rainfall variable as the driest month variable yields smaller values for the marginal effects of climate amenities, and the parameter estimates used to calculate the marginal effect values are more precise.

Because I am unable to discriminate statistically between models that include combinations of the February, March, June, and August rainfall variables, I estimate models that include the February and June rainfall variables in the same model, and the March and August rainfall variables in the same model. There seem to be advantages and disadvantages to using both of these specifications. The parameter and standard error estimates are also sensitive to these specifications.

Issue #4: The Aridity Index Variable has a strong correlation with the rainfall variables.

In the baseline model, I include the aridity index variable to serve as a proxy for other variables that are correlated with rainfall and are also determinants of housing prices. Due to its construction, the aridity index variable is highly correlated with the rainfall variables. It is not clear if the index is picking up an effect on housing prices distinct from the effect of rainfall. If the Aridity index is not successful at capturing an additional effect, then the variable itself may be adding imprecision to the models estimates. In other words, I may be

Table 5.17: Results from Semilog Model Including February and August Rainfall

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	7.2554***	2.2449	1.8412
Flusht	0.3858***	0.0322	0.0336
Filter	0.1481***	0.0257	0.0264
Br1×A	0.8690***	0.0359	0.0364
Br2×A	1.0213***	0.0364	0.0334
Br3×A	1.2878***	0.0490	0.0487
Brgt3×A	1.3730***	0.1645	0.1511
Br2×H	0.3094***	0.0288	0.0282
Br3×H	0.7057***	0.0460	0.0557
Brgt3×H	1.0863***	0.0961	0.1349
Popdens	-0.0103**	0.0052	0.0045
Banks	0.1379*	0.0888	0.0785
Deaths	-0.0010	0.0022	0.0023
Schools	-0.0032	0.0085	0.0073
Arid	-0.3199	0.3353	0.3204
Altitude	-0.0038	0.0045	0.0038
N	1.5732***	0.6667	0.6062
NE	1.7625	1.5161	1.3698
S	-0.5242	0.6432	0.5807
MW	-0.2816	0.2300	0.1860
Avetemp	-0.1811***	0.0835	0.0674
Augrain	0.0007	0.0037	0.0039
Febrain	0.0012***	0.0003	0.0003
SSR	1389.92		
Adj. R-sq	0.44		
F[22,3492]	125.83***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table 5.18: Results from Double-log Model Including February and August

Rainfall			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	44.8358***	13.2512	11.7158
Flusht	0.3942***	0.0323	0.0338
Filter	0.1501***	0.0256	0.0263
Br1×A	0.8592***	0.0360	0.0365
Br2×A	1.0153***	0.0364	0.0334
Br3×A	1.2817***	0.0490	0.0489
Brgt3×A	1.3713***	0.1644	0.1512
Br2×H	0.3085***	0.0288	0.0281
Br3×H	0.7040***	0.0459	0.0556
Brgt3×H	1.0884***	0.0960	0.1353
Popdens	-0.0033	0.0042	0.0034
Banks	-0.1967*	0.1252	0.1084
Deaths	0.0070***	0.0024	0.0022
Schools	0.0063	0.0085	0.0066
Arid	0.5801**	0.3232	0.2792
Altitude	-0.0334***	0.0111	0.0099
N	-0.6365	0.8421	0.7374
NE	-1.8313	1.5795	1.3287
S	-2.3450***	0.9223	0.7749
MW	0.2310	0.3189	0.2627
Ln(Avetemp)	-12.2165***	3.8056	3.3370
Ln(Augrain)	-0.9459***	0.2788	0.2585
Ln(Febrain)	0.7690***	0.1683	0.1545
SSR	1387.41		
Adj. R-sq	0.44		
F[22,3492]	126.35***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table 5.19: Results from Linear Box-Cox Model Including February and August

Rainfall(Lambda=0.1247)

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	57.2061***	22.0948	21.9350
Flusht	0.7075***	0.0710	0.0615
Filter	0.2906***	0.0514	0.0480
Br1×A	1.6611***	0.1285	0.0683
Br2×A	1.9568***	0.1384	0.0747
Br3×A	2.5264***	0.1845	0.0887
Brgt3×A	2.7130***	0.3523	0.3111
Br2×H	0.5774***	0.0695	0.0589
Br3×H	1.3727***	0.1253	0.0757
Brgt3×H	2.1464***	0.1881	0.1244
Popdens	-0.0049	1.8661	1.8495
Banks	-0.3046	3.6451	3.6073
Deaths	0.0117*	2.0494	2.0309
Schools	0.0109	0.7061	0.7041
Arid	1.0167**	5.1398	5.1292
Altitude	-0.0499***	0.3444	0.3426
N	-0.9641***	0.1671	0.1667
NE	-3.184263	0.0103	0.0102
S	-3.724863	0.2717	0.2688
MW	0.2647***	0.0052	0.0051
BC(Avetemp)	-12.4612	0.0217	0.0216
BC(Augrain)	-0.9557	0.7293	0.7185
BC(Febrain)	0.6573**	0.0214	0.0211
Value of LLF	-21651.45		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The Wald statistics are calculated using the heteroskedasticity-robust standard errors.

Table 5.20: Results from Semilog Model Including March and August Rainfall

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	13.0560***	2.8469	2.3383
Flusht	0.3908***	0.0322	0.0336
Filter	0.1479***	0.0256	0.0264
Br1×A	0.8647***	0.0359	0.0363
Br2×A	1.0186***	0.0364	0.0334
Br3×A	1.2850***	0.0489	0.0487
Brgt3×A	1.3697***	0.1644	0.1511
Br2×H	0.3097***	0.0288	0.0282
Br3×H	0.7048***	0.0459	0.0557
Brgt3×H	1.0848***	0.0960	0.1347
Popdens	-0.0049	0.0057	0.0049
Banks	0.0234	0.1004	0.0889
Deaths	-0.0000	0.0022	0.0023
Schools	0.0055	0.0092	0.0079
Arid	0.0990	0.3753	0.3552
Altitude	-0.0143***	0.0057	0.0048
N	0.9186	0.7187	0.6536
NE	-0.0017	1.6795	1.5177
S	-1.8677***	0.7831	0.6992
MW	0.1685	0.2782	0.2277
Avetemp	-0.3907***	0.1017	0.0815
Augrain	-0.0031	0.0040	0.0041
Marrain	0.0021***	0.0005	0.0005
SSR	1387.62		
Adj. R-sq	0.44		
F[22,3492]	126.30***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table 5.21: Results from Double-log Model Including March and August

		Rainfall	
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	105.9355***	23.3115	20.5741
Flusht	0.3964***	0.0323	0.0338
Filter	0.1487***	0.0256	0.0263
Br1×A	0.8576***	0.0360	0.0364
Br2×A	1.0145***	0.0364	0.0333
Br3×A	1.2803***	0.0490	0.0489
Brgt3×A	1.3667***	0.1643	0.1509
Br2×H	0.3087***	0.0288	0.0281
Br3×H	0.7033***	0.0459	0.0555
Brgt3×H	1.0853***	0.0959	0.1347
Popdens	0.0018	0.0048	0.0040
Banks	-0.3981***	0.1561	0.1354
Deaths	0.0054***	0.0019	0.0018
Schools	0.0229***	0.0105	0.0084
Arid	1.2345***	0.4260	0.3700
Altitude	-0.0755***	0.0182	0.0161
N	-1.2077	0.9033	0.7876
NE	-4.5169***	1.9711	1.6797
S	-6.6509***	1.5858	1.3767
MW	1.6226***	0.5264	0.4532
Ln(Avetemp)	-30.9028***	6.8714	6.0564
Ln(Augrain)	-1.4603***	0.3609	0.3262
Ln(Marrain)	1.2123***	0.2481	0.2248
SSR	1386.22		
Adj. R-sq	0.44		
F[22,3492]	126.59***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table 5.22: Results from Linear Box-Cox Model Including March and August

Rainfall(Lambda=0.1254)

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	133.5028***	35.8814	35.3864
Flusht	0.7154***	0.0716	0.0618
Filter	0.2892***	0.0516	0.0482
Br1×A	1.6638***	0.1287	0.0686
Br2×A	1.9625***	0.1388	0.0750
Br3×A	2.5338***	0.1851	0.0890
Brgt3×A	2.7153***	0.3538	0.3127
Br2×H	0.5802***	0.0697	0.0591
Br3×H	1.3770***	0.1257	0.0761
Brgt3×H	2.1495***	0.1885	0.1252
Popdens	0.0043	1.9722	1.9469
Banks	-0.6168*	4.3589	4.2835
Deaths	0.0086***	3.1034	3.0329
Schools	0.0378**	1.0548	1.0387
Arid	2.0499***	8.3837	8.3446
Altitude	-0.1113***	0.4192	0.4172
N	-1.9253***	0.2339	0.2334
NE	-7.5354	0.0115	0.0114
S	-10.2422**	0.3257	0.3203
MW	2.4222**	0.0043	0.0042
BC(Avetemp)	-31.3009	0.0250	0.0247
BC(Augrain)	-1.3804**	0.9146	0.8946
BC(Marrain)	0.9947***	0.0332	0.0325
Value of LLF	-21649.47		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The Wald statistics are calculated using the heteroskedasticity-robust standard errors.

Table 5.23: Marginal Effects of Climate Amenities on Monthly Rents

	Semi-log		Double-log		Box-Cox	
	Mean	Median	Mean	Median	Mean	Median
Avetemp	-38.48 (21.10)	-30.87 (44.00)	-121.32 (71.27)	-103.54 (137.47)	-92.89† (47.09)	-83.16† (101.22)
Augrain	-0.15† (0.08)	-0.12† (0.09)	-6.15 (6.74)	-3.79 (7.15)	-4.76† (4.50)	-3.31† (4.73)
Febrain	0.25 (0.14)	0.20 (0.19)	0.92 (0.61)	0.66 (4.75)	0.77 (0.44)	0.61 (4.10)
Rent	256.44	196.27	256.44	196.27	256.44	196.27

† The parameter used to compute the marginal effect value was not significant at the 10 percent critical level.

* The values in parentheses are the standard deviations of the marginal effect values among the sample of renters.

Table 5.24: Marginal Effects of Climate Amenities on Monthly Rents

	Semi-log		Double-log		Box-Cox	
	Mean	Median	Mean	Median	Mean	Median
Avetemp	-84.13 (46.20)	-67.62 (95.52)	-308.57 (181.14)	-262.90 (352.80)	-234.08† (118.53)	-209.47† (258.14)
Augrain	-0.67† (0.37)	-0.54† (0.39)	-9.55 (10.49)	-5.87 (11.12)	-6.90 (6.53)	-4.79 (6.86)
Marrain	0.45 (0.25)	0.36 (1.02)	1.63 (1.09)	1.28 (7.57)	1.28 (0.75)	1.08 (6.12)
Rent	256.44	196.27	256.44	196.27	256.44	196.27

† The parameter used to compute the marginal effect value was not significant at the 10 percent critical level.

* The values in parentheses are the standard deviations of the marginal effect values among the sample of renters.

unnecessarily increasing the standard errors of the parameter estimates by including the index in the model. There is some evidence that provides support that the index is in fact irrelevant to the model, as many of the coefficients on this variable in the models estimated thus far have been statistically insignificant at the 10 percent critical level.

In this section, I estimate six models excluding the Aridity index variable from the models. Three models include the February and June rainfall variables. The other three models include the March and August rainfall variables. The estimates of the parameters and standard errors for each model are in Tables 5.25-5.30. The marginal effect values of the climate amenities on housing prices are computed using the parameter estimates from the models and are displayed in Tables 5.31 and 5.32 .

Comparing the results from comparable models (refer to Tables 5.9-5.11 and Tables 5.20-5.22), the adjusted R-square values do not change upon the exclusion of the Aridity index variable suggesting that this variable is irrelevant to the model. Additionally, excluding the variable seems to add precision to the climate and non-climate amenity parameter estimates overall.

The marginal effect values for the climate amenities have also changed in result of excluding the index variable from the model. The change of the magnitude of the marginal effect values depends on the functional form assumed and rainfall variables included in the model.

The value of the marginal effect of average temperature on housing prices decreased in the both semilog models (including June and February rainfall and August and March rainfall variables), and substantially decreased in the double-log model including the March and August rainfall variables. The magnitude

of the marginal effect of average temperature increased in the double-log model including the February and June rainfall variables. The average temperature parameter still remained insignificant in the newer version of the Box-Cox model. I therefore place little confidence on the marginal effect of temperature in that model.

The magnitude of the marginal effects of June and February rainfall decreased in the semilog model and increased in the double-log model (and the Box-Cox model for the February rainfall parameter). The changes on the rainfall effects however are slight. I do not compare the marginal effect values for the June variable from the Box-Cox models, as the parameter on the variable remained insignificant at the 10 percent critical level.

Lastly, the marginal effect values for the August and March rainfall variables on housing prices decreased substantially in the double-log and Box-Cox models. The August rainfall parameter remained insignificant in the semi-log model. Thus, I do not review the change in the variable's marginal effect in the model that excludes the aridity index variable. The marginal effect value of the March rainfall variable however decreased in the semilog model.

The results from the models provide support for excluding the aridity index from the model altogether, as it appears to be irrelevant to the model. Including the aridity index caused the magnitudes of the parameter estimates to vary. As adding any irrelevant variable to the model, including the index also reduced the precision of the remaining parameter estimates. The severity of the effects of including this variable in the model depended on the specification of the model. In the remaining analyses, I exclude the aridity index variable from the rent model.

Table 5.25: Results from Semilog Model Excluding the Aridity Index Variable

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	7.8672***	1.5351	1.3547
Flusht	0.3977***	0.0323	0.0338
Filter	0.1464***	0.0255	0.0262
Br1×A	0.8596***	0.0359	0.0364
Br2×A	1.0162***	0.0363	0.0333
Br3×A	1.2811***	0.0489	0.0487
Brgt3×A	1.3609***	0.1642	0.1505
Br2×H	0.3084***	0.0288	0.0281
Br3×H	0.7022***	0.0459	0.0555
Brgt3×H	1.0807***	0.0959	0.1339
Popdens	-0.0097***	0.0019	0.0015
Banks	0.1170***	0.0305	0.0269
Deaths	0.0013*	0.0008	0.0007
Schools	-0.0043	0.0045	0.0033
Altitude	-0.0035	0.0029	0.0025
N	1.7898***	0.3582	0.3310
NE	2.2096***	0.6675	0.5418
S	-1.1556***	0.2867	0.2454
MW	-0.3442***	0.1572	0.1342
Avetemp	-0.2013***	0.0639	0.0552
Junerain	-0.0045***	0.0012	0.0010
Febrain	0.0011***	0.0003	0.0003
SSR	1386.11		
Adj. R-sq	0.44		
F[21,3493]	132.68***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table 5.26: Results from Double-log Model Excluding the Aridity Index Variable

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	39.8923***	9.9511	9.6200
Flusht	0.3893***	0.0323	0.0336
Filter	0.1415***	0.0256	0.0264
Br1×A	0.8680***	0.0360	0.0363
Br2×A	1.0171***	0.0364	0.0334
Br3×A	1.2814***	0.0490	0.0487
Brgt3×A	1.3571***	0.1647	0.1499
Br2×H	0.3102***	0.0288	0.0283
Br3×H	0.7035***	0.0460	0.0556
Brgt3×H	1.0816***	0.0962	0.1336
Popdens	-0.0113***	0.0029	0.0027
Banks	0.0374**	0.0177	0.0172
Deaths	0.0010	0.0012	0.0012
Schools	-0.0000	0.0034	0.0032
Altitude	-0.0252***	0.0073	0.0072
N	1.3760***	0.3473	0.3408
NE	1.9030***	0.6939	0.7112
S	-1.8124***	0.4660	0.4102
MW	-0.1850	0.1585	0.1514
Ln(Avetemp)	-11.9700***	3.1489	3.0336
Ln(Junrain)	-0.5838***	0.2223	0.2256
Ln(Febrain)	0.9012***	0.2377	0.2431
SSR	1391.75		
Adj. R-sq	0.44		
F[21,3493]	131.47***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table 5.27: Results from Linear Box-Cox Model Excluding the Aridity Index

Variable (Lambda=0.1306)

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	61.9245***	14.5579	14.4431
Flusht	0.7264***	0.0740	0.0637
Filter	0.2830***	0.0528	0.0495
Br1×A	1.7232***	0.1332	0.0703
Br2×A	2.0202***	0.1430	0.0770
Br3×A	2.6059***	0.1906	0.0916
Brgt3×A	2.7679***	0.3646	0.3230
Br2×H	0.5977***	0.0714	0.0606
Br3×H	1.4141***	0.1287	0.0780
Brgt3×H	2.1973***	0.1944	0.1290
Popdens	-0.0244***	0.7508	0.7247
Banks	0.0950***	1.4340	1.3830
Deaths	0.0033***	0.9794	0.9719
Schools	-0.0053*	0.3476	0.3404
Altitude	-0.0463***	3.6769	3.6736
N	3.0457***	0.2398	0.2388
NE	4.7085***	0.1935	0.1933
S	-3.2400***	0.0062	0.0060
MW	-0.5629***	0.0352	0.0344
BC(Avetemp)	-14.9929	0.0023	0.0023
BC(Junrain)	-0.7798	0.0079	0.0078
BC(Febrain)	0.8985***	0.0117	0.0115
Value of LLF	-21653.01		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The Wald statistics are calculated using the heteroskedasticity-robust standard errors.

Table 5.28: Results from Semilog Model Excluding the Aridity Index Variable

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	12.5033***	1.9273	1.6407
Flusht	0.3911***	0.0322	0.0336
Filter	0.1478***	0.0256	0.0264
Br1×A	0.8650***	0.0358	0.0363
Br2×A	1.0189***	0.0363	0.0333
Br3×A	1.2852***	0.0489	0.0487
Brgt3×A	1.3692***	0.1644	0.1510
Br2×H	0.3095***	0.0288	0.0282
Br3×H	0.7046***	0.0459	0.0556
Brgt3×H	1.0844***	0.0960	0.1344
Popdens	-0.0064***	0.0015	0.0013
Banks	0.0489*	0.0276	0.0264
Deaths	-0.0005	0.0012	0.0011
Schools	0.0033	0.0041	0.0031
Altitude	-0.0130***	0.0032	0.0028
N	1.0970***	0.2430	0.2408
NE	0.4321	0.3415	0.3024
S	-1.6782***	0.3120	0.2363
MW	0.1110	0.1728	0.1637
Avetemp	-0.3733***	0.0773	0.0632
Augrain	-0.0021	0.0017	0.0015
Marrain	0.0020***	0.0003	0.0004
SSR	1387.65		
Adj. R-sq	0.44		
F[21,3493]	132.35***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table 5.29: Results from Double-log Model Excluding the Aridity Index Variable

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	39.9737***	5.0233	4.8837
Flusht	0.3955***	0.0324	0.0338
Filter	0.1502***	0.0256	0.0263
Br1×A	0.8646***	0.0360	0.0365
Br2×A	1.0192***	0.0364	0.0334
Br3×A	1.2849***	0.0490	0.0488
Brgt3×A	1.3712***	0.1645	0.1521
Br2×H	0.3064***	0.0288	0.0281
Br3×H	0.7024***	0.0460	0.0556
Brgt3×H	1.0886***	0.0960	0.1352
Popdens	-0.0109***	0.0020	0.0017
Banks	0.0519***	0.0157	0.0143
Deaths	0.0010	0.0012	0.0011
Schools	-0.0053**	0.0040	0.0027
Altitude	-0.0238***	0.0036	0.0035
N	1.3352***	0.2142	0.2070
NE	1.1399***	0.2721	0.2313
S	-2.1411***	0.3043	0.2577
MW	0.1390	0.1225	0.1142
Ln(Avetemp)	-11.4764***	1.5065	1.4559
Ln(Augrain)	-0.4867***	0.1319	0.1145
Ln(Marrain)	0.5538***	0.0995	0.0904
SSR	1389.56		
Adj. R-sq	0.44		
F[21,3493]	131.94***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table 5.30: Results from Linear Box-Cox Model Excluding the Aridity Index

Variable (Lambda=0.1265)

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	53.9149***	7.4199	7.3401
Flusht	0.7176***	0.0720	0.0622
Filter	0.2931***	0.0520	0.0486
Br1×A	1.6861***	0.1305	0.0686
Br2×A	1.9826***	0.1404	0.0752
Br3×A	2.5576***	0.1870	0.0896
Brgt3×A	2.7389***	0.3546	0.3127
Br2×H	0.5797***	0.0700	0.0594
Br3×H	1.3836***	0.1264	0.0764
Brgt3×H	2.1669***	0.1906	0.1252
Popdens	-0.0190***	0.4484	0.4337
Banks	0.1106***	0.6941	0.6874
Deaths	0.0012***	0.7942	0.7850
Schools	-0.0091	0.2749	0.2742
Altitude	-0.0373***	1.9034	1.8973
N	2.4122***	0.1806	0.1806
NE	1.9842***	0.1066	0.1063
S	-3.5756***	0.0043	0.0042
MW	0.1672***	0.0343	0.0336
BC(Avetemp)	-12.6399	0.0030	0.0030
BC(Augrain)	-0.4734	0.0123	0.0123
BC(Marrain)	0.4998***	0.0059	0.0057
Value of LLF	-21653.07		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The Wald statistics are calculated using the heteroskedasticity-robust standard errors.

Table 5.31: Marginal Effects of Climate Amenities on Monthly Rents

	Semi-log		Double-log		Box-Cox	
	Mean	Median	Mean	Median	Mean	Median
Avetemp	-42.86 (23.54)	-34.22 (48.24)	-118.81 (69.53)	-100.07 (135.69)	-110.11† (55.28)	-97.82† (120.86)
Junrain	-0.96 (0.53)	-0.76 (0.56)	-4.01 (5.50)	-1.70 (5.97)	-3.91† (4.64)	-2.00† (5.02)
Febrain	0.23 (0.13)	0.19 (1.01)	1.07 (0.71)	0.81 (2.86)	1.04 (0.60)	0.84 (3.10)
Rent	256.44	196.27	256.44	196.27	256.44	196.27

† The parameter used to compute the marginal effect value was not significant at the 10 percent critical level.

* The values in parentheses are the standard deviations of the marginal effect values among the sample of renters.

Table 5.32: Marginal Effects of Climate Amenities on Monthly Rents

	Semi-log		Double-log		Box-Cox	
	Mean	Median	Mean	Median	Mean	Median
Avetemp	-80.03 (43.98)	-64.30 (91.01)	-114.25 (67.26)	-97.31 (130.91)	-93.97† (47.54)	-83.84† (103.88)
Augrain	-0.45† (0.25)	-0.36† (0.26)	-3.17 (3.46)	-1.95 (3.67)	-2.35 (2.21)	-1.63 (2.33)
Marrain	0.43 (0.24)	0.34 (0.82)	0.74 (0.50)	0.59 (2.74)	0.64 (0.37)	0.54 (2.30)
Rent	256.44	196.27	256.44	196.27	256.44	196.27

† The parameter used to compute the marginal effect value was not significant at the 10 percent critical level.

* The values in parentheses are the standard deviations of the marginal effect values among the sample of renters.

Issue #5: *Interactions of climate variables may provide insight on the instability of the effect of climate amenities on housing prices.*

The impact of climate on housing prices may be enhanced or mitigated by additional climatic and geographic features of the municipio. In this section, I estimate twenty-six models that include variables that interact the climate amenity variables, and the climate amenity variables with geographic dummy variables. The purpose of these models is to reveal whether any additional explanatory power may be added to the model by including these interaction variables, and if the marginal effect values of climate amenities change when conditioned on other features of a given municipio.

The interaction variables are the multiples of the average temperature and February rainfall variables, average temperature and March rainfall variables, average temperature and June rainfall variables, average temperature and August rainfall variables, average temperature and altitude variables, June rainfall and northeastern dummy, August rainfall and northeastern dummy variables, and average temperature and south dummy variables. I do not estimate models including the climate-region interaction variables assuming the linear Box-Cox functional form as the Box-Cox transformation of variables requires the variables to be strictly positive.⁹

The first set of interaction variables are meant to capture the combined effect of temperature and rainfall on housing prices. The wettest periods generally occur during the summer. Rainfall can greatly reduce the heat in a given area, and therefore the impact of increases in temperature on housing prices. For a

⁹It is not possible to transform the variables that interact climate amenities with regional dummy variables because a number of observations are equal to zero.

similar reason, I also include a variable that interacts temperature and altitude.

The set of climate-geographic interaction variables are included to capture two distinct geographical features of climate in Brazil. That is, the Northeast's proclivity for drought during the dry periods, and the more temperate climate of the South. Some households grow corn in their backyards in Fortaleza, for example, relying predominantly on rain as a water source. They may actually benefit from increases in rainfall during the dry period. Furthermore, including a variable that interacts temperature and the southern dummy variable may reveal that increases in average temperature might actually have less of a negative or even a positive impact on housing prices.

The estimates of the parameters and the standard errors for these models are included in the Appendix in Tables A.7-A.32. I briefly summarize the results from the models that include the interaction variables. I then report the values of the marginal effects of climate amenities on housing prices for the models that yield significant parameter estimates on the climate amenity and interaction variables.

Of the twelve models that included the average temperature and rainfall interaction variables, eight of the models yielded significant coefficients on the interaction variables and the single variables used to create the interaction variables. The models that assumed the semilog functional form did not provide significant coefficients (at the 10 percent critical level) for all of these variables.

Of the six models that included the average temperature and altitude interaction variables, only two models yielded significant coefficients on the interaction variables and the average temperature variables. These models assumed the Box-Cox functional form, and the double-log functional form including the

March and August rainfall variables.

All of the four models which included the regional and rainfall interaction variables produced coefficients on the interaction variables that were significant at the 10 percent critical level, except for the semilog model that included the June and February rainfall variables. Of the models that rendered significant coefficients on the interaction variables, none rendered coefficients on the single variables used to create the interaction variables significant. The lack of significance may be attributable to the few northeastern municipios represented in the dataset.

All of the four models which included the regional and temperature interaction variables yielded significant coefficients on these variables, with the exception of the semilog model that included the June and February rainfall variables. The sign on the average temperature and southern dummy interaction variables was consistently positive in the three models. It is therefore likely that location may impact the effect of an increase in temperature on housing prices.

Tables 5.33-5.35 display the values of the marginal effects of climate amenities on housing prices computed with the coefficients from Tables A.7-A.32. Values are calculated using coefficients that are at least significant at the 10 percent critical level. For this reason, I do not include a table of marginal effect values from the models that included the regional dummy and rainfall interaction variables.

The expressions used to calculate these marginal effects differ by functional form. To illustrate, the expressions for calculating the marginal effects of average temperature on housing prices for the semilog, double-log, and Box-Cox models that include the average temperature and February rainfall interaction

variable are:

$$\widehat{P} \times \left(\widehat{\beta}_{Avetemp} + \widehat{\beta}_{Avetemp \times Febrain} Febrain \right), \quad (5.6)$$

$$\frac{\widehat{P}}{Avetemp} \times \left(\widehat{\beta}_{Ln(Avetemp)} + \widehat{\beta}_{Ln(Avetemp) \times Ln(Febrain)} \times Ln(Febrain) \right), \quad (5.7)$$

$$\widehat{P}^{1-\widehat{\lambda}} \times \left(\begin{array}{c} \widehat{\beta}_{Avetemp} \times Avetemp^{\widehat{\lambda}-1} + \\ \widehat{\beta}_{Avetemp \times Febrain} \times (Avetemp \times Febrain)^{\widehat{\lambda}-1} \times Febrain \end{array} \right). \quad (5.8)$$

A marginal effect value is calculated for each individual in the sample of renters, and then the mean of the distribution of values is reported in Tables 5.33-5.35. The marginal effects are only reported for the variables that are included in the interaction variables.

Adding the variables that interact temperature and rainfall does not substantially change the marginal effects of the climate variables. The one exception is for the marginal effect of March rainfall on housing prices computed with the coefficients from the double-log and Box-Cox models. These models indicate that the marginal effect of March rainfall on housing prices is negative.

The magnitudes of the marginal effect values for both temperature and rainfall are highly dependent on the functional form assumed and the variables included in the model. The marginal effect value for average temperature is rather large when a double-log or Box-Cox functional form is assumed, and the March and August rainfall variables are included in the model. I would expect the values to be smaller than the values computed from the models excluding the temperature and rainfall interaction variables, because rainfall often reduces the impact of increases in average temperature (see Table 5.32).

Additional multicollinearity may be introduced to the model when including the interaction variable. Recall any model that includes the March rainfall

variable is subjected to the high correlation between the March rainfall and average temperature variables. The Pearson correlation coefficients, however, only detect partial (one-to-one) linear correlations between variables. Nonlinear relationships between variables may heighten the impact of multicollinearity on the models' results. The nonlinear relationships between explanatory variables may be the cause of the high magnitudes for the marginal effects of average temperature in the double-log and Box-Cox functional models.

5.4 Summary of Findings

The findings in this chapter suggest that the marginal effects of climate amenities on housing prices is highly sensitive to functional form, the variables used to represent climate amenities, and the combination of variables used in the model.

There are a few consistent results across models. Increases in annual average temperature negatively impact housing prices. The magnitude of the effect and significance of the results vary by model specification. Based on the models results, the negative impact of a $1^{\circ} C$ increase in annual average temperature on rents per year ranges anywhere from 474 1995 Reais (9 percent of median annual income) to 3155 1995 Reais (59 percent of median annual income). The pervasive strong relationships between temperature and other explanatory variables in the model are one of the causes of the higher estimates. The other cause is likely that there are important variables omitted from the model biasing the parameter estimates. The lowest value projected for a change in average temperature seems reasonable, but is not particularly robust across model specifications.

Table 5.33: Mean Marginal Effects of Temperature and Rainfall from Models that Include Temperature and Rainfall Interaction Variables

Model	Febrain/ Junrain/ Avetemp Marrain Augrain		
	Semilog (February and June rainfall)		
Semilog (February and June rainfall)			
Semilog (March and August rainfall)			0.76
Semilog (March and August rainfall)			
Double-log (February and June rainfall)	-65.27	3.19	
Double-log (February and June rainfall)	-102.65		-2.15
Double-log (March and August rainfall)	-91.81	-0.28	
Double-log (March and August rainfall)	-207.58		-5.84
Box-Cox (February and June rainfall)	-45.72	2.37	
Box-Cox (February and June rainfall)	-106.32		-3.03
Box-Cox (March and August rainfall)	-71.58	-0.48	
Box-Cox (March and August rainfall)	-186.60		-5.10

Note: The marginal effect values are only reported if the coefficients necessary for the computation of the values were atleast significant at the 10 percent critical level.

Note: The parenthetical comments indicate which rainfall variables were included in the model.

Table 5.34: Mean Marginal Effects of Average Temperature from Models that Include Temperature and Altitude Interaction Variables

Model	Avetemp
Semilog (February and June rainfall)	
Semilog (March and August rainfall)	
Double-log (February and June rainfall)	
Double-log (March and August rainfall)	-69.58
Box-Cox (February and June rainfall)	
Box-Cox (March and August rainfall)	-135.26

Note: The marginal effect values are only reported if the coefficients necessary for the computation of the values were atleast significant at the 10 percent critical level.

Note: The parenthetical comments indicate which rainfall variables were included in the model.

Table 5.35: Mean Marginal Effects of Average Temperature from Models that Include Temperature and Region Interaction Variables

Model	Avetemp
Semilog (February and June rainfall)	
Semilog (March and August rainfall)	-64.37
Double-log (February and June rainfall)	
Double-log (March and August rainfall)	-87.92

Note: The marginal effect values are only reported if the coefficients necessary for the computation of the values were atleast significant at the 10 percent critical level.

Note: The parenthetical comments indicate which rainfall variables were included in the model.

Second, an increase in rainfall during the wet months (summertime) has a positive impact on rents, and the opposite is true for an increase in rainfall during the dry months. Few models contradicted this finding in the chapter. Specifically, a 1-mm decrease in rainfall during the wet months is predicted to cause a decrease in rents anywhere from 2 to 20 1995 Reais annually. This implies that if rainfall decreased during the wet months by 20 percent, approximately 40 mm, rents could decrease anywhere from 80 to 800 1995 Reais annually. Alternatively, the model also indicates that a 1-mm decrease in rainfall during the dry months could cause annual housing rents to increase from 7 to 115 1995 Reais. The rainfall values appear robust in sign but not magnitude across models. These values may be affected by the multicollinearity between climate variables and especially from omitted variable bias. Aware that rainfall could be capturing the effect of another variable associated with rainfall, such as forest coverage, I tried to include a proxy for forest coverage in the model, the aridity index variable. The variable however was irrelevant to the rent model. Access to additional variables

that are correlated with rainfall and believed to influence housing prices would greatly improve the preceding analysis.

Chapter 6

The Hedonic Wage Model

In this chapter, I estimate the hedonic wage equation expressed in (2.26) using the sample of workers. The sample of workers is larger than the sample in the previous chapter, as it comprises owners and renters of housing. Using a similar framework to that in Chapter 5, I show how sensitive the wage differentials of climate amenities are to the specification of the hedonic wage model. The organization of the chapter is as follows. In Section 6.1, I define the assumptions applied in the empirical models of this chapter. Section 6.2 describes the variables included in a baseline wage model and its results. In Section 6.3, I present evidence suggesting that the wage differential estimates depend on the functional form assumed and combination of variables included in the model. Much of the volatility of the wage differentials is attributable to the data issues mentioned in Chapter 4. Section 6.4 concludes with a summary of the findings of this chapter.

6.1 Model Assumptions

6.1.1 Functional Form

Each version of the hedonic wage model is estimated assuming three functional forms: semilog, double log, and the linear Box-Cox transformation of the dependent and independent variables. Using the same notation as in equation (2.26), the semilog, double-log, and Box-Cox models are respectively:

$$\ln w_{ij} = \gamma_0 + \gamma_1 D_{ij} + \gamma_2 N_j + \gamma_3 Z_j + \eta_{ij}, \quad (6.1)$$

$$\ln w_{ij} = \gamma_0 + \gamma_1 D_{ij} + \gamma_2 N_j + \gamma_3 \ln Z_j + \eta_{ij}, \quad (6.2)$$

$$\frac{w_{ij}^\lambda - 1}{\lambda} = \gamma_0 + \gamma_1 D_{ij} + \gamma_2 N_j + \gamma_3 \frac{Z_j^\lambda - 1}{\lambda} + \eta_{ij}. \quad (6.3)$$

As in the rent model, the head of household demographic characteristic and non-climate amenity variables remain untransformed.

All of the statistical analysis is performed using Intercooled Stata 8.0. Equations (6.1) and (6.2) are estimated using OLS. Assuming the error term η_{ij} is normally distributed with mean zero and variance σ^2 , the log-likelihood function used to estimate the parameters in equation (6.3) is:

$$-\frac{n}{2} \ln(2\pi) - \frac{n}{2} \ln \sigma^2 + (\lambda - 1) \sum_{i=1}^n \ln w_{ij} - \frac{1}{2\sigma^2} \sum_{i=1}^n \left(\frac{w_{ij}^\lambda - 1}{\lambda} - \gamma_0 - \gamma_1 D_{ij} - \gamma_2 N_j - \gamma_3 \frac{Z_j^\lambda - 1}{\lambda} \right)^2.$$

For the Box-Cox procedure, Stata does not report the variance estimates of the coefficients. Thus, estimates for the standard errors of the parameters in the Box-Cox regressions are calculated using Gauss 5.0. The flatness of the likelihood function precluded the estimation of more complex versions of the Box-Cox model.

6.1.2 Heteroskedasticity

Each model in this chapter is estimated under the assumptions of homoskedasticity and heteroskedasticity of the error term. To avoid recapitulation of Section 5.1.2, I simply describe the estimators used to calculate the standard errors under the assumption of heteroskedasticity. When the semilog and double-log functional forms are assumed, I use the HR estimator in (5.4) to calculate the standard errors. When the Box-Cox linear functional form is assumed, I use the HR estimator in (5.5) to calculate the standard errors.

For each model, I report the standard errors under the assumption of homoskedasticity and heteroskedasticity. For ease of presentation, the t (for the semilog and double-log models) and Wald (for the Box-Cox models) tests are used to determine whether each coefficient is significantly different from zero and are calculated using the HR standard errors.

6.2 The Baseline Hedonic Wage Model

The variables considered determinants of real monthly wages D_{ij} , N_j , and Z_j are:

1) Education: dummy variables for highest education level completed, 5 to 8 years of education ($Ed_{5to8}=1$), 9 to 12 years of education ($Ed_{9to12}=1$), greater than 12 years of education ($Ed_{gt12}=1$);

2) Experience: on job experience enters in the wage function linearly and quadratically (OJE and OJEsq);

3) Socioeconomic variables: dummy variables for race ($Black=1$), and gender ($Male=1$);

4) Occupation: dummy variables for occupation—legislators, senior officials and managers (Dir=1); professionals (SP=1); technicians, and associate professionals (Mid=1); service workers, and shop markets and sales workers (Ser=1); plant and machine operators and assemblers (Oper=1); elementary occupations (EO=1);¹

5) Location attributes: number of banks (Banks), violent deaths (Deaths), schools (Schools) per 100,000 residents, population density (population/km²) divided by 100 (Popdens), the aridity index for the driest month (Arid), and altitude divided by 10 (Altitude);

6) Climate: winter (Junetemp) and summer (Febtemp) temperature, and winter (Junerain) and summer (Febrain) rainfall; and

7) Region: dummy variables for region—north(N=1), northeast (NE=1), south (S=1), and midwest (MW=1).

As in the rent model, only 14 municipio-level parameters can be identified from the model. Thus, the models proposed in this chapter may exclude variables or combination of variables that may contribute to wages.

The first version of the baseline wage model assumes the semilog functional form described in equation (6.1). In order to test for the joint significance of the demographic, non-climate amenity, region dummy, and climate amenity

¹The wage regression excludes the craft and related trade workers dummy variable as many of the workers lie in this category. Based on the results of a preliminary wage regression, I additionally exclude the dummy variables for the skilled agricultural and fishery workers (Ag=1), clerks (Off=1), armed forces (AF=1), and other (Other=1) job categories. The Off, AF, and Other parameters were insignificant at the 10 percent critical level (see Table A.33). An additional F test indicated that we cannot reject that the Off, AF, Other, and Ag parameters are jointly equal to zero at the 1 percent critical level, $F=0.56 < F_{4,14843}^{0.99}=3.32$.

parameters, I use the results from four block regressions to calculate the log likelihood-ratio statistics. The estimated coefficients, standard errors under the assumptions of homoskedasticity and heteroskedasticity, the sum of squared residuals of the model (SSR), the F-statistics, and adjusted R-squares are displayed in Tables 6.1-6.4.

The sum of squared residuals reported in Tables 6.1-6.4 are used to calculate the F statistics testing the joint significance of parameters. The F statistic testing the joint significance of the non-climate amenity parameters is equal to 134.75 which is greater than the critical value at the 1 percent significance level, 2.80. Therefore, we reject the hypothesis that the parameters are jointly equal to zero. Using the same methodology, the regional dummy parameters ($F=17.11 > F_{4,14837}^{0.99}=3.32$) and climate amenity parameters ($F=8.69 > F_{4,14833}^{0.99}=3.32$) are also not jointly equal to zero.

The demographic variable parameters are all significant at the 1 percent critical level. The parameters indicate that real wages increase with education and on-job-experience (at a decreasing rate). The gender and race parameters suggest that there may be evidence of gender and racial biases inherent in labor markets.² The occupational dummy variable parameters also show that there are differences in average earnings across occupations.

Table 6.5 includes the average predicted wage values by municipio. In comparing the predicted and actual values, it becomes clear that a substantial portion of the wage values remains unexplained by the variation in demographic variables for the households living in Campinas, Santos, Sao Paulo, Sao Luis,

²De Oliveira and Machado (2000) show that men tend to receive a wage premium in Brazilian labor markets.

Table 6.1: Results from Semilog Model Assuming Semilog Functional Form

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	4.9394***	0.0247	0.0244
Ed5to8	0.2470***	0.0187	0.0175
Ed9to12	0.6290***	0.0189	0.0185
Edgt12	1.4772***	0.0233	0.0240
OJE	0.0443***	0.0019	0.0021
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.310***	0.0127	0.0126
Male	0.5198***	0.0157	0.0163
Dir	0.3667***	0.0209	0.0219
SP	0.1571***	0.0231	0.0237
Mid	0.1859***	0.0225	0.0225
Ser	0.3022***	0.0191	0.0206
Oper	0.1697***	0.0242	0.0220
EO	-0.2108***	0.0215	0.0190
SSR	7935.04		
Adj. R-sq	0.50		
F[13,14847]	1132.20***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table 6.2: Results from Wage Model Assuming Semilog Functional Form

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	5.1382***	0.0489	0.0502
Ed5to8	0.2099***	0.0182	0.0168
Ed9to12	0.6154***	0.0184	0.0179
Edgt12	1.4500***	0.0228	0.0237
OJE	0.0452***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1984***	0.0133	0.0132
Male	0.5205***	0.0153	0.0158
Dir	0.3814***	0.0204	0.0214
SP	0.1611***	0.0225	0.0233
Mid	0.1925***	0.0219	0.0219
Ser	0.3067***	0.0186	0.0202
Oper	0.1711***	0.0236	0.0213
EO	-0.2007***	0.0210	0.0181
Popdens	-0.0009***	0.0003	0.0003
Banks	0.0107***	0.0024	0.0024
Deaths	-0.0012***	0.0002	0.0002
Schools	-0.0037***	0.0003	0.0003
Arid	0.0068	0.0056	0.0057
Altitude	0.0013***	0.0002	0.0002
SSR	7525.09		
Adj. R-sq	0.52		
F[19,14841]	859.08***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table 6.3: Results from Wage Model Assuming Semilog Functional Form

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	4.0792***	0.1554	0.1522
Ed5to8	0.2106***	0.0182	0.0167
Ed9to12	0.6193***	0.0184	0.0179
Edgt12	1.4550***	0.0228	0.0237
OJE	0.0454***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1854***	0.0134	0.0133
Male	0.5199***	0.0153	0.0158
Dir	0.3789***	0.0203	0.0213
SP	0.1630***	0.0225	0.0234
Mid	0.1931***	0.0219	0.0219
Ser	0.3086***	0.0185	0.0201
Oper	0.1715***	0.0235	0.0213
EO	-0.1976***	0.0209	0.0180
Popdens	-0.0095***	0.0013	0.0012
Banks	0.1451***	0.0187	0.0178
Deaths	-0.0005**	0.0003	0.0003
Schools	-0.0119***	0.0016	0.0015
Arid	-0.3419***	0.0507	0.0485
Altitude	0.0041***	0.0004	0.0004
N	1.2306***	0.1695	0.1632
NE	2.0946***	0.3106	0.2962
S	0.3057***	0.0760	0.0760
MW	-0.4314***	0.0630	0.0593
SSR	7490.54		
Adj. R-sq	0.53		
F[23,14837]	715.47***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table 6.4: Results from the Baseline Wage Model Assuming Semilog Functional

Variable	Form		
	Coeff.	Std. Error	Robust Std. Error
Constant	-3.6791	4.9646	5.0099
Ed5to8	0.2116***	0.0182	0.0167
Ed9to12	0.6213***	0.0184	0.0179
Edgt12	1.4533***	0.0227	0.0237
OJE	0.0456***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1817***	0.0134	0.0133
Male	0.5192***	0.0153	0.0158
Dir	0.3800***	0.0203	0.0213
SP	0.1617***	0.0225	0.0233
Mid	0.1929***	0.0219	0.0219
Ser	0.3077***	0.0185	0.0201
Oper	0.1710***	0.0235	0.0213
EO	-0.1981***	0.0209	0.0180
Popdens	-0.0110**	0.0045	0.0044
Banks	0.1495	0.1053	0.1032
Deaths	0.0014**	0.0006	0.0007
Schools	-0.018**	0.0089	0.0087
Arid	-0.2677	0.2178	0.2194
Altitude	0.0191**	0.0096	0.0096
N	1.3282*	0.6974	0.6743
NE	2.7603**	1.4211	1.3702
S	1.2491	0.8788	0.8890
MW	-0.6958**	0.2888	0.2781
Junetemp	0.0641	0.0787	0.0784
Junerain	-0.0021***	0.0008	0.0008
Febtemp	0.2347**	0.1045	0.1070
Febrain	0.0006***	0.0002	0.0002
SSR	7473.03		
Adj. R-sq	0.53		
F[27,14833]	612.25***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Fortaleza, and Recife. Thus, if variation in climate and non-climate amenity variables across municipios does contribute to wage variation, then the wage model could be improved by including these variables. Even if the amenities included in the model do not significantly affect wages, including regional dummy variables should improve the predicted wage estimates since Campinas, Santos, and Sao Paulo are in the southeast region of Brazil, and Sao Luis, Fortaleza, and Recife are in the northeast region of Brazil.

The values from Table 6.5 also suggest that the average individual may be different across municipios. If there are more skilled and experienced workers in densely-populated municipios, which I would expect, then the parameter estimates on the demographic variables may overestimate the effect of demographic characteristics on the wages of workers in other municipios. This reasoning offers one explanation for the large difference in the average predicted and actual wage values in Campinas, Santos, and Sao Luis.

Many of the climate and non-climate amenity variable parameters have signs that are significant at the 5 percent critical level. Specifically, the parameters on the population density, the number of deaths, the number of schools, February temperature, and June and February rainfall variables are significant determinants of wages.

Tables 6.6 and 6.7 present the results from the estimated regression equations (6.2) and (6.3). $\text{Ln}(\cdot)$ and $\text{BC}(\cdot)$ signify that the variables were transformed logarithmically or using a Box-Cox transformation. None of the climate amenity and non-climate amenity variables are statistically significant for the double-log and Box-Cox models. There are two potential causes of these results. The semi-log model may better resemble the functional relationship between wages, climate

Table 6.5: Predicted Wage Values from Semilog Model Including Demographic

Variables		
Município	Predicted Ln(Wage)	Actual Ln(Wage)
Manaus	5.98	6.02
Belem	6.14	6.19
Sao Luis	6.15	5.85
Fortaleza	6.00	5.77
Recife	6.09	5.81
Salvador	5.98	5.80
Belo Horizonte	6.19	6.27
Rio de Janeiro	6.34	6.29
Campinas	6.36	6.70
Santos	6.55	6.89
Sao Paulo	6.27	6.48
Curitiba	6.39	6.54
Porto Alegre	6.46	6.53
Goiania	6.14	6.10
Brasilia	6.22	6.35

and non-climate amenities, and thus be subjected to less specification error. Alternatively, the multicollinearity between variables may be more severe in the latter two models. In the next section, I estimate several models that differ by functional form and the variables included in the models to see how sensitive these results are to model specification.

6.3 Sensitivity Analysis

In this section, I use the same framework for the analysis as in Section 5.3.

Issue #1: *All temperature variables are highly correlated and lack variation.*

As in the rent model, the multicollinearity between the temperature variables, and lack of seasonal and cross-sectional variation in temperature may prevent one from capturing distinct effects of winter and summer temperatures on housing prices. Including the annual average temperature variable in the wage model may be more suitable for capturing the effect of temperature on wages in Brazil.

Empirical results from wage models that include average annual temperature instead of seasonal temperature variables are displayed in Tables 6.8, 6.9, and 6.10. Table 6.11 includes the marginal effect values calculated using the parameters from Tables 6.8-6.10.

Comparing the results from Tables 6.4-6.7 and Tables 6.8-6.10, it becomes evident that the symptoms of multicollinearity have been greatly reduced in the models that include the average annual temperature variable. In the model assuming a semilog functional form, many of the climate and non-climate amenities that were significant at only the 5 percent critical level are now significant

Table 6.6: Results from Baseline Wage Model Assuming Double-Log Functional

Form			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	-44.5556	121.0752	125.1714
Ed5to8	0.2116***	0.0182	0.0167
Ed9to12	0.6213***	0.0184	0.0179
Edgt12	1.4533***	0.0227	0.0237
OJE	0.0456***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1817***	0.0134	0.0133
Male	0.5192***	0.0153	0.0158
Dir	0.3800***	0.0203	0.0213
SP	0.1617***	0.0225	0.0233
Mid	0.1929***	0.0219	0.0219
Ser	0.3077***	0.0185	0.0201
Oper	0.1710***	0.0235	0.0213
EO	-0.1981***	0.0209	0.0180
Popdens	-0.0199	0.0348	0.0358
Banks	0.3383	1.0394	1.0735
Deaths	0.0001	0.0083	0.0086
Schools	-0.0357	0.0759	0.0782
Arid	-0.7655	1.8486	1.9065
Altitude	0.0386	0.1009	0.1043
N	1.7567	4.5947	4.7366
NE	4.7512	10.3645	10.6703
S	4.1874	10.3388	10.6741
MW	-1.4414	2.7296	2.8112
Ln(Junetemp)	6.8920	24.2842	25.1043
Ln(Junerain)	0.1206	1.0051	1.0432
Ln(Febtemp)	7.3089	10.6934	11.0560
Ln(Febrain)	0.3377	0.2159	0.2263
SSR	7473.03		
Adj. R-sq	0.53		
F[27,14833]	612.25***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table 6.7: Results from Baseline Wage Model with Linear Box-Cox

Transformation (Lambda=-0.0800)

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	-6.6164	202.7930	202.6300
Ed5to8	0.1367***	0.0118	0.0115
Ed9to12	0.3874***	0.0146	0.0111
Edgt12	0.8664***	0.0266	0.0134
OJE	0.0279***	0.0013	0.0011
OJEsq	-0.0005***	0.0000	0.0000
Black	-0.1096***	0.0086	0.0081
Male	0.3210***	0.0117	0.0088
Dir	0.2243***	0.0133	0.0118
SP	0.0983***	0.0136	0.0134
Mid	0.1201***	0.0136	0.0133
Ser	0.1762***	0.0120	0.0106
Oper	0.1065***	0.0157	0.0155
EO	-0.1328***	0.0147	0.0141
Popdens	-0.0063	6.8093	6.8041
Banks	0.0269	15.3064	15.2950
Deaths	0.0016	15.8433	15.8309
Schools	-0.0089	4.0503	4.0473
Arid	-0.1562	48.8877	48.8472
Altitude	0.0061	2.2267	2.2248
N	0.2703	17.6982	17.6849
NE	1.1192	0.5982	0.5977
S	0.7940	0.0510	0.0509
MW	-0.4209	1.5972	1.5959
BC(Junetemp)	0.0168	0.0138	0.0137
BC(Junerain)	-0.1326	0.1129	0.1129
BC(Febtemp)	3.3760	2.7133	2.7112
BC(Febrain)	0.3781	0.1545	0.1544
Value of LLF	-108047.62		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The Wald statistics are calculated using the heteroskedasticity-robust standard errors.

at the 1 percent level. The number of banks parameter is significant in the newer version of the model. The confidence in the Febrain parameter also improved, and the magnitude of the parameter also drops.

The results from the models assuming double-log and Box-Cox models are less stark when replacing seasonal temperature variables with the annual average temperature variable. Many of the climate and non-climate amenity parameters become significant at the 1 percent critical level. Specifically, the significance of the Popdens, Banks, Schools, Arid, regional dummy (excluding N), and February parameters improves in the double log model, and the significance of the Banks, Deaths, Schools, regional dummy (excluding MW), average temperature, and June rainfall parameters improves for the Box-Cox model.

The magnitudes of the marginal effects of the climate variables seem reasonable. The marginal effect of temperature on wages from the Box-Cox model indicates that a $1^{\circ}C$ increase in annual average temperature will cause an increase in wages of 77.12 1995 Reais, approximately 9 percent of monthly wages. The effect of temperature on wages is not particularly robust since is only significant in the model that assumes the Box-Cox functional form. The rainfall effects on wages are more robust, however. The magnitudes of the marginal effects of June and February rainfall obtained from the double-log and Box-Cox models are comparable in magnitude, and only slightly different than those produced from the semilog model.

In the remainder of the chapter, I use annual average temperature instead of seasonal temperatures in the wage model. The specification reduces the error in the model by eliminating the collinearity between the temperature variables.

Issue #2: *March is the wettest month. The March rainfall variable also has*

Table 6.8: Results from Semilog Model Including Annual Average Temperature

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	3.2888***	1.1688	1.1670
Ed5to8	0.2109***	0.0182	0.0167
Ed9to12	0.6209***	0.0184	0.0179
Edgt12	1.4532***	0.0227	0.0237
OJE	0.0455***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1816***	0.0134	0.0133
Male	0.5180***	0.0153	0.0158
Dir	0.3793***	0.0203	0.0213
SP	0.1624***	0.0225	0.0233
Mid	0.1935***	0.0219	0.0219
Ser	0.3073***	0.0185	0.0201
Oper	0.1709***	0.0235	0.0213
EO	-0.1985***	0.0209	0.0180
Popdens	-0.0088***	0.0018	0.0016
Banks	0.1011***	0.0317	0.0306
Deaths	0.0010***	0.0005	0.0005
Schools	-0.012***	0.0032	0.0030
Arid	-0.1091	0.0976	0.1002
Altitude	0.0059***	0.0021	0.0020
N	0.7493***	0.2562	0.2471
NE	1.8664***	0.4856	0.4461
S	0.2011	0.2789	0.2842
MW	-0.5390	0.1160	0.1059
Avetemp	0.0462	0.0446	0.0446
Junerain	-0.0024***	0.0008	0.0009
Febrain	0.0007***	0.0002	0.0002
SSR	7476.19		
Adj. R-sq	0.53		
F[26,14834]	635.33***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table 6.9: Results from Double-log Model Including Annual Average

Temperature

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	-4.2448	5.3044	5.4941
Ed5to8	0.2113***	0.0182	0.0167
Ed9to12	0.6211***	0.0184	0.0179
Edgt12	1.4540***	0.0227	0.0237
OJE	0.0455***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1822***	0.0134	0.0133
Male	0.5184***	0.0153	0.0158
Dir	0.3793***	0.0203	0.0213
SP	0.1624***	0.0225	0.0233
Mid	0.1940***	0.0219	0.0219
Ser	0.3073***	0.0185	0.0201
Oper	0.1706***	0.0235	0.0213
EO	-0.1976***	0.0209	0.0180
Popdens	-0.0104***	0.0024	0.0021
Banks	0.1054***	0.0293	0.0273
Deaths	0.0008	0.0006	0.0006
Schools	-0.0157***	0.0034	0.0030
Arid	-0.2862***	0.0802	0.0733
Altitude	0.0072*	0.0037	0.0039
N	0.4889	0.3278	0.3198
NE	1.9051***	0.6486	0.5992
S	0.9861***	0.2961	0.2867
MW	-0.6792***	0.1428	0.1262
Ln(Avetemp)	2.4334	1.6555	1.7130
Ln(Junerain)	-0.0518	0.1060	0.1092
Ln(Febrain)	0.2881***	0.1060	0.1105
SSR	7476.69		
Adj. R-sq	0.53		
F[26,14834]	635.25***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table 6.10: Results from Linear Box-Cox Model Including Annual Average

Temperature(Lambda=-0.0799)

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	-2.2648	3.7306	3.7259
Ed5to8	0.1366***	0.0118	0.0115
Ed9to12	0.3876***	0.0146	0.0112
Edgt12	0.8674***	0.0266	0.0134
OJE	0.0279***	0.0013	0.0011
OJEsq	-0.0005***	0.0000	0.0000
Black	-0.1100***	0.0086	0.0081
Male	0.3207***	0.0117	0.0088
Dir	0.2240***	0.0134	0.0118
SP	0.0988***	0.0136	0.0134
Mid	0.1209***	0.0137	0.0133
Ser	0.1760***	0.0120	0.0106
Oper	0.1063***	0.0157	0.0155
EO	-0.1325***	0.0147	0.0142
Popdens	-0.0064	0.2226	0.2225
Banks	0.0642***	0.4637	0.4628
Deaths	0.0005***	0.1893	0.1883
Schools	-0.0096***	0.1040	0.1037
Arid	-0.1785	1.3330	1.3314
Altitude	0.0043	0.0913	0.0912
N	0.2984***	0.1039	0.1039
NE	1.1624***	0.0018	0.0018
S	0.6101***	0.0200	0.0199
MW	-0.4179	0.0004	0.0004
BC(Avetemp)	1.8736***	0.0024	0.0024
BC(Junerain)	-0.0406***	0.0571	0.0569
BC(Febrain)	0.2711*	0.0024	0.0024
Value of LLF	-108047.62		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The Wald statistics are calculated using the heteroskedasticity-robust standard errors.

Table 6.11: Marginal Effects of Climate Amenities on Monthly Wages

	Semi-log		Double-log		Box-Cox	
	Mean	Median	Mean	Median	Mean	Median
Avetemp	31.48† (26.84)	21.75† (41.12)	75.03† (69.63)	49.90† (101.84)	77.12 (80.67)	47.56 (111.12)
Junerain	-1.64 (1.39)	-1.13 (2.41)	-1.03† (1.85)	-0.34† (2.54)	-1.08 (2.17)	-0.30 (2.82)
Febrain	0.48 (0.41)	0.33 (0.43)	1.10 (1.07)	0.72 (1.14)	1.17 (1.27)	0.71 (1.36)
Wage	875.51	448.83	875.51	448.83	875.51	448.83

† The parameter used to compute the marginal effect value was not significant at the 10 percent critical level.

* The values in parentheses are the standard deviations of the marginal effect values among the sample of workers.

the most variation, but it is highly correlated with the temperature variables.

In the baseline model, I opted to use the February instead of March rainfall variable because the March rainfall variable was highly correlated with the temperature variables. To observe how sensitive the results are to the inclusion of the February and March rainfall variables, I estimate three additional models (assuming semilog, double-log, and linear Box-Cox functional forms) which include average annual temperature, June rainfall, and March rainfall to represent the effect of climate amenities on wages. The results from these models are presented in Tables 6.12-6.14. The values of the marginal effect of these climate amenities on housing prices are included in Table 6.15.

Drawing on the results from Tables 6.12-6.14, it appears that substituting March rainfall for February rainfall in the model has changed the significance of some of the climate and non-climate amenity parameters. The effects on parameter significance differ by the functional specification. The Deaths, Altitude, and Junerain parameters are no longer significant at the 10 percent critical level,

when the semilog functional form is assumed. The altitude and South dummy variable parameters are no longer significant at the 10 percent critical level, when the double-log functional form is assumed. With the exception of the altitude variable, the partial correlations are stronger between the non-climate amenity variables and the February rainfall variable than the March rainfall variable (see Tables 4.18 and 4.20). Thus, the effect is not likely caused by multicollinearity.

Table 6.15 summarizes the marginal effects of climate variables on wages in each model. The marginal effect of temperature on wages has not significantly changed when substituting the March rainfall for the February rainfall variable. The marginal effect calculation for June rainfall has significantly changed, particularly for the Box-Cox model (where the parameter used for the calculation was significant). The sign is now positive instead of negative. The marginal effect of March rainfall is slightly smaller than the effect of February rainfall on wages (when the double-log and Box-Cox functional forms are assumed). The order of magnitudes are the same, though.

Based on these results, including June and March rainfall in the same regression may not be appropriate. June rainfall appears to be a redundant variable in this context. Furthermore, including March and June rainfall (instead of February and June) in the same regression model doesn't drastically affect the remaining parameter estimates and standard errors.

Issue #3: August is the driest month on average, but the minimum rainfall levels are lowest cross-sectionally for the month of June.

As in Section 5.3, I estimate six additional models including the August rainfall variable as the driest month variable to see how sensitive the model results are to specification of the dry month. Three models include February as the wet

Table 6.12: Results from Semilog Model Including March Rainfall

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	5.1391***	1.2532	1.2195
Ed5to8	0.2108***	0.0182	0.0167
Ed9to12	0.6208***	0.0184	0.0179
Edgt12	1.4531***	0.0227	0.0237
OJE	0.0455***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1818***	0.0134	0.0133
Male	0.5180***	0.0153	0.0158
Dir	0.3792***	0.0203	0.0213
SP	0.1625***	0.0225	0.0233
Mid	0.1935***	0.0219	0.0219
Ser	0.3074***	0.0185	0.0201
Oper	0.1710***	0.0235	0.0213
EO	-0.1985***	0.0209	0.0180
Popdens	-0.0090***	0.0017	0.0016
Banks	0.0996***	0.0322	0.0312
Deaths	0.0001	0.0005	0.0005
Schools	-0.0118***	0.0032	0.0030
Arid	-0.1523	0.0959	0.0985
Altitude	0.0028	0.0023	0.0022
N	0.7830***	0.2576	0.2498
NE	1.7534***	0.5071	0.4697
S	-0.0255	0.2788	0.2819
MW	-0.4072***	0.1266	0.1150
Avetemp	-0.0276	0.0464	0.0450
Junerain	-0.0015	0.0009	0.0009
Marrain	0.0009***	0.0003	0.0003
SSR	7477.04		
Adj. R-sq	0.53		
F[26,14834]	635.20***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table 6.13: Results from Double-log Model Including March Rainfall

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	-2.3859	6.8616	7.1480
Ed5to8	0.2114***	0.0182	0.0167
Ed9to12	0.6210***	0.0184	0.0179
Edgt12	1.4545***	0.0227	0.0237
OJE	0.0455***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1827***	0.0134	0.0133
Male	0.5186***	0.0153	0.0158
Dir	0.3792***	0.0203	0.0214
SP	0.1625***	0.0225	0.0233
Mid	0.1942***	0.0219	0.0219
Ser	0.3073***	0.0185	0.0201
Oper	0.1705***	0.0235	0.0213
EO	-0.1972***	0.0209	0.0180
Popdens	-0.0090***	0.0023	0.0020
Banks	0.1122***	0.0292	0.0269
Deaths	-0.0006**	0.0003	0.0003
Schools	-0.0136***	0.0032	0.0028
Arid	-0.2698***	0.0801	0.0739
Altitude	0.0070	0.0046	0.0048
N	0.5145	0.3427	0.3316
NE	1.5177***	0.6161	0.5641
S	0.6287	0.3934	0.4021
MW	-0.4667***	0.1319	0.1224
Ln(Avetemp)	1.8387	2.1651	2.2530
Ln(Junerain)	0.0640	0.0869	0.0889
Ln(Marrain)	0.1830*	0.0941	0.0974
SSR	7478.5		
Adj. R-sq	0.53		
F[26,14834]	635.25***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table 6.14: Results from Linear Box-Cox Model Including March

Rainfall(Lambda=-0.0799)

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	-2.1296	4.7616	4.7578
Ed5to8	0.1367***	0.0118	0.0115
Ed9to12	0.3876***	0.0146	0.0112
Edgt12	0.8680***	0.0266	0.0134
OJE	0.0279***	0.0013	0.0011
OJEsq	-0.0005***	0.0000	0.0000
Black	-0.1104***	0.0086	0.0081
Male	0.3210***	0.0118	0.0088
Dir	0.2240***	0.0134	0.0119
SP	0.0989***	0.0136	0.0134
Mid	0.1210***	0.0137	0.0133
Ser	0.1762***	0.0120	0.0106
Oper	0.1062***	0.0157	0.0155
EO	-0.1322***	0.0147	0.0142
Popdens	-0.0053	0.2384	0.2383
Banks	0.0681**	0.4450	0.4443
Deaths	-0.0003*	0.2387	0.2381
Schools	-0.0083***	0.0893	0.0890
Arid	-0.1645	1.7180	1.7168
Altitude	0.0050	0.0749	0.0749
N	0.2883*	0.0909	0.0909
NE	0.8825***	0.0017	0.0017
S	0.4380***	0.0204	0.0203
MW	-0.2911	0.0002	0.0002
BC(Avetemp)	1.8461***	0.0023	0.0023
BC(Junerain)	0.069***	0.0565	0.0563
BC(Marrain)	0.1478*	0.0028	0.0028
Value of LLF	-108053.43		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The Wald statistics are calculated using the heteroskedasticity-robust standard errors.

Table 6.15: Marginal Effects of Climate Amenities on Monthly Wages

	Semi-log		Double-log		Box-Cox	
	Mean	Median	Mean	Median	Mean	Median
Avetemp	-18.48† (15.78)	-12.75† (23.78)	56.86† (52.75)	37.82† (77.20)	76.49 (80.35)	46.96 (110.59)
Junerain	-1.00† (0.86)	-0.69† (0.91)	1.27† (2.28)	0.42† (2.41)	1.86 (3.72)	0.51 (3.96)
Marrain	0.60 (0.51)	0.42 (1.39)	0.76 (0.77)	0.49 (0.81)	0.70 (0.80)	0.42 (0.82)
Wage	875.51	448.83	875.51	448.83	875.51	448.83

† The parameter used to compute the marginal effect value was not significant at the 10 percent critical level.

* The values in parentheses are the standard deviations of the marginal effect values among the sample of workers.

month variable, and three models include March as the wet month variable. The results from these models are displayed in Tables 6.16-6.21. The corresponding marginal effects of climate amenities on wages are presented in Tables 6.22 and 6.23.

To observe the effect of including the August rainfall variable on the models' results, I compare the parameter estimates and the parameter significance of the climate variables reported in Tables 6.8, 6.9, 6.10 with 6.16, 6.17, and 6.18 and Tables 6.12, 6.13, 6.14 with 6.19, 6.20, and 6.21.

Comparing the first set of tables, it appears that including August rainfall as the driest month variable (instead of June rainfall) has caused the driest rainfall parameter to be insignificant in the semilog model. Additionally, the magnitude of the Febrin parameters increase in the semilog and double-log models. In the model that assumes a Box-Cox functional form, the climate amenity parameter estimates change from significant at the 10 percent critical levels to insignificant. The correlation between the August and February rainfall variables (Pearson

correlation of -0.42) may be causing the change in the parameter estimates, since collinearity between explanatory variables can inflate standard error estimates and increase the likelihood of obtaining parameter estimates that are closer to the tails of the distributions.

The second pair of tables reveal that including the March and August rainfall variables in the same model actually improves the significance of some of the climate parameter estimates. In particular, the dry month parameter (Augrain) becomes significant when the semilog functional and double-log functional forms are assumed. Average temperature also becomes significant for the semilog and double-log models. We may expect to see an improvement since both of these variables have the most variation among the candidate wet and dry month variables. Also, the combined effect of average temperature, August rainfall, and March rainfall on wages may be important, since average temperature is significant across model specifications.

Despite the improvement in significance in the model that includes the March and August rainfall variables, the marginal effects of August rainfall and temperature especially in the double-log and Box-Cox models seem relatively high. The correlation between March rainfall and average temperature variables (the correlation coefficient is -0.69) may be part of the cause. However, including the March rainfall variable in the models of the previous section did not yield such drastic changes in the marginal effect values of annual average temperature.

Alternatively, the omission of the June rainfall variable from the model may be the cause of the changes in parameters. June rainfall is more correlated with temperature (0.47) than August rainfall (0.22). Thus, omitting June rainfall could bias the parameter estimates on the temperature variable. However,

regressions including both June and March rainfall variables in the same model suggested that June was redundant to the model. The parameters on the June rainfall variable were only significant in the Box-Cox model. Because the results of the climate parameter depend on model specification, I continue to estimate additional versions of the wage model including temperature, June rainfall, and February rainfall, and temperature, August rainfall, and March rainfall.

Issue #4: The Aridity Index Variable has a strong correlation with the rainfall variables.

The aridity index variable was included in the model to serve as a proxy for variables that may be correlated with rainfall and are also determinants of wages and rents. Essentially, I was interested in reducing the bias that often plagues the rainfall variable in hedonic studies. The empirical results suggest that the aridity index variable may be irrelevant to wage variation, however. Adding an irrelevant variable could add more error to the model. In this section, I estimate six models excluding the aridity index variable from the models. Three models include the February and June rainfall variables. The other three models include the March and August rainfall variables. The estimates of the parameters and standard errors for each model are displayed in Tables 6.24-6.29. The marginal effect values of the climate amenities on wages are computed using the parameter estimates from the models and displayed in Tables 6.30 and 6.31 .

Comparing the results from comparable models (refer to Tables 6.8-6.10 and Tables 6.19-6.21), the adjusted R-square values do not change upon the exclusion of the Aridity index variable. Additionally, excluding the variable seems to add precision to the climate and non-climate amenity parameter estimates

Table 6.16: Results from Semilog Model Including February and August Rainfall

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	2.6350**	1.1608	1.0898
Ed5to8	0.2115***	0.0182	0.0167
Ed9to12	0.6204***	0.0184	0.0179
Edgt12	1.4550***	0.0227	0.0236
OJE	0.0455***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1828***	0.0134	0.0134
Male	0.5188***	0.0153	0.0158
Dir	0.3793***	0.0203	0.0213
SP	0.1624***	0.0225	0.0233
Mid	0.1938***	0.0219	0.0219
Ser	0.3073***	0.0185	0.0201
Oper	0.1703***	0.0235	0.0213
EO	-0.1973***	0.0209	0.0180
Popdens	-0.0068***	0.0028	0.0025
Banks	0.0786*	0.0482	0.0444
Deaths	0.0010	0.0010	0.0010
Schools	-0.0101***	0.0043	0.0039
Arid	-0.1152	0.1715	0.1637
Altitude	0.0055***	0.0023	0.0021
N	0.3251	0.3881	0.3691
NE	1.0330	0.8081	0.7516
S	0.4352	0.3084	0.2893
MW	-0.4697***	0.1286	0.1123
Avetemp	0.0784*	0.0429	0.0410
Augrain	-0.0018	0.0017	0.0017
Febrain	0.0009***	0.0002	0.0002
SSR	7479.65		
Adj. R-sq	0.53		
F[26,14834]	634.78***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table 6.17: Results from Double-log Model Including February and August

Rainfall			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	10.4518	7.1493	7.1217
Ed5to8	0.2118***	0.0182	0.0167
Ed9to12	0.6213***	0.0184	0.0179
Edgt12	1.4537***	0.0227	0.0236
OJE	0.0456***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1819***	0.0134	0.0133
Male	0.5194***	0.0153	0.0158
Dir	0.3800***	0.0203	0.0213
SP	0.1617***	0.0225	0.0233
Mid	0.1930***	0.0219	0.0219
Ser	0.3077***	0.0185	0.0201
Oper	0.1709***	0.0235	0.0213
EO	-0.1978***	0.0209	0.0180
Popdens	-0.0053**	0.0024	0.0022
Banks	-0.0692	0.0719	0.0718
Deaths	0.0037***	0.0013	0.0013
Schools	-0.0068*	0.0044	0.0041
Arid	0.1607	0.1840	0.1821
Altitude	-0.0063	0.0061	0.0061
N	-0.7236	0.5032	0.5076
NE	-0.3112	0.9010	0.8794
S	-0.0013	0.4825	0.4695
MW	-0.3250**	0.1789	0.1636
Ln(Avetemp)	-1.6183	2.0438	2.0280
Ln(Augrain)	-0.3947***	0.1502	0.1552
Ln(Febrain)	0.4732***	0.1002	0.1039
SSR	7473.33		
Adj. R-sq	0.53		
F[26,14834]	635.79***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table 6.18: Results from Linear Box-Cox Model Including February and August

Rainfall(Lambda=-0.0800)

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	9.5809*	5.5118	5.5115
Ed5to8	0.1369***	0.0118	0.0115
Ed9to12	0.3874***	0.0146	0.0111
Edgt12	0.8666***	0.0266	0.0134
OJE	0.0279***	0.0013	0.0011
OJEsq	-0.0005***	0.0000	0.0000
Black	-0.1097***	0.0086	0.0081
Male	0.3211***	0.0117	0.0088
Dir	0.2243***	0.0133	0.0118
SP	0.0983***	0.0136	0.0134
Mid	0.1201***	0.0136	0.0133
Ser	0.1762***	0.0120	0.0106
Oper	0.1064***	0.0156	0.0155
EO	-0.1326***	0.0147	0.0141
Popdens	-0.0034	0.3114	0.3114
Banks	-0.049	0.5761	0.5760
Deaths	0.0024	0.3293	0.3292
Schools	-0.0041	0.1265	0.1264
Arid	0.1028	1.8179	1.8174
Altitude	-0.0052***	0.1291	0.1290
N	-0.4568***	0.0977	0.0976
NE	-0.2139**	0.0016	0.0016
S	-0.0732	0.0460	0.0460
MW	-0.1808***	0.0008	0.0008
BC(Avetemp)	-1.9276	0.0029	0.0029
BC(Augrain)	-0.3554	0.1164	0.1164
BC(Febrain)	0.4681	0.0042	0.0042
Value of LLF	-108047.91		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The Wald statistics are calculated using the heteroskedasticity-robust standard errors.

Table 6.19: Results from Semilog Model Including March and August Rainfall

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	7.2439***	1.5616	1.4702
Ed5to8	0.2117***	0.0182	0.0167
Ed9to12	0.6209***	0.0184	0.0179
Edgt12	1.4543***	0.0227	0.0236
OJE	0.0456***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1820***	0.0134	0.0133
Male	0.5189***	0.0153	0.0158
Dir	0.3797***	0.0203	0.0213
SP	0.1620***	0.0225	0.0233
Mid	0.1933***	0.0219	0.0219
Ser	0.3073***	0.0185	0.0201
Oper	0.1704***	0.0235	0.0213
EO	-0.1976***	0.0209	0.0180
Popdens	-0.0027	0.0031	0.0029
Banks	-0.0129	0.0571	0.0546
Deaths	0.0017*	0.0010	0.0010
Schools	-0.0028	0.0049	0.0046
Arid	0.2171	0.2041	0.1996
Altitude	-0.0028	0.0032	0.0030
N	-0.2161	0.4296	0.4201
NE	-0.3969	0.9411	0.9033
S	-0.6428	0.4203	0.4036
MW	-0.1268	0.1590	0.1424
Avetemp	-0.0886*	0.0542	0.0508
Augrain	-0.0047**	0.0019	0.0020
Marrain	0.0016***	0.0003	0.0003
SSR	7475.39		
Adj. R-sq	0.53		
F[26,14834]	635.46***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table 6.20: Results from Double-log Model Including March and August

Rainfall			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	45.9988***	13.4067	13.7640
Ed5to8	0.2115***	0.0182	0.0167
Ed9to12	0.6213***	0.0184	0.0179
Edgt12	1.4532***	0.0227	0.0236
OJE	0.0456***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1816***	0.0134	0.0133
Male	0.5190***	0.0153	0.0158
Dir	0.3800***	0.0203	0.0213
SP	0.16178***	0.0225	0.0233
Mid	0.1929***	0.0219	0.0219
Ser	0.3077***	0.0185	0.0201
Oper	0.1711***	0.0235	0.0213
EO	-0.1983***	0.0209	0.0180
Popdens	-0.0028	0.0028	0.0026
Banks	-0.1744*	0.0915	0.0935
Deaths	0.0027***	0.0011	0.0011
Schools	0.0021	0.0058	0.0057
Arid	0.5103**	0.2486	0.2533
Altitude	-0.0304***	0.0105	0.0108
N	-0.9275*	0.5386	0.5521
NE	-1.6951	1.1466	1.1564
S	-2.488***	0.9069	0.9242
MW	0.4629	0.3040	0.3001
Ln(Avetemp)	-12.4871***	3.9520	4.0540
Ln(Augrain)	-0.6886***	0.2052	0.2135
Ln(Marrain)	0.7066	0.1481	0.1547
SSR	7473.1		
Adj. R-sq	0.53		
F[26,14834]	635.83***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table 6.21: Results from Linear Box-Cox Model Including March and August

Rainfall(Lambda=-0.0800)

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	38.9589***	10.5806	10.5805
Ed5to8	0.1367***	0.0118	0.0115
Ed9to12	0.3874***	0.0145	0.0111
Edgt12	0.8664***	0.0266	0.0134
OJE	0.0279***	0.0013	0.0011
OJEsq	-0.0005***	0.0000	0.0000
Black	-0.1096***	0.0086	0.0081
Male	0.3209***	0.0117	0.0088
Dir	0.2243***	0.0133	0.0118
SP	0.0983***	0.0136	0.0134
Mid	0.1201***	0.0136	0.0133
Ser	0.1762***	0.0120	0.0106
Oper	0.1065***	0.0156	0.0154
EO	-0.1329***	0.0147	0.0141
Popdens	-0.0018*	0.3328	0.3328
Banks	-0.1272*	0.7316	0.7316
Deaths	0.0019***	0.6289	0.6288
Schools	0.0021*	0.2118	0.2118
Arid	0.3555***	3.5829	3.5817
Altitude	-0.0232***	0.1878	0.1877
N	-0.6198***	0.1516	0.1514
NE	-1.1974	0.0018	0.0018
S	-1.8702**	0.0593	0.0593
MW	0.3790***	0.0007	0.0007
BC(Avetemp)	-12.1347	0.0038	0.0038
BC(Augrain)	-0.6770**	0.1594	0.1594
BC(Marrain)	0.7426***	0.0074	0.0074
Value of LLF	-108047.7		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The Wald statistics are calculated using the heteroskedasticity-robust standard errors.

Table 6.22: Marginal Effects of Climate Amenities on Monthly Wages

	Semi-log		Double-log		Box-Cox	
	Mean	Median	Mean	Median	Mean	Median
Avetemp	51.90 (44.39)	35.82 (67.99)	-49.51† (45.86)	-32.95† (64.91)	-77.40† (80.71)	47.72† (109.31)
Augrain	-1.19† (1.02)	-0.82† (1.90)	-7.44 (10.79)	-3.58 (11.46)	-8.70† (14.15)	-3.69† (15.01)
Febrain	0.60 (0.51)	0.41 (0.54)	1.80 (1.75)	1.17 (5.66)	1.98† (2.14)	1.20† (6.06)
Wage	875.51	448.83	875.51	448.83	875.51	448.83

† The parameter used to compute the marginal effect value was not significant at the 10 percent critical level.

* The values in parentheses are the standard deviations of the marginal effect values among the sample of workers.

Table 6.23: Marginal Effects of Climate Amenities on Monthly Wages

	Semi-log		Double-log		Box-Cox	
	Mean	Median	Mean	Median	Mean	Median
Avetemp	-58.61 (50.18)	-40.39 (75.55)	-382.60 (354.85)	-254.59 (517.26)	-501.58† (526.68)	-307.13† (722.38)
Augrain	-3.11 (2.66)	-2.14 (2.83)	-13.03 (18.93)	-6.26 (20.11)	-17.14 (28.07)	-7.19 (29.79)
Marrain	1.06 (0.91)	0.73 (3.33)	2.90† (2.95)	1.88† (9.62)	3.52 (4.01)	2.10 (11.43)
Wage	875.51	448.83	875.51	448.83	875.51	448.83

† The parameter used to compute the marginal effect value was not significant at the 10 percent critical level.

* The values in parentheses are the standard deviations of the marginal effect values among the sample of workers.

overall. As in the rent model, the aridity index variable is likely irrelevant to the wage model.

The marginal effect values of the climate amenities in the newer models are markedly different. Among the models that include the February and June rainfall variables, the magnitude of the marginal effect of temperature on wages did not change significantly. The marginal effect values for June and February rainfall also did not change much except for the marginal effect of June rainfall in the Box-Cox model where the effect changed from negative to positive. I do not believe this is because of omitted variable bias since the aridity index variable was not statistically significant according to the Wald test (see Table 6.10). Also, the parameter results on June rainfall are not particularly robust across model specifications.

Among the models that include the March and August rainfall variables, the marginal effect values for average temperature were only relevant for the double-log and the Box-Cox models. The effects decreased substantially when the aridity index variable was excluded from the models. The values remain negative, however, which contradicts theoretical predictions from a model that assumes firms costs are independent of temperature. This may provide evidence that increases in temperature may in fact increase the production costs of goods. I discuss more of the theoretical implications of the empirical results in the Discussion Chapter.

The marginal effects for August and March decreased substantially in all of the models irrespective of the assumption of functional form. The signs of the August marginal effects are consistently negative and significant, unlike the model that includes the June rainfall variable. The signs of the March mar-

ginal effects also were significant but consistently positive and greater than the February marginal effects on wages.

In sum, excluding the aridity index variable reduces the error in the wage models and magnitudes of the marginal effects of climate amenities on wages. From hereon, I exclude the aridity index variable from the model.

Issue #5: *Interactions of climate variables may provide insight on the instability of the effect of climate amenities on wages.*

As in Chapter 5, I estimate twenty-six models that include variables that interact the climate amenity variables, and the climate amenity variables with geographic dummy variables. The purpose of these models is to reveal whether the signs and magnitudes of the marginal effect values change when conditioned on other geographical characteristics of a municipio.

I include the same interaction variables as in the rent model, the multiples of the average temperature and February rainfall variables, average temperature and March rainfall variables, average temperature and June rainfall variables, average temperature and August rainfall variables, average temperature and altitude variables, June rainfall and northeastern dummy, August rainfall and northeastern dummy variables, and average temperature and south dummy variables.

The estimates of the parameters and the standard errors for these models are included in the Appendix in Tables A.34-A.59. I briefly summarize the results from the models that include the interaction variables. I then report the values of the marginal effects of climate amenities on wages for the models that yield significant parameter estimates on the climate amenity and interaction variables.

The significance of the parameters of interest depends on the functional form assumed and rainfall variables included in the models. Of the twelve models

Table 6.24: Results from Semilog Model Excluding the Aridity Index Variable

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	4.1852***	0.8504	0.8563
Ed5to8	0.2107***	0.0182	0.0167
Ed9to12	0.6205***	0.0184	0.0178
Edgt12	1.4522***	0.0227	0.0236
OJE	0.0455***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1819***	0.0134	0.0133
Male	0.5179***	0.0153	0.0158
Dir	0.3795***	0.0203	0.0213
SP	0.1621***	0.0225	0.0233
Mid	0.1930***	0.0219	0.0219
Ser	0.3071***	0.0185	0.0201
Oper	0.1709***	0.0235	0.0213
EO	-0.1992***	0.0209	0.0180
Popdens	-0.0073***	0.0011	0.0010
Banks	0.0707***	0.0164	0.0151
Deaths	0.0012***	0.0004	0.0004
Schools	-0.0095***	0.0020	0.0019
Altitude	0.0044***	0.0016	0.0015
N	0.5786***	0.2057	0.2012
NE	1.4812***	0.3422	0.3154
S	-0.0615	0.1504	0.1526
MW	-0.4613***	0.0929	0.0870
Avetemp	0.0155	0.0351	0.0355
Junerain	-0.0030***	0.0007	0.0006
Febrain	0.0007***	0.0002	0.0002
SSR	7476.82		
Adj. R-sq	0.53		
F[25,14835]	660.68***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table 6.25: Results from Double-log Model Excluding the Aridity Index Variable

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	-1.9468	5.2673	5.4875
Ed5to8	0.2109***	0.0182	0.0167
Ed9to12	0.6190***	0.0184	0.0179
Edgt12	1.4525***	0.0228	0.0237
OJE	0.0455***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1844***	0.0134	0.0133
Male	0.5182***	0.0153	0.0158
Dir	0.3795***	0.0203	0.0214
SP	0.1615***	0.0225	0.0233
Mid	0.1930***	0.0219	0.0219
Ser	0.3061***	0.0185	0.0201
Oper	0.1694***	0.0235	0.0213
EO	-0.1988***	0.0209	0.0180
Popdens	-0.0034***	0.0014	0.0014
Banks	0.0057	0.0088	0.0089
Deaths	0.0000	0.0006	0.0006
Schools	-0.0050***	0.0015	0.0015
Altitude	0.0047	0.0037	0.0038
N	-0.4480**	0.1964	0.2027
NE	-0.1090	0.3199	0.3360
S	0.4290*	0.2517	0.2558
MW	-0.2898***	0.0922	0.0931
Ln(Avetemp)	1.7943	1.6464	1.7124
Ln(Junerain)	0.0350	0.1032	0.1083
Ln(Febrain)	0.2675**	0.1059	0.1110
SSR	7483.11		
Adj. R-sq	0.53		
F[25,14835]	659.63***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table 6.26: Results from Linear Box-Cox Model Excluding the Aridity Index

Variable (Lambda=-0.0800)

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	-2.2941	3.7147	3.7108
Ed5to8	0.1364***	0.0118	0.0115
Ed9to12	0.3862***	0.0146	0.0111
Edgt12	0.8662***	0.0266	0.0134
OJE	0.0279***	0.0013	0.0011
OJEsq	-0.0005***	0.0000	0.0000
Black	-0.1113***	0.0086	0.0081
Male	0.3206***	0.0117	0.0088
Dir	0.2241***	0.0134	0.0119
SP	0.0982***	0.0136	0.0134
Mid	0.1203***	0.0137	0.0133
Ser	0.1753***	0.0120	0.0106
Oper	0.1054***	0.0157	0.0155
EO	-0.1330***	0.0146	0.0141
Popdens	-0.0018***	0.1152	0.1148
Banks	0.0041	0.1752	0.1750
Deaths	-0.0001**	0.1608	0.1604
Schools	-0.0030***	0.0562	0.0562
Altitude	0.0039	1.3276	1.3263
N	-0.3108	0.0826	0.0826
NE	-0.1518**	0.1001	0.1000
S	0.3127**	0.0008	0.0008
MW	-0.1695	0.0056	0.0056
BC(Avetemp)	1.9463	0.0003	0.0003
BC(Junerain)	0.0677***	0.0009	0.0009
BC(Febrain)	0.2090*	0.0023	0.0023
Value of LLF	-108057.9		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The Wald statistics are calculated using the heteroskedasticity-robust standard errors.

Table 6.27: Results from Semilog Model Excluding the Aridity Index Variable

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	5.9171***	0.9394	0.9259
Ed5to8	0.2115***	0.0182	0.0167
Ed9to12	0.6210***	0.0184	0.0179
Edgt12	1.4545***	0.0227	0.0236
OJE	0.0455***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1818***	0.0134	0.0133
Male	0.5186***	0.0153	0.0158
Dir	0.3794***	0.0203	0.0213
SP	0.1623***	0.0225	0.0233
Mid	0.1937***	0.0219	0.0219
Ser	0.3073***	0.0185	0.0201
Oper	0.1706***	0.0235	0.0213
EO	-0.1976***	0.0209	0.0180
Popdens	-0.0060***	0.0008	0.0008
Banks	0.0461***	0.0136	0.0137
Deaths	0.0008	0.0005	0.0005
Schools	-0.0077***	0.0018	0.0017
Altitude	0.0001	0.0016	0.0016
N	0.2229*	0.1191	0.1235
NE	0.5902***	0.1564	0.1541
S	-0.2215*	0.1405	0.1349
MW	-0.2673***	0.0883	0.0861
Avetemp	-0.0467	0.0373	0.0364
Augrain	-0.0028***	0.0007	0.0007
Marrain	0.0013***	0.0002	0.0002
SSR	7475.96		
Adj. R-sq	0.53		
F[25,14835]	660.83***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table 6.28: Results from Double-log Model Excluding the Aridity Index Variable

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	19.1089***	2.8520	2.8409
Ed5to8	0.2114***	0.0182	0.0167
Ed9to12	0.6215***	0.0184	0.0179
Edgt12	1.4541***	0.0227	0.0236
OJE	0.0455***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1818***	0.0134	0.0133
Male	0.5187***	0.0153	0.0158
Dir	0.3794***	0.0203	0.0213
SP	0.1624***	0.0225	0.0233
Mid	0.1939***	0.0219	0.0219
Ser	0.3077***	0.0185	0.0201
Oper	0.1710***	0.0235	0.0213
EO	-0.1975***	0.0209	0.0180
Popdens	-0.0081***	0.0011	0.0010
Banks	0.0127	0.0079	0.0078
Deaths	0.0009	0.0006	0.0006
Schools	-0.0092***	0.0017	0.0016
Altitude	-0.0093***	0.0020	0.0020
N	0.1513	0.1179	0.1206
NE	0.6426***	0.1332	0.1265
S	-0.6540***	0.1548	0.1511
MW	-0.1433**	0.0721	0.0698
Ln(Avetemp)	-4.5657***	0.8522	0.8439
Ln(Augrain)	-0.2890***	0.0648	0.0626
Ln(Marrain)	0.4243***	0.0550	0.0537
SSR	7475.23		
Adj. R-sq	0.53		
F[25,14835]	660.95***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table 6.29: Results from Linear Box-Cox Model Excluding the Aridity Index

Variable (Lambda=-0.0798)

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	15.5760***	2.2677	2.2611
Ed5to8	0.1368***	0.0118	0.0115
Ed9to12	0.3880***	0.0146	0.0112
Edgt12	0.8680***	0.0266	0.0134
OJE	0.0279***	0.0013	0.0011
OJEsq	-0.0005***	0.0000	0.0000
Black	-0.1099***	0.0086	0.0081
Male	0.3211***	0.0117	0.0088
Dir	0.2242***	0.0134	0.0119
SP	0.0989***	0.0136	0.0134
Mid	0.1209***	0.0137	0.0133
Ser	0.1764***	0.0120	0.0106
Oper	0.1066***	0.0157	0.0155
EO	-0.1325***	0.0147	0.0142
Popdens	-0.0052	0.0730	0.0730
Banks	0.0055***	0.0888	0.0882
Deaths	0.0006***	0.1053	0.1051
Schools	-0.0056	0.0451	0.0451
Altitude	-0.0069***	0.7689	0.7685
N	0.1094***	0.0602	0.0602
NE	0.4037***	0.0563	0.0563
S	-0.4810***	0.0008	0.0008
MW	-0.0693	0.0050	0.0050
BC(Avetemp)	-4.2219*	0.0004	0.0004
BC(Augrain)	-0.2658***	0.0011	0.0011
BC(Marrain)	0.4150***	0.0015	0.0015
Value of LLF	-108050.2		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The Wald statistics are calculated using the heteroskedasticity-robust standard errors.

Table 6.30: Marginal Effects of Climate Amenities on Monthly Wages

	Semi-log		Double-log		Box-Cox	
	Mean	Median	Mean	Median	Mean	Median
Avetemp	10.26† (8.76)	7.08† (13.25)	55.13† (51.11)	36.78† (74.69)	79.29 (80.09)	48.89 (114.48)
Junerain	-1.99 (1.70)	-1.37 (2.86)	0.69† (1.24)	0.23† (1.24)	1.80 (3.60)	0.50 (3.82)
Febrain	0.46 (0.40)	0.32 (0.42)	1.02 (0.99)	0.67 (1.05)	0.89 (0.97)	0.54 (1.03)
Wage	875.51	448.83	875.51	448.83	875.51	448.83

† The parameter used to compute the marginal effect value was not significant at the 10 percent critical level.

* The values in parentheses are the standard deviations of the marginal effect values among the sample of workers.

Table 6.31: Marginal Effects of Climate Amenities on Monthly Wages

	Semi-log		Double-log		Box-Cox	
	Mean	Median	Mean	Median	Mean	Median
Avetemp	-30.55† (26.16)	-21.04† (39.27)	-139.77 (129.63)	-93.03 (188.72)	-173.89 (182.11)	-106.93 (249.87)
Augrain	-1.83 (1.57)	-1.26 (1.67)	-5.45 (7.89)	-2.62 (8.38)	-6.68 (10.86)	-2.82 (11.52)
Marrain	0.85 (0.73)	0.59 (2.23)	1.74 (1.77)	1.13 (4.710)	1.96 (2.23)	1.17 (5.27)
Wage	875.51	448.83	875.51	448.83	875.51	448.83

† The parameter used to compute the marginal effect value was not significant at the 10 percent critical level.

* The values in parentheses are the standard deviations of the marginal effect values among the sample of workers.

that included the average temperature and rainfall interaction variables, two of the models yielded significant coefficients (at the 10 percent critical level) on the interaction variables and the single variables used to create the interaction variables. The two models included the February and January Rainfall variables and assumed the semilog and double-log functional forms.

Of the six models that included the average temperature and altitude interaction variables, three models produced significant coefficients on the interaction variables and the average temperature variables. They are the double-log and Box-Cox models including the February and June rainfall parameters and the semilog model including the August and March rainfall variables.

None of the four models which included the regional and rainfall interaction variables produced coefficients on the interaction and rainfall that were significant at the 10 percent critical level. Additionally, only when the double-log functional form was assumed did the coefficients on the temperature and regional interaction variables, and the temperature variables become significant.

Tables 6.33-5.35 display the values of the marginal effects of climate amenities on wages computed with the coefficients from Tables A.34-A.59. I calculate the values using coefficients that are atleast significant at the 10 percent critical level. For this reason, I do not include a table of marginal effect values from the models that included the regional dummy and rainfall interaction variables. A marginal effect value is calculated for each individual in the sample of workers, and then the mean of the distribution of values is reported in Tables 6.32-6.34.

Of the marginal effect values computed from the models that include the temperature and rainfall interaction variables, the signs remain consistent across

models. The one exception is for the marginal effect of August rainfall on wages computed with the coefficients from the Box-Cox model. Less confidence is placed on these results, since many of the coefficients needed to compute the marginal effect values were insignificant at the 10 percent critical level.

Few parameters in the models with the temperature and altitude and temperature and south interaction variables were significant at the 10 percent level. Therefore, few marginal effect values are shown in the tables. The results in Tables 6.33 and 6.34 indicate that including these interaction variables does provide great insight on the values of climate amenities conditioned on other geographic characteristics, since the results are not robust to the specification of the model.

6.4 Summary of Findings

The empirical results of this chapter suggest that obtaining the marginal effect values of climate amenities on wages is problematic. Unlike the empirical results from the rent model, there is not a clear association between wages and climate.

In particular, average temperature is often insignificant in the wage model or yields different marginal effects on wages (positive and negative). The results indicate that a $1^{\circ}C$ increase in average temperature may cause a decrease in wages ranging from 1116 to 1284 1995 Reais (21 to 24 percent of annual median income). This finding combined with those from Chapter 5 are consistent with a location choice model where temperature increases firms production costs. The effect of changes in temperature on wages is greater than one would expect, however. These direct of the effect is not the same across models, since one model predicted

Table 6.32: Mean Marginal Effects of Temperature and Rainfall from Models that Include Temperature and Rainfall Interaction Variables

Model	Febrain/ Junrain/ Avetemp Marrain Augrain		
	Semilog (February and June rainfall)	101.09	1.22
Semilog (February and June rainfall)			
Semilog (March and August rainfall)			1.42
Semilog (March and August rainfall)			
Double-log (February and June rainfall)	96.96	5.30	
Double-log (February and June rainfall)			2.59
Double-log (March and August rainfall)			
Double-log (March and August rainfall)			
Box-Cox (February and June rainfall)			
Box-Cox (February and June rainfall)			
Box-Cox (March and August rainfall)		2.56	
Box-Cox (March and August rainfall)			-8.86

Note: The marginal effect values are only reported if the coefficients necessary for the computation of the values were atleast significant at the 10 percent critical level.

Note: The parenthetical comments indicate which rainfall variables were included in the model.

Table 6.33: Mean Marginal Effects of Average Temperature from Models that Include Temperature and Altitude Interaction Variables

Model	Avetemp
Semilog (February and June rainfall)	
Semilog (March and August rainfall)	-36.14
Double-log (February and June rainfall)	126.42
Double-log (March and August rainfall)	
Box-Cox (February and June rainfall)	-84.07
Box-Cox (March and August rainfall)	

Note: The marginal effect values are only reported if the coefficients necessary for the computation of the values were atleast significant at the 10 percent critical level.

Note: The parenthetical comments indicate which rainfall variables were included in the model.

Table 6.34: Mean Marginal Effects of Average Temperature from Models that Include Temperature and Region Interaction Variables

Model	Avetemp
Semilog (February and June rainfall)	
Semilog (March and August rainfall)	
Double-log (February and June rainfall)	136.11
Double-log (March and August rainfall)	-117.52

Note: The marginal effect values are only reported if the coefficients necessary for the computation of the values were atleast significant at the 10 percent critical level.

Note: The parenthetical comments indicate which rainfall variables were included in the model.

a positive effect on wages of 11 percent of individual annual median income.

The predicted August, February, and March rainfall effects on wages are consistent across functional specifications. A 1-mm decrease in rainfall in August is projected to have a positive effect on wages of 15 to 34 1995 Reais. Using June rainfall in the model yields negative and significant marginal effects on wages but only for the semilog specification, in contrast. The model also predicts a 1-mm decrease in rainfall during the wet months will decrease wages anywhere from 4 to 14 1995 Reais annually. The effects of marginal changes on rainfall during the wet season on wages is robust. February rainfall, like March rainfall, shows to have a positive effect on wages, with March rainfall having a greater effect than February rainfall.

In the next chapter, I estimate the rent and wage equations as a system of seemingly unrelated regression equations. The results from the next chapter may shed some light on whether trying a more efficient estimation procedure will improve the robustness of the results from the wage regression equation.

Chapter 7

The System of Hedonic Rent and Wage Equations

In Chapters 5 and 6, I estimated the rent and wage equations separately. By using the single-equation method, I implicitly assumed that the disturbances in the equations were uncorrelated:

$$P_{ij} = f(S_{ij}, N_j, Z_j; \beta) + \varepsilon_{ij} \quad (7.1)$$

$$w_{ij} = g(D_{ij}, N_j, Z_j; \gamma) + \eta_{ij}, \quad (7.2)$$

$$E[\varepsilon_{ij}, \eta_{ij}] = 0. \quad (7.3)$$

In this Chapter, I allow for correlation in the error terms and estimate (7.1) and (7.2) as a system of seemingly unrelated regression equations (SURE).

The single-equation method produces consistent but inefficient estimators of the parameters. As long as the sample is large, the single-equation method parameter estimates will be close to the true parameter values with high probability (Judge, 1988). By estimating the rent and wage equations simultaneously, however, I obtain efficient estimates of the amenity parameters, which are the basis of the climate amenity values. This is true as long as the disturbances

are in fact correlated and not all of the explanatory variables are identical in the equations. By definition, an efficient estimator is one where the asymptotic covariance matrix is not larger than the covariance matrix of another consistent estimator (Greene, 1997). In practice, this usually means that the standard errors of the efficient parameters are smaller. In result, the efficient parameters are more precise and inferences based on hypothesis tests may change.

In addition to the change in the variances of the climate amenity parameters, I anticipate that the point estimates from the system of SURE will differ from the single-equation method. Zellner (1962) notes that the point estimates of the single-equation and SURE models will differ because one is more efficient and the estimation procedure of both models involves minimizing quadratic forms. The covariance matrix is used to estimate the parameters of the regression model. Since the estimator of the covariance matrix differ for the SURE model, and also is more efficient, then I expect there to be differences in the point estimates across models.

The organization of the chapter is as follows. In Section 7.1, I describe the methodology used to estimate the model. In Section 7.2, I report the results from the system of SURE models. In Section 7.3, I compare the marginal values of climate amenities using the parameter estimates from the single-equation hedonic rent and wage models and the system of SURE models.

7.1 Methodology

The SURE model estimated in this chapter is a variant of the usual model. I have an unequal number of observations in each equation of the system. There are two consequences of estimating a system with unbalanced data. First,

the estimation procedure is slightly different than for the case with equal number of observations in each equation. Second, I choose one of few estimators for the covariance matrix. These issues are discussed in more detail in this section.

I first define the variables in Chapters 5 and 6 in matrix form:

$$\begin{bmatrix} \mathbf{P} \\ \mathbf{w} \end{bmatrix} = \begin{bmatrix} \mathbf{X}_1 & 0 \\ 0 & \mathbf{X}_2 \end{bmatrix} \begin{bmatrix} \boldsymbol{\beta} \\ \boldsymbol{\gamma} \end{bmatrix} + \begin{bmatrix} \boldsymbol{\varepsilon} \\ \boldsymbol{\eta} \end{bmatrix}, \quad (7.4)$$

$$\mathbf{X}_1 = (\mathbf{S} \ \mathbf{N} \ \mathbf{Z}),$$

$$\mathbf{X}_2 = (\mathbf{D} \ \mathbf{N} \ \mathbf{Z}),$$

where there are N observations in the first equation, and $N + E$ observations in the second equation. I assume that the vectors $(\varepsilon_{ij} \ \eta_{ij})'$ are independently and identically distributed, and drawn from a bivariate normal distribution $N(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ where $\boldsymbol{\mu} = (0 \ 0)'$, $\boldsymbol{\Sigma} = \begin{pmatrix} \sigma_1^2 & \sigma_1\sigma_2\rho \\ \sigma_1\sigma_2\rho & \sigma_2^2 \end{pmatrix}$. Note the single-equation method implicitly assumes that $\rho = 0$.

For convenience, equation (7.4) can be re-written as:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\theta} + \mathbf{u} \quad (7.5)$$

Because there are an unequal number of observations in each equation,

$$E[\mathbf{u}\mathbf{u}'] \neq \boldsymbol{\Sigma} \otimes \mathbf{I}_N.$$

Rather,

$$E[\mathbf{u}\mathbf{u}'] = \boldsymbol{\Phi} = \begin{bmatrix} \sigma_1\mathbf{I}_N & \sigma_1\sigma_2\rho\mathbf{I}_N & \mathbf{0} \\ \sigma_1\sigma_2\rho\mathbf{I}_N & \sigma_2\mathbf{I}_N & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \sigma_2\mathbf{I}_E \end{bmatrix}.$$

Thus, the generalized least squares estimator does not correspond to the that for the case of equal number of observations in each equation.

In this chapter, I estimate the system of SURE model using iterated FGLS.¹ Since I assume the random errors to be normally distributed, estimates for the SURE model using iterated FGLS and maximum likelihood are equivalent asymptotically (Judge et al., 1988). The properties of the estimators using both techniques are well-established when the number of observations in each equation of the system is the same. The model here however consists of a system of SURE with unbalanced data.

Zellner (1962) first showed that the variances of SURE estimates are smaller the larger the correlation between disturbances. Schmidt (1977) found contradictions to Zellner's finding when the number of observations differs for each equation. In particular, he notices that the variances do not necessarily fall when the extra number of observations in the one equation increases. Im (1994) shows analytically, for the case of unequal numbers of observations in two equations and identical regressors, that the efficiency gains are limited to the equation of the smaller number of observations.

Experimental results and analytical findings indicate that the estimator used for the covariance matrix also matters for the SURE model with unequal number of observations. Schmidt (1977) finds that the maximum likelihood estimator is the best estimator of the covariance matrix when the correlation coefficient is high, yet the Hocking and Smith (1968) estimator is the best overall.

¹I attempted to maximize the likelihood function for each model directly. Due to the size of the sample and number of regressors, it was difficult to estimate the Hessian matrix evaluated at the maximum to verify that at least the necessary condition was met for a maximum.

Hwang (1990) finds that the Hocking and Smith estimator of the covariance matrix yields significantly more efficient estimates when the correlation between disturbances is high and the proportion of missing observations is large.

Using the analytical expressions derived in Schmidt (1977) and Hocking and Smith estimator (1968) of the covariance matrix, I estimate the system of SURE model defined in (7.5). To estimate the model, I partition the matrices as follows:

$$\mathbf{x}_2 = \begin{bmatrix} \mathbf{x}_2^* \\ \mathbf{x}_2^0 \end{bmatrix}, \mathbf{w} = \begin{bmatrix} \mathbf{w}^* \\ \mathbf{w}^0 \end{bmatrix}, \quad (7.6)$$

where \mathbf{x}_2^* and \mathbf{w}^* contain the N households represented in both equations, and \mathbf{x}_2^0 and \mathbf{w}^0 has the E observations of the households only represented in the wage equation. The estimator for $\boldsymbol{\theta}$ is:

$$\begin{aligned} \hat{\boldsymbol{\theta}} &= \begin{pmatrix} \hat{\boldsymbol{\beta}} \\ \hat{\boldsymbol{\gamma}} \end{pmatrix} = \begin{bmatrix} \sigma^{11} \mathbf{x}'_1 \mathbf{x}_1 & \sigma^{12} \mathbf{x}'_1 \mathbf{x}_2^* \\ \sigma^{12} \mathbf{x}_2^{*'} \mathbf{x}_1 & \sigma^{22} \mathbf{x}_2^{*'} \mathbf{x}_2^* + \frac{1}{\sigma_{22}} \mathbf{x}_2^{0'} \mathbf{x}_2^0 \end{bmatrix}^{-1} \\ &\quad \times \begin{bmatrix} \sigma^{11} \mathbf{x}'_1 \mathbf{P} + \sigma^{12} \mathbf{x}'_1 \mathbf{w}^* \\ \sigma^{12} \mathbf{x}_2^{*'} \mathbf{P} + \sigma^{22} \mathbf{x}_2^{*'} \mathbf{w}^* + \frac{1}{\sigma_{22}} \mathbf{x}_2^{0'} \mathbf{w}_2^0 \end{bmatrix}, \end{aligned} \quad (7.7)$$

where σ_{ij} are the elements of $\boldsymbol{\Sigma}$ and σ^{ij} are the elements of $\boldsymbol{\Sigma}^{-1}$. With the exception of directly maximizing the likelihood function, the Hocking and Smith estimator is the only estimator of the covariance matrix that uses the extra ob-

servations in computing all elements of Σ :

$$\begin{aligned}\hat{\sigma}_{11} &= S_{11} - \frac{E}{N + E} \left(\frac{S_{12}}{S_{22}^*} \right)^2 (S_{22}^* - S_{22}^0), \\ \hat{\sigma}_{12} &= S_{12} \left(\frac{S_{22}}{S_{22}^*} \right), \\ \hat{\sigma}_{22} &= S_{22}, \\ S_{11} &= \frac{e_1' e_1}{N}, \quad S_{22}^0 = \frac{e_2^{0'} e_2^0}{E}, \\ S_{12} &= \frac{e_1' e_2^*}{N}, \quad S_{22} = \frac{e_2' e_2}{N + E}, \\ S_{22}^* &= \frac{e_2^{*'} e_2^*}{N},\end{aligned}$$

where e_2 is the vector of residuals in the second equation (e.g., the wage equation) and partitioned in a similar fashion to \mathbf{x}_2 and \mathbf{y}_2 .

Up until now, homoskedasticity has been assumed. I also estimate the SURE model under the assumption of heteroskedasticity. Because the SURE model has an unequal number of observations, the estimator of the covariance matrix is slightly different than the usual estimator for the SURE model, e.g. p.160 in Wooldridge (2002). Following the derivation of the usual estimator of the HR covariance matrix, I derive the estimator for the unequal observations case. Many of the terms that typically fall out of the expression for the usual SURE model do not for the case when the number of observations are unequal.

Wooldridge shows that in the FGLS context an estimator of the covariance matrix for the usual SURE model assuming heteroskedasticity is $\mathbf{A}^{-1} \mathbf{B} \mathbf{A}^{-1}$, where $\hat{\mathbf{A}}$ and $\hat{\mathbf{B}}$ are consistent estimators of \mathbf{A} and \mathbf{B} :

$$\hat{\mathbf{A}} = \frac{\sum_{i=1}^N \mathbf{X}_i' \hat{\Omega}^{-1} \mathbf{X}_i}{N}, \quad (7.8)$$

$$\hat{\mathbf{B}} = \frac{\sum_{i=1}^N \mathbf{X}_i' \hat{\Sigma}^{-1} \hat{\mathbf{u}}_i \hat{\mathbf{u}}_i' \hat{\Omega}^{-1} \mathbf{X}_i}{N}, \quad (7.9)$$

where $\hat{\mathbf{u}}_i = \mathbf{y}_i - \mathbf{X}_i\hat{\boldsymbol{\theta}}$, $\hat{\boldsymbol{\theta}}$ is the FGLS estimate of parameters, and $\hat{\boldsymbol{\Omega}}^{-1} = \left[\frac{\sum_{i=1}^N \hat{\mathbf{u}}_i \hat{\mathbf{u}}_i'}{N} \right]^{-1}$. The estimator of the covariance matrix is:

$$\frac{\hat{\mathbf{A}}^{-1} \hat{\mathbf{B}} \hat{\mathbf{A}}^{-1}}{N} = \left[\sum_{i=1}^N \mathbf{X}_i' \hat{\boldsymbol{\Omega}}^{-1} \mathbf{X}_i \right]^{-1} \left[\sum_{i=1}^N \mathbf{X}_i' \hat{\boldsymbol{\Omega}}^{-1} \hat{\mathbf{u}}_i \hat{\mathbf{u}}_i' \hat{\boldsymbol{\Omega}}^{-1} \mathbf{X}_i \right] \left[\sum_{i=1}^N \mathbf{X}_i' \hat{\boldsymbol{\Omega}}^{-1} \mathbf{X}_i \right]^{-1}. \quad (7.10)$$

In other words, the N (the number of observations) terms cancel out.

For the SURE model with unbalanced data, the estimator of the covariance of $\hat{\boldsymbol{\theta}}$ is slightly different. For the two-equation case, the individual matrices in (7.10) and the multiple of the three matrices again are divided by a matrix \mathbf{W} that weighs each element by the appropriate number of observations:

$$\mathbf{W} = \begin{bmatrix} \mathbf{N}_{k1 \times k1} & \mathbf{N}_{k1 \times k2} \\ \mathbf{N}_{k2 \times k1} & \mathbf{N} + \mathbf{E}_{k2 \times k2} \end{bmatrix} \quad (7.11)$$

where \mathbf{N} and $\mathbf{N} + \mathbf{E}$ refer to matrices with each element of the matrix containing the value of N for \mathbf{N} and $N + E$ for $\mathbf{N} + \mathbf{E}$. The indices of the matrices denote the dimensions of the matrix where $k1$ is the number of explanatory variables included in the first equation (including the intercept), and $k2$ is the number of explanatory variables included in the second equation (including the intercept).

The HR covariance estimator of $\hat{\boldsymbol{\theta}}$ for the two-equation case is:

$$\frac{\left[\frac{\sum_{i=1}^N \mathbf{X}_i \hat{\boldsymbol{\Omega}}^{-1} \mathbf{X}_i}{\mathbf{W}} \right]^{-1} \left[\frac{\sum_{i=1}^N \mathbf{X}_i \hat{\boldsymbol{\Omega}}^{-1} \hat{\mathbf{u}}_i \hat{\mathbf{u}}_i' \hat{\boldsymbol{\Omega}}^{-1} \mathbf{X}_i}{\mathbf{W}} \right] \left[\frac{\sum_{i=1}^N \mathbf{X}_i \hat{\boldsymbol{\Omega}}^{-1} \mathbf{X}_i}{\mathbf{W}} \right]^{-1}}{\mathbf{W}}. \quad (7.12)$$

Note, $\hat{\boldsymbol{\Omega}}^{-1}$ is also different for the SURE model with unbalanced data. As mentioned earlier, I use the Hocking and Smith (1968) estimator.

7.2 Results from the system of SURE model

In this section, I estimate the system of SURE model assuming 28 different specifications of the hedonic rent and wage equations.² Each model shares the same housing variables, demographic variables, and non-climate amenity variables. The models differ by the functional form assumed on the rent and wage equations, and the climate amenity variables included in the model. Table 7.1 shows which climate amenity variables are included in the models. Each version of the SURE model is estimated assuming the semilog, double-log, and linear Box-Cox functional forms for the rent and wage equations, which is why the models are grouped in multiples of three in Table 7.1.³

The parameter and standard error estimates (assuming homoskedasticity and heteroskedasticity) for each model are reported in Tables A.60-B.8, except for Models 11, 12, 17, and 18 due to the lack of convergence. The estimates for each equation are presented in separate tables. The correlation coefficient ρ is displayed in the table that obtains the parameter estimates for the wage equations. The parameter and standard error estimates from the single-equation models are also included in the tables for comparative purposes.

Drawing attention to the first six models that exclude amenity interaction variables (see Tables A.60-A.71), there are a few stable findings across the SURE models. First, the parameters vary substantially in the equation that has less observations, i.e., the rent equation, as Im (1994) found.

Second, the efficiency gains are greatest in the models that assume double-

²The models in this chapter are estimated using Gauss 5.0.

³The optimal values for the Box-Cox transformation parameters found in Chapters 5 and 6 are assumed in the SURE and single-equation versions of the models.

Table 7.1: Specification of the Models Estimated in the Chapter

Functional Form	Models									
Semilog	1	4	7	10	13	16	19	22	25	27
Double-log	2	5	8	11	14	17	20	23	26	28
Box-Cox	3	6	9	12	15	18	21	24		
Variables in models										
Avetemp	X	X	X	X	X	X	X	X	X	X
Junerain	X		X	X			X		X	
Febrain	X		X	X			X		X	
Augrain		X			X	X		X		X
Marrain		X			X	X		X		X
Avetemp×Altitude							X	X		
Avetemp×S									X	X
Avetemp×Junerain			X							
Avetemp×Febrain				X						
Avetemp×Augrain					X					
Avetemp×Marrain						X				

log and Box-Cox functional forms. For the SURE model with balanced data, Greene (1997) notes that the gains in efficiency are greater when the correlation between the disturbances is high. The correlation coefficient values are greater in the models that assume the double-log and Box-Cox functional forms.

Third, the coefficients on the housing and demographic variables in the rent and wage equations vary in all models. This observation likely corresponds to the presence of unobservable variables (at the individual level) that impact one's residential and occupational choice yet are excluded from the model. By allowing the disturbances of the regression equations to be correlated, the parameter efficiency improves, especially for the parameters of the variables that vary by individual.

Of the models that include the interaction variables, it appears that any improvement in the precision of the parameter estimates that is added from estimating the equations as a system of SURE is practically lost when one adds variables that are already highly correlated with each other. This is evident especially from the results of models that include the temperature and rainfall interaction variables. The magnitudes of the parameter estimates are substantially large and many are statistically insignificant in both the rent and wage equations. This corroborates a general finding from the SURE model with balanced data, which is that the gains in efficiency in estimating this type of model are greater the less correlation between the explanatory variables in the equations (Greene, 1997).

7.3 Marginal Values of Climate Amenities

In this section, I impute the marginal values of climate amenities (2.24) from the parameters of the models estimated in the previous section. Marginal values are only computed with parameters that are significantly different from zero at the 10 percent critical level. I first calculate the marginal values of climate amenities from the models that do not include interaction variables. The expressions used to calculate these marginal values are (7.13), (7.14), and (7.15) for the models that assume the semilog, double-log, and Box-Cox functional forms respectively. To calculate the marginal values, I use the sample mean and median values for the monthly real rental payments P , real wages w , each climate amenity variable Z_k , and the corresponding estimated coefficient in the rent and wage equations, β_{Z_k} and γ_{Z_k} , respectively.⁴ In expression (7.15), λ_P and λ_w denote the Box-Cox transformation parameter of the rent and wage models respectively.

$$12 \times (P \times \beta_{Z_k} - w \times \gamma_{Z_k}), \quad (7.13)$$

$$12 \times \left(\frac{P}{Z_k} \times \beta_{Z_k} - \frac{w}{Z_k} \times \gamma_{Z_k} \right), \quad (7.14)$$

$$12 \times \left[\left(\beta_{Z_k} \times P^{1-\lambda_P} Z_k^{\lambda_P-1} \right) - \left(\gamma_{Z_k} \times w^{1-\lambda_w} Z_k^{\lambda_w-1} \right) \right]. \quad (7.15)$$

The marginal values of the climate amenities from Models 1-6 are reported in Tables 7.2-7.7. The mean and median real annual wages and rents of the sample are also included in the tables.

The values reported for average temperature are substantially different for each model (Tables 7.2 and 7.3). The average temperature parameter is

⁴I do not use the predicted values for monthly rental payments and wages (as done in Chapters 5 and 6) because many of the models have atleast a few statistically insignificant parameters.

significant in the rent equation in all six models, and only significant in the wage equation for two models. Thus, the results are robust for the rent equation but not the wage equation.

I compute the marginal values of average temperature only for Models 5 and 6. The marginal values are positive which is contrary to what one would expect, if average temperature in fact affects utility. For example, a positive marginal values may be observed if increases in cooler temperatures (or decrease in warmer temperatures) adversely affect production and do not affect utility. It should be noted that a small negative marginal value is also found when the median values of housing prices, wages, and average temperature are used to calculate the marginal value of temperature in Model 5. Thus, the marginal values of temperature are not informative.

Though the marginal values of temperature lack robustness, it still remains evident that the SURE model produces different values for the rent and wage differentials than the single-equation models. The differences in the magnitudes of the rent differentials are substantial. Focusing on the mean values for the rent differentials, the rent differentials from the SURE models are between 117 and 299 1995 Reais less than those from the single-equation method. That difference amounts to 1 to 3 percent of individual mean income.

The implications of the empirical results greatly differ by the model applied. For all of the six model specifications, the estimates from the rent equation of the SURE model indicate that a 1° C increase in cooler temperatures would have a positive impact on welfare ranging from 496 to 1425 1995 Reais (5 to 14 percent of mean annual income). If Models 5 and 6 accurately reflect the relationships between rents and climate and wages and climate, then a 1° C increase in

cooler temperatures is actually predicted to have a negative impact on welfare of 687 to 1470 1995 Reais (7 to 14 percent of mean income). These numerical figures are simply extrapolated from the mean marginal values. Drawing on the median marginal values assuming Model 5, however, an increase in cooler temperatures is predicted to also negatively impact welfare, but by a negligible amount, 9 1995 Reais annually. This suggests that in using the available dataset, only the rent differential estimates are stable. To measure the impact of changes in temperature on welfare, one would need to have information regarding how preferences and technologies are structured.

The marginal values reported for June/August rainfall are positive but can only be calculated for three of the six models (see Tables 7.4 and 7.5). These figures imply that a 1-mm decrease in rainfall during the dry months would have a negative impact on welfare. Specifically, the marginal values indicate that a 20 percent (approximately 15mm) decrease in rainfall during the month of August would have a negative impact on welfare of 315 to 435 1995 mean Reais (approximately 3 to 4 percent of mean annual income). If drier weather during the dry season (winter) complements the consumption of leisure activities, however, then we would expect individuals to prefer drier weather, and thus observe a negative marginal value. The positive marginal value of August rainfall could be the result of biased rainfall parameters. Recall, rainfall is likely to be highly correlated with amenities valued by consumers, like forested areas and national parks. The positive marginal value here may be picking up the aesthetic value of trees in the winter months.

Comparing the marginal values of rainfall during the dry months from the single-equation and SURE methods, the differences are slight. Of the models

that allow one to calculate the marginal values, the largest difference is 8.85 1995 Reais annually.

Hulme and Sheard (1999) predict that rainfall will greatly change during the wet season in result of the level of greenhouse gas emissions. Using the parameter estimates from Models 1-6, the marginal values for rainfall during the wet season are calculated. These values are not particularly robust, as they depend on the model specification and whether mean or median variables are used.

Even if the focus is restricted to the mean marginal values of Models 2-6 (which are similar in sign and magnitude), see Table 7.6, the figures suggest that an increase in rainfall during the wet season hardly affects welfare. Based on the signs of the wage and rent differentials, one could extrapolate from the Roback model that a decrease in rainfall during the wet season may not affect welfare at all but may reduce production costs. This result is particularly intuitive especially for industries like construction, where productivity is limited in the presence of rainfall. What remains unclear is why this result may be of importance only in the summer.

Next, I compute the marginal values of average temperature, June/August rainfall, and February/March rainfall using the parameter estimates from Models 7-18. The expressions used to compute the marginal values of temperature and rainfall will depend on the functional form assumed. I use expressions (7.16) and (7.17) to calculate the marginal values of average temperature and rainfall for the models that assume a semilog functional form. The expressions have the generic term *Rain* to represent the rainfall variable used in the interaction variable, which differs in each model, i.e., Febrain, Marrain, Junerain, Augrain.

Table 7.2: Mean Annual Marginal Values of Average Temperature in 1995 Reais

Model	Single-Equation Models			SURE Model		
	Rent differential	Wage differential	Marginal value	Rent differential	Wage differential	Marginal value
1	-619.46	162.84†		-496.37	168.10†	
2	-1618.41	828.26†		-1319.26	784.68†	
3	-1477.51	1203.06†		-1180.52	1077.27†	
4	-1148.75	-490.64†		-1018.27	-520.05†	
5	-1551.67	-2107.55	555.87	-1425.50	-2112.86	687.36
6	-1257.98	-2607.76	1349.78	-1140.99	-2610.73	1469.74
Wage/Rent	3077.28	10506.12		3077.28	10506.12	

† The parameter used to compute the differential is not significantly different from zero at the 10 percent critical level.

Table 7.3: Median Annual Marginal Values of Average Temperature in 1995

Reais

Model	Single-Equation Models			SURE Model		
	Rent differential	Wage differential	Marginal value	Rent differential	Wage differential	Marginal value
1	-474.52	83.48†		-380.23	86.18†	
2	-1216.23	416.55†		-991.42	394.64†	
3	-1152.56	572.68†		-920.89	512.80†	
4	-879.97	-251.52†		-780.02	-266.61†	
5	-1166.08	-1059.94	-106.14	-1071.26	-1062.61	-8.65
6	-980.16	-1241.52	261.36	-889.00	-1242.93	353.93
Wage/Rent	2357.28	5385.96		2357.28	5385.96	

† The parameter used to compute the differential is not significantly different from zero at the 10 percent critical level.

Table 7.4: Mean Annual Marginal Values of June/August Rainfall in 1995 Reais

Model	Single-Equation Models			SURE Model		
	Rent differential	Wage differential	Marginal value	Rent differential	Wage differential	Marginal value
1	-13.85	-31.52	17.67	-13.85	-31.52	17.67
2	-14.11	2.89†		-12.23	2.89†	
3	-17.20	6.52†		-14.70	5.01†	
4	-6.46†	-29.42		-6.46†	-28.37	
5	-20.04	-40.62	20.58	-19.31	-40.48	21.17
6	-16.67	-45.46	28.79	-16.07	-45.14	29.07
Wage/Rent	3077.28	10506.12		3077.28	10506.12	

† The parameter used to compute the differential is not significantly different from zero at the 10 percent critical level.

Table 7.5: Median Annual Marginal Values of June/August Rainfall in 1995

Reais

Model	Single-Equation Models			SURE Model		
	Rent differential	Wage differential	Marginal value	Rent differential	Wage differential	Marginal value
1	-10.61	-16.16	5.55	-10.61	-16.16	5.55
2	-14.04	1.92†		-12.17	1.92†	
3	-17.13	4.20†		-14.64	3.23†	
4	-4.95†	-15.08		-4.95†	-14.54	
5	-15.50	-21.03	5.53	-14.94	-20.96	6.02
6	-13.33	-22.34	9.01	-12.84	-22.18	9.34
Wage/Rent	2357.28	5385.96		2357.28	5385.96	

† The parameter used to compute the differential is not significantly different from zero at the 10 percent critical level.

Table 7.6: Mean Annual Marginal Values of February/March Rainfall in 1995

Reais						
Model	Single-Equation Models			SURE Model		
	Rent differential	Wage differential	Marginal value	Rent differential	Wage differential	Marginal value
1	-3.39	-7.35	3.97	-3.39	-7.35	3.97
2	14.02	14.21	-0.19	13.22	14.90	-1.68
3	13.52	12.51	1.01	12.61	13.78	-1.17
4	6.15	13.66	-7.50	6.15	14.71	-8.55
5	8.69	22.72	-14.03	8.88	22.95	-14.07
6	7.58	25.04	-17.46	7.74	25.28	-17.54
Wage/Rent	3077.28	10506.12		3077.28	10506.12	

† The parameter used to compute the differential is not significantly different from zero at the 10 percent critical level.

Table 7.7: Median Annual Marginal Values of February/March Rainfall in 1995

Reais						
Model	Single-Equation Models			SURE Model		
	Rent differential	Wage differential	Marginal value	Rent differential	Wage differential	Marginal value
1	-2.59	-3.77	1.18	-2.59	-3.77	1.18
2	11.30	7.66	3.64	10.66	8.04	2.62
3	11.20	6.42	4.78	10.45	7.07	3.38
4	4.71	7.00	-2.29	4.71	7.54	-2.83
5	8.01	14.02	-6.01	8.19	14.16	-5.97
6	7.06	14.87	-7.81	7.21	15.01	-7.80
Wage/Rent	2357.28	5385.96		2357.28	5385.96	

† The parameter used to compute the differential is not significantly different from zero at the 10 percent critical level.

Expressions (7.18)-(7.21) are used to calculate the marginal values of average temperature and rainfall for the models that assume double-log and Box-Cox functional forms respectively.

$$12 \times \left\{ \begin{array}{l} [P \times (\beta_{Avetemp} + \beta_{Avetemp \times Rain} \times Rain)] - \\ [w \times (\gamma_{Avetemp} + \gamma_{Avetemp \times Rain} \times Rain)] \end{array} \right\} \quad (7.16)$$

$$12 \times \left\{ \begin{array}{l} [P \times (\beta_{Rain} + \beta_{Avetemp \times Rain} \times Avetemp)] - \\ [w \times (\gamma_{Rain} + \gamma_{Avetemp \times Rain} \times Avetemp)] \end{array} \right\} \quad (7.17)$$

$$12 \times \left\{ \begin{array}{l} \left[\frac{P}{Avetemp} \times (\beta_{Ln(Avetemp)} + \beta_{Ln(Avetemp) \times Ln(Rain)} \times Ln(Rain)) \right] - \\ \left[\frac{w}{Avetemp} \times (\gamma_{Ln(Avetemp)} + \gamma_{Ln(Avetemp) \times Ln(Rain)} \times Ln(Rain)) \right] \end{array} \right\} \quad (7.18)$$

$$12 \times \left\{ \begin{array}{l} \left[\frac{P}{Rain} \times (\beta_{Ln(Rain)} + \beta_{Ln(Avetemp) \times Ln(Rain)} \times Ln(Avetemp)) \right] - \\ \left[\frac{w}{Rain} \times (\gamma_{Ln(Rain)} + \gamma_{Ln(Avetemp) \times Ln(Rain)} \times Ln(Avetemp)) \right] \end{array} \right\} \quad (7.19)$$

$$12 \times \left\{ \begin{array}{l} P^{1-\lambda_P} \times \left(\begin{array}{l} \beta_{Avetemp} \times Avetemp^{\lambda_P-1} + \\ \beta_{Avetemp \times Rain} \times (Avetemp \times Rain)^{\lambda_P-1} \times Rain \end{array} \right) - \\ w^{1-\lambda_w} \times \left(\begin{array}{l} \gamma_{Avetemp} \times Avetemp^{\lambda_w-1} + \\ \gamma_{Avetemp \times Rain} \times (Avetemp \times Rain)^{\lambda_w-1} \times Rain \end{array} \right) \end{array} \right\} \quad (7.20)$$

$$12 \times \left\{ \begin{array}{l} P^{1-\lambda_P} \times \left(\begin{array}{l} \beta_{Rain} \times Rain^{\lambda_P-1} + \\ \beta_{Avetemp \times Rain} \times (Avetemp \times Rain)^{\lambda_P-1} \times Avetemp \end{array} \right) - \\ w^{1-\lambda_w} \times \left(\begin{array}{l} \gamma_{Rain} \times Rain^{\lambda_w-1} + \\ \gamma_{Avetemp \times Rain} \times (Avetemp \times Rain)^{\lambda_w-1} \times Avetemp \end{array} \right) \end{array} \right\} \quad (7.21)$$

I compute the mean and median marginal values of average temperature, June/August rainfall, and February/March rainfall using the parameters from Models 7-18. They are included in Tables 7.8-7.13. Since the SURE version of

Models 11, 12, 17, and 18 did not converge, I do not compute the marginal values for the climate variables.

Adding the temperature and rainfall interaction variables to the models takes away precision in the parameter estimates in the single-equation and SURE models. Thus, I do not have much confidence in the computed wage and rent differentials, and marginal values from these models. Most of the parameter estimates used to compute the rent and wage differentials are insignificant at the 10 percent critical level. Additionally, the magnitudes of the rent and wage differentials are high, especially for the models that include the August and March rainfall variables (Models 13-18). Recall, the March rainfall and average temperature variables are extremely correlated. Adding variables that interact the temperature and rainfall variables may have exacerbated the impact of the multicollinearity between these variables on the parameter estimates from both single-equation and SURE models.

I make the last set of marginal value calculations using the parameters from the models that include variables that interact the temperature and altitude variables, and the temperature and the south dummy variables. For the models that assume semilog functional forms, expressions (7.22) and (7.23) are used to calculate the marginal value of average temperature from the model that includes the temperature and altitude interaction variable, and the model that includes the temperature and south interaction variable respectively. For the models that assume double-log functional forms, expressions (7.24) and (7.25) are used to calculate the marginal value of average temperature from the model that includes the temperature and altitude interaction variable, and the model that includes the temperature and south interaction variable respectively. For the models that

Table 7.8: Mean Annual Marginal Values of Average Temperature in 1995 Reais

Model	Single-Equation Models			SURE Model		
	Rent differential	Wage differential	Marginal value	Rent differential	Wage differential	Marginal value
7	-662.64†	401.31†		-545.70†	361.39†	
8	-1302.02	1221.70†		-998.16	1188.58†	
9	-1357.73†	558.58		-1057.64	516.76	-1574.40
10	-439.97†	1477.95		-335.27†	1430.67	
13	-815.86†	200.40†		-656.61†	203.56†	
14	-2696.97	-2934.28†		-2520.67	-3013.51†	
15	-2364.55	-1250.28†		-2206.81	-1278.27†	
16	-862.77†	-312.85†		-778.83†	-344.37†	
Wage/Rent	3077.28	10506.12		3077.28	10506.12	

† The parameters used to compute the differential were not significantly different from zero at the 10 percent critical level.

Table 7.9: Median Annual Marginal Values of Average Temperature in 1995

Reais

Model	Single-Equation Models			SURE Model		
	Rent differential	Wage differential	Marginal value	Rent differential	Wage differential	Marginal value
7	-521.43†	253.14†		-431.85†	232.67†	
8	-1002.77	586.25†		-775.59	568.86†	
9	-1077.32†	284.98		-977.58	262.85	-1240.44
10	-334.73†	773.42		-252.23†	749.19	
13	-622.32†	107.18†		-499.98†	108.80†	
14	-2028.99	-1476.72†		-1896.40	-1516.65†	
15	-1845.01	-662.68†		-1722.00	-677.54†	
16	-707.89†	-178.28†		-635.76†	-194.43†	
Wage/Rent	3077.28	10506.12		3077.28	10506.12	

† The parameters used to compute the differential were not significantly different from zero at the 10 percent critical level.

Table 7.10: Mean Annual Marginal Values of June/August Rainfall in 1995

Reais						
Model	Single-Equation Models			SURE Model		
	Rent differential	Wage differential	Marginal value	Rent differential	Wage differential	Marginal value
7	-16.15†	-16.05†		-16.77†	-23.41†	
8	-6.36	12.94	-19.30	-4.33	12.44	-16.78
9	-12.36†	5.79		-9.37	5.28	-14.64
13	7.57	14.33	-6.76	8.64	20.63	-11.99
14	-32.27	-51.24†		-31.13	-52.03†	
15	-31.23	-57.98†		-30.18	-58.79†	
Wage/Rent	3077.28	10506.12		3077.28	10506.12	

† The parameters used to compute the differential were not significantly different from zero at the 10 percent critical level.

Table 7.11: Median Annual Marginal Values of June/August Rainfall in 1995

Reais						
Model	Single-Equation Models			SURE Model		
	Rent differential	Wage differential	Marginal value	Rent differential	Wage differential	Marginal value
7	-12.16†	-8.94†		-12.64†	-12.71†	
8	-5.91	9.11	-15.02	-3.87	8.79	-12.66
9	-12.00†	4.35		-8.95	3.98	-12.93
13	4.24	4.74	-0.50	4.86	7.97	-3.12
14	-23.64	-25.94†		-22.83	-26.30†	
15	-23.42	-27.83†		-22.64	-28.19†	
Wage/Rent	3077.28	10506.12		3077.28	10506.12	

† The parameters used to compute the differential were not significantly different from zero at the 10 percent critical level.

Table 7.12: Mean Annual Marginal Values of February/March Rainfall in 1995

Reais						
Model	Single-Equation Models			SURE Model		
	Rent differential	Wage differential	Marginal value	Rent differential	Wage differential	Marginal value
10	6.54†	15.47		-1.70†	13.36	
16	-81.41†	-26.01†		-66.10†	-27.06†	
Wage/Rent	3077.28	10506.12		3077.28	10506.12	

† The parameters used to compute the differential were not significantly different from zero at the 10 percent critical level.

Table 7.13: Median Annual Marginal Values of February/March Rainfall in

1995 Reais						
Model	Single-Equation Models			SURE Model		
	Rent differential	Wage differential	Marginal value	Rent differential	Wage differential	Marginal value
10	4.90†	7.22		-1.51†	6.14	
16	-62.99†	-13.57†		-51.15†	-14.11†	
Wage/Rent	3077.28	10506.12		3077.28	10506.12	

† The parameters used to compute the differential were not significantly different from zero at the 10 percent critical level.

assume linear Box-Cox functional forms, I use expression (7.26) to calculate the marginal value of average temperature from the models that include the temperature and altitude interaction variable. The wage differentials, rent differentials, and marginal values of temperature are displayed in Table 7.14.

The results show that these models suffer from the same multicollinearity issues as the previous group of models. Many of the parameter estimates used to calculate the wage and rent differentials are insignificant at the 10 percent critical level. The magnitudes of the differentials also seem to be remarkably large. Perhaps, these estimates could be improved by adding counties to the dataset.

$$12 \times \left\{ \begin{array}{l} [P \times (\beta_{Avetemp} + \beta_{Avetemp \times Altitude} \times Altitude)] - \\ [w \times (\gamma_{Avetemp} + \gamma_{Avetemp \times Altitude} \times Altitude)] \end{array} \right\} \quad (7.22)$$

$$12 \times \left\{ \begin{array}{l} [P \times (\beta_{Avetemp} + \beta_{Avetemp \times S} \times S)] - \\ [w \times (\gamma_{Avetemp} + \gamma_{Avetemp \times S} \times S)] \end{array} \right\} \quad (7.23)$$

$$12 \times \left\{ \begin{array}{l} \left[\frac{P}{Avetemp} \times (\beta_{Ln(Avetemp)} + \beta_{Ln(Avetemp) \times Altitude} \times Altitude) \right] - \\ \left[\frac{w}{Avetemp} \times (\gamma_{Ln(Avetemp)} + \gamma_{Ln(Avetemp) \times Altitude} \times Altitude) \right] \end{array} \right\} \quad (7.24)$$

$$12 \times \left\{ \begin{array}{l} \left[\frac{P}{Avetemp} \times (\beta_{Ln(Avetemp)} + \beta_{Ln(Avetemp) \times S} \times S) \right] - \\ \left[\frac{w}{Avetemp} \times (\gamma_{Ln(Avetemp)} + \gamma_{Ln(Avetemp) \times S} \times S) \right] \end{array} \right\} \quad (7.25)$$

$$12 \times \left\{ \begin{array}{l} P^{1-\lambda_P} \times \left(\begin{array}{l} \beta_{Avetemp} \times Avetemp^{\lambda_P-1} + \\ \beta_{Avetemp \times Altitude} \times (Avetemp \times Altitude)^{\lambda_P-1} \\ \times Altitude \end{array} \right) - \\ w^{1-\lambda_w} \times \left(\begin{array}{l} \gamma_{Avetemp} \times Avetemp^{\lambda_w-1} + \\ \gamma_{Avetemp \times Altitude} \times (Avetemp \times Altitude)^{\lambda_w-1} \\ \times Altitude \end{array} \right) \end{array} \right\} \quad (7.26)$$

7.4 Summary of Findings

In this section, I briefly discuss the implications of the empirical estimates on weighing the benefits and costs of policies aimed at reducing greenhouse gas (GHG) emissions. As an illustration, I estimate the impact of GHG emission-induced climate change in Brazil, using the minimum and maximum values for the mean housing price differentials of temperature and the marginal values of March rainfall from Models 2-6.⁵ Table 7.15 presents the range of values measuring the impact of climate change. In calculating the impact, I assume that the marginal effects are the same for each household. Given the disparities in household incomes, housing prices, and differences in geographical locations, the effect of climate change will likely vary by household.

The values are also based on climate predictions made in Hulme and Sheard (1999). In their analysis, they measure the impact of four GHG emission

⁵To calculate these figures I use the number of households present in the 15 municipios in 1995, 7,795,390, the 1995 U.S. exchange rate for the 1995 Real, and the conversion factor for 1995 to 2004 US dollars, 0.807.

Table 7.14: Mean Annual Marginal Values of Average Temperature in 1995

Reais						
Model	Single-Equation Models			SURE Model		
	Rent differential	Wage differential	Marginal value	Rent differential	Wage differential	Marginal value
19	-360.12†	1206.04†		-155.84†	1216.55†	
20	-478.48†	1775.56		-281.11†	1737.49	
21	-1445.13	-1261.93†		-1230.25	-1346.84†	
22	-1131.42†	-604.88		-1013.25	-642.70	-370.552
23	-1027.71	-1725.08†		-923.30	-1702.83†	
24	-1809.06†	-3184.24		-1664.41†	-3258.94	
25	-522.40†	365.30†		-375.41†	387.36†	
26	-553.42†	1986.87		-309.38†	1955.0876	
27	-917.58	-224.78†		-789.88	-247.94†	
28	-1217.70	-1791.44	573.74	-1099.69	-1778.30	678.61
Wage/Rent	3077.28	10506.12		3077.28	10506.12	

† The parameters used to compute the differential were not significantly different from zero at the 10 percent critical level.

scenarios on temperature and precipitation changes throughout Brazil by 2050. I calculate the economic impact of GHG emissions for the extreme cases presented in the Hulme and Sheard analysis. One case assumes that the level of emissions is relatively low, 479 parts per million by volume (ppmv) of CO₂ emissions, and the Earth's sensitivity to climate is low. The other case assumes that the level of emissions is high, 579 ppmv of CO₂ emissions, and the Earth is particularly vulnerable to the change in climate. Both cases assume that there is no implementation of GHG emission reduction policies over time. For simplicity, I calculate the impact of these two climate change scenarios using the projected aggregate changes in temperature, 0.9° C (low) and 2.6° C (high), and rainfall during the wet season (March-May), 0.08 percent- increase (low) and 3.04 percent-decrease (high), in Brazil. In reality, the changes in climate will vary by location.

The estimated impact of changes in temperature caused by GHG emissions ranges between 8.45 and 38.78 billion USD. These estimates are based on the number of households in 15 counties of Brazil, which represents only 21 percent of the Brazilian population. These calculations indicate that the effect of climate change on 21 percent of the Brazilian population is equivalent to 0.6 and 2.6 percent of Brazil's GDP.⁶ Although the hedonic estimates serve as upper bounds for the impact on welfare, these figures still appear unreasonably large. Since only the housing price differentials are used to calculate the impact of temperature changes, the effect of climate change on wages could potentially increase or decrease these estimates a great deal. From this model, the effect of a change in temperature on wages, however, was indeterminate.

The estimated aggregate impacts of changes in rainfall during the wet season are relatively low in comparison. Since many areas of Brazil are plagued by floods and droughts annually, perhaps more insight could be gained from integrating these factors into a hedonic framework. Rainfall will affect the propensity for an area to have a flood or drought. Including a rainfall variable in the model, however, will not capture these effects which perhaps are more deleterious and irreparable, since they depend on other factors like terrain and slope.

Lastly, the calculations also show the large difference in impact estimates obtained from the single-equation and SURE Models. The differences in the calculations for the impact of temperature changes reflect that neglecting the correlation between the disturbances could lead to recommendations based on figures that overestimate the impact by 1 to 5 billion USD. These differences in

⁶According to the CIA World Factbook, available at www.cia.gov, Brazil's estimated GDP for 2004 is 1.492 trillion USD.

estimates could lead to completely different policy recommendations.

In the next chapter, I summarize the overall findings of the empirical chapters. Using the Roback framework, I also carefully infer the meaning of the empirical results. The discussion concludes with suggestions for future work in this area.

Table 7.15: Impact of Climate Change in Brazil (Millions of USD)

Scenario	Low Emissions and Sensitivity		High Emissions and Sensitivity	
	Temperature	March Rainfall	Temperature	March Rainfall
Minimum Values				
Single-Equation	-9,530	0	-27,520	-54
SURE	-8,450	-12	-24,400	464
Difference	1,080	12	3,120	410
Maximum Values				
Single-Equation	-13,420	-25	-38,780	922
SURE	-11,820	-25	-34,150	951
Difference	1,600	0	4,630	29

Chapter 8

Discussion

In the dissertation, I apply the location equilibrium model to measure the marginal values of climate amenities in Brazil. I estimate several empirical rent and wage models. Each model has a different specification for the functional form of the rent and wage equations, includes different sets of climate variables, and assumes different structures on the disturbances in the equations. Particularly, I explore how assuming semilog, double-log, and linear Box-Cox functional specifications on the rent and wage equations affect climate parameter estimates. I also compare the parameter estimates of rent and wage models that include average temperature, June rainfall, and February rainfall instead of average temperature, August rainfall, and March rainfall. Finally, I compare the parameter estimates of models that do and do not assume the disturbances in the rent and wage equations are correlated. From these models, a few results are robust across model specifications.

For example, climate amenities are significant only in the rent equation. There are three possible explanations. First, wages may only vary slightly across climates. Unobservable factors may be more influential in wage variation. An individual's characteristics and domestic situation, for instance, may play a sig-

nificant role in her decision to accept a given level of wages given her skills and experience. These factors could possibly carry more weight in deciding where to work than climate conditions. Another example is that institutions and policies such as unions and labor laws may play a more significant role on wage variation than climate. In essence, there are several factors that influence wages that are likely omitted from the model but are more important (in terms of explaining wage variation) than climate.

Second, even if climate does influence wage variation, detecting the association between climate and wages may be difficult. Error in the model arises from misspecifying the relationship between wages and climate. If the semilog functional, double-log, and linear Box-Cox specifications of the wage model (assumed in this dissertation) deviate from the true functional relationship between wages and climate then error is introduced in the model. Thus, inferences based on standard t statistics may indicate that climate is statistically insignificant in the wage regression because the functional relationship between wages and climate is misspecified.

The third explanation is consistent with the predictions from the Roback theoretical model. Figure 8.1 illustrates the effect of an increase in warmer temperatures on Brazilian real estate values and wages. Consider two geographical areas. One area has cooler temperatures z_i^0 , and the other area has warmer temperatures $z_i^1, z_i^0 < z_i^1$. According to the Roback model, individuals attain the same level of utility across locations at equilibrium since migration is costless, $V(w^0, p^0, z_i^0) = V(w^1, p^1, z_i^1)$. If warmer temperatures are a disamenity in a tropical country like Brazil, it must be true that (all else equal) consumers in the area with warmer temperatures pay lower real estate prices and/or earn higher wages

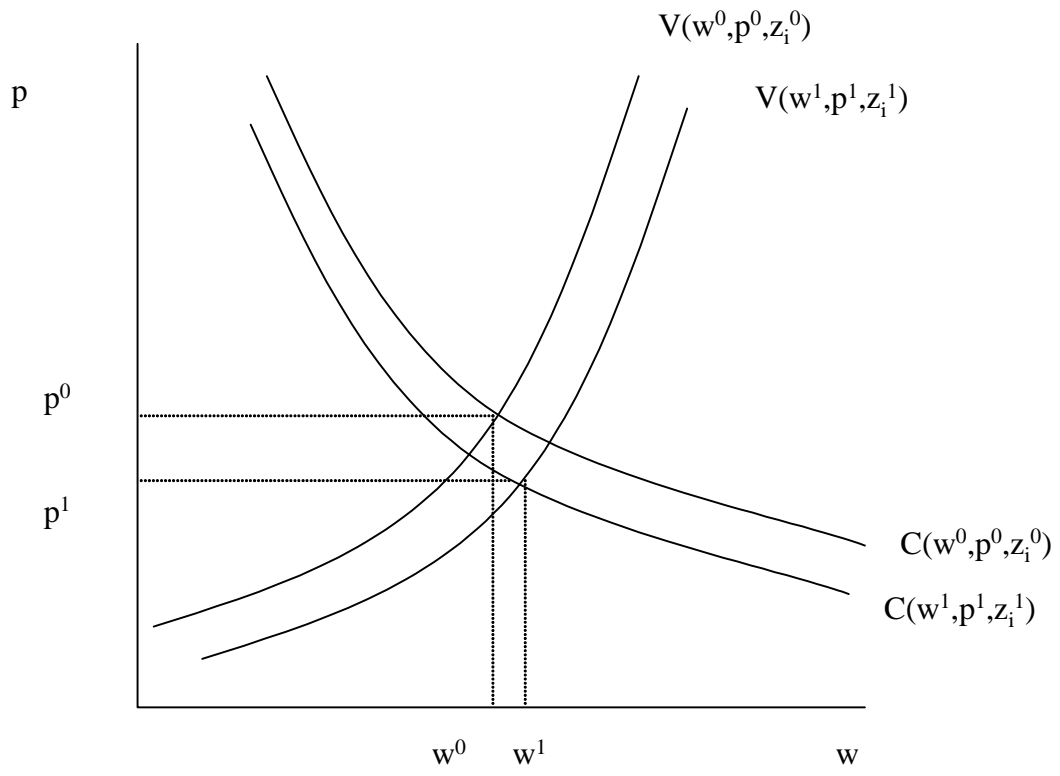


Figure 8.1: The Effect of an Increase in Warmer Temperatures on Brazilian Real Estate Prices and Wages

than consumers in the area with cooler temperatures. This is why $V(w^0, p^0, z_i^0)$ lies above $V(w^1, p^1, z_i^1)$ in Figure 8.1.

The empirical results indicate that an increase in temperatures is associated with a decrease in housing prices and an indeterminate effect on wages. This is consistent with an increase in warmer temperatures adversely affecting production ($C_{Z_i} > 0$) as shown in Figure 8.1. The effect on wages depends on its combined effect on production and utility. Some researchers have examined the effect of climate on agricultural costs. Studies that focus on the effect of climate change in urban areas, however, typically assume that production costs are unaffected by climate. Instead, they focus on either its effect on housing prices or wages alone (as discussed in Chapter 3).

For the Brazilian case, an increase in warmer temperatures could adversely affect production in urban areas for a few reasons. As a developing country, firms tend to have less resources to mitigate the effect of heat on production. Some firms may not invest in air conditioners, allowing the heat to affect the productivity of labor and capital. Others face increases in energy bills. There are also firms that work outdoors, such as construction firms and street vendors. Increases in warmer temperatures, for example, could greatly limit a construction worker's capacity to build, making it costlier for the contractor as it takes more time and money to complete a project.

Using the results from the SURE model, the results from the rent equation show that a 1° C increase in annual average temperature would cause a decline in annual rental payments ranging from 380 (16 percent of median annual rents) to 1,426 (60 percent of median annual rents) 1995 Reais. The wide range in these magnitudes can be attributed to the functional form assumed and the

inherent correlation between explanatory variables in the models. A consequence of multicollinearity between variables is that the standard errors of the parameter estimates are large. By increasing the variance of the distributions of parameters, the likelihood of obtaining parameter estimates at the tails is greater. In fact, the empirical models that included climate amenity variables that were highly correlated tended to produce greater magnitudes on the marginal effects of rents. The impact of the multicollinearity between climate amenity variables on the models results was worse when climate interaction variables were included in the models.

In summary, these results provide limited evidence that warmer temperatures adversely affect costs. To measure the welfare impact of a change in average temperature in Brazil, future studies may benefit from gathering structural information on preferences and technologies. This information would allow one to explicitly model individual preferences and firms production costs and compute the change in total welfare caused by an increase in warmer temperature.

The second finding relates to the welfare impact of changes in rainfall. Climatologists predict significant changes in Brazilian rainfall, particularly in coastal areas. It is therefore imperative to quantify the impact of changes in rainfall, if one wishes to model the effect of climate change in Brazil. As shown in the dissertation, though, the impact of rainfall changes on housing prices and wages is difficult to estimate. Rainfall is often correlated with several amenities and disamenities that are likely omitted from the model. Because the researcher does not have complete information regarding preferences, and production technologies, and data availability is limited, the estimates of the marginal effects of changes in rainfall on rents and wages are likely biased.

I use June and February rainfall and August and March rainfall in separate models to capture the effects of seasonal rainfall on rents and wages. I anticipated that an increase in rainfall would negatively affect welfare but the magnitude of the effect would differ by season. For example, an increase in rainfall could negatively impact welfare because drier weather is complementary input in the consumption of leisure activities, such as hiking, swimming, and sun-bathing. The empirical models, however, provide mixed results and depend on how the model was specified.

From the SURE models in Chapter 7, the marginal values of June/August rainfall can only be computed from three of six models because the variable is not significant in two wage equations and one rent equation. Of the marginal values that are calculated, the values are all positive and large in magnitude. Specifically, the marginal values indicate that a 20 percent (approximately 15mm) decrease in rainfall during the dry season would have a negative impact on welfare of 83 to 140 1995 mean Reais (approximately 1.5 to 2.6 percent of median annual income). Not only do the estimates appear large but the effect is not consistent with drier rainfall being complementary to leisure activities. I attribute the result to omitted variable bias. Recall, rainfall is highly correlated with other amenities valued by consumers, like forested areas and national parks. In Chapter 4, I show that the aridity indexes for the dry months (a proxy for forest and woodland areas) are correlated with rainfall. In the end, I exclude the index from the model as it was determined irrelevant to the wage and rent models. The point is that the positive marginal value of rainfall during the dry season is likely to be picking up other values, such as the aesthetic value of trees in winter months as well as other amenities omitted from the model.

Climatologists predict that changes in rainfall will be greatest during the wet season in Brazil. I include February or March rainfall variables in the models to measure the value of rainfall during the wet season. The mean marginal values were compatible in five of six models. The median marginal values produced mixed results, however: half of the values are positive, and the other half of the values are negative. For the most part, the marginal values are small.

Third, there are apparent differences in the parameter estimates between the single-equation rent and wage models and the system of SURE models. Here, the SURE model consists of equations that have unequal numbers of observations. Thus, the statistical differences between the two models are less established. While the correlation coefficients are relatively low ($\rho < 0.3$), the parameter estimates in the equation with fewer number of observations (the rent equation) are greatly affected. Specifically, the mean rent differentials for average temperature from the SURE models are 117 to 299 1995 Reais less than those from the single-equation model. The median rent differentials for average temperature from the SURE models are 91 to 232 1995 less than those from the single-equation model. The difference in rent differential estimates amounts to 1 to 3 percent of annual mean income and 4 percent of annual median income respectively. The results imply that greater caution should be taken in applying location equilibrium models, particularly when one may suspect that unobservable variables in the rent and wage equations are correlated.

The findings from this dissertation suggest that there is room for improvement in climate economics research. First, the empirical results provide support that climate affects firm costs in urban areas. The results are particularly robust for the impact of changes in average temperatures. Because the

rent effect is negative and the wage effect is indeterminate, the marginal value of average temperature cannot be used as a measure of the impact on individual welfare. Future studies may benefit from developing a structural model for utility and production. Then, from the structural model, observe how sensitive welfare estimates are to the curvatures assumed for the utility and technology functions. Second, the major forecasted changes in Brazilian climate are related to precipitation. In the dissertation, I focus on seasonal rainfall because values of seasonal rainfall are important for measuring one of many impacts of greenhouse gas emissions on welfare. There are other prescient welfare issues in Brazil related to precipitation changes, such as the impact of droughts and floods. For all of these, the value of rainfall (or a diminutive of rainfall) is particularly important in discovering any gains to be made from implementing future climate-related policies—whether related to global warming or flood and drought insurance.

One major limitation was the inability to disentangle effectively the impact of changes in rainfall on housing prices and wages. In applying the hedonic framework, I focused on 15 major counties of Brazil. In these areas, the major differences in precipitation levels were between the northeastern municipios and the rest of the municipios. Perhaps including additional urban areas in the analysis could improve the precision of the parameter estimates on rainfall. However, there is still quite a bit of work to be done on developing a methodology that can isolate the effect of rainfall on rents and wages in this context.

A final recommendation for future work is to develop a better understanding of how behavior and production are influenced by climate. This understanding could help improve the design of policies that are aimed at reducing the vulnerability of individuals to greenhouse gas emissions-induced climate change.

Appendix A

Empirical Results

A.1 Constructing the Cost of Living Index

If the wage and housing payments are nominal in the PNAD survey, then they do not account for interregional differences in standard of living. I would expect there to be considerable variation in living standards across municipios in a large and diverse country like Brazil. By not controlling for cost of living, the estimated coefficients on the location amenities in the housing rent and wage regressions would be biased. Suppose food, transportation, housing, and other goods and services in a municipio are expensive. By using nominal prices as the dependent variable in the model, we would not be able to disentangle whether the coefficients of amenities are positive because all goods in a particular municipio are expensive or if the municipio's attributes are in fact desirable. To avoid this potential bias, I convert the nominal prices into real terms, using a cost of living index.

Azzoni, Carmo, and Menezes (2000) calculate cost of living indexes for 11 metropolitan areas of Brazil based on the multilateral translog version of the Törnqvist-Theil price index proposed in Caves, Christensen, and Diewert (1982).

The formula used to calculate the cost of living index is:

$$\ln \delta_{bl} = \frac{1}{2} \sum_{i=1}^I (R_i^l + R_i^b) \ln \left(\frac{p_i^l}{p_i^b} \right), \quad (\text{A.1})$$

where b represents the base city, here, the geometric mean of all J cities, l refers to the city being compared to the base city, i refers to one of the I category of goods and services included in the index, R_i^j refers to the share of total expenditures on good i in city j , and refers to the price of good i in city j . They construct the cost of living index from a list of prices and weights for goods and services in seven groups: 1) transportation and communication, 2) medical care, 3) residential items, 4) housing, 5) apparel, 6) food and beverages, and 7) other goods and services.¹ The base of the price index consists of the geometric mean of the cost of living for Belém, Fortaleza, Recife, Salvador, Belo Horizonte, Rio de Janeiro, São Paulo, Curitiba, Porto Alegre, Brasilia, and Goiânia.

Two issues arise in using the Azzoni et al. (2000) cost of living index to deflate rental prices and wages. First, since I am interested in measuring real housing payments and wages, I am unable to use the index calculated in Azzoni et

¹The goods and services included in each of the 7 categories are: 1) urban bus, gasoline, alcohol, new automobiles, used automobiles, and telephone; 2) physicians, dentists, and clinical monthly payments; 3) refrigerator and television; 4) rent, water and sewage, powdered soap, bar of soap, and electricity; 5) men's long pant, shirt, skirt, dress, women's pant, blouse, men's shoes, and women's shoes; 6) rice, bean, macaroni, wheat flour, cassava flour, English potatoes, tomatoes, onion, sugar, candy, lettuce, cabbage, parsley and shallot, banana, orange, apple, liver, pork, top quality meat, second grade meat, fish, dried meat, sausage, cod, chicken, egg, milk, cheese, cookies, French bread, soybean oil, vegetable margarine, soft drink, ground coffee, canned sardines, tomato paste, garlic, refined salt, mayonnaise; and 7) clubs, tobacco, and formal courses.

al. if the shares of housing and residential item expenditures are relatively high. While the exact expenditure shares used in the index are not presented in the paper, weights for each of the seven groups of goods and services are available from the Brazilian Institute of Geography and Statistics (IBGE).² In order to observe how much of the index depends on housing and residential item goods and services, I look at the average shares of total expenditure on housing and residential items categories in 1995. The shares of housing and housing item expenditures were 11.17 and 8.11 (the minimum and maximum average values of the shares of total expenditures for housing were 9.22 and 14.85, and 7.01, and 9.64 for residential items). Thus, the sum of the shares of total expenditure for housing and residential items is close to 20 percent, which is considerably high.³

To convert nominal prices into real terms, I recalculate index (A.1) excluding the goods and services in the housing and residential items categories. Since Azzoni et al. include prices of each of the 7 composite goods and services for 11 cities in 1995, I use the price data to compute (A.1). The shares of total expenditure are calculated using the average monthly shares of total expenditures in 1995 for each good.⁴

²The authors include the prices used for each of the seven groups to calculate the cost of living index but not the shares of total expenditure. The shares of total expenditure are calculated from the Pesquisas de Orçamentos Familiares (POF) 1987 and 1996 surveys. In particular, they use the average shares of total expenditures of 1987 and 1996, in computing the cost of living index for 1995. The monthly weights for each composite good are now available, however, on the IBGE website: www.sidra.ibge.gov.br.

³The average shares of total expenditures on food and beverages, housing, residential items, apparel, transportation and communication, medical care, and other goods and services in 1995 were: 29.00, 11.16, 8.11, 11.91, 16.23, 9.17, and 14.42 respectively.

⁴Note the shares of total expenditure taken from the website depend on 7 composite goods.

In Table A.1, I compare the cost of living index I constructed excluding housing and residential item goods and services to the cost of living index formulated in Azzoni et al. (2003). From Table A.1, it is evident that São Paulo and Brasília are still the most expensive places to live. Excluding housing goods and services from the index, however, has considerably affected the indexes for cities in the North and Northeast regions, Rio de Janeiro, and Curitiba. In these cities, the indexes increase when housing goods and services are excluded from the index, implying that housing is relatively cheaper. Alternatively, the index for Rio de Janeiro decreases substantially upon excluding housing prices, which indicates that housing in Rio de Janeiro is rather expensive.

The second complication comes from the fact that cost of living indexes were not available for all of the cities in my dataset. With the information available, I can only calculate cost of living indexes for 11 municípios (as shown in Table A.1). For the remaining 4 municípios,⁵ I resort to a technique performed in Smith (1983). Since regional cost of living indexes were not available for each city in his dataset, Smith regressed cost of living indexes on factors believed to influence cost of living.⁶ He then used the parameter estimates from this cost of

Upon excluding two of the composite goods, I adjust the weights in the index so the sum of the weights is equal to one.

⁵The remaining 4 cities are: Manaus, Sao Luis, Campinas, and Santos.

⁶Cebula (1980) investigated the determinants of regional cost of living differentials. He illustrates that population density, total population, per capital income, per capital level of property taxes paid by businesses, and the existence of right-to-work legislation in the state influence cost of living. Smith (1983) expands on the analysis in Cebula to impute cost of living indexes for cities excluded from the Bureau of Labor and Statistics set of indexes. He incorporates population density, total population, and the percentage of population under 125%

Table A.1: Cost of Living Indexes, 1995

Município	Mueller	Azzoni et al.
Belem	0.914	0.958
Fortaleza	0.980	0.933
Recife	1.052	0.958
Salvador	1.019	0.969
Belo Horizonte	0.965	0.916
Rio de Janeiro	1.014	1.085
Sao Paulo	1.114	1.164
Curitiba	1.006	0.972
Porto Alegre	0.954	0.979
Brasilia	1.101	1.123
Goiania	0.950	0.975

living index regression to impute cost of living indexes for cities in his dataset excluded from the set of Bureau of Labor and Statistics (BLS) intermediate-budget living cost indexes.

Before applying the methodology used in Smith, I considered several variables to explain the variation in cost of living. Having excluded prices of composite housing goods from the index, the cost of living index here depends substantially on interregional variation in food and transportation prices. I test alternative specifications for the cost of living index regression, using the following explanatory variables: population (pop), distance from Sao Paulo (dsp), distance from Brasilia (dbras), percent poor (pctpoor), vehicles per capita (vehiclepc), and distance to the nearest principal port (nearport). Percent poor was defined as the percent of households in each municipio that live in inadequate surroundings. Inadequate is defined as homes with the following characteristics: without or little water supply originating from a general network or other source, without flush toilet or functional equivalent, without means of trash disposal, and homes that have more than 2 inhabitants in a room in the residence.

Tables A.2 and A.3 include the Pearson correlation coefficients between the potential regressors for the cost of living index regression and the dependent variable, cost of living index. The correlation coefficients indicate that cost of living is highly correlated with population and population density (popdens). Population density is excluded from the regression because it is highly correlated with population.⁷

of the poverty standard in his cost of living index regression.

⁷I regressed the cost of living index on the constant and population density variables, and the population density parameter was determined to be insignificant at the 10 percent critical level. An additional regression was estimated including the population variable leaving the

Table A.2: Pearson Correlation Coefficients of Variables in Cost of Living Index

Regressions				
	COLI	pop	popdens	dsp
COLI	1.00	0.58	0.24	-0.15
pop	0.58	1.00	0.56	-0.01
popdens	0.24	0.56	1.00	-0.23
pctrural	-0.24	0.00	-0.31	-0.38
dsp	-0.15	-0.01	-0.23	1.00
dbras	0.11	0.15	-0.12	0.79
pctpoor	0.03	-0.25	-0.44	-0.06
vehiclepc	0.19	0.13	0.04	-0.01
nearport	0.13	-0.24	-0.47	-0.09

Tables A.4 and A.5 report the results of each cost of living index model estimated. A restricted regression model is estimated where only the constant and population variables are included. Chow statistics are used to test if there is any statistical difference between the restricted and unrestricted models. The Chow statistics indicate that there is no additional gain in explaining cost of living variation across municipios from variables other than those included in the restricted model.⁸

Following the methodology in Smith, I impute cost of living indexes from the estimated model in (A.2):

parameter on the population density variable still insignificant at the 10 percent critical level.

⁸Variables were scaled to reduce the amount variance in the regression. The population data are divided by 100,000. Distance from Sao Paulo and distance from Brasilia are divided by 1,000. The distance to the nearest port is divided by 100.

Table A.3: Pearson Correlation Coefficients of Variables in Cost of Living Index

Regressions				
	dbras	pctpoor	vehiclepc	nearport
COLI	0.11	0.03	0.19	0.13
pop	0.15	-0.36	0.65	0.15
popdens	-0.12	-0.25	0.13	-0.24
lpop	0.13	-0.31	0.01	-0.20
lpopdens	-0.07	-0.53	0.16	-0.54
pctrural	-0.33	0.09	-0.25	-0.03
dsp	0.79	-0.06	-0.01	-0.09
dbras	1.00	-0.40	0.16	-0.22
pctpoor	-0.40	1.00	-0.55	0.37
vehiclepc	0.16	-0.55	1.00	0.18
neaport	-0.09	0.37	0.18	1.00

Table A.4: Results from Cost of Living Index Regressions

Variable	Parameter (t-statistic)	Parameter (t-statistic)	Parameter (t-statistic)
Intercept	0.9703 (41.11)	0.9805 (34.30)	0.9721 (27.04)
Pop	0.0013 (2.12)	0.0014 (2.10)	0.0013 (1.96)
Dsp		-0.0084 (-0.68)	
Dbras			-0.0015 (-0.07)
Adj-R ²	0.26	0.21	0.16
F value	4.48	2.34	2.00
SSE	0.0265	0.0251	0.0265
Chow statistic		0.17	0.00

Table A.5: Results from Cost of Living Index Regressions

Variable	Parameter (t-statistic)	Parameter (t-statistic)	Parameter (t-statistic)
Intercept	0.9527 (29.08)	0.9531 (19.54)	0.9482 (31.15)
Pop	0.0015 (2.22)	0.0013 (1.95)	0.0015 (2.37)
Pctpoor	0.0365 (0.79)		
Vehiclepc		0.0500 (0.41)	
Nearport			0.0074 (1.12)
Adj-R ²	0.23	0.18	0.28
F value	2.46	2.12	2.94
SSE	0.0246	0.0260	0.0229
Chow statistic	0.23	0.06	0.47

$$C_j = 0.9703 + 0.0013Pop_j. \quad (A.2)$$

The variables included in the cost of living index regression are a constant, and the population in municipio j . The predicted cost of living indexes are displayed in Table A.6. The resulting cost of living indexes are used in deflating housing payments and wages.

Table A.6: Cost of Living Indexes, 1995

Município	COLI	Predicted COLI
Manaus	N/A	0.985
Belém	0.914	0.988
Sao Luis	N/A	0.980
Fortaleza	0.980	0.995
Recife	1.052	0.988
Salvador	1.019	1.000
Belo Horizonte	0.965	0.998
Rio de Janeiro	1.014	1.044
Campinas	N/A	0.982
Santos	N/A	0.976
São Paulo	1.114	1.104
Curitiba	1.006	0.988
Porto Alegre	0.954	0.987
Brasília	1.101	0.993
Goiânia	0.950	0.983

A.2 Hedonic Rent Model

Table A.7: Results from Semilog Model Including Temperature and February

Rainfall Interaction Variable			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	5.9954	4.3234	4.1503
Flusht	0.3977***	0.0324	0.0338
Filter	0.1474***	0.0256	0.0264
Br1×A	0.8595***	0.0359	0.0365
Br2×A	1.0164***	0.0363	0.0333
Br3×A	1.2816***	0.0489	0.0487
Brgt3×A	1.3631***	0.1643	0.1511
Br2×H	0.3082***	0.0288	0.0281
Br3×H	0.7024***	0.0459	0.0555
Brgt3×H	1.0819***	0.0960	0.1343
Popdens	-0.0102***	0.0022	0.0019
Banks	0.1229***	0.0330	0.0289
Deaths	0.0015**	0.0008	0.0007
Schools	-0.0054	0.0051	0.0035
Altitude	-0.0014	0.0054	0.0049
N	1.7915***	0.3583	0.3308
NE	2.2600***	0.6763	0.5369
S	-0.9084*	0.6058	0.5566
MW	-0.4412*	0.2619	0.2504
Avetemp	-0.1232	0.1802	0.1718
Junerain	-0.0046***	0.0013	0.0010
Febrain	0.0044	0.0071	0.0074
Avetemp×Febrain	-0.0001	0.0003	0.0003
SSR	1386.02		
Adj. R-sq	0.44		
F[22,3492]	126.49***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.8: Results from Semilog Model Including Temperature and June

Rainfall Interaction Variable			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	8.9086***	2.9280	2.4421
Flusht	0.3978***	0.0324	0.0338
Filter	0.1456***	0.0256	0.0263
Br1×A	0.8588***	0.0360	0.0364
Br2×A	1.0154***	0.0364	0.0333
Br3×A	1.2800***	0.0490	0.0488
Brgt3×A	1.3589***	0.1643	0.1505
Br2×H	0.3087***	0.0288	0.0282
Br3×H	0.70216***	0.0459	0.0555
Brgt3×H	1.0799***	0.0960	0.1337
Popdens	-0.0094***	0.0020	0.0016
Banks	0.1079***	0.0376	0.0311
Deaths	0.0012	0.0009	0.0008
Schools	-0.0037	0.0047	0.0033
Altitude	-0.0052	0.0049	0.0040
N	1.7098***	0.4063	0.3588
NE	2.0779***	0.7383	0.5707
S	-1.1301***	0.2931	0.2585
MW	-0.2826	0.2156	0.1800
Avetemp	-0.2408***	0.1143	0.0943
Junerain	-0.0098	0.0127	0.0118
Febrain	0.0013***	0.0004	0.0004
Avetemp×Junerain	0.0002	0.0005	0.0005
SSR	1386.04		
Adj. R-sq	0.44		
F[22,3492]	126.63***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.9: Results from Semilog Model Including Temperature and March

Rainfall Interaction Variable			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	13.1763***	2.0651	1.9101
Flusht	0.3935***	0.0323	0.0337
Filter	0.1471***	0.0256	0.0264
Br1×A	0.8642***	0.0359	0.0364
Br2×A	1.0188***	0.0363	0.0334
Br3×A	1.2845***	0.0489	0.0487
Brgt3×A	1.3659***	0.1644	0.1512
Br2×H	0.3089***	0.0288	0.0282
Br3×H	0.7036***	0.0459	0.0556
Brgt3×H	1.0825***	0.0960	0.1343
Popdens	-0.0070***	0.0016	0.0013
Banks	0.0654**	0.0330	0.0278
Deaths	-0.0002	0.0013	0.0011
Schools	-0.0002	0.0057	0.0041
Altitude	-0.0096***	0.0049	0.0039
N	1.0042***	0.2636	0.2682
NE	0.6173**	0.3978	0.3113
S	-1.6489***	0.3137	0.2318
MW	0.0726	0.1779	0.1569
Avetemp	-0.3981***	0.0820	0.0729
Augrain	-0.0022	0.0017	0.0015
Marrain	-0.0128	0.0163	0.0151
Avetemp×Marrain	0.0006	0.0006	0.0006
SSR	1387.33		
Adj. R-sq	0.44		
F[22,3492]	126.36***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.10: Results from Semilog Model Including Temperature and August

Rainfall Interaction Variable			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	7.4650**	3.7146	3.4473
Flusht	0.3928***	0.0322	0.0336
Filter	0.1480***	0.0256	0.0264
Br1×A	0.8604***	0.0360	0.0363
Br2×A	1.0157***	0.0364	0.0333
Br3×A	1.2819***	0.0490	0.0488
Brgt3×A	1.3680***	0.1643	0.1507
Br2×H	0.3098***	0.0288	0.0281
Br3×H	0.7045***	0.0459	0.0556
Brgt3×H	1.0850***	0.0960	0.1347
Popdens	-0.0052***	0.0017	0.0014
Banks	0.01356	0.0354	0.0306
Deaths	-0.0001	0.0012	0.0012
Schools	0.0018	0.0042	0.0031
Altitude	-0.0036	0.0067	0.0063
N	0.6345*	0.3795	0.3383
NE	0.0668	0.4118	0.3503
S	-1.5927***	0.3166	0.2362
MW	-0.1311	0.2304	0.2308
Avetemp	-0.1530	0.1589	0.1447
Augrain	0.0366*	0.0245	0.0224
Marrain	0.0018***	0.0004	0.0004
Avetemp×Augrain	-0.0015*	0.0009	0.0009
SSR	1386.65		
Adj. R-sq	0.44		
F[22,3492]	126.50***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.11: Results from Double-log Model Including Temperature and
February Rainfall Interaction Variable

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	-144.5286***	52.7963	51.2551
Flusht	0.3933***	0.0322	0.0336
Filter	0.1446***	0.0256	0.0264
Br1×A	0.8577***	0.0360	0.0364
Br2×A	1.0130***	0.0364	0.0333
Br3×A	1.2780***	0.0490	0.0488
Brgt3×A	1.3596***	0.1644	0.1496
Br2×H	0.3105***	0.0288	0.0281
Br3×H	0.7039***	0.0459	0.0555
Brgt3×H	1.0814***	0.0960	0.1341
Popdens	-0.0231***	0.0044	0.0039
Banks	-0.0331***	0.0266	0.0234
Deaths	0.0071***	0.0021	0.0018
Schools	-0.0118***	0.0047	0.0039
Altitude	-0.0220***	0.0073	0.0072
N	0.9702***	0.3650	0.3578
NE	3.2109***	0.7843	0.7392
S	1.8300***	1.1248	1.0449
MW	-1.8262***	0.4878	0.4488
Ln(Avetemp)	46.2942***	16.6809	16.1887
Ln(Junrain)	-1.3359***	0.3065	0.2794
Ln(Febrain)	33.5642***	9.1869	8.7707
Ln(Avetemp)×Ln(Febrain)	-10.0491***	2.8255	2.7086
SSR	1386.73		
Adj. R-sq	0.44		
F[22,3492]	126.49***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.12: Results from Double-log Model Including Temperature and June

Rainfall Interaction Variable			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	46.3586***	10.4226	9.7576
Flusht	0.3881***	0.0323	0.0336
Filter	0.1416***	0.0256	0.0264
Br1×A	0.8634***	0.0360	0.0363
Br2×A	1.0142***	0.0364	0.0334
Br3×A	1.2789***	0.0490	0.0488
Brgt3×A	1.3571***	0.1646	0.1490
Br2×H	0.3116***	0.0288	0.0282
Br3×H	0.7047***	0.0460	0.0556
Brgt3×H	1.0813***	0.0961	0.1338
Popdens	-0.0068**	0.0036	0.0035
Banks	0.0340**	0.0177	0.0171
Deaths	-0.0007	0.0014	0.0014
Schools	0.0047	0.0041	0.0039
Altitude	-0.0212***	0.0075	0.0076
N	1.0209***	0.3869	0.3851
NE	0.6971	0.9046	0.9266
S	-1.7054***	0.4686	0.4172
MW	0.1633	0.2308	0.2215
Ln(Avetemp)	-14.0561***	3.3039	3.0809
Ln(Junrain)	-3.1170***	1.2401	1.1036
Ln(Febrain)	0.6074**	0.2765	0.2861
Ln(Avetemp)×Ln(Junrain)	0.9132**	0.4398	0.3989
SSR	1390.04		
Adj. R-sq	0.44		
F[22,3492]	125.81***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.13: Results from Double-log Model Including Temperature and March

Rainfall Interaction Variable			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	99.1996*	56.7534	57.6959
Flusht	0.3969***	0.0324	0.0338
Filter	0.1485***	0.0256	0.0264
Br1×A	0.8643***	0.0360	0.0365
Br2×A	1.0191***	0.0364	0.0334
Br3×A	1.2842***	0.0490	0.0488
Brgt3×A	1.3666***	0.1645	0.1520
Br2×H	0.3064***	0.0288	0.0281
Br3×H	0.7017***	0.0460	0.0556
Brgt3×H	1.0855***	0.0961	0.1349
Popdens	-0.0100***	0.0022	0.0021
Banks	0.0633***	0.0191	0.0177
Deaths	0.0004	0.0013	0.0013
Schools	-0.0062**	0.0041	0.0029
Altitude	-0.0178***	0.0068	0.0072
N	1.1210***	0.2961	0.3016
NE	1.0723***	0.2796	0.2455
S	-2.2825***	0.3329	0.2710
MW	0.1800	0.1286	0.1264
Ln(Avetemp)	-29.8811*	17.6317	17.9296
Ln(Augrain)	-0.3601**	0.1789	0.1788
Ln(Marrain)	-12.5870	12.5432	12.9091
Ln(Avetemp)×Ln(Marrain)	4.0472	3.8630	3.9747
SSR	1389.12		
Adj. R-sq	0.44		
F[22,3492]	126.00***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.14: Results from Double-log Model Including Temperature and August

Rainfall Interaction Variable			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	96.3348***	19.6441	18.0638
Flusht	0.3989***	0.0323	0.0338
Filter	0.1459***	0.0256	0.0264
Br1×A	0.8583***	0.0360	0.0364
Br2×A	1.0153***	0.0364	0.0333
Br3×A	1.2798***	0.0490	0.0488
Brgt3×A	1.3589***	0.1643	0.1506
Br2×H	0.3082***	0.0288	0.0281
Br3×H	0.7017***	0.0459	0.0555
Brgt3×H	1.0802***	0.0960	0.1338
Popdens	-0.0130***	0.0021	0.0018
Banks	0.0281*	0.0176	0.0163
Deaths	0.0003	0.0012	0.0011
Schools	-0.0010	0.0043	0.0028
Altitude	-0.0473***	0.0087	0.0081
N	1.6133***	0.2336	0.2222
NE	1.2899***	0.2764	0.2368
S	-3.2219***	0.4744	0.3998
MW	0.7271***	0.2329	0.2239
Ln(Avetemp)	-29.3119***	6.1957	5.6918
Ln(Augrain)	-7.5672***	2.3896	2.2338
Ln(Marrain)	0.8414***	0.1389	0.1304
Ln(Avetemp)×Ln(Augrain)	2.1707***	0.7315	0.6840
SSR	1386.06		
Adj. R-sq	0.44		
F[22,3492]	126.62***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.15: Results from Box-Cox Model Including Temperature and February

Rainfall Interaction Variable (Lambda=0.1276)

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	-124.8613***	0.9861	0.9843
Flusht	0.7244***	0.0004	0.0004
Filter	0.2856***	0.0003	0.0003
Br1×A	1.6799***	0.0006	0.0005
Br2×A	1.9822***	0.0006	0.0005
Br3×A	2.5588***	0.0008	0.0006
Brgt3×A	2.7303***	0.0020	0.0019
Br2×H	0.5880***	0.0004	0.0003
Br3×H	1.3915***	0.0006	0.0005
Brgt3×H	2.1641***	0.0013	0.0012
Popdens	-0.0409***	0.0102	0.0102
Banks	0.0274***	0.0300	0.0298
Deaths	0.0119***	0.0321	0.0319
Schools	-0.0257***	0.0147	0.0139
Altitude	-0.0294***	0.4922	0.4881
N	2.4444***	0.3707	0.3578
NE	6.5868***	0.0093	0.0060
S	2.7652***	0.2426	0.2360
MW	-3.0705***	0.0002	0.0001
BC(Avetemp)	74.1912***	0.0010	0.0005
BC(Junrain)	-1.376***	0.0001	0.0001
BC(Febrain)	63.0001***	0.0002	0.0002
BC(Avetemp×Febrain)	-41.1277***	0.0003	0.0001
Value of LLF	-21648.31		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The Wald statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.16: Results from Box-Cox Model Including Temperature and June

Rainfall Interaction Variable (Lambda=0.1293)

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	69.7341***	2.3175	2.1984
Flusht	0.7196***	0.0056	0.0037
Filter	0.2803***	0.0035	0.0030
Br1×A	1.7070***	0.0126	0.0042
Br2×A	2.0031***	0.0144	0.0041
Br3×A	2.5847***	0.0192	0.0052
Brgt3×A	2.7481***	0.0263	0.0171
Br2×H	0.5960***	0.0049	0.0031
Br3×H	1.4062***	0.0110	0.0050
Brgt3×H	2.1819***	0.0197	0.0112
Popdens	-0.0188***	0.0923	0.0923
Banks	0.0739***	0.1487	0.1483
Deaths	0.0012***	0.1281	0.1195
Schools	0.0015**	0.0482	0.0470
Altitude	-0.0444***	0.8479	0.8465
N	2.4816***	0.0242	0.0196
NE	3.0542*	0.4987	0.4694
S	-3.173***	0.3402	0.3164
MW	-0.1014***	0.0006	0.0005
BC(Avetemp)	-20.9778***	0.0064	0.0055
BC(Junrain)	-6.3569***	0.0003	0.0003
BC(Febrain)	0.7595	0.0010	0.0010
BC(Avetemp×Junrain)	3.8697***	0.0017	0.0014
Value of LLF	-21652.12		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The Wald statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.17: Results from Box-Cox Model Including Temperature and March

Rainfall Interaction Variable (Lambda=0.1272)

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	134.5177***	2.0185	2.0137
Flusht	0.7236***	0.0010	0.0007
Filter	0.2901***	0.0006	0.0006
Br1×A	1.6905***	0.0020	0.0008
Br2×A	1.9889***	0.0022	0.0008
Br3×A	2.5643***	0.0029	0.0010
Brgt3×A	2.7368***	0.0044	0.0032
Br2×H	0.5813***	0.0008	0.0006
Br3×H	1.3863***	0.0017	0.0009
Brgt3×H	2.1668***	0.0030	0.0018
Popdens	-0.0176***	0.0114	0.0114
Banks	0.1346***	0.0136	0.0126
Deaths	0.0001***	0.0357	0.0145
Schools	-0.0122***	0.0116	0.0054
Altitude	-0.0254***	1.0992	1.0972
N	1.9324	0.9088	0.8812
NE	1.9052***	0.0084	0.0032
S	-3.9745***	0.5999	0.5866
MW	0.2755***	0.0001	0.0001
BC(Avetemp)	-58.3716***	0.0028	0.0009
BC(Augrain)	-0.3215***	0.0001	0.0001
BC(Marrain)	-37.9798***	0.0001	0.0001
BC(Avetemp×Marrain)	25.4736***	0.0008	0.0002
Value of LLF	-21652.15		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The Wald statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.18: Results from Box-Cox Model Including Temperature and August

Rainfall Interaction Variable (Lambda=0.1266)

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	140.9707***	1.5828	1.5598
Flusht	0.7259***	0.0017	0.0011
Filter	0.2848***	0.0011	0.0009
Br1×A	1.6747***	0.0038	0.0013
Br2×A	1.9762***	0.0044	0.0013
Br3×A	2.5488***	0.0058	0.0015
Brgt3×A	2.7153***	0.0078	0.0050
Br2×H	0.5828***	0.0015	0.0009
Br3×H	1.3825***	0.0033	0.0014
Brgt3×H	2.1519***	0.0056	0.0028
Popdens	-0.0234***	0.0258	0.0247
Banks	0.0644***	0.0222	0.0203
Deaths	0.0003***	0.0547	0.0383
Schools	-0.0017***	0.0174	0.0164
Altitude	-0.0842***	0.6432	0.6290
N	2.9779***	0.0147	0.0106
NE	2.3725**	0.4477	0.3546
S	-5.4827***	0.3016	0.2297
MW	1.3073***	0.0002	0.0001
BC(Avetemp)	-50.1139***	0.0032	0.0014
BC(Augrain)	-23.5516**	0.0001	0.0001
BC(Marrain)	0.7939***	0.0001	0.0001
BC(Avetemp×Augrain)	15.2567***	0.0012	0.0010
Value of LLF	-21648.50		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The Wald statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.19: Results from Semilog Model Including Temperature and Altitude

Interaction Variable			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	8.3491***	1.5999	1.4191
Flusht	0.3980***	0.0323	0.0338
Filter	0.1463***	0.0255	0.0262
Br1×A	0.8569***	0.0360	0.0364
Br2×A	1.0141***	0.0364	0.0333
Br3×A	1.2790***	0.0489	0.0488
Brgt3×A	1.3602***	0.1642	0.1502
Br2×H	0.3088***	0.0288	0.0281
Br3×H	0.7024***	0.0459	0.0555
Brgt3×H	1.0812***	0.0959	0.1341
Popdens	-0.0071**	0.0031	0.0025
Banks	-0.0270	0.1381	0.1233
Deaths	0.0037	0.0023	0.0021
Schools	-0.0014	0.0053	0.0042
Altitude	-0.0303	0.0253	0.0230
N	0.2736	1.4630	1.3214
NE	0.6479	1.6064	1.4235
S	-0.1753	0.9608	0.8463
MW	-0.5401**	0.2415	0.2227
Avetemp	-0.1680**	0.0711	0.0611
Junerain	-0.0023	0.0024	0.0021
Febrain	0.0023**	0.0011	0.0010
Avetemp×Altitude	0.0013	0.0012	0.0011
SSR	1385.66		
Adj. R-sq	0.44		
F[22,3492]	126.71***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.20: Results from Double-log Model Including Temperature and

Altitude Interaction Variable			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	18.3737*	11.3486	11.0000
Flusht	0.3975***	0.0323	0.0336
Filter	0.1465***	0.0256	0.0264
Br1×A	0.8569***	0.0360	0.0365
Br2×A	1.0140***	0.0364	0.0333
Br3×A	1.2791***	0.0490	0.0488
Brgt3×A	1.3611***	0.1643	0.1505
Br2×H	0.3090***	0.0288	0.0281
Br3×H	0.7027***	0.0459	0.0555
Brgt3×H	1.0816***	0.0960	0.1343
Popdens	-0.0070**	0.0031	0.0030
Banks	-0.1054***	0.0405	0.0358
Deaths	0.0044***	0.0014	0.0013
Schools	-0.0006	0.0034	0.0030
Altitude	-0.1253***	0.0265	0.0247
N	-0.5170	0.5946	0.5712
NE	-0.0803	0.8578	0.9077
S	0.1431	0.6822	0.5921
MW	-0.5728***	0.1866	0.1636
Ln(Avetemp)	-5.0524	3.6046	3.4825
Ln(Junrain)	-0.1486***	0.2481	0.2593
Ln(Febrain)	0.7707***	0.2396	0.2465
Ln(Avetemp)×Altitude	0.0386***	0.0099	0.0094
SSR	1385.67		
Adj. R-sq	0.44		
F[22,3492]	126.71***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.21: Results from Box-Cox Model Including Temperature and Altitude

Interaction Variable (Lambda=0.1285)

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	61.0689***	4.5237	4.3464
Flusht	0.7277***	0.0175	0.0115
Filter	0.2850***	0.0110	0.0092
Br1×A	1.7026***	0.0389	0.0129
Br2×A	2.0005***	0.0444	0.0128
Br3×A	2.5792***	0.0593	0.0159
Brgt3×A	2.7424***	0.0795	0.0507
Br2×H	0.5881***	0.0151	0.0095
Br3×H	1.3962***	0.0337	0.0153
Brgt3×H	2.1747***	0.0607	0.0327
Popdens	-0.0291***	0.3468	0.3449
Banks	-0.0024***	0.4485	0.4327
Deaths	0.0106***	0.4848	0.4828
Schools	-0.0164***	0.1398	0.1363
Altitude	-0.0575***	1.1549	1.1321
N	2.3187***	0.0838	0.0829
NE	5.6627***	0.0830	0.0828
S	-2.0887***	0.0172	0.0172
MW	-1.1731***	0.0016	0.0015
BC(Avetemp)	-14.7374	0.0289	0.0287
BC(Junrain)	-1.0689***	0.0016	0.0016
BC(Febrain)	1.2092***	0.0039	0.0039
BC(Avetemp×Altitude)	0.0917***	0.0039	0.0035
Value of LLF	-21651.69		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The Wald statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.22: Results from Semilog Model Including Temperature and Altitude

Interaction Variable			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	14.3822***	2.1053	1.8857
Flusht	0.3984***	0.0323	0.0337
Filter	0.1465***	0.0256	0.0264
Br1×A	0.8576***	0.0360	0.0365
Br2×A	1.0148***	0.0364	0.0333
Br3×A	1.2797***	0.0490	0.0488
Brgt3×A	1.3605***	0.1643	0.1507
Br2×H	0.3085***	0.0288	0.0281
Br3×H	0.7022***	0.0459	0.0555
Brgt3×H	1.0811***	0.0960	0.1340
Popdens	-0.0065***	0.0015	0.0013
Banks	-0.0384	0.0481	0.0448
Deaths	0.0012	0.0014	0.0012
Schools	0.0017	0.0042	0.0029
Altitude	-0.0362***	0.0109	0.0100
N	0.3644	0.4108	0.3747
NE	0.0417	0.3842	0.3583
S	-1.2396***	0.3696	0.2591
MW	-0.0498	0.1873	0.1671
Avetemp	-0.4108***	0.0791	0.0667
Augrain	-0.0014	0.0017	0.0016
Marrain	0.0029***	0.0005	0.0005
Avetemp×Altitude	0.0011	0.0005	0.0004
SSR	1385.71		
Adj. R-sq	0.44		
F[22,3492]	126.70***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.23: Results from Double-log Model Including Temperature and

Altitude Interaction Variable			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	32.1063***	5.6221	5.4883
Flusht	0.3985***	0.0323	0.0338
Filter	0.1462***	0.0256	0.0263
Br1×A	0.8575***	0.0360	0.0364
Br2×A	1.0147***	0.0364	0.0333
Br3×A	1.2794***	0.0490	0.0489
Brgt3×A	1.3597***	0.1643	0.1505
Br2×H	0.3085***	0.0288	0.0281
Br3×H	0.7021***	0.0459	0.0555
Brgt3×H	1.0807***	0.0959	0.1339
Popdens	-0.0053**	0.0027	0.0024
Banks	-0.1135**	0.0056	0.0508
Deaths	0.0006	0.0012	0.0010
Schools	0.0039	0.0050	0.0035
Altitude	-0.1698***	0.0472	0.0429
N	-0.4979	0.6286	0.5791
NE	-0.7233	0.6595	0.5780
S	-0.9421**	0.4918	0.4555
MW	-0.0848	0.1421	0.1289
Ln(Avetemp)	-9.6243***	1.6189	1.5775
Ln(Augrain)	0.1419	0.2418	0.2136
Ln(Marrain)	0.7486***	0.1176	0.1094
Ln(Avetemp)×Altitude	0.0516***	0.0167	0.0151
SSR	1385.74		
Adj. R-sq	0.44		
F[22,3492]	126.69***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.24: Results from Box-Cox Model Including Temperature and Altitude

Interaction Variable (Lambda=0.1273)

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	76.0661***	4.7811	4.3603
Flusht	0.7278***	0.0324	0.0215
Filter	0.2858***	0.0203	0.0172
Br1×A	1.6795***	0.0695	0.0249
Br2×A	1.9821***	0.0791	0.0252
Br3×A	2.5570***	0.1058	0.0296
Brgt3×A	2.7247***	0.1441	0.0955
Br2×H	0.5849***	0.0277	0.0179
Br3×H	1.3872***	0.0599	0.0273
Brgt3×H	2.1593***	0.1034	0.0508
Popdens	-0.0257***	0.4658	0.4410
Banks	0.2563***	0.4375	0.4203
Deaths	-0.0018***	0.3899	0.3370
Schools	-0.0105***	0.1037	0.1021
Altitude	-0.0392***	1.0942	1.0554
N	4.6204***	0.0409	0.0402
NE	3.9725***	0.0850	0.0844
S	-5.4469***	0.0212	0.0212
MW	0.3537***	0.0020	0.0018
BC(Avetemp)	-17.9547***	0.0317	0.0307
BC(Augrain)	-0.7589*	0.0010	0.0010
BC(Marrain)	0.4248***	0.0023	0.0023
BC(Avetemp×Altitude)	-0.1608***	0.0029	0.0025
Value of LLF	-21648.35		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The Wald statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.25: Results from Semilog Model Including June Rainfall and Northeast

Interaction Variable			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	7.0566***	1.7375	1.4974
Flusht	0.3979***	0.0323	0.0338
Filter	0.1476***	0.0256	0.0263
Br1×A	0.8578***	0.0360	0.0365
Br2×A	1.0151***	0.0363	0.0333
Br3×A	1.2804***	0.0489	0.0488
Brgt3×A	1.3632***	0.1643	0.1508
Br2×H	0.3084***	0.0288	0.0281
Br3×H	0.7025***	0.0459	0.0555
Brgt3×H	1.0825***	0.0959	0.1345
Popdens	-0.0080***	0.0026	0.0022
Banks	0.1112***	0.0311	0.0275
Deaths	0.0010	0.0009	0.0008
Schools	-0.0028	0.0048	0.0039
Altitude	-0.0011	0.0038	0.0033
N	1.6062***	0.4028	0.3825
NE	2.1373***	0.6714	0.5512
S	-1.345***	0.3440	0.3377
MW	-0.2745*	0.1721	0.1496
Avetemp	-0.1706***	0.0709	0.0593
Junerain	-0.0004	0.0042	0.0043
Febrain	0.0001	0.0011	0.0011
Junrain×NE	-0.0038	0.0038	0.0038
SSR	1385.72		
Adj. R-sq	0.44		
F[22,3492]	126.69***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.26: Results from Semilog Model Including August Rainfall and

Northeast Interaction Variable

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	5.2393	4.4994	4.1103
Flusht	0.3938***	0.0322	0.0336
Filter	0.1479***	0.0256	0.0264
Br1×A	0.8593***	0.0360	0.0364
Br2×A	1.0151***	0.0364	0.0333
Br3×A	1.2812***	0.0490	0.0488
Brgt3×A	1.3668***	0.1643	0.1507
Br2×H	0.3097***	0.0288	0.0281
Br3×H	0.7042***	0.0459	0.0556
Brgt3×H	1.0846***	0.0960	0.1346
Popdens	-0.0062***	0.0015	0.0013
Banks	0.1287***	0.0525	0.0517
Deaths	0.0029	0.0023	0.0022
Schools	0.0001	0.0045	0.0034
Altitude	0.0025	0.0092	0.0085
N	1.7679***	0.4472	0.4413
NE	1.6218**	0.7483	0.6974
S	-1.3596***	0.3593	0.2740
MW	-0.4228	0.3451	0.3331
Avetemp	-0.1273	0.1579	0.1409
Augrain	0.0005	0.0022	0.0019
Marrain	-0.0001	0.0012	0.0012
Augrain×NE	-0.0073**	0.0041	0.0037
SSR	1386.39		
Adj. R-sq	0.44		
F[22,3492]	126.56***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.27: Results from Double-log Model Including June Rainfall and

Northeast Interaction Variable

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	19.7471***	11.2309	10.7360
Flusht	0.3993***	0.0323	0.0337
Filter	0.1472***	0.0256	0.0264
Br1×A	0.8581***	0.0360	0.0365
Br2×A	1.0154***	0.0364	0.0333
Br3×A	1.2803***	0.0490	0.0488
Brgt3×A	1.3615***	0.1643	0.1511
Br2×H	0.3080***	0.0288	0.0281
Br3×H	0.7019***	0.0459	0.0555
Brgt3×H	1.0818***	0.0960	0.1343
Popdens	-0.0097***	0.0029	0.0027
Banks	0.1377***	0.0315	0.0318
Deaths	0.0007	0.0012	0.0012
Schools	-0.0050*	0.0036	0.0029
Altitude	-0.0039	0.0091	0.0090
N	1.9640***	0.3789	0.3656
NE	8.0064***	1.7331	1.5269
S	-1.7642***	0.4652	0.3961
MW	-0.2563*	0.1593	0.1481
Ln(Avetemp)	-5.1893	3.6044	3.4315
Ln(Junrain)	-0.1056	0.2544	0.2639
Ln(Febrain)	-0.0111	0.3357	0.3499
Ln(Junrain)×NE	-1.1647***	0.3032	0.2796
SSR	1385.9		
Adj. R-sq	0.44		
F[22,3492]	126.66***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.28: Results from Double-log Model Including August Rainfall and

Northeast Interaction Variable

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	2.3963	13.1105	11.6373
Flusht	0.3974***	0.0323	0.0338
Filter	0.1475***	0.0256	0.0263
Br1×A	0.8570***	0.0360	0.0364
Br2×A	1.0142***	0.0364	0.0333
Br3×A	1.2795***	0.0490	0.0489
Brgt3×A	1.3632***	0.1643	0.1506
Br2×H	0.3088***	0.0288	0.0281
Br3×H	0.7029***	0.0459	0.0555
Brgt3×H	1.0830***	0.0959	0.1343
Popdens	-0.0071***	0.0024	0.0019
Banks	0.1595***	0.0381	0.0335
Deaths	0.0023**	0.0013	0.0011
Schools	-0.0054**	0.0040	0.0027
Altitude	0.0093	0.0113	0.0099
N	1.8918***	0.2792	0.2588
NE	4.5651***	1.1370	1.0170
S	-1.0159**	0.4732	0.4167
MW	-0.5159**	0.2440	0.2179
Ln(Avetemp)	0.2483	4.0678	3.6116
Ln(Augrain)	0.0803	0.2253	0.1878
Ln(Marrain)	-0.2773	0.2857	0.2437
Ln(Augrain)×NE	-0.7591***	0.2447	0.2139
SSR	1385.74		
Adj. R-sq	0.44		
F[22,3492]	126.69***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.29: Results from Semilog Model Including Temperature and South

Interaction Variable			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	7.6427***	1.5552	1.3878
Flusht	0.3980***	0.0323	0.0338
Filter	0.1455***	0.0255	0.0262
Br1×A	0.8573***	0.0360	0.0364
Br2×A	1.0142***	0.0364	0.0333
Br3×A	1.2789***	0.0490	0.0488
Brgt3×A	1.3585***	0.1643	0.1501
Br2×H	0.3089***	0.0288	0.0281
Br3×H	0.7023***	0.0459	0.0555
Brgt3×H	1.0802***	0.0959	0.1337
Popdens	-0.0087***	0.0022	0.0017
Banks	0.0771*	0.0537	0.0439
Deaths	0.0017**	0.0009	0.0008
Schools	-0.0031	0.0047	0.0034
Altitude	-0.0029	0.0030	0.0027
N	1.3178**	0.6342	0.5424
NE	1.6602**	0.9037	0.7193
S	-1.8050***	0.7750	0.6751
MW	-0.3687***	0.1595	0.1386
Avetemp	-0.1772***	0.0692	0.0612
Junerain	-0.0036***	0.0016	0.0013
Febrain	0.0014***	0.0004	0.0004
Avetemp×S	0.0496	0.0550	0.0479
SSR	1385.79		
Adj. R-sq	0.44		
F[22,3492]	126.68***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.30: Results from Semilog Model Including Temperature and South

Interaction Variable			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	11.4776***	1.9798	1.6386
Flusht	0.3976***	0.0323	0.0337
Filter	0.1469***	0.0256	0.0264
Br1×A	0.8570***	0.0360	0.0364
Br2×A	1.0142***	0.0364	0.0333
Br3×A	1.2793***	0.0490	0.0489
Brgt3×A	1.3618***	0.1643	0.1506
Br2×H	0.3089***	0.0288	0.0281
Br3×H	0.7027***	0.0459	0.0555
Brgt3×H	1.0821***	0.0959	0.1342
Popdens	-0.0070***	0.0015	0.0014
Banks	0.01958	0.0305	0.0286
Deaths	0.0011	0.0014	0.0012
Schools	-0.0000	0.0044	0.0030
Altitude	-0.0099***	0.0035	0.0029
N	0.7525***	0.2874	0.2694
NE	0.4057	0.3415	0.3012
S	-2.9058***	0.6304	0.5721
MW	-0.0830	0.1931	0.1766
Avetemp	-0.3118***	0.0819	0.0642
Augrain	-0.0027*	0.0017	0.0015
Marrain	0.0023***	0.0004	0.0004
Avetemp×S	0.0908***	0.0405	0.0358
SSR	1385.66		
Adj. R-sq	0.44		
F[22,3492]	126.71***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.31: Results from Double-log Model Including Temperature and South

Interaction Variable			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	16.7106	11.9027	11.7318
Flusht	0.3932***	0.0322	0.0336
Filter	0.1445***	0.0256	0.0264
Br1×A	0.8578***	0.0360	0.0364
Br2×A	1.0130***	0.0364	0.0333
Br3×A	1.2780***	0.0490	0.0488
Brgt3×A	1.3595***	0.1644	0.1496
Br2×H	0.3106***	0.0288	0.0281
Br3×H	0.7039***	0.0459	0.0555
Brgt3×H	1.0814***	0.0960	0.1341
Popdens	-0.0061*	0.0032	0.0032
Banks	-0.026	0.0252	0.0222
Deaths	0.0015	0.0012	0.0011
Schools	0.0020	0.0034	0.0032
Altitude	-0.0070	0.0089	0.0090
N	0.1121	0.4979	0.4892
NE	0.0317	0.8717	0.9213
S	-8.8570***	2.0457	1.9658
MW	-0.2655*	0.1599	0.1494
Ln(Avetemp)	-4.5199	3.7844	3.7195
Ln(Junrain)	-0.0929	0.2617	0.2745
Ln(Febrain)	0.5231*	0.2603	0.2745
Ln(Avetemp)×S	2.8448***	0.8045	0.7709
SSR	1386.79		
Adj. R-sq	0.44		
F[22,3492]	126.47***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.32: Results from Double-log Model Including Temperature and South

Interaction Variable			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	32.6142***	5.5374	5.3227
Flusht	0.3979***	0.0323	0.0338
Filter	0.1469***	0.0256	0.0263
Br1×A	0.8570***	0.0360	0.0364
Br2×A	1.01426***	0.0364	0.0333
Br3×A	1.2794***	0.0490	0.0489
Brgt3×A	1.3616***	0.1643	0.1505
Br2×H	0.3088***	0.0288	0.0281
Br3×H	0.7026***	0.0459	0.0555
Brgt3×H	1.0819***	0.0959	0.1341
Popdens	-0.0083***	0.0022	0.0018
Banks	-0.0059	0.0242	0.0218
Deaths	0.0004	0.0012	0.0010
Schools	-0.0007	0.0043	0.0028
Altitude	-0.0167***	0.0043	0.0040
N	0.5764**	0.3227	0.2985
NE	0.3108	0.3789	0.3115
S	-9.4460***	2.3461	2.0560
MW	0.0550	0.1253	0.1159
Ln(Avetemp)	-9.4086***	1.6424	1.5762
Ln(Augrain)	-0.1970	0.1608	0.1355
Ln(Marrain)	0.5688***	0.0995	0.0904
Ln(Avetemp)×S	2.6823***	0.8542	0.7556
SSR	1385.65		
Adj. R-sq	0.44		
F[22,3492]	126.71***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

A.3 Hedonic Wage Model

Table A.33: Results from Semilog Wage Regression Including only Demographic

Variable	Variables		
	Coeff.	Std. Error	Robust Std. Error
Constant	4.9289***	0.0257	0.0253
Ed5to8	0.2461***	0.0187	0.0176
Ed9to12	0.6246***	0.0194	0.0194
Edgt12	1.4718***	0.0238	0.0248
OJE	0.0442***	0.0019	0.0021
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.3096***	0.0127	0.0126
Male	0.5220***	0.0159	0.0166
Dir	0.3791***	0.0227	0.0237
SP	0.1712***	0.0253	0.0259
Mid	0.1991***	0.0245	0.0245
Off	0.0365	0.0370	0.0321
Ser	0.3146***	0.0209	0.0221
Ag	0.0523***	0.0502	0.0620
Oper	0.1804***	0.0253	0.0230
EO	-0.2002***	0.0227	0.0201
AF	0.0169	0.0467	0.0353
Other	0.0369	0.0432	0.0450
SSR	7933.23		
Adj. R-sq	0.50		
F[17,14843]	865.96***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.34: Results from Semilog Model Including Temperature and February

Rainfall Interaction Variable			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	-0.2341	1.9324	2.0001
Ed5to8	0.2116***	0.0182	0.0167
Ed9to12	0.6215***	0.0184	0.0179
Edgt12	1.4539***	0.0227	0.0236
OJE	0.0456***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1815***	0.0134	0.0133
Male	0.5189***	0.0153	0.0158
Dir	0.3797***	0.0203	0.0213
SP	0.1621***	0.0225	0.0233
Mid	0.1934***	0.0219	0.0219
Ser	0.3077***	0.0185	0.0201
Oper	0.1710***	0.0235	0.0213
EO	-0.1978***	0.0209	0.0180
Popdens	-0.0084***	0.0012	0.0011
Banks	0.0820***	0.0170	0.0158
Deaths	0.0014***	0.0004	0.0004
Schools	-0.0120***	0.0022	0.0021
Altitude	0.0093***	0.0025	0.0025
N	0.5060***	0.2077	0.2035
NE	1.5334***	0.3427	0.3152
S	0.5373*	0.2791	0.2867
MW	-0.6841***	0.1276	0.1260
Avetemp	0.2000**	0.0805	0.0833
Junerain	-0.0032***	0.0007	0.0006
Febrain	0.0083***	0.0030	0.0031
Avetemp×Febrain	-0.0003**	0.0001	0.0001
SSR	7473.56		
Adj. R-sq	0.53		
F[26,14834]	635.76***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.35: Results from Semilog Model Including Temperature and June

Rainfall Interaction Variable			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	2.5805*	1.5356	1.5455
Ed5to8	0.2110***	0.0182	0.0167
Ed9to12	0.6210***	0.0184	0.0179
Edgt12	1.4533***	0.0227	0.0237
OJE	0.0455***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1816***	0.0134	0.0133
Male	0.5181***	0.0153	0.0158
Dir	0.3793***	0.0203	0.0213
SP	0.1624***	0.0225	0.0233
Mid	0.1935***	0.0219	0.0219
Ser	0.3073***	0.0185	0.0201
Oper	0.1709***	0.0235	0.0213
EO	-0.1984***	0.0209	0.0180
Popdens	-0.0077***	0.0011	0.0010
Banks	0.0844***	0.0197	0.0181
Deaths	0.0014***	0.0005	0.0004
Schools	-0.0103***	0.0021	0.0019
Altitude	0.0069***	0.0025	0.0025
N	0.6881***	0.2234	0.2153
NE	1.6649***	0.3722	0.3342
S	-0.1020	0.1538	0.1565
MW	-0.5510***	0.1172	0.1076
Avetemp	0.0764	0.0599	0.0603
Junerain	0.0053	0.0066	0.0069
Febrain	0.0005**	0.0002	0.0002
Avetemp×Junrain	-0.0003	0.0003	0.0003
SSR	7476.03		
Adj. R-sq	0.53		
F[26,14834]	635.36***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.36: Results from Semilog Model Including Temperature and March

Rainfall Interaction Variable			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	5.9840***	1.0212	1.0436
Ed5to8	0.2115***	0.0182	0.0167
Ed9to12	0.6210***	0.0184	0.0179
Edgt12	1.4544***	0.0227	0.0236
OJE	0.0455***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1817***	0.0134	0.0133
Male	0.5185***	0.0153	0.0158
Dir	0.3794***	0.0203	0.0213
SP	0.1624***	0.0225	0.0233
Mid	0.1937***	0.0219	0.0219
Ser	0.3074***	0.0185	0.0201
Oper	0.1706***	0.0235	0.0213
EO	-0.1976***	0.0209	0.0180
Popdens	-0.0060***	0.0009	0.0008
Banks	0.0481***	0.0180	0.0165
Deaths	0.0009	0.0006	0.0006
Schools	-0.0080***	0.0027	0.0024
Altitude	0.0004	0.0026	0.0024
N	0.2200*	0.1203	0.1250
NE	0.6115***	0.2020	0.1820
S	-0.2204*	0.1407	0.1346
MW	-0.2728***	0.0942	0.0859
Avetemp	-0.0494	0.0405	0.0411
Augrain	-0.0028***	0.0008	0.0007
Marrain	-0.0002	0.0091	0.0086
Avetemp×Marrain	0.0001	0.0004	0.0003
SSR	7475.94		
Adj. R-sq	0.53		
F[26,14834]	635.37***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.37: Results from Semilog Model Including Temperature and August

Variable	Rainfall Interaction Variable		
	Coeff.	Std. Error	Robust Std. Error
Constant	2.5946	1.8052	1.8416
Ed5to8	0.2118***	0.0182	0.0167
Ed9to12	0.6211***	0.0184	0.0179
Edgt12	1.4537***	0.0227	0.0237
OJE	0.0456***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1819***	0.0134	0.0133
Male	0.5193***	0.0153	0.0158
Dir	0.3801***	0.0203	0.0213
SP	0.1616***	0.0225	0.0233
Mid	0.1928***	0.0219	0.0219
Ser	0.3075***	0.0185	0.0201
Oper	0.1707***	0.0235	0.0213
EO	-0.1980***	0.0209	0.0180
Popdens	-0.0049***	0.0009	0.0009
Banks	0.0129	0.0205	0.0207
Deaths	0.0008	0.0005	0.0005
Schools	-0.0081***	0.0018	0.0018
Altitude	0.0065*	0.0034	0.0034
N	-0.1960	0.2279	0.2351
NE	0.2275	0.2298	0.2278
S	-0.2086	0.1406	0.1350
MW	-0.4177***	0.1125	0.1170
Avetemp	0.1013	0.0782	0.0798
Augrain	0.0264*	0.0136	0.0139
Marrain	0.0013***	0.0002	0.0002
Avetemp×Augrain	-0.0011**	0.0005	0.0005
SSR	7473.62		
Adj. R-sq	0.53		
F[26,14834]	635.75***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.38: Results from Double-log Model Including Temperature and
February Rainfall Interaction Variable

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	-97.7613***	25.6195	26.6641
Ed5to8	0.2115***	0.0182	0.0167
Ed9to12	0.6201***	0.0184	0.0179
Edgt12	1.4523***	0.0227	0.0237
OJE	0.0457***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1829***	0.0134	0.0133
Male	0.5193***	0.0153	0.0158
Dir	0.3804***	0.0203	0.0213
SP	0.1609***	0.0225	0.0233
Mid	0.1919***	0.0219	0.0219
Ser	0.3072***	0.0185	0.0201
Oper	0.1704***	0.0235	0.0213
EO	-0.1990***	0.0209	0.0180
Popdens	-0.0117***	0.0026	0.0026
Banks	-0.0372***	0.0143	0.0149
Deaths	0.0039***	0.0012	0.0012
Schools	-0.0123***	0.0024	0.0025
Altitude	0.0020	0.0037	0.0039
N	-0.5232***	0.1973	0.2032
NE	1.0354**	0.4381	0.4559
S	2.2502***	0.5389	0.5560
MW	-1.2512***	0.2679	0.2800
Ln(Avetemp)	32.0556***	8.0880	8.4184
Ln(Junrain)	-0.5166***	0.1774	0.1849
Ln(Febrain)	18.4180***	4.7508	4.9498
Ln(Avetemp)×Ln(Febrain)	-5.5411***	1.4500	1.5111
SSR	7475.75		
Adj. R-sq	0.53		
F[26,14834]	635.40***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.39: Results from Double-log Model Including Temperature and June

Rainfall Interaction Variable			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	2.3681	5.7372	5.9633
Ed5to8	0.2110***	0.0182	0.0167
Ed9to12	0.6189***	0.0184	0.0179
Edgt12	1.4519***	0.0228	0.0237
OJE	0.0456***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1843***	0.0134	0.0133
Male	0.5188***	0.0153	0.0158
Dir	0.3800***	0.0203	0.0213
SP	0.1609***	0.0225	0.0233
Mid	0.1921***	0.0219	0.0219
Ser	0.3063***	0.0185	0.0201
Oper	0.1695***	0.0235	0.0213
EO	-0.1993***	0.0209	0.0180
Popdens	-0.0016	0.0016	0.0016
Banks	0.0013	0.0091	0.0093
Deaths	-0.0006	0.0006	0.0007
Schools	-0.0033*	0.0017	0.0018
Altitude	0.0058	0.0037	0.0039
N	-0.6181***	0.2159	0.2246
NE	-0.5920	0.4089	0.4219
S	0.4869*	0.2535	0.2585
MW	-0.1418	0.1208	0.1170
Ln(Avetemp)	0.4006	1.8028	1.8710
Ln(Junrain)	-1.2913*	0.7069	0.7251
Ln(Febrain)	0.1702	0.1177	0.1212
Ln(Avetemp)×Ln(Junrain)	0.4634*	0.2443	0.2497
SSR	7481.29		
Adj. R-sq	0.53		
F[26,14834]	634.51***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.40: Results from Double-log Model Including Temperature and March

Rainfall Interaction Variable			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	6.1196	27.7515	28.2457
Ed5to8	0.2116***	0.0182	0.0167
Ed9to12	0.6215***	0.0184	0.0179
Edgt12	1.4543***	0.0227	0.0236
OJE	0.0456***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1819***	0.0134	0.0133
Male	0.5189***	0.0153	0.0158
Dir	0.3795***	0.0203	0.0213
SP	0.1624***	0.0225	0.0233
Mid	0.1939***	0.0219	0.0219
Ser	0.3077***	0.0185	0.0201
Oper	0.1709***	0.0235	0.0213
EO	-0.1974***	0.0209	0.0180
Popdens	-0.0082***	0.0011	0.0011
Banks	0.0107	0.0090	0.0089
Deaths	0.0009	0.0006	0.0006
Schools	-0.0089***	0.0018	0.0017
Altitude	-0.0103***	0.0030	0.0031
N	0.1807	0.1335	0.1372
NE	0.6414***	0.1332	0.1262
S	-0.6112***	0.1797	0.1745
MW	-0.1499**	0.0734	0.0726
Ln(Avetemp)	-0.5472	8.5826	8.7376
Ln(Augrain)	-0.3053***	0.0735	0.0748
Ln(Marrain)	3.2225	5.9470	6.0880
Ln(Avetemp)×Ln(Marrain)	-0.8610	1.8299	1.8720
SSR	7475.11		
Adj. R-sq	0.53		
F[26,14834]	635.51***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.42: Results from Box-Cox Model Including Temperature and February

Rainfall Interaction Variable (Lambda=-0.0794)

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	-83.7288***	21.3418	21.3269
Ed5to8	0.1371***	0.0118	0.0115
Ed9to12	0.3878***	0.0146	0.0112
Edgt12	0.8690***	0.0266	0.0135
OJE	0.0280***	0.0013	0.0011
OJEsq	-0.0005***	0.0000	0.0000
Black	-0.1110***	0.0087	0.0081
Male	0.3222***	0.0118	0.0088
Dir	0.2254***	0.0134	0.0119
SP	0.0981***	0.0136	0.0134
Mid	0.1199***	0.0137	0.0134
Ser	0.1765***	0.0120	0.0106
Oper	0.1063***	0.0157	0.0155
EO	-0.1337***	0.0147	0.0142
Popdens	-0.0070***	0.1166	0.1163
Banks	-0.0294**	0.2478	0.2478
Deaths	0.0024***	0.3187	0.3177
Schools	-0.0070***	0.1598	0.1595
Altitude	0.0006***	14.7230	14.4474
N	-0.3870***	0.1502	0.1501
NE	0.5162***	17.0733	16.8346
S	1.3824***	21.9964	21.8551
MW	-0.7580***	0.0016	0.0015
BC(Avetemp)	-53.7233***	0.0102	0.0102
BC(Junrain)	-0.4165***	0.0007	0.0007
BC(Febrain)	-64.9790***	0.0014	0.0014
BC(Avetemp×Febrain)	84.6337	0.0025	0.0025
Value of LLF	-108051.59		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The Wald statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.41: Results from Double-log Model Including Temperature and August

Rainfall Interaction Variable			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	30.6428***	10.8709	11.3774
Ed5to8	0.2112***	0.0182	0.0167
Ed9to12	0.6214***	0.0184	0.0179
Edgt12	1.4534***	0.0227	0.0237
OJE	0.0455***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1816***	0.0134	0.0133
Male	0.5185***	0.0153	0.0158
Dir	0.3795***	0.0203	0.0213
SP	0.1623***	0.0225	0.0233
Mid	0.1935***	0.0219	0.0219
Ser	0.3077***	0.0185	0.0201
Oper	0.1712***	0.0235	0.0213
EO	-0.1981***	0.0209	0.0180
Popdens	-0.0086***	0.0012	0.0011
Banks	0.0069	0.0095	0.0098
Deaths	0.0010*	0.0006	0.0006
Schools	-0.0086***	0.0018	0.0017
Altitude	-0.0142***	0.0049	0.0051
N	0.2231*	0.1348	0.1372
NE	0.6994***	0.1428	0.1373
S	-0.8758***	0.2543	0.2579
MW	-0.0348	0.1221	0.1242
Ln(Avetemp)	-8.1846**	3.3999	3.5573
Ln(Augrain)	-1.6886	1.2746	1.3398
Ln(Marrain)	0.4798***	0.0747	0.0759
Ln(Avetemp)×Ln(Augrain)	0.4237	0.3854	0.4053
SSR	7474.62		
Adj. R-sq	0.53		
F[26,14834]	635.59***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.43: Results from Box-Cox Model Including Temperature and June

Rainfall Interaction Variable (Lambda=-0.0803)

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	1.8494***	4.1179	4.1155
Ed5to8	0.1363***	0.0118	0.0115
Ed9to12	0.3853***	0.0145	0.0111
Edgt12	0.8639***	0.0265	0.0134
OJE	0.0279***	0.0013	0.0011
OJEsq	-0.0005***	0.0000	0.0000
Black	-0.1109***	0.0086	0.0081
Male	0.3203***	0.0117	0.0088
Dir	0.2239***	0.0133	0.0118
SP	0.0975***	0.0136	0.0134
Mid	0.1194***	0.0136	0.0133
Ser	0.1750***	0.0120	0.0106
Oper	0.1054***	0.0156	0.0154
EO	-0.1332***	0.0146	0.0141
Popdens	-0.0006***	0.1201	0.1195
Banks	0.0028**	0.2162	0.2157
Deaths	-0.0005**	0.1606	0.1602
Schools	-0.0018	0.0739	0.0739
Altitude	0.0047***	2.6696	2.6451
N	-0.4013**	2.3556	2.3341
NE	-0.4495	0.1113	0.1113
S	0.3430**	2.9528	2.9365
MW	-0.0674	0.0010	0.0010
BC(Avetemp)	7.3523	0.0056	0.0056
BC(Junrain)	5.5443	0.0004	0.0004
BC(Febrain)	0.0989*	0.0010	0.0010
BC(Avetemp×Junrain)	-6.8966**	0.0024	0.0024
Value of LLF	-108055.20		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The Wald statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.44: Results from Box-Cox Model Including Temperature and March

Rainfall Interaction Variable (Lambda=-0.0798)

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	6.3267	24.8677	24.8631
Ed5to8	0.1368***	0.0118	0.0115
Ed9to12	0.3880***	0.0146	0.0112
Edgt12	0.8682***	0.0266	0.0134
OJE	0.0279***	0.0013	0.0011
OJEsq	-0.0005***	0.0000	0.0000
Black	-0.1099***	0.0086	0.0081
Male	0.3212***	0.0118	0.0088
Dir	0.2243***	0.0134	0.0119
SP	0.0989***	0.0136	0.0134
Mid	0.1209***	0.0137	0.0133
Ser	0.1765***	0.0120	0.0106
Oper	0.1065***	0.0157	0.0155
EO	-0.1324***	0.0147	0.0142
Popdens	-0.0052	0.0827	0.0826
Banks	0.0044***	0.0890	0.0884
Deaths	0.0006***	0.1210	0.1209
Schools	-0.0055	0.0453	0.0453
Altitude	-0.0075	19.2321	19.2095
N	0.1249***	0.0659	0.0658
NE	0.4055	21.5363	21.5141
S	-0.4614	27.9032	27.8809
MW	-0.0724***	0.0008	0.0008
BC(Avetemp)	-11.4793	0.0057	0.0057
BC(Augrain)	-0.2788*	0.0004	0.0004
BC(Marrain)	-7.6889***	0.0012	0.0012
BC(Avetemp×Marrain)	10.5039***	0.0020	0.0020
Value of LLF	-108050.13		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The Wald statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.45: Results from Box-Cox Model Including Temperature and August

Rainfall Interaction Variable (Lambda=-0.0799)

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	25.8211***	7.6257	7.6255
Ed5to8	0.1365***	0.0118	0.0115
Ed9to12	0.3875***	0.0146	0.0112
Edgt12	0.8667***	0.0266	0.0134
OJE	0.0279***	0.0013	0.0011
OJEsq	-0.0005***	0.0000	0.0000
Black	-0.1096***	0.0086	0.0081
Male	0.3207***	0.0117	0.0088
Dir	0.2241***	0.0133	0.0118
SP	0.0987***	0.0136	0.0134
Mid	0.1205***	0.0136	0.0133
Ser	0.1762***	0.0120	0.0106
Oper	0.1066***	0.0156	0.0155
EO	-0.1329***	0.0147	0.0141
Popdens	-0.0056**	0.0837	0.0837
Banks	0.0011***	0.0936	0.0930
Deaths	0.0006***	0.1663	0.1662
Schools	-0.0052	0.0749	0.0749
Altitude	-0.0107	2.1772	2.1665
N	0.1630	3.5555	3.5505
NE	0.4445***	0.0717	0.0717
S	-0.6589	4.6264	4.6239
MW	0.0134***	0.0008	0.0008
BC(Avetemp)	-1.3474	0.0057	0.0057
BC(Augrain)	4.7488*	0.0004	0.0004
BC(Marrain)	0.4795***	0.0012	0.0012
BC(Avetemp×Augrain)	-6.5316***	0.0030	0.0030
Value of LLF	-108049.28		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The Wald statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.46: Results from Semilog Model Including Temperature and Altitude

Variable	Interaction Variable		
	Coeff.	Std. Error	Robust Std. Error
Constant	4.4586***	0.8606	0.8616
Ed5to8	0.2111***	0.0182	0.0167
Ed9to12	0.6206***	0.0184	0.0179
Edgt12	1.4519***	0.0227	0.0236
OJE	0.0456***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1821***	0.0134	0.0133
Male	0.5187***	0.0153	0.0158
Dir	0.3801***	0.0203	0.0213
SP	0.1614***	0.0225	0.0233
Mid	0.1923***	0.0219	0.0219
Ser	0.3073***	0.0185	0.0201
Oper	0.1709***	0.0235	0.0213
EO	-0.1993***	0.0209	0.0180
Popdens	-0.0047***	0.0017	0.0015
Banks	-0.0799	0.0751	0.0749
Deaths	0.0037***	0.0013	0.0013
Schools	-0.0066***	0.0025	0.0023
Altitude	-0.0232*	0.0135	0.0137
N	-1.0549	0.8206	0.8211
NE	-0.1688	0.8723	0.8468
S	1.0035*	0.5393	0.5461
MW	-0.6811***	0.1416	0.1488
Avetemp	0.0599	0.0412	0.0420
Junerain	-0.0006	0.0013	0.0013
Febrain	0.0020***	0.0006	0.0007
Avetemp×Altitude	0.0014**	0.0007	0.0007
SSR	7474.69		
Adj. R-sq	0.53		
F[26,14834]	635.57***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.47: Results from Double-log Model Including Temperature and

Altitude Interaction Variable			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	-5.5891	5.3295	5.5251
Ed5to8	0.2116***	0.0182	0.0167
Ed9to12	0.6209***	0.0184	0.0179
Edgt12	1.4529***	0.0227	0.0237
OJE	0.0457***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1820***	0.0134	0.0133
Male	0.5193***	0.0153	0.0158
Dir	0.3802***	0.0203	0.0213
SP	0.1614***	0.0225	0.0233
Mid	0.1924***	0.0219	0.0219
Ser	0.3076***	0.0185	0.0201
Oper	0.1709***	0.0235	0.0213
EO	-0.1985***	0.0209	0.0180
Popdens	-0.0032**	0.0014	0.0014
Banks	-0.0763***	0.0207	0.0211
Deaths	0.0025***	0.0008	0.0008
Schools	-0.0058***	0.0015	0.0015
Altitude	-0.0566***	0.0145	0.0148
N	-1.2644***	0.2708	0.2754
NE	-0.6857*	0.3458	0.3645
S	1.1974***	0.3068	0.3079
MW	-0.5578***	0.1106	0.1103
Ln(Avetemp)	3.0074*	1.6686	1.7272
Ln(Junerain)	0.1064	0.1044	0.1097
Ln(Febrain)	0.3550***	0.1077	0.1119
Ln(Avetemp)×Altitude	0.0214***	0.0049	0.0050
SSR	7473.47		
Adj. R-sq	0.53		
F[26,14834]	635.77***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.48: Results from Box-Cox Model Including Temperature and Altitude

Interaction Variable (Lambda=-0.0800)

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	8.4276*	5.0459	5.0449
Ed5to8	0.1366***	0.0118	0.0115
Ed9to12	0.3874***	0.0146	0.0112
Edgt12	0.8671***	0.0266	0.0134
OJE	0.0279***	0.0013	0.0011
OJEsq	-0.0005***	0.0000	0.0000
Black	-0.1100***	0.0086	0.0081
Male	0.3206***	0.0117	0.0088
Dir	0.2239***	0.0133	0.0118
SP	0.0988***	0.0136	0.0134
Mid	0.1208***	0.0137	0.0133
Ser	0.1760***	0.0120	0.0106
Oper	0.1062***	0.0157	0.0155
EO	-0.1325***	0.0147	0.0141
Popdens	-0.0059***	0.1348	0.1343
Banks	-0.0571**	0.3050	0.3048
Deaths	0.0040***	0.1661	0.1652
Schools	-0.0074***	0.1257	0.1254
Altitude	-0.0089	1.8581	1.8569
N	-0.5150**	0.1912	0.1910
NE	0.6056***	0.2634	0.2631
S	0.4190***	0.0340	0.0339
MW	-0.4985***	0.0016	0.0016
BC(Avetemp)	-2.1211***	0.0203	0.0203
BC(Junerain)	-0.4628***	0.0013	0.0013
BC(Febrain)	0.9512***	0.0017	0.0017
BC(Avetemp×Altitude)	0.1071*	0.0047	0.0047
Value of LLF	-108051.41		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The Wald statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.49: Results from Semilog Model Including Temperature and Altitude

Interaction Variable			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	7.2490***	1.1347	1.1781
Ed5to8	0.2114***	0.0182	0.0167
Ed9to12	0.6214***	0.0184	0.0179
Edgt12	1.4535***	0.0227	0.0237
OJE	0.0456***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1815***	0.0134	0.0133
Male	0.5188***	0.0153	0.0158
Dir	0.3797***	0.0203	0.0213
SP	0.1622***	0.0225	0.0233
Mid	0.1933***	0.0219	0.0219
Ser	0.3077***	0.0185	0.0201
Oper	0.1712***	0.0235	0.0213
EO	-0.1981***	0.0209	0.0180
Popdens	-0.0060***	0.0008	0.0008
Banks	-0.0025	0.0269	0.0283
Deaths	0.0016***	0.0007	0.0006
Schools	-0.0076***	0.0018	0.0017
Altitude	-0.0126**	0.0063	0.0065
N	-0.1558	0.2167	0.2235
NE	0.3337	0.1987	0.2065
S	-0.0558	0.1613	0.1516
MW	-0.3448***	0.0958	0.0913
Avetemp	-0.0811**	0.0408	0.0415
Augrain	-0.0023***	0.0008	0.0008
Marrain	0.0018***	0.0003	0.0003
Avetemp×Altitude	0.0006**	0.0003	0.0003
SSR	7473.75		
Adj. R-sq	0.53		
F[26,14834]	635.73***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.50: Results from Double-log Model Including Temperature and

Altitude Interaction Variable			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	17.6651***	3.0330	3.0355
Ed5to8	0.2112***	0.0182	0.0167
Ed9to12	0.6213***	0.0184	0.0179
Edgt12	1.4533***	0.0227	0.0237
OJE	0.0455***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1815***	0.0134	0.0133
Male	0.5186***	0.0153	0.0158
Dir	0.3796***	0.0203	0.0213
SP	0.1622***	0.0225	0.0233
Mid	0.1933***	0.0219	0.0219
Ser	0.3077***	0.0185	0.0201
Oper	0.1712***	0.0235	0.0213
EO	-0.1983***	0.0209	0.0180
Popdens	-0.0069***	0.0014	0.0013
Banks	-0.0294	0.0311	0.0329
Deaths	0.0010*	0.0006	0.0006
Schools	-0.0072***	0.0022	0.0021
Altitude	-0.0456*	0.0260	0.0273
N	-0.2864	0.3344	0.3532
NE	0.2126	0.3351	0.3449
S	-0.3650	0.2582	0.2662
MW	-0.2062**	0.0850	0.0859
Ln(Avetemp)	-4.2351***	0.8844	0.8788
Ln(Augrain)	-0.1519	0.1175	0.1195
Ln(Marrain)	0.4733***	0.0652	0.0660
Ln(Avetemp)×Altitude	0.0127	0.0091	0.0095
SSR	7474.23		
Adj. R-sq	0.53		
F[26,14834]	635.65***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.51: Results from Box-Cox Model Including Temperature and Altitude

Interaction Variable (Lambda=-0.0798)

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	18.3841***	3.6321	3.6309
Ed5to8	0.1366***	0.0118	0.0115
Ed9to12	0.3879***	0.0146	0.0112
Edgt12	0.8676***	0.0266	0.0134
OJE	0.0279***	0.0013	0.0011
OJEsq	-0.0005***	0.0000	0.0000
Black	-0.1097***	0.0086	0.0081
Male	0.3209***	0.0117	0.0088
Dir	0.2242***	0.0134	0.0119
SP	0.0988***	0.0136	0.0134
Mid	0.1207***	0.0137	0.0133
Ser	0.1764***	0.0120	0.0106
Oper	0.1066***	0.0157	0.0155
EO	-0.1328***	0.0147	0.0142
Popdens	-0.0057	0.1607	0.1607
Banks	0.0121***	0.1622	0.1620
Deaths	0.0005***	0.1777	0.1776
Schools	-0.0058	0.0484	0.0483
Altitude	-0.0079***	1.2054	1.2051
N	0.2514***	0.0833	0.0832
NE	0.5385***	0.0567	0.0567
S	-0.6222	0.0210	0.0210
MW	-0.0516***	0.0010	0.0010
BC(Avetemp)	-5.1392	0.0084	0.0084
BC(Augrain)	-0.3218	0.0004	0.0004
BC(Marrain)	0.4074***	0.0011	0.0011
BC(Avetemp×Altitude)	-0.0213***	0.0018	0.0018
Value of LLF	-108049.72		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The Wald statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.52: Results from Semilog Model Including June Rainfall and Northeast

Interaction Variable			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	2.9328***	0.9672	0.9819
Ed5to8	0.2116***	0.0182	0.0167
Ed9to12	0.6212***	0.0184	0.0179
Edgt12	1.4530***	0.0227	0.0236
OJE	0.0456***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1818***	0.0134	0.0133
Male	0.5192***	0.0153	0.0158
Dir	0.3801***	0.0203	0.0213
SP	0.1616***	0.0225	0.0233
Mid	0.1927***	0.0219	0.0219
Ser	0.3077***	0.0185	0.0201
Oper	0.1710***	0.0235	0.0213
EO	-0.1984***	0.0209	0.0180
Popdens	-0.0053***	0.0013	0.0012
Banks	0.0616***	0.0167	0.0154
Deaths	0.0008*	0.0004	0.0004
Schools	-0.0078***	0.0021	0.0020
Altitude	0.0077***	0.0020	0.0020
N	0.2645	0.2360	0.2312
NE	1.3331***	0.3464	0.3185
S	-0.2307	0.1627	0.1671
MW	-0.3910***	0.0964	0.0890
Avetemp	0.0644	0.0395	0.0400
Junerain	0.0020	0.0020	0.0020
Febrain	-0.0004	0.0005	0.0005
Junerain×NE	-0.0045***	0.0017	0.0017
SSR	7473.11		
Adj. R-sq	0.53		
F[26,14834]	635.83***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.53: Results from Semilog Model Including August Rainfall and

Northeast Interaction Variable

Variable	Coeff.	Std. Error	Robust Std. Error
Constant	1.3027	2.2322	2.2831
Ed5to8	0.2117***	0.0182	0.0167
Ed9to12	0.6211***	0.0184	0.0179
Edgt12	1.4535***	0.0227	0.0237
OJE	0.0456***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1819***	0.0134	0.0133
Male	0.5193***	0.0153	0.0158
Dir	0.3801***	0.0203	0.0213
SP	0.1616***	0.0225	0.0233
Mid	0.1928***	0.0219	0.0219
Ser	0.3076***	0.0185	0.0201
Oper	0.1708***	0.0235	0.0213
EO	-0.1980***	0.0209	0.0180
Popdens	-0.0057***	0.0008	0.0008
Banks	0.0945***	0.0252	0.0260
Deaths	0.0029***	0.0011	0.0011
Schools	-0.0091***	0.0019	0.0019
Altitude	0.0103**	0.0047	0.0049
N	0.6189***	0.2106	0.2176
NE	1.3226***	0.3575	0.3688
S	-0.0588	0.1576	0.1528
MW	-0.6107***	0.1746	0.1833
Avetemp	0.1079	0.0774	0.0788
Augrain	-0.0004	0.0013	0.0013
Marrain	-0.0000	0.0006	0.0007
Augrain×NE	-0.0051**	0.0022	0.0023
SSR	7473.34		
Adj. R-sq	0.53		
F[26,14834]	635.79***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.54: Results from Double-log Model Including June Rainfall and

Northeast Interaction Variable			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	-4.5057	5.2949	5.4895
Ed5to8	0.2116***	0.0182	0.0167
Ed9to12	0.6213***	0.0184	0.0179
Edgt12	1.4534***	0.0227	0.0237
OJE	0.0456***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1817***	0.0134	0.0133
Male	0.5191***	0.0153	0.0158
Dir	0.3800***	0.0203	0.0213
SP	0.1618***	0.0225	0.0233
Mid	0.1929***	0.0219	0.0219
Ser	0.3077***	0.0185	0.0201
Oper	0.1710***	0.0235	0.0213
EO	-0.1981***	0.0209	0.0180
Popdens	-0.0047***	0.0014	0.0014
Banks	0.0615***	0.0153	0.0153
Deaths	0.0004	0.0006	0.0006
Schools	-0.0080***	0.0016	0.0016
Altitude	0.0106***	0.0039	0.0040
N	0.1534	0.2379	0.2440
NE	3.9134***	0.9548	0.9385
S	0.0861	0.2629	0.2676
MW	-0.3737***	0.0940	0.0934
Ln(Avetemp)	2.8431*	1.6620	1.7196
Ln(Junerain)	0.1384	0.1057	0.1112
Ln(Febrain)	-0.1035	0.1345	0.1414
Ln(Junerain)×NE	-0.6678***	0.1494	0.1476
SSR	7473.04		
Adj. R-sq	0.53		
F[26,14834]	635.84***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.55: Results from Double-log Model Including August Rainfall and

Northeast Interaction Variable			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	6.2409	7.4825	7.6326
Ed5to8	0.2113***	0.0182	0.0167
Ed9to12	0.6213***	0.0184	0.0179
Edgt12	1.4531***	0.0227	0.0236
OJE	0.0456***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1815***	0.0134	0.0133
Male	0.5188***	0.0153	0.0158
Dir	0.3798***	0.0203	0.0213
SP	0.1619***	0.0225	0.0233
Mid	0.1930***	0.0219	0.0219
Ser	0.3077***	0.0185	0.0201
Oper	0.1711***	0.0235	0.0213
EO	-0.1984***	0.0209	0.0180
Popdens	-0.0069***	0.0013	0.0011
Banks	0.0485**	0.0208	0.0210
Deaths	0.0015**	0.0007	0.0007
Schools	-0.0096***	0.0017	0.0016
Altitude	0.0021	0.0064	0.0066
N	0.3375**	0.1547	0.1566
NE	1.8437***	0.6593	0.6873
S	-0.2535	0.2652	0.2696
MW	-0.3781***	0.1454	0.1537
Ln(Avetemp)	-0.5375	2.3272	2.3760
Ln(Augrain)	-0.1028	0.1193	0.1177
Ln(Marrain)	0.1433	0.1608	0.1617
Ln(Augrain)×NE	-0.2621*	0.1409	0.1459
SSR	7473.48		
Adj. R-sq	0.53		
F[26,14834]	635.77***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.56: Results from Semilog Model Including Temperature and South

Interaction Variable			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	4.0012***	0.8813	0.8954
Ed5to8	0.2107***	0.0182	0.0167
Ed9to12	0.6203***	0.0184	0.0179
Edgt12	1.4518***	0.0227	0.0236
OJE	0.0455***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1821***	0.0134	0.0133
Male	0.5181***	0.0153	0.0158
Dir	0.3797***	0.0203	0.0213
SP	0.1618***	0.0225	0.0233
Mid	0.1926***	0.0219	0.0219
Ser	0.3071***	0.0185	0.0201
Oper	0.1709***	0.0235	0.0213
EO	-0.1995***	0.0209	0.0180
Popdens	-0.0068***	0.0013	0.0011
Banks	0.0499*	0.0309	0.0289
Deaths	0.0014***	0.0005	0.0005
Schools	-0.0090***	0.0021	0.0019
Altitude	0.0048***	0.0017	0.0017
N	0.3224	0.3823	0.3676
NE	1.1955***	0.4963	0.4472
S	-0.3855	0.4344	0.4396
MW	-0.4806***	0.0960	0.0942
Avetemp	0.0309	0.0401	0.0411
Junerain	-0.0025***	0.0009	0.0008
Febrain	0.0009***	0.0003	0.0003
Avetemp×S	0.0258	0.0324	0.0327
SSR	7476.5		
Adj. R-sq	0.53		
F[26,14834]	635.28***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.57: Results from Semilog Model Including Temperature and South

Interaction Variable			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	5.7712***	0.9413	0.9233
Ed5to8	0.2115***	0.0182	0.0167
Ed9to12	0.6214***	0.0184	0.0179
Edgt12	1.4534***	0.0227	0.0237
OJE	0.0456***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1816***	0.0134	0.0133
Male	0.5190***	0.0153	0.0158
Dir	0.3799***	0.0203	0.0213
SP	0.1619***	0.0225	0.0233
Mid	0.1930***	0.0219	0.0219
Ser	0.3077***	0.0185	0.0201
Oper	0.1711***	0.0235	0.0213
EO	-0.1981***	0.0209	0.0180
Popdens	-0.0062***	0.0008	0.0008
Banks	0.0241	0.0165	0.0173
Deaths	0.0015***	0.0006	0.0006
Schools	-0.0085***	0.0019	0.0018
Altitude	0.0013	0.0017	0.0016
N	-0.0002	0.1523	0.1591
NE	0.4961***	0.1614	0.1617
S	-1.0087***	0.3634	0.3783
MW	-0.3628***	0.0972	0.0948
Avetemp	-0.0293	0.0380	0.0367
Augrain	-0.0028***	0.0007	0.0007
Marrain	0.0015***	0.0002	0.0002
Avetemp×S	0.0527**	0.0224	0.0231
SSR	7473.18		
Adj. R-sq	0.53		
F[26,14834]	635.82***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.58: Results from Double-log Model Including Temperature and South

Interaction Variable			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	-8.9559	5.5795	5.7925
Ed5to8	0.2115***	0.0182	0.0167
Ed9to12	0.6200***	0.0184	0.0179
Edgt12	1.4522***	0.0227	0.0237
OJE	0.0457***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1829***	0.0134	0.0133
Male	0.5193***	0.0153	0.0158
Dir	0.3804***	0.0203	0.0213
SP	0.1609***	0.0225	0.0233
Mid	0.1919***	0.0219	0.0219
Ser	0.3071***	0.0185	0.0201
Oper	0.1704***	0.0235	0.0213
EO	-0.1990***	0.0209	0.0180
Popdens	-0.0023	0.0014	0.0014
Banks	-0.0333**	0.0136	0.0141
Deaths	0.0008	0.0006	0.0006
Schools	-0.0048***	0.0015	0.0015
Altitude	0.0104***	0.0040	0.0041
N	-0.9997***	0.2443	0.2528
NE	-0.7227*	0.3583	0.3769
S	-3.6392***	1.1011	1.1487
MW	-0.3904***	0.0959	0.0976
Ln(Avetemp)	4.0689**	1.7514	1.8159
Ln(Junerain)	0.1705	0.1091	0.1145
Ln(Febrain)	0.1977*	0.1074	0.1127
Ln(Avetemp)×S	1.5691***	0.4135	0.4310
SSR	7475.85		
Adj. R-sq	0.53		
F[26,14834]	635.39***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.59: Results from Double-log Model Including Temperature and South

Interaction Variable			
Variable	Coeff.	Std. Error	Robust Std. Error
Constant	17.1541***	3.0743	3.0618
Ed5to8	0.2113***	0.0182	0.0167
Ed9to12	0.6213***	0.0184	0.0179
Edgt12	1.4531***	0.0227	0.0237
OJE	0.0456***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001
Black	-0.1815***	0.0134	0.0133
Male	0.5187***	0.0153	0.0158
Dir	0.3797***	0.0203	0.0213
SP	0.1620***	0.0225	0.0233
Mid	0.1931***	0.0219	0.0219
Ser	0.3077***	0.0185	0.0201
Oper	0.1712***	0.0235	0.0213
EO	-0.1984***	0.0209	0.0180
Popdens	-0.0074***	0.0012	0.0010
Banks	-0.0065	0.0137	0.0144
Deaths	0.0009	0.0006	0.0006
Schools	-0.0081***	0.0018	0.0017
Altitude	-0.0073***	0.0023	0.0023
N	-0.0781	0.1790	0.1879
NE	0.4128**	0.1896	0.1854
S	-2.8929**	1.3241	1.3779
MW	-0.1778**	0.0749	0.0743
Ln(Avetemp)	-4.0044***	0.9137	0.9059
Ln(Augrain)	-0.2142***	0.0783	0.0759
Ln(Marrain)	0.4327***	0.0553	0.0542
Ln(Avetemp)×S	0.8234*	0.4837	0.5041
SSR	7473.76		
Adj. R-sq	0.53		
F[26,14834]	635.72***		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

A.4 System of Seemingly Unrelated Rent and Wage Regression Equations

Table A.60: Results from the Rent Equation of Model 1

Model	Single Equation			SURE		
	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Constant	7.8672***	1.5351	1.3547	7.0375***	1.4996	1.3372
Flusht	0.3977***	0.0323	0.0338	0.3892***	0.0314	0.0328
Filter	0.1464***	0.0255	0.0262	0.1425***	0.0247	0.0254
Br1×A	0.8596***	0.0359	0.0364	0.7833***	0.0348	0.0358
Br2×A	1.0162***	0.0363	0.0333	0.9448***	0.0352	0.0325
Br3×A	1.2811***	0.0489	0.0487	1.1669***	0.0474	0.0468
Brgt3×A	1.3609***	0.1642	0.1505	1.1905***	0.1592	0.1597
Br2×H	0.3084***	0.0288	0.0281	0.2743***	0.0279	0.0276
Br3×H	0.7022***	0.0459	0.0555	0.6252***	0.0445	0.0536
Brgt3×H	1.0807***	0.0959	0.1339	0.9774***	0.0930	0.1221
Popdens	-0.0097***	0.0019	0.0015	-0.0099***	0.0019	0.0016
Banks	0.1170***	0.0305	0.0269	0.1160***	0.0298	0.0271
Deaths	0.0013*	0.0008	0.0007	0.0016**	0.0008	0.0007
Schools	-0.0043	0.0045	0.0033	-0.0058*	0.0044	0.0033
Altitude	-0.0035	0.0029	0.0025	-0.0019	0.0029	0.0025
N	1.7898***	0.3582	0.3310	1.6487***	0.3501	0.3296
NE	2.2096***	0.6675	0.5418	2.2023***	0.6513	0.5455
S	-1.1556***	0.2867	0.2454	-0.9734***	0.2798	0.2424
MW	-0.3442***	0.1572	0.1342	-0.4032***	0.1537	0.1347
Avetemp	-0.2013***	0.0639	0.0552	-0.1613***	0.0624	0.0544
Junerain	-0.0045***	0.0012	0.0010	-0.0045***	0.0012	0.0010
Febrain	0.0011***	0.0003	0.0003	0.0011***	0.0003	0.0003

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.61: Results from the Wage Equation of Model 1

Model	Single Equation			SURE		
Variable	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Constant	4.1852***	0.8504	0.8563	4.1901***	0.8498	0.8449
Ed5to8	0.2107***	0.0182	0.0167	0.2055***	0.0181	0.0167
Ed9to12	0.6205***	0.0184	0.0178	0.6038***	0.0182	0.0178
Edgt12	1.4522***	0.0227	0.0236	1.4172***	0.0226	0.0236
OJE	0.0455***	0.0019	0.0020	0.0454***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001	-0.0008***	0.0001	0.0001
Black	-0.1819***	0.0134	0.0133	-0.1736***	0.0133	0.0133
Male	0.5179***	0.0153	0.0158	0.5128***	0.0152	0.0157
Dir	0.3795***	0.0203	0.0213	0.3701***	0.0202	0.0212
SP	0.1621***	0.0225	0.0233	0.1570***	0.0223	0.0231
Mid	0.1930***	0.0219	0.0219	0.1863***	0.0217	0.0217
Ser	0.3071***	0.0185	0.0201	0.2965***	0.0184	0.0200
Oper	0.1709***	0.0235	0.0213	0.1717***	0.0233	0.0212
EO	-0.1992***	0.0209	0.0180	-0.1996***	0.0207	0.0179
Popdens	-0.0073***	0.0011	0.0010	-0.0074***	0.0011	0.0010
Banks	0.0707***	0.0164	0.0151	0.0711***	0.0164	0.0154
Deaths	0.0012***	0.0004	0.0004	0.0012***	0.0004	0.0004
Schools	-0.0095***	0.0020	0.0019	-0.0096***	0.0020	0.0019
Altitude	0.0044***	0.0016	0.0015	0.0044***	0.0016	0.0015
N	0.5786***	0.2057	0.2012	0.5735***	0.2056	0.2019
NE	1.4812***	0.3422	0.3154	1.4855***	0.3420	0.3193
S	-0.0615	0.1504	0.1526	-0.0573	0.1503	0.1506
MW	-0.4613***	0.0929	0.0870	-0.4694***	0.0928	0.0871
Avetemp	0.0155	0.0351	0.0355	0.0160	0.0351	0.0350
Junerain	-0.0030***	0.0007	0.0006	-0.0030***	0.0007	0.0006
Febrain	0.0007***	0.0002	0.0002	0.0007***	0.0002	0.0002
Rho				0.2484		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.62: Results from the Rent Equation of Model 2

Model	Single Equation			SURE		
Variable	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Constant	39.8923***	9.9511	9.6200	32.9732***	9.7111	9.4506
Flusht	0.3893***	0.0323	0.0336	0.3823***	0.0313	0.0326
Filter	0.1415***	0.0256	0.0264	0.1382***	0.0248	0.0255
Br1×A	0.8680***	0.0360	0.0363	0.7895***	0.0349	0.0357
Br2×A	1.0171***	0.0364	0.0334	0.9448***	0.0353	0.0326
Br3×A	1.2814***	0.0490	0.0487	1.1658***	0.0475	0.0468
Brgt3×A	1.3571***	0.1647	0.1499	1.1850***	0.1595	0.1592
Br2×H	0.3102***	0.0288	0.0283	0.2754***	0.0279	0.0278
Br3×H	0.7035***	0.0460	0.0556	0.6254***	0.0446	0.0537
Brgt3×H	1.0816***	0.0962	0.1336	0.9771***	0.0932	0.1217
Popdens	-0.0113***	0.0029	0.0027	-0.0105***	0.0028	0.0027
Banks	0.0374**	0.0177	0.0172	0.0323*	0.0172	0.0171
Deaths	0.0010	0.0012	0.0012	0.0012	0.0011	0.0012
Schools	-0.0000	0.0034	0.0032	-0.0015	0.0033	0.0031
Altitude	-0.0252***	0.0073	0.0072	-0.0206***	0.0071	0.0071
N	1.3760***	0.3473	0.3408	1.0704***	0.3392	0.3329
NE	1.9030***	0.6939	0.7112	1.6401**	0.6759	0.7052
S	-1.8124***	0.4660	0.4102	-1.4117***	0.4549	0.3974
MW	-0.1850	0.1585	0.1514	-0.2449*	0.1549	0.1507
Ln(Avetemp)	-11.9700***	3.1489	3.0336	-9.7574***	3.0724	2.9804
Ln(Junerain)	-0.5838***	0.2223	0.2256	-0.5061**	0.2165	0.2235
Ln(Febrain)	0.9012***	0.2377	0.2431	0.8498***	0.2315	0.2409

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.63: Results from the Wage Equation of Model 2

Model	Single Equation			SURE		
Variable	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Constant	-1.9468	5.2673	5.4875	-1.6426	5.2639	5.4154
Ed5to8	0.2109***	0.0182	0.0167	0.2056***	0.0181	0.0167
Ed9to12	0.6190***	0.0184	0.0179	0.6022***	0.0182	0.0178
Edgt12	1.4525***	0.0228	0.0237	1.4172***	0.0226	0.0237
OJE	0.0455***	0.0019	0.0020	0.0455***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001	-0.0008***	0.0001	0.0001
Black	-0.1844***	0.0134	0.0133	-0.1758***	0.0133	0.0133
Male	0.5182***	0.0153	0.0158	0.5129***	0.0152	0.0157
Dir	0.3795***	0.0203	0.0214	0.3700***	0.0202	0.0212
SP	0.1615***	0.0225	0.0233	0.1563***	0.0223	0.0231
Mid	0.1930***	0.0219	0.0219	0.18611***	0.0217	0.0217
Ser	0.3061***	0.0185	0.0201	0.2954***	0.0184	0.0200
Oper	0.1694***	0.0235	0.0213	0.1703***	0.0233	0.0212
EO	-0.1988***	0.0209	0.0180	-0.1994***	0.0207	0.0180
Popdens	-0.0034***	0.0014	0.0014	-0.0036***	0.0013	0.0014
Banks	0.0057	0.0088	0.0089	0.0052	0.0088	0.0091
Deaths	0.0000	0.0006	0.0006	0.0001	0.0006	0.0006
Schools	-0.0050***	0.0015	0.0015	-0.0051***	0.0015	0.0015
Altitude	0.0047	0.0037	0.0038	0.0044	0.0037	0.0038
N	-0.4480**	0.1964	0.2027	-0.4516**	0.1962	0.1996
NE	-0.1090	0.3199	0.3360	-0.0907	0.3197	0.3386
S	0.4290*	0.2517	0.2558	0.4267*	0.2515	0.2497
MW	-0.2898***	0.0922	0.0931	-0.3004***	0.0921	0.0933
Ln(Avetemp)	1.7943	1.6464	1.7124	1.6999	1.6454	1.6911
Ln(Junerain)	0.0350	0.1032	0.1083	0.0259	0.1031	0.1091
Ln(Febrain)	0.2675**	0.1059	0.1110	0.2805***	0.1058	0.1123
Rho				0.2503		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.64: Results from the Rent Equation of Model 3

Model	Single Equation			SURE		
	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Lambda	0.1306			0.1306		
Constant	61.9298***	12.9668	12.4960	50.2361***	12.6325	12.2594
Flusht	0.7265***	0.0631	0.0633	0.7097***	0.0610	0.0614
Filter	0.2830***	0.0500	0.0509	0.2776***	0.0484	0.0493
Br1×A	1.7235***	0.0702	0.0718	1.5653***	0.0680	0.0706
Br2×A	2.0205***	0.0711	0.0663	1.8726***	0.0689	0.0646
Br3×A	2.6063***	0.0958	0.1015	2.3821***	0.0927	0.0976
Brgt3×A	2.7683***	0.3215	0.3202	2.4478***	0.3111	0.3347
Br2×H	0.5978***	0.0563	0.0529	0.5259***	0.0545	0.0520
Br3×H	1.4143***	0.0898	0.1080	1.2607***	0.0869	0.1044
Brgt3×H	2.1976***	0.1877	0.2830	1.9939***	0.1817	0.2604
Popdens	-0.0244***	0.0052	0.0048	-0.0225***	0.0051	0.0048
Banks	0.0951***	0.0315	0.0303	0.0822***	0.0307	0.0302
Deaths	0.0033	0.0022	0.0021	0.0034	0.0021	0.0021
Schools	-0.0053	0.0070	0.0066	-0.0075	0.0068	0.0064
Altitude	-0.0463***	0.0107	0.0106	-0.0371***	0.0104	0.0104
N	3.0462***	0.6742	0.6722	2.3678***	0.6573	0.6582
NE	4.7093***	1.3584	1.3723	4.0082***	1.3208	1.3595
S	-3.2404***	0.8002	0.7123	-2.4581***	0.7801	0.6922
MW	-0.5630*	0.3120	0.2939	-0.6494**	0.3046	0.2923
BC(Avetemp)	-14.9935***	3.2685	3.1284	-11.9797***	3.1838	3.0684
BC(Junerain)	-0.7798***	0.2306	0.2303	-0.6665***	0.2242	0.2281
BC(Febrain)	0.8985***	0.1890	0.1898	0.8386***	0.1838	0.1878

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.65: Results from the Wage Equation of Model 3

Model	Single Equation			SURE		
	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Lambda	-0.0800			-0.0800		
Constant	-2.2942	3.8140	3.9420	-1.7319	3.8093	3.8684
Ed5to8	0.1364***	0.0110	0.0106	0.1334***	0.0109	0.0106
Ed9to12	0.3861***	0.0111	0.0112	0.3761***	0.0110	0.0112
Edgt12	0.8661***	0.0138	0.0142	0.8432***	0.0137	0.0142
OJE	0.0279***	0.0011	0.0012	0.0278***	0.0011	0.0012
OJEsq	-0.0005***	0.0000	0.0000	-0.0005***	0.0000	0.0000
Black	-0.1113***	0.0081	0.0081	-0.1060***	0.0080	0.0081
Male	0.3205***	0.0093	0.0098	0.3169***	0.0092	0.0097
Dir	0.2240***	0.0123	0.0129	0.2178***	0.0122	0.0128
SP	0.0981***	0.0136	0.0138	0.0952***	0.0135	0.0138
Mid	0.1202***	0.0132	0.0132	0.1162***	0.0131	0.0131
Ser	0.1752***	0.0112	0.0121	0.1683***	0.0111	0.0120
Oper	0.1054***	0.0142	0.0131	0.1060***	0.0141	0.0131
EO	-0.1330***	0.0127	0.0114	-0.1336***	0.0125	0.0114
Popdens	-0.0018**	0.0008	0.0008	-0.0020**	0.0008	0.0008
Banks	0.0041	0.0057	0.0058	0.0036	0.0057	0.0060
Deaths	-0.0001	0.0003	0.0003	-0.0000	0.0003	0.0004
Schools	-0.0030***	0.0009	0.0009	-0.0030***	0.0009	0.0009
Altitude	0.0039	0.0024	0.0025	0.0035	0.0024	0.0025
N	-0.3107***	0.1160	0.1176	-0.3055***	0.1159	0.1147
NE	-0.1518	0.1840	0.1944	-0.1250	0.1838	0.1951
S	0.3126**	0.1605	0.1615	0.2993*	0.1604	0.1568
MW	-0.1695***	0.0557	0.0557	-0.1770***	0.0557	0.0553
BC(Avetemp)	1.9463	1.3631	1.4092	1.7428	1.3614	1.3853
BC(Junerain)	0.0677	0.0866	0.0914	0.0520	0.0865	0.0917
BC(Febrain)	0.2090*	0.1053	0.1116	0.2303*	0.1052	0.1125
Rho				0.2558		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.66: Results from the Rent Equation of Model 4

Model	Single Equation			SURE		
Variable	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Constant	12.5033***	1.9273	1.6407	11.6145***	1.8793	1.6351
Flusht	0.3911***	0.0322	0.0336	0.3835***	0.0312	0.0327
Filter	0.1478***	0.0256	0.0264	0.1434***	0.0248	0.0255
Br1×A	0.8650***	0.0358	0.0363	0.7879***	0.0348	0.0357
Br2×A	1.0189***	0.0363	0.0333	0.9470***	0.0352	0.0325
Br3×A	1.2852***	0.0489	0.0487	1.1702***	0.0474	0.0468
Brgt3×A	1.3692***	0.1644	0.1510	1.1970***	0.1593	0.1599
Br2×H	0.3095***	0.0288	0.0282	0.2753***	0.0279	0.0277
Br3×H	0.7046***	0.0459	0.0556	0.6273***	0.0445	0.0537
Brgt3×H	1.0844***	0.0960	0.1344	0.9802***	0.0930	0.1225
Popdens	-0.0064***	0.0015	0.0013	-0.0066***	0.0014	0.0013
Banks	0.0489*	0.0276	0.0264	0.0489*	0.0269	0.0264
Deaths	-0.0005	0.0012	0.0011	-0.0003	0.0012	0.0011
Schools	0.0033	0.0041	0.0031	0.0016	0.0040	0.0030
Altitude	-0.0130***	0.0032	0.0028	-0.0113***	0.0031	0.0028
N	1.0970***	0.2430	0.2408	0.9550***	0.2369	0.2401
NE	0.4321	0.3415	0.3024	0.4437	0.3327	0.3012
S	-1.6782***	0.3120	0.2363	-1.4863***	0.3040	0.2342
MW	0.1110	0.1728	0.1637	0.0499	0.1686	0.1632
Avetemp	-0.3733***	0.0773	0.0632	-0.3309***	0.0753	0.0629
Augrain	-0.0021	0.0017	0.0015	-0.0021	0.0016	0.0015
Marrain	0.0020***	0.0003	0.0004	0.0020***	0.0003	0.0004

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.67: Results from the Wage Equation of Model 4

Model	Single Equation			SURE		
Variable	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Constant	5.9171***	0.9394	0.9259	6.0110***	0.9387	0.9279
Ed5to8	0.2115***	0.0182	0.0167	0.2062***	0.0181	0.0167
Ed9to12	0.6210***	0.0184	0.0179	0.6042***	0.0183	0.0178
Edgt12	1.4545***	0.0227	0.0236	1.4193***	0.0226	0.0237
OJE	0.0455***	0.0019	0.0020	0.0455***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001	-0.0008***	0.0001	0.0001
Black	-0.1818***	0.0134	0.0133	-0.1734***	0.0133	0.0133
Male	0.5186***	0.0153	0.0158	0.5134***	0.0152	0.0157
Dir	0.3794***	0.0203	0.0213	0.3700***	0.0202	0.0212
SP	0.16234***	0.0225	0.0233	0.1571***	0.0223	0.0231
Mid	0.1937***	0.0219	0.0219	0.1869***	0.0217	0.0217
Ser	0.3073***	0.0185	0.0201	0.2966***	0.0184	0.0199
Oper	0.1706***	0.0235	0.0213	0.1714***	0.0233	0.0212
EO	-0.1976***	0.0209	0.0180	-0.1982***	0.0207	0.0179
Popdens	-0.0059***	0.0008	0.0008	-0.0060***	0.0008	0.0008
Banks	0.0461***	0.0136	0.0137	0.0453***	0.0136	0.0139
Deaths	0.0008	0.0005	0.0005	0.0008	0.0005	0.0005
Schools	-0.0077***	0.0018	0.0017	-0.0076***	0.0018	0.0017
Altitude	0.0001	0.0016	0.0016	-0.0000	0.0016	0.0016
N	0.2229*	0.1191	0.1235	0.2085*	0.1190	0.1241
NE	0.5902***	0.1564	0.1541	0.5734***	0.1563	0.1549
S	-0.2215*	0.1405	0.1349	-0.2283*	0.1404	0.1342
MW	-0.2673***	0.0883	0.0861	-0.2671***	0.0883	0.0861
Avetemp	-0.0467	0.0373	0.0364	-0.0495	0.0373	0.0364
Augrain	-0.0028***	0.0007	0.0007	-0.0027***	0.0007	0.0007
Marrain	0.0013***	0.0002	0.0002	0.0014***	0.0002	0.0002
Rho				0.2485		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.68: Results from the Rent Equation of Model 5

Model	Single Equation			SURE		
	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Constant	39.9737***	5.0233	4.8837	37.0386***	4.9085	4.8828
Flusht	0.3955***	0.0324	0.0338	0.3874***	0.0314	0.0329
Filter	0.1502***	0.0256	0.0263	0.1456***	0.0248	0.0255
Br1×A	0.8646***	0.0360	0.0365	0.7874***	0.0349	0.0359
Br2×A	1.0192***	0.0364	0.0334	0.9471***	0.0353	0.0326
Br3×A	1.2849***	0.0490	0.0488	1.1697***	0.0475	0.0469
Brgt3×A	1.3712***	0.1645	0.1521	1.1986***	0.1594	0.1606
Br2×H	0.3064***	0.0288	0.0281	0.2725***	0.0279	0.0277
Br3×H	0.7024***	0.0460	0.0556	0.6251***	0.0445	0.0537
Brgt3×H	1.0886***	0.0960	0.1352	0.9839***	0.0931	0.1233
Popdens	-0.0109***	0.0020	0.0017	-0.0110***	0.0020	0.0017
Banks	0.0519***	0.0157	0.0143	0.0473***	0.0154	0.0144
Deaths	0.0010	0.0012	0.0011	0.0011	0.0012	0.0011
Schools	-0.0053**	0.0040	0.0027	-0.0064**	0.0039	0.0028
Altitude	-0.0238***	0.0036	0.0035	-0.0219***	0.0035	0.0035
N	1.3352***	0.2142	0.2070	1.1550***	0.2092	0.2050
NE	1.1399***	0.2721	0.2313	1.0897***	0.2653	0.2334
S	-2.1411***	0.3043	0.2577	-1.9265***	0.2969	0.2591
MW	0.1390	0.1225	0.1142	0.0789	0.1198	0.1147
Ln(Avetemp)	-11.4764***	1.5065	1.4559	-10.5432***	1.4720	1.4579
Ln(Augrain)	-0.4867***	0.1319	0.1145	-0.4690***	0.1286	0.1151
Ln(Marrain)	0.5538***	0.0995	0.0904	0.5662***	0.0972	0.0900

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.69: Results from the Wage Equation of Model 5

Model	Single Equation			SURE		
Variable	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Constant	19.1089***	2.8520	2.8409	19.1440***	2.8500	2.8682
Ed5to8	0.2114***	0.0182	0.0167	0.2062***	0.0181	0.0167
Ed9to12	0.6215***	0.0184	0.0179	0.6047***	0.0183	0.0178
Edgt12	1.4541***	0.0227	0.0236	1.4190***	0.0226	0.0237
OJE	0.0455***	0.0019	0.0020	0.0455***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001	-0.0008***	0.0001	0.0001
Black	-0.1818***	0.0134	0.0133	-0.1734***	0.0133	0.0133
Male	0.5187***	0.0153	0.0158	0.5136***	0.0152	0.0157
Dir	0.3794***	0.0203	0.0213	0.3701***	0.0202	0.0212
SP	0.1624***	0.0225	0.0233	0.1573***	0.0223	0.0231
Mid	0.1939***	0.0219	0.0219	0.1870***	0.0217	0.0217
Ser	0.3077***	0.0185	0.0201	0.2969***	0.0184	0.0200
Oper	0.1710***	0.0235	0.0213	0.1718***	0.0233	0.0212
EO	-0.1975***	0.0209	0.0180	-0.1982***	0.0207	0.0179
Popdens	-0.0081***	0.0011	0.0010	-0.0081***	0.0011	0.0010
Banks	0.0127	0.0079	0.0078	0.0127	0.0079	0.0080
Deaths	0.0009	0.0006	0.0006	0.0009	0.0006	0.0006
Schools	-0.0092***	0.0017	0.0016	-0.0092***	0.0017	0.0016
Altitude	-0.0093***	0.0020	0.0020	-0.0093***	0.0020	0.0020
N	0.1513	0.1179	0.1206	0.1403	0.1178	0.1202
NE	0.6426***	0.1332	0.1265	0.6330***	0.1331	0.1285
S	-0.6540***	0.1548	0.1511	-0.6541***	0.1547	0.1525
MW	-0.1433**	0.0721	0.0698	-0.1467**	0.0720	0.0704
Ln(Avetemp)	-4.5657***	0.8522	0.8439	-4.5772***	0.8516	0.8543
Ln(Augrain)	-0.2890***	0.0648	0.0626	-0.2880***	0.0648	0.0632
Ln(Marrain)	0.4243***	0.0550	0.0537	0.4286***	0.0550	0.0534
Rho				0.2488		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.70: Results from the Rent Equation of Model 6

Model	Single Equation			SURE		
Variable	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Lambda	0.1265			0.1265		
Constant	53.9113***	6.8172	6.6759	49.4750***	6.6579	6.6869
Flusht	0.7176***	0.0619	0.0624	0.6995***	0.0599	0.0607
Filter	0.2931***	0.0490	0.0498	0.2854***	0.0474	0.0482
Br1×A	1.6859***	0.0688	0.0706	1.5321***	0.0666	0.0694
Br2×A	1.9823***	0.0696	0.0650	1.8372***	0.0674	0.0633
Br3×A	2.5572***	0.0937	0.0994	2.3373***	0.0908	0.0956
Brgt3×A	2.7385***	0.3146	0.3168	2.4218***	0.3045	0.3295
Br2×H	0.5796***	0.0551	0.0517	0.5105***	0.0534	0.0508
Br3×H	1.3834***	0.0879	0.1058	1.2338***	0.0851	0.1022
Brgt3×H	2.1666***	0.1837	0.2800	1.9656***	0.1778	0.2575
Popdens	-0.0190***	0.0036	0.0032	-0.0191***	0.0035	0.0032
Banks	0.1106***	0.0287	0.0272	0.1015***	0.0280	0.0273
Deaths	0.0012	0.0023	0.0020	0.0016	0.0023	0.0020
Schools	-0.0091*	0.0078	0.0053	-0.0116**	0.0076	0.0054
Altitude	-0.0373***	0.0056	0.0056	-0.0339***	0.0055	0.0056
N	2.4118***	0.4026	0.3987	2.0711***	0.3929	0.3949
NE	1.9839***	0.5238	0.4502	1.8930***	0.5103	0.4549
S	-3.5752***	0.5623	0.4578	-3.1738***	0.5479	0.4622
MW	0.1672	0.2475	0.2298	0.0565	0.2417	0.2315
BC(Avetemp)	-12.6396***	1.6929	1.6252	-11.4641***	1.6529	1.6312
BC(Augrain)	-0.4734***	0.1444	0.1274	-0.4561***	0.1407	0.1283
BC(Marrain)	0.4998***	0.0891	0.0829	0.5108***	0.0870	0.0823

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.71: Results from the Wage Equation of Model 6

Model	Single Equation			SURE		
Variable	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Lambda	-0.0798			-0.0798		
Constant	15.5761***	2.1994	2.1630	15.5808***	2.1979	2.1785
Ed5to8	0.1368***	0.0110	0.0106	0.1338***	0.0109	0.0106
Ed9to12	0.3880***	0.0111	0.0112	0.3780***	0.0111	0.0112
Edgt12	0.8680***	0.0138	0.0142	0.8453***	0.0137	0.0142
OJE	0.0279***	0.0011	0.0012	0.0279***	0.0011	0.0012
OJEsq	-0.0005***	0.0000	0.0000	-0.0005***	0.0000	0.0000
Black	-0.1099***	0.0081	0.0082	-0.1046***	0.0080	0.0081
Male	0.3211***	0.0093	0.0098	0.3176***	0.0092	0.0097
Dir	0.2242***	0.0123	0.0129	0.2180***	0.0122	0.0128
SP	0.0989***	0.0136	0.0139	0.0959***	0.0135	0.0138
Mid	0.1209***	0.0133	0.0132	0.1168***	0.0131	0.0131
Ser	0.1764***	0.0112	0.0121	0.1694***	0.0111	0.0120
Oper	0.1066***	0.0142	0.0131	0.1071***	0.0141	0.0131
EO	-0.1325***	0.0127	0.0114	-0.1331***	0.0126	0.0114
Popdens	-0.0052***	0.0007	0.0006	-0.0052***	0.0007	0.0006
Banks	0.0055	0.0049	0.0049	0.0055	0.0049	0.0050
Deaths	0.0006*	0.0004	0.0004	0.0006*	0.0004	0.0004
Schools	-0.0056***	0.0010	0.0010	-0.0056***	0.0010	0.0010
Altitude	-0.0069***	0.0014	0.0014	-0.0069***	0.0014	0.0014
N	0.1094	0.0729	0.0732	0.1020	0.0728	0.0727
NE	0.4037***	0.0824	0.0779	0.3964***	0.0824	0.0791
S	-0.4810***	0.1011	0.0981	-0.4809***	0.1010	0.0989
MW	-0.0693*	0.0430	0.0413	-0.0710*	0.0430	0.0415
BC(Avetemp)	-4.2219***	0.7437	0.7275	-4.2267***	0.7432	0.7352
BC(Augrain)	-0.2658***	0.0572	0.0551	-0.2639***	0.0571	0.0555
BC(Marrain)	0.4150***	0.0533	0.0511	0.4191***	0.0533	0.0508
Rho				0.2548		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.72: Results from the Rent Equation of Model 7

Model	Single Equation			SURE		
	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Constant	8.9086***	2.9280	2.4421	8.1305***	2.8575	2.4547
Flusht	0.3978***	0.0324	0.0338	0.3894***	0.0314	0.0328
Filter	0.1456***	0.0256	0.0263	0.1414***	0.0248	0.0255
Br1×A	0.8588***	0.0360	0.0364	0.7823***	0.0349	0.0358
Br2×A	1.0154***	0.0364	0.0333	0.9438***	0.0353	0.0325
Br3×A	1.2800***	0.0490	0.0488	1.1655***	0.0475	0.0469
Brgt3×A	1.3589***	0.1643	0.1505	1.1880***	0.1593	0.1597
Br2×H	0.3087***	0.0288	0.0282	0.2747***	0.0279	0.0277
Br3×H	0.70216***	0.0459	0.0555	0.6251***	0.0445	0.0536
Brgt3×H	1.0799***	0.0960	0.1337	0.9764***	0.0930	0.1219
Popdens	-0.0094***	0.0020	0.0016	-0.0096***	0.0020	0.0016
Banks	0.1079***	0.0376	0.0311	0.1063***	0.0367	0.0314
Deaths	0.0012	0.0009	0.0008	0.0014*	0.0009	0.0008
Schools	-0.0037	0.0047	0.0033	-0.0052	0.0046	0.0033
Altitude	-0.0052	0.0049	0.0040	-0.0036	0.0048	0.0040
N	1.7098***	0.4063	0.3588	1.5620***	0.3968	0.3588
NE	2.0779***	0.7383	0.5707	2.0601***	0.7202	0.5769
S	-1.1301***	0.2931	0.2585	-0.9469***	0.2861	0.2553
MW	-0.2826	0.2156	0.1800	-0.3374*	0.2105	0.1813
Avetemp	-0.2408***	0.1143	0.0943	-0.2028**	0.1115	0.0946
Junerain	-0.0098	0.0127	0.0118	-0.0100	0.0124	0.0118
Febrain	0.0013***	0.0004	0.0004	0.0013***	0.0004	0.0004
Avetemp× Junerain	0.0002	0.0005	0.0005	0.0002	0.0005	0.0005

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.73: Results from the Wage Equation of Model 7

Model	Single Equation			SURE		
	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Constant	2.5805*	1.5356	1.5455	2.6998*	1.5345	1.5582
Ed5to8	0.2110***	0.0182	0.0167	0.2058***	0.0181	0.0167
Ed9to12	0.6210***	0.0184	0.0179	0.6042***	0.0183	0.0178
Edgt12	1.4533***	0.0227	0.0237	1.4182***	0.0226	0.0237
OJE	0.0455***	0.0019	0.0020	0.0454***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001	-0.0008***	0.0001	0.0001
Black	-0.1816***	0.0134	0.0133	-0.1733***	0.0133	0.0133
Male	0.5181***	0.0153	0.0158	0.5130***	0.0152	0.0157
Dir	0.3793***	0.0203	0.0213	0.3699***	0.0202	0.0212
SP	0.1624***	0.0225	0.0233	0.1573***	0.0223	0.0231
Mid	0.1935***	0.0219	0.0219	0.1868***	0.0217	0.0217
Ser	0.3073***	0.0185	0.0201	0.2968***	0.0184	0.0200
Oper	0.1709***	0.0235	0.0213	0.1718***	0.0233	0.0212
EO	-0.1984***	0.0209	0.0180	-0.1988***	0.0207	0.0179
Popdens	-0.0077***	0.0011	0.0010	-0.0077***	0.0011	0.0010
Banks	0.0844***	0.0197	0.0181	0.0838***	0.0197	0.0184
Deaths	0.0014***	0.0005	0.0004	0.0014***	0.0004	0.0004
Schools	-0.0103***	0.0021	0.0019	-0.0103***	0.0021	0.0019
Altitude	0.0069***	0.0025	0.0025	0.0067***	0.0025	0.0025
N	0.6881***	0.2234	0.2153	0.6751***	0.2233	0.2155
NE	1.6649***	0.3722	0.3342	1.6561***	0.3719	0.3371
S	-0.1020	0.1538	0.1565	-0.0949	0.1537	0.1547
MW	-0.5510***	0.1172	0.1076	-0.5527***	0.1171	0.1080
Avetemp	0.0764	0.0599	0.0603	0.0726	0.0599	0.0607
Junerain	0.0053	0.0066	0.0069	0.0046	0.0066	0.0070
Febrain	0.0005**	0.0002	0.0002	0.0006**	0.0002	0.0002
Avetemp× Junerain	-0.0003	0.0003	0.0003	-0.0003	0.0003	0.0003
Rho				0.2484		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.74: Results from the Rent Equation of Model 8

Model	Single Equation			SURE		
	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Constant	46.3586***	10.4226	9.7576	39.9930***	10.1759	9.6447
Flusht	0.3881***	0.0323	0.0336	0.3812***	0.0313	0.0326
Filter	0.1416***	0.0256	0.0264	0.1382***	0.0248	0.0255
Br1×A	0.8634***	0.0360	0.0363	0.7852***	0.0349	0.0357
Br2×A	1.0142***	0.0364	0.0334	0.9421***	0.0353	0.0325
Br3×A	1.2789***	0.0490	0.0488	1.1635***	0.0475	0.0469
Brgt3×A	1.3571***	0.1646	0.1490	1.1852***	0.1594	0.1587
Br2×H	0.3116***	0.0288	0.0282	0.2768***	0.0279	0.0277
Br3×H	0.7047***	0.0460	0.0556	0.6266***	0.0445	0.0537
Brgt3×H	1.0813***	0.0961	0.1338	0.9769***	0.0931	0.1219
Popdens	-0.0068**	0.0036	0.0035	-0.0060*	0.0035	0.0035
Banks	0.0340**	0.0177	0.0171	0.0281*	0.0173	0.0170
Deaths	-0.0007	0.0014	0.0014	-0.0006	0.0014	0.0014
Schools	0.0047	0.0041	0.0039	0.0033	0.0040	0.0038
Altitude	-0.0212***	0.0075	0.0076	-0.01659**	0.0073	0.0075
N	1.0209***	0.3869	0.3851	0.7008*	0.3779	0.3779
NE	0.6971	0.9046	0.9266	0.4056	0.8809	0.9198
S	-1.7054***	0.4686	0.4172	-1.2991***	0.4574	0.4047
MW	0.1633	0.2308	0.2215	0.1137	0.2251	0.2213
Ln(Avetemp)	-14.0561***	3.3039	3.0809	-12.0224***	3.2253	3.0454
Ln(Junerain)	-3.1170***	1.2401	1.1036	-3.1708***	1.2114	1.1173
Ln(Febrain)	0.6074**	0.2765	0.2861	0.5536**	0.2691	0.2835
Ln(Avetemp)×Ln(Junerain)	0.9132**	0.4398	0.3989	0.9573**	0.4295	0.4027

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.75: Results from the Wage Equation of Model 8

Model	Single Equation			SURE		
Variable	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Constant	2.3681	5.7372	5.9633	2.7834	5.7333	5.9666
Ed5to8	0.2110***	0.0182	0.0167	0.2057***	0.0181	0.0167
Ed9to12	0.6189***	0.0184	0.0179	0.6021***	0.0182	0.0178
Edgt12	1.4519***	0.0228	0.0237	1.4165***	0.0226	0.0237
OJE	0.0456***	0.0019	0.0020	0.0455***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001	-0.0008***	0.0001	0.0001
Black	-0.1843***	0.0134	0.0133	-0.1758***	0.0133	0.0133
Male	0.5188***	0.0153	0.0158	0.5135***	0.0152	0.0157
Dir	0.3800***	0.0203	0.0213	0.3705***	0.0202	0.0212
SP	0.1609***	0.0225	0.0233	0.1556***	0.0223	0.0231
Mid	0.1921***	0.0219	0.0219	0.1854***	0.0217	0.0217
Ser	0.3063***	0.0185	0.0201	0.2956***	0.0184	0.0200
Oper	0.1695***	0.0235	0.0213	0.1704***	0.0233	0.0212
EO	-0.1993***	0.0209	0.0180	-0.1998***	0.0207	0.0180
Popdens	-0.0016	0.0016	0.0016	-0.0018	0.0016	0.0016
Banks	0.0013	0.0091	0.0093	0.0007	0.0091	0.0095
Deaths	-0.0006	0.0006	0.0007	-0.0006	0.0006	0.0007
Schools	-0.0033*	0.0017	0.0018	-0.0033*	0.0017	0.0018
Altitude	0.0058	0.0037	0.0039	0.0056	0.0037	0.0039
N	-0.6181***	0.2159	0.2246	-0.6261***	0.2157	0.2224
NE	-0.5920	0.4089	0.4219	-0.5863	0.4086	0.4247
S	0.4869*	0.2535	0.2585	0.4863**	0.2533	0.2529
MW	-0.1418	0.1208	0.1170	-0.1486	0.1207	0.1186
Ln(Avetemp)	0.4006	1.8028	1.8710	0.2702	1.8016	1.8738
Ln(Junerain)	-1.2913*	0.7069	0.7251	-1.3351*	0.7064	0.7451
Ln(Febrain)	0.1702	0.1177	0.1212	0.1806	0.1176	0.1223
Ln(Avetemp)×Ln(Junerain)	0.4634*	0.2443	0.2497	0.4755*	0.2442	0.2562
Rho				0.2502		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.76: Results from the Rent Equation of Model 9

Model	Single Equation			SURE		
	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Lambda	0.1293			0.1293		
Constant	69.7295***	14.2657	13.1784	60.4121***	13.9198	13.0552
Flusht	0.7195***	0.0627	0.0630	0.7026***	0.0606	0.0610
Filter	0.2803***	0.0497	0.0506	0.2748***	0.0481	0.0489
Br1×A	1.7068***	0.0698	0.0713	1.5498***	0.0677	0.0702
Br2×A	2.0029***	0.0707	0.0658	1.8560***	0.0685	0.0641
Br3×A	2.5844***	0.0951	0.1009	2.3618***	0.0921	0.0971
Brgt3×A	2.7477***	0.3193	0.3164	2.4293***	0.3089	0.3312
Br2×H	0.5959***	0.0559	0.0527	0.5247***	0.0541	0.0517
Br3×H	1.4061***	0.0892	0.1073	1.2537***	0.0863	0.1037
Brgt3×H	2.1816***	0.1865	0.2810	1.9794***	0.1804	0.2584
Popdens	-0.0188***	0.0066	0.0062	-0.0162***	0.0064	0.0062
Banks	0.0739**	0.0348	0.0320	0.0567*	0.0340	0.0321
Deaths	0.0012	0.0027	0.0026	0.0011	0.0026	0.0026
Schools	0.0015	0.0085	0.0081	0.0001	0.0083	0.0080
Altitude	-0.044***	0.0107	0.0107	-0.0356***	0.0105	0.0105
N	2.4812***	0.7832	0.7794	1.7369**	0.7630	0.7679
NE	3.0537*	1.8137	1.8054	2.1618	1.7625	1.7970
S	-3.1732***	0.7965	0.7141	-2.4044***	0.7764	0.6946
MW	-0.1013	0.4616	0.4290	-0.1181	0.4497	0.4307
BC(Avetemp)	-20.9784***	5.5659	4.8832	-19.3055***	5.4341	4.9112
BC(Junerain)	-6.3579*	4.1906	3.7057	-7.3130**	4.0879	3.7537
BC(Febrain)	0.7595***	0.2164	0.2188	0.6888***	0.2103	0.2170
BC(Avetemp×Junerain)	3.8707	2.9027	2.5801	4.5989*	2.8308	2.6114

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.77: Results from the Wage Equation of Model 9

Model	Single Equation			SURE		
Variable	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Lambda	-0.0803			-0.0803		
Constant	1.8496	4.2100	4.3407	2.3881	4.2063	4.3216
Ed5to8	0.1363***	0.0110	0.0106	0.1333***	0.0109	0.0106
Ed9to12	0.3854***	0.0111	0.0112	0.3754***	0.0110	0.0111
Edgt12	0.8640***	0.0137	0.0142	0.8412***	0.0136	0.0142
OJE	0.0279***	0.0011	0.0012	0.0278***	0.0011	0.0012
OJEsq	-0.0005***	0.0000	0.0000	-0.0005***	0.0000	0.0000
Black	-0.1109***	0.0081	0.0081	-0.1057***	0.0080	0.0081
Male	0.3203***	0.0093	0.0098	0.3168***	0.0092	0.0097
Dir	0.2240***	0.0123	0.0129	0.2177***	0.0122	0.0128
SP	0.0975***	0.0136	0.0138	0.0946***	0.0134	0.0137
Mid	0.1194***	0.0132	0.0132	0.1154***	0.0131	0.0131
Ser	0.1750***	0.0112	0.0121	0.1681***	0.0111	0.0120
Oper	0.1054***	0.0142	0.0131	0.1060***	0.0141	0.0131
EO	-0.1332***	0.0126	0.0114	-0.1337***	0.0125	0.0114
Popdens	-0.0006	0.0010	0.0010	-0.0008	0.0010	0.0010
Banks	0.0028	0.0057	0.0059	0.0023	0.0057	0.0060
Deaths	-0.0005	0.0004	0.0004	-0.0004	0.0004	0.0004
Schools	-0.0018*	0.0010	0.0010	-0.0019*	0.0010	0.0010
Altitude	0.0047*	0.0024	0.0026	0.0043*	0.0024	0.0025
N	-0.4014***	0.1223	0.1257	-0.3964***	0.1221	0.1233
NE	-0.4495*	0.2243	0.2345	-0.4219*	0.2239	0.2352
S	0.3430**	0.1608	0.1622	0.3306**	0.1606	0.1578
MW	-0.067	0.0709	0.0685	-0.0755	0.0709	0.0688
BC(Avetemp)	7.3536***	2.7072	2.7965	7.1414***	2.7034	2.8189
BC(Junerain)	5.5456**	2.3720	2.4406	5.5164**	2.3697	2.4972
BC(Febrain)	0.0989	0.1155	0.1207	0.1207	0.1154	0.1215
BC(Avetemp× Junerain)	-6.8980**	2.9850	3.0725	-6.8809**	2.9822	3.1455
Rho				0.2557		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.78: Results from the Rent Equation of Model 10

Model	Single Equation			SURE		
Variable	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Constant	5.9954	4.3234	4.1503	4.8341	4.2114	4.1137
Flusht	0.3977***	0.0324	0.0338	0.3893***	0.0314	0.0328
Filter	0.1474***	0.0256	0.0264	0.1432***	0.0248	0.0255
Br1×A	0.8595***	0.0359	0.0365	0.7834***	0.0348	0.0358
Br2×A	1.0164***	0.0363	0.0333	0.9451***	0.0352	0.0325
Br3×A	1.2816***	0.0489	0.0487	1.1675***	0.0474	0.0468
Brgt3×A	1.3631***	0.1643	0.1511	1.1924***	0.1593	0.1601
Br2×H	0.3082***	0.0288	0.0281	0.2742***	0.0279	0.0277
Br3×H	0.7024***	0.0459	0.0555	0.6255***	0.0445	0.0536
Brgt3×H	1.0819***	0.0960	0.1343	0.9784***	0.0930	0.1225
Popdens	-0.0102***	0.0022	0.0019	-0.0104***	0.0022	0.0019
Banks	0.1229***	0.0330	0.0289	0.1224***	0.0322	0.0291
Deaths	0.0015**	0.0008	0.0007	0.0017**	0.0008	0.0007
Schools	-0.0054	0.0051	0.0035	-0.0071**	0.0050	0.0036
Altitude	-0.0014	0.0054	0.0049	0.00061	0.0053	0.0049
N	1.7915***	0.3583	0.3308	1.6347***	0.3502	0.3296
NE	2.2600***	0.6763	0.5369	2.2474***	0.6598	0.5422
S	-0.9084*	0.6058	0.5566	-0.6792	0.5903	0.5519
MW	-0.4412*	0.2619	0.2504	-0.5160**	0.2554	0.2487
Avetemp	-0.1232	0.1802	0.1718	-0.0694	0.1755	0.1702
Junerain	-0.0046***	0.0013	0.0010	-0.0046***	0.0013	0.0011
Febrain	0.0044	0.0071	0.0074	0.0049	0.0069	0.0073
Avetemp× Febrain	-0.0001	0.0003	0.0003	-0.0002	0.0003	0.0003

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.79: Results from the Wage Equation of Model 10

Model	Single Equation			SURE		
Variable	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Constant	-0.2341	1.9324	2.0001	-0.1099	1.9311	1.9804
Ed5to8	0.2116***	0.0182	0.0167	0.2064***	0.0181	0.0167
Ed9to12	0.6215***	0.0184	0.0179	0.6047***	0.0182	0.0178
Edgt12	1.4539***	0.0227	0.0236	1.4189***	0.0226	0.0237
OJE	0.0456***	0.0019	0.0020	0.0455***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001	-0.0008***	0.0001	0.0001
Black	-0.1815***	0.0134	0.0133	-0.1731***	0.0133	0.0133
Male	0.5189***	0.0153	0.0158	0.5138***	0.0152	0.0157
Dir	0.3797***	0.0203	0.0213	0.3703***	0.0201	0.0212
SP	0.1621***	0.0225	0.0233	0.1570***	0.0223	0.0231
Mid	0.1934***	0.0219	0.0219	0.1866***	0.0217	0.0217
Ser	0.3077***	0.0185	0.0201	0.2971***	0.0184	0.0200
Oper	0.1710***	0.0235	0.0213	0.1718***	0.0233	0.0212
EO	-0.1978***	0.0209	0.0180	-0.1983***	0.0207	0.0179
Popdens	-0.0084***	0.0012	0.0011	-0.0085***	0.0012	0.0011
Banks	0.0820***	0.0170	0.0158	0.0822***	0.0170	0.0160
Deaths	0.0014***	0.0004	0.0004	0.0015***	0.0004	0.0004
Schools	-0.0120***	0.0022	0.0021	-0.0120***	0.0022	0.0021
Altitude	0.0093***	0.0025	0.0025	0.0092***	0.0025	0.0025
N	0.5060***	0.2077	0.2035	0.5028***	0.2075	0.2040
NE	1.5334***	0.3427	0.3152	1.5362***	0.3425	0.3192
S	0.5373*	0.2791	0.2867	0.5253*	0.2789	0.2831
MW	-0.6841***	0.1276	0.1260	-0.6862***	0.1275	0.1251
Avetemp	0.2000**	0.0805	0.0833	0.1955**	0.0804	0.0824
Junerain	-0.0032***	0.0007	0.0006	-0.0033***	0.0007	0.0006
Febrain	0.0083***	0.0030	0.0031	0.0081***	0.0030	0.0031
Avetemp× Febrain	-0.0003**	0.0001	0.0001	-0.0003**	0.0001	0.0001
Rho				0.2481		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.80: Results from the Rent Equation of Model 13

Model	Single Equation			SURE		
Variable	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Constant	7.4650**	3.7146	3.4473	6.0366*	3.6215	3.4321
Flusht	0.3928***	0.0322	0.0336	0.3851***	0.0312	0.0327
Filter	0.1480***	0.0256	0.0264	0.1436***	0.0248	0.0255
Br1×A	0.8604***	0.0360	0.0363	0.7834***	0.0349	0.0357
Br2×A	1.0157***	0.0364	0.0333	0.9439***	0.0353	0.0325
Br3×A	1.2819***	0.0490	0.0488	1.1670***	0.0475	0.0469
Brgt3×A	1.3680***	0.1643	0.1507	1.1958***	0.1592	0.1598
Br2×H	0.3098***	0.0288	0.0281	0.2756***	0.0279	0.0277
Br3×H	0.7045***	0.0459	0.0556	0.6272***	0.0445	0.0537
Brgt3×H	1.0850***	0.0960	0.1347	0.9808***	0.0930	0.1228
Popdens	-0.0052***	0.0017	0.0014	-0.0052***	0.0016	0.0014
Banks	0.01356	0.0354	0.0306	0.0075	0.0346	0.0311
Deaths	-0.0001	0.0012	0.0012	0.0001	0.0012	0.0012
Schools	0.0018	0.0042	0.0031	-0.0000	0.0041	0.0031
Altitude	-0.0036	0.0067	0.0063	-0.0008	0.0066	0.0063
N	0.6345*	0.3795	0.3383	0.4174	0.3712	0.3405
NE	0.0668	0.4118	0.3503	0.0119	0.4022	0.3547
S	-1.5927***	0.3166	0.2362	-1.4015***	0.3083	0.2360
MW	-0.1311	0.2304	0.2308	-0.2160	0.2247	0.2290
Avetemp	-0.1530	0.1589	0.1447	-0.0863	0.1549	0.1442
Augrain	0.0366*	0.0245	0.0224	0.0415*	0.0239	0.0225
Marrain	0.0018***	0.0004	0.0004	0.0018***	0.0004	0.0004
Avetemp×	-0.0015*	0.0009	0.0009	-0.0017**	0.0009	0.0009
Augrain						

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.81: Results from the Wage Equation of Model 13

Model	Single Equation			SURE		
	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Constant	2.5946	1.8052	1.8416	2.6204	1.8039	1.8489
Ed5to8	0.2118***	0.0182	0.0167	0.2064***	0.0181	0.0167
Ed9to12	0.6211***	0.0184	0.0179	0.6043***	0.0182	0.0178
Edgt12	1.4537***	0.0227	0.0237	1.4185***	0.0226	0.0237
OJE	0.0456***	0.0019	0.0020	0.0456***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001	-0.0008***	0.0001	0.0001
Black	-0.1819***	0.0134	0.0133	-0.1736***	0.0133	0.0133
Male	0.5193***	0.0153	0.0158	0.5142***	0.0152	0.0157
Dir	0.3801***	0.0203	0.0213	0.3705***	0.0202	0.0212
SP	0.1616***	0.0225	0.0233	0.1562***	0.0223	0.0231
Mid	0.1928***	0.0219	0.0219	0.1861***	0.0217	0.0217
Ser	0.3075***	0.0185	0.0201	0.2968***	0.0184	0.0200
Oper	0.1707***	0.0235	0.0213	0.1715***	0.0233	0.0212
EO	-0.1980***	0.0209	0.0180	-0.1985***	0.0207	0.0179
Popdens	-0.0049***	0.0009	0.0009	-0.0050***	0.0009	0.0009
Banks	0.0129	0.0205	0.0207	0.0114	0.0205	0.0213
Deaths	0.0008	0.0005	0.0005	0.0008	0.0005	0.0005
Schools	-0.0081***	0.0018	0.0018	-0.0080***	0.0018	0.0017
Altitude	0.0065*	0.0034	0.0034	0.0065*	0.0034	0.0035
N	-0.1960	0.2279	0.2351	-0.2189	0.2278	0.2390
NE	0.2275	0.2298	0.2278	0.2033	0.2296	0.2332
S	-0.2086	0.1406	0.1350	-0.2151	0.1405	0.1345
MW	-0.4177***	0.1125	0.1170	-0.4205***	0.1125	0.1170
Avetemp	0.1013	0.0782	0.0798	0.1016	0.0781	0.0801
Augrain	0.0264*	0.0136	0.0139	0.0270*	0.0135	0.0142
Marrain	0.0013***	0.0002	0.0002	0.0013***	0.0002	0.0002
Avetemp× Augrain	-0.0011**	0.0005	0.0005	-0.0011**	0.0005	0.0005
Rho	0.2486					

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.82: Results from the Rent Equation of Model 14

Model	Single Equation			SURE		
Variable	Coeff.	Robust		Coeff.	Robust	
		Std. Error	Std. Error		Std. Error	Std. Error
Constant	96.3348***	19.6441	18.0638	90.8297***	19.1869	18.1165
Flusht	0.3989***	0.0323	0.0338	0.3904***	0.0313	0.0328
Filter	0.1459***	0.0256	0.0264	0.1417***	0.0248	0.0255
Br1×A	0.8583***	0.0360	0.0364	0.7819***	0.0349	0.0358
Br2×A	1.0153***	0.0364	0.0333	0.9438***	0.0353	0.0325
Br3×A	1.2798***	0.0490	0.0488	1.1654***	0.0475	0.0469
Brgt3×A	1.3589***	0.1643	0.1506	1.1879***	0.1593	0.1598
Br2×H	0.3082***	0.0288	0.0281	0.2742***	0.0279	0.0277
Br3×H	0.7017***	0.0459	0.0555	0.6248***	0.0445	0.0536
Brgt3×H	1.0802***	0.0960	0.1338	0.9766***	0.0930	0.1220
Popdens	-0.0130***	0.0021	0.0018	-0.01297***	0.0021	0.0018
Banks	0.0281*	0.0176	0.0163	0.0244	0.0172	0.0164
Deaths	0.0003	0.0012	0.0011	0.0006	0.0012	0.0011
Schools	-0.0010	0.0043	0.0028	-0.0025	0.0041	0.0029
Altitude	-0.0473***	0.0087	0.0081	-0.0444***	0.0085	0.0081
N	1.6133***	0.2336	0.2222	1.4247***	0.2283	0.2198
NE	1.2899***	0.2764	0.2368	1.2393***	0.2697	0.2387
S	-3.2219***	0.4744	0.3998	-2.9587***	0.4631	0.4015
MW	0.7271***	0.2329	0.2239	0.6374***	0.2273	0.2233
Ln(Avetemp)	-29.3119***	6.1957	5.6918	-27.5580***	6.0507	5.7086
Ln(Augrain)	-7.5672***	2.3896	2.2338	-7.2137***	2.3327	2.2396
Ln(Marrain)	0.8414***	0.1389	0.1304	0.8398***	0.1356	0.1302
Ln(Avetemp)× Ln(Augrain)	2.1707***	0.7315	0.6840	2.0664***	0.7139	0.6857

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.83: Results from the Wage Equation of Model 14

Model	Single Equation			SURE		
	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Constant	30.6428***	10.8709	11.3774	31.7123***	10.8636	11.5746
Ed5to8	0.2112***	0.0182	0.0167	0.2061***	0.0181	0.0167
Ed9to12	0.6214***	0.0184	0.0179	0.6046***	0.0183	0.0178
Edgt12	1.4534***	0.0227	0.0237	1.4184***	0.0226	0.0237
OJE	0.0455***	0.0019	0.0020	0.0455***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001	-0.0008***	0.0001	0.0001
Black	-0.1816***	0.0134	0.0133	-0.1732***	0.0133	0.0133
Male	0.5185***	0.0153	0.0158	0.5134***	0.0152	0.0157
Dir	0.3795***	0.0203	0.0213	0.3701***	0.0202	0.0212
SP	0.1623***	0.0225	0.0233	0.1572***	0.0223	0.0231
Mid	0.1935***	0.0219	0.0219	0.1868***	0.0217	0.0217
Ser	0.3077***	0.0185	0.0201	0.2971***	0.0184	0.0200
Oper	0.1712***	0.0235	0.0213	0.1720***	0.0233	0.0212
EO	-0.1981***	0.0209	0.0180	-0.1986***	0.0207	0.0179
Popdens	-0.0086***	0.0012	0.0011	-0.0088***	0.0012	0.0012
Banks	0.0069	0.0095	0.0098	0.0064	0.0094	0.0100
Deaths	0.0010*	0.0006	0.0006	0.0010*	0.0006	0.0006
Schools	-0.0086***	0.0018	0.0017	-0.0085***	0.0018	0.0017
Altitude	-0.0142***	0.0049	0.0051	-0.0147***	0.0049	0.0052
N	0.2231*	0.1348	0.1372	0.2187	0.1347	0.1369
NE	0.6994***	0.1428	0.1373	0.6950***	0.1427	0.1399
S	-0.8758***	0.2543	0.2579	-0.8958***	0.2541	0.2606
MW	-0.0348	0.1221	0.1242	-0.0286	0.1221	0.1250
Ln(Avetemp)	-8.1846**	3.3999	3.5573	-8.5206**	3.3976	3.6198
Ln(Augrain)	-1.6886	1.2746	1.3398	-1.8133	1.2737	1.3658
Ln(Marrain)	0.4798***	0.0747	0.0759	0.4891***	0.0746	0.0771
Ln(Avetemp)× Ln(Augrain)	0.4237	0.3854	0.4053	0.4618	0.3851	0.4130
Rho				0.2483		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.84: Results from the Rent Equation of Model 15

Model	Single Equation			SURE		
Variable	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Lambda	0.1266			0.1266		
Constant	140.9485***	29.6653	27.6548	133.1920***	28.9521	27.7326
Flusht	0.7257***	0.0619	0.0623	0.7070***	0.0599	0.0605
Filter	0.2847***	0.0490	0.0500	0.2778***	0.0475	0.0483
Br1×A	1.6742***	0.0689	0.0706	1.5221***	0.0667	0.0694
Br2×A	1.9756***	0.0696	0.0649	1.8317***	0.0674	0.0632
Br3×A	2.5480***	0.0937	0.0995	2.3297***	0.0908	0.0957
Brgt3×A	2.7145***	0.3145	0.3142	2.4010***	0.3044	0.3281
Br2×H	0.5827***	0.0551	0.0518	0.5135***	0.0533	0.0509
Br3×H	1.3821***	0.0878	0.1056	1.2331***	0.0850	0.1020
Brgt3×H	2.1512***	0.1836	0.2773	1.9524***	0.1778	0.2551
Popdens	-0.0233***	0.0039	0.0033	-0.0234***	0.0038	0.0033
Banks	0.0643**	0.0325	0.0309	0.0568*	0.0317	0.0309
Deaths	0.0003	0.0024	0.0021	0.0008	0.0023	0.0021
Schools	-0.0017	0.0082	0.0056	-0.0045	0.0079	0.0057
Altitude	-0.0842***	0.0165	0.0155	-0.0790***	0.0161	0.0155
N	2.9771***	0.4437	0.4323	2.6235***	0.4334	0.4277
NE	2.3719***	0.5390	0.4657	2.2756***	0.5255	0.4696
S	-5.4815***	0.8457	0.7097	-5.0089***	0.8246	0.7133
MW	1.3070***	0.4519	0.4467	1.1481***	0.4406	0.4459
BC(Avetemp)	-50.1186***	12.5489	11.7910	-47.4742***	12.2435	11.8246
BC(Augrain)	-23.5584***	7.6605	7.2917	-22.6173***	7.4728	7.3123
BC(Marrain)	0.7940***	0.1321	0.1249	0.7922***	0.1289	0.1246
BC(Avetemp× Augrain)	15.2638***	5.0642	4.8247	14.6504***	4.9398	4.8382

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.85: Results from the Wage Equation of Model 15

Model	Single Equation			SURE		
	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Lambda	-0.0799			-0.0799		
Constant	25.8240***	7.8894	8.2438	26.5744***	7.8837	8.3679
Ed5to8	0.1366***	0.0110	0.0106	0.1336***	0.0109	0.0106
Ed9to12	0.3876***	0.0111	0.0112	0.3777***	0.0110	0.0112
Edgt12	0.8669***	0.0138	0.0142	0.8443***	0.0137	0.0143
OJE	0.0279***	0.0011	0.0012	0.0278***	0.0011	0.0012
OJEsq	-0.0005***	0.0000	0.0000	-0.0005***	0.0000	4.1480
Black	-0.1096***	0.0081	0.0081	-0.1045***	0.0080	0.0081
Male	0.3208***	0.0093	0.0098	0.3173***	0.0092	0.0097
Dir	0.2241***	0.0123	0.0129	0.2180***	0.0122	0.0128
SP	0.0987***	0.0136	0.0139	0.0958***	0.0135	0.0138
Mid	0.1205***	0.0133	0.0132	0.1165***	0.0131	0.0131
Ser	0.1763***	0.0112	0.0121	0.1694***	0.0111	0.0120
Oper	0.1066***	0.0142	0.0131	0.1072***	0.0141	0.0131
EO	-0.1329***	0.0127	0.0114	-0.1334***	0.0126	0.0114
Popdens	-0.0056***	0.0008	0.0007	-0.0057***	0.0008	0.0007
Banks	0.0011	0.0059	0.0061	0.0008	0.0059	0.0062
Deaths	0.0006*	0.0004	0.0004	0.0006*	0.0004	0.0004
Schools	-0.0052***	0.0011	0.0010	-0.0052***	0.0011	0.0010
Altitude	-0.0107***	0.0031	0.0032	-0.0109***	0.0031	0.0033
N	0.1630**	0.0829	0.0826	0.1598**	0.0829	0.0820
NE	0.4446***	0.0878	0.0839	0.4420***	0.0878	0.0854
S	-0.6590***	0.1660	0.1676	-0.6714***	0.1659	0.1692
MW	0.0134	0.0747	0.0751	0.0169	0.0746	0.0754
BC(Avetemp)	-1.3444	2.2527	2.3647	-1.1491	2.2509	2.4061
BC(Augrain)	4.7521	3.7090	3.9084	5.1092	3.7062	3.9739
BC(Marrain)	0.4795***	0.0716	0.0727	0.4886***	0.0715	0.0738
BC(Avetemp× Augrain)	-6.5349	4.8298	5.0890	-6.9994	4.8261	5.1749
Rho				0.2542		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.86: Results from the Rent Equation of Model 16

Model	Single Equation			SURE		
	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Constant	13.1763***	2.0651	1.9101	12.1643***	2.0138	1.8923
Flusht	0.3935***	0.0323	0.0337	0.3853***	0.0313	0.0328
Filter	0.1471***	0.0256	0.0264	0.1429***	0.0248	0.0255
Br1×A	0.8642***	0.0359	0.0364	0.7874***	0.0348	0.0357
Br2×A	1.0188***	0.0363	0.0334	0.9470***	0.0352	0.0325
Br3×A	1.2845***	0.0489	0.0487	1.1697***	0.0474	0.0468
Brgt3×A	1.3659***	0.1644	0.1512	1.1945***	0.1593	0.1600
Br2×H	0.3089***	0.0288	0.0282	0.2748***	0.0279	0.0277
Br3×H	0.7036***	0.0459	0.0556	0.6265***	0.0445	0.0537
Brgt3×H	1.0825***	0.0960	0.1343	0.9788***	0.0931	0.1224
Popdens	-0.0070***	0.0016	0.0013	-0.0071***	0.0016	0.0013
Banks	0.0654**	0.0330	0.0278	0.0624**	0.0322	0.0281
Deaths	-0.0002	0.0013	0.0011	-0.0000	0.0012	0.0011
Schools	-0.0002	0.0057	0.0041	-0.0013	0.0055	0.0041
Altitude	-0.0096***	0.0049	0.0039	-0.0085**	0.0048	0.0040
N	1.0042***	0.2636	0.2682	0.8809***	0.2569	0.2671
NE	0.6173**	0.3978	0.3113	0.5955*	0.3880	0.3132
S	-1.6489***	0.3137	0.2318	-1.4629***	0.3056	0.2306
MW	0.0726	0.1779	0.1569	0.0182	0.1736	0.1576
Avetemp	-0.3981***	0.0820	0.0729	-0.3512***	0.0799	0.0721
Augrain	-0.0022	0.0017	0.0015	-0.0022	0.0016	0.0015
Marrain	-0.0128	0.0163	0.0151	-0.0101	0.0160	0.0150
Avetemp× Marrain	0.0006	0.0006	0.0006	0.0005	0.0006	0.0006

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.87: Results from the Wage Equation of Model 16

Model	Single Equation			SURE		
	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Constant	5.9840***	1.0212	1.0436	6.0836***	1.0205	1.0372
Ed5to8	0.2115***	0.0182	0.0167	0.2062***	0.0181	0.0167
Ed9to12	0.6210***	0.0184	0.0179	0.6043***	0.0183	0.0178
Edgt12	1.4544***	0.0227	0.0236	1.4194***	0.0226	0.0237
OJE	0.0455***	0.0019	0.0020	0.0455***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001	-0.0008***	0.0001	0.0001
Black	-0.1817***	0.0134	0.0133	-0.1734***	0.0133	0.0133
Male	0.5185***	0.0153	0.0158	0.5134***	0.0152	0.0157
Dir	0.3794***	0.0203	0.0213	0.3700***	0.0202	0.0212
SP	0.1624***	0.0225	0.0233	0.1572***	0.0223	0.0232
Mid	0.1937***	0.0219	0.0219	0.1869***	0.0217	0.0217
Ser	0.3074***	0.0185	0.0201	0.2967***	0.0184	0.0200
Oper	0.1706***	0.0235	0.0213	0.1714***	0.0233	0.0212
EO	-0.1976***	0.0209	0.0180	-0.1982***	0.0207	0.0179
Popdens	-0.0060***	0.0009	0.0008	-0.0060***	0.0009	0.0008
Banks	0.0481***	0.0180	0.0165	0.0474***	0.0180	0.0167
Deaths	0.0009	0.0006	0.0006	0.0009	0.0006	0.0006
Schools	-0.0080***	0.0027	0.0024	-0.0079***	0.0027	0.0024
Altitude	0.0004	0.0026	0.0024	0.0003	0.0026	0.0024
N	0.2200*	0.1203	0.1250	0.2054*	0.1202	0.1258
NE	0.6115***	0.2020	0.1820	0.5966***	0.2019	0.1832
S	-0.2204*	0.1407	0.1346	-0.2271*	0.1406	0.1340
MW	-0.2728***	0.0942	0.0859	-0.2730***	0.0942	0.0867
Avetemp	-0.0494	0.0405	0.0411	-0.0524	0.0405	0.0407
Augrain	-0.0028***	0.0008	0.0007	-0.0028***	0.0008	0.0007
Marrain	-0.0002	0.0091	0.0086	-0.0003	0.0091	0.0086
Avetemp× Marrain	0.0001	0.0004	0.0003	0.0001	0.0004	0.0003
Rho				0.2484		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.88: Results from the Rent Equation of Model 19

Model	Single Equation			SURE		
	Variable	Coeff.	Robust	Coeff.	Std. Error	Robust
Std. Error			Std. Error			
Constant	8.3491***	1.5999	1.4191	7.5927***	1.5619	1.4069
Flusht	0.3980***	0.0323	0.0338	0.3896***	0.0314	0.0328
Filter	0.1463***	0.0255	0.0262	0.1425***	0.0247	0.0254
Br1×A	0.8569***	0.0360	0.0364	0.7804***	0.0349	0.0358
Br2×A	1.0141***	0.0364	0.0333	0.9426***	0.0353	0.0325
Br3×A	1.2790***	0.0489	0.0488	1.1647***	0.0474	0.0469
Brgt3×A	1.3602***	0.1642	0.1502	1.1898***	0.1592	0.1596
Br2×H	0.3088***	0.0288	0.0281	0.2747***	0.0279	0.0276
Br3×H	0.7024***	0.0459	0.0555	0.6254***	0.0445	0.0536
Brgt3×H	1.0812***	0.0959	0.1341	0.9779***	0.0930	0.1223
Popdens	-0.0071**	0.0031	0.0025	-0.0067***	0.0030	0.0025
Banks	-0.0270	0.1381	0.1233	-0.0651	0.1349	0.1236
Deaths	0.0037	0.0023	0.0021	0.0046**	0.0023	0.0021
Schools	-0.0014	0.0053	0.0042	-0.0022	0.0052	0.0043
Altitude	-0.0303	0.0253	0.0230	-0.0355	0.0247	0.0231
N	0.2736	1.4630	1.3214	-0.2692	1.4292	1.3194
NE	0.6479	1.6064	1.4235	0.2340	1.5685	1.4263
S	-0.1753	0.9608	0.8463	0.2685	0.9386	0.8431
MW	-0.5401**	0.2415	0.2227	-0.6529***	0.2361	0.2216
Avetemp	-0.1680**	0.0711	0.0611	-0.1173**	0.0695	0.0599
Junerain	-0.0023	0.0024	0.0021	-0.0017	0.0023	0.0021
Febrain	0.0023**	0.0011	0.0010	0.0026***	0.0011	0.0010
Avetemp× Altitude	0.0013	0.0012	0.0011	0.0017	0.0012	0.0011

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.89: Results from the Wage Equation of Model 19

Model	Single Equation			SURE		
Variable	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Constant	4.4586***	0.8606	0.8616	4.4659***	0.8600	0.8546
Ed5to8	0.2111***	0.0182	0.0167	0.2059***	0.0181	0.0167
Ed9to12	0.6206***	0.0184	0.0179	0.6038***	0.0182	0.0178
Edgt12	1.4519***	0.0227	0.0236	1.4168***	0.0226	0.0237
OJE	0.0456***	0.0019	0.0020	0.0455***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001	-0.0008***	0.0001	0.0001
Black	-0.1821***	0.0134	0.0133	-0.1738***	0.0133	0.0133
Male	0.5187***	0.0153	0.0158	0.5136***	0.0152	0.0157
Dir	0.3801***	0.0203	0.0213	0.3706***	0.0202	0.0212
SP	0.1614***	0.0225	0.0233	0.1562***	0.0223	0.0231
Mid	0.1923***	0.0219	0.0219	0.1856***	0.0217	0.0217
Ser	0.3073***	0.0185	0.0201	0.2967***	0.0184	0.0200
Oper	0.1709***	0.0235	0.0213	0.1717***	0.0233	0.0212
EO	-0.1993***	0.0209	0.0180	-0.1997***	0.0207	0.0179
Popdens	-0.0047***	0.0017	0.0015	-0.0048***	0.0017	0.0015
Banks	-0.0799	0.0751	0.0749	-0.0810	0.0750	0.0754
Deaths	0.0037***	0.0013	0.0013	0.0037***	0.0013	0.0013
Schools	-0.0066***	0.0025	0.0023	-0.0067***	0.0024	0.0023
Altitude	-0.0232*	0.0135	0.0137	-0.0234*	0.0135	0.0138
N	-1.0549	0.8206	0.8211	-1.0762	0.8200	0.8225
NE	-0.1688	0.8723	0.8468	-0.1807	0.8717	0.8503
S	1.0035*	0.5393	0.5461	1.0182*	0.5389	0.5446
MW	-0.6811***	0.1416	0.1488	-0.6914***	0.1415	0.1489
Avetemp	0.0599	0.0412	0.0420	0.0609	0.0412	0.0410
Junerain	-0.0006	0.0013	0.0013	-0.0007	0.0013	0.0013
Febrain	0.0020***	0.0006	0.0007	0.0020***	0.0006	0.0007
Avetemp× Altitude	0.0014**	0.0007	0.0007	0.0014**	0.0007	0.0007
Rho				0.2485		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.90: Results from the Rent Equation of Model 20

Model	Single Equation			SURE		
	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Constant	18.3737*	11.3486	11.0000	13.7423	11.0600	10.8714
Flusht	0.3975***	0.0323	0.0336	0.3895***	0.0313	0.0327
Filter	0.1465***	0.0256	0.0264	0.1425***	0.0248	0.0255
Br1×A	0.8569***	0.0360	0.0365	0.7805***	0.0349	0.0358
Br2×A	1.0140***	0.0364	0.0333	0.9427***	0.0353	0.0325
Br3×A	1.2791***	0.0490	0.0488	1.1649***	0.0475	0.0469
Brgt3×A	1.3611***	0.1643	0.1505	1.1902***	0.1592	0.1599
Br2×H	0.3090***	0.0288	0.0281	0.2748***	0.0279	0.0276
Br3×H	0.7027***	0.0459	0.0555	0.6255***	0.0445	0.0536
Brgt3×H	1.0816***	0.0960	0.1343	0.9781***	0.0930	0.1225
Popdens	-0.0070**	0.0031	0.0030	-0.0068**	0.0030	0.0030
Banks	-0.1054***	0.0405	0.0358	-0.1085***	0.0395	0.0359
Deaths	0.0044***	0.0014	0.0013	0.0046***	0.0014	0.0013
Schools	-0.0006	0.0034	0.0030	-0.0021	0.0033	0.0030
Altitude	-0.1253***	0.0265	0.0247	-0.1202***	0.0259	0.0248
N	-0.5170	0.5946	0.5712	-0.7335	0.5793	0.5658
NE	-0.0803	0.8578	0.9077	-0.1889	0.8347	0.8983
S	0.1431	0.6822	0.5921	0.4347	0.6646	0.5881
MW	-0.5728***	0.1866	0.1636	-0.6367***	0.1825	0.1644
Ln(Avetemp)	-5.0524	3.6046	3.4825	-3.5652	3.5124	3.4424
Ln(Junerain)	-0.1486***	0.2481	0.2593	-0.1170	0.2415	0.2566
Ln(Febrain)	0.7707***	0.2396	0.2465	0.7572***	0.2334	0.2444
Ln(Avetemp)× Altitude	0.0386***	0.0099	0.0094	0.0379***	0.0096	0.0094

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.91: Results from the Wage Equation of Model 20

Model	Single Equation			SURE		
	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Constant	-5.5891	5.3295	5.5251	-5.3092	5.3259	5.4399
Ed5to8	0.2116***	0.0182	0.0167	0.2064***	0.0181	0.0167
Ed9to12	0.6209***	0.0184	0.0179	0.6042***	0.0182	0.0178
Edgt12	1.4529***	0.0227	0.0237	1.4178***	0.0226	0.0237
OJE	0.0457***	0.0019	0.0020	0.0456***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001	-0.0008***	0.0001	0.0001
Black	-0.1820***	0.0134	0.0133	-0.1737***	0.0133	0.0133
Male	0.5193***	0.0153	0.0158	0.5142***	0.0152	0.0157
Dir	0.3802***	0.0203	0.0213	0.3708***	0.0201	0.0212
SP	0.1614***	0.0225	0.0233	0.1562***	0.0223	0.0231
Mid	0.1924***	0.0219	0.0219	0.1858***	0.0217	0.0217
Ser	0.3076***	0.0185	0.0201	0.2970***	0.0184	0.0200
Oper	0.1709***	0.0235	0.0213	0.1717***	0.0233	0.0212
EO	-0.1985***	0.0209	0.0180	-0.1989***	0.0207	0.0179
Popdens	-0.0032**	0.0014	0.0014	-0.0034***	0.0013	0.0014
Banks	-0.0763***	0.0207	0.0211	-0.0772***	0.0207	0.0215
Deaths	0.0025***	0.0008	0.0008	0.0026***	0.0008	0.0008
Schools	-0.0058***	0.0015	0.0015	-0.0059***	0.0015	0.0015
Altitude	-0.0566***	0.0145	0.0148	-0.0572***	0.0145	0.0150
N	-1.2644***	0.2708	0.2754	-1.2721***	0.2706	0.2752
NE	-0.6857*	0.3458	0.3645	-0.6705*	0.3456	0.3654
S	1.1974***	0.3068	0.3079	1.1992***	0.3066	0.3043
MW	-0.5578***	0.1106	0.1103	-0.5697***	0.1106	0.1117
Ln(Avetemp)	3.0074*	1.6686	1.7272	2.9210*	1.6675	1.7020
Ln(Junerain)	0.1064	0.1044	0.1097	0.0978	0.1043	0.1100
Ln(Febrain)	0.3550***	0.1077	0.1119	0.3683***	0.1076	0.1134
Ln(Avetemp)× Altitude	0.0214***	0.0049	0.0050	0.0215***	0.0049	0.0050
Rho				0.2483		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.92: Results from the Rent Equation of Model 21

Model	Single Equation			SURE		
	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Lambda	0.1285			0.1285		
Constant	61.0681***	12.9095	12.3680	52.7591***	12.6094	12.1048
Flusht	0.7277***	0.0626	0.0630	0.7091***	0.0606	0.0611
Filter	0.2850***	0.0496	0.0505	0.2784***	0.0480	0.0489
Br1×A	1.7025***	0.0695	0.0711	1.5472***	0.0673	0.0699
Br2×A	2.0004***	0.0704	0.0656	1.8540***	0.0681	0.0639
Br3×A	2.5791***	0.0947	0.1004	2.3575***	0.0917	0.0965
Brgt3×A	2.7423***	0.3179	0.3184	2.4250***	0.3077	0.3319
Br2×H	0.5881***	0.0557	0.0524	0.5181***	0.0539	0.0515
Br3×H	1.3961***	0.0888	0.1069	1.2453***	0.0860	0.1032
Brgt3×H	2.1746***	0.1857	0.2803	1.9732***	0.1797	0.2577
Popdens	-0.0291***	0.0060	0.0051	-0.0282***	0.0059	0.0052
Banks	-0.0024	0.0667	0.0555	-0.0125	0.0650	0.0557
Deaths	0.0106***	0.0050	0.0040	0.0108***	0.0048	0.0040
Schools	-0.0164**	0.0097	0.0071	-0.0185***	0.0095	0.0072
Altitude	-0.0575***	0.0128	0.0120	-0.0508***	0.0125	0.0118
N	2.3186***	0.7902	0.7470	1.8109***	0.7698	0.7345
NE	5.6626***	1.4813	1.3776	5.2266***	1.4448	1.3713
S	-2.0886***	1.0512	0.8297	-1.4970*	1.0230	0.8213
MW	-1.1731***	0.4896	0.3954	-1.2702***	0.4777	0.4010
BC(Avetemp)	-14.7374***	3.2680	3.1056	-12.5665***	3.1912	3.0415
BC(Junerain)	-1.0689***	0.2919	0.2574	-0.9999***	0.2849	0.2570
BC(Febrain)	1.2092***	0.2687	0.2281	1.1736***	0.2620	0.2294
BC(Avetemp× Altitude)	0.0917*	0.0563	0.0477	0.0908*	0.0549	0.0479

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.93: Results from the Wage Equation of Model 21

Model	Single Equation			SURE		
	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Lambda	-0.0800			-0.0800		
Constant	8.4274*	4.8425	4.7449	8.8078*	4.8387	4.6015
Ed5to8	0.1366***	0.0110	0.0106	0.1336***	0.0109	0.0106
Ed9to12	0.3873***	0.0111	0.0112	0.3773***	0.0110	0.0112
Edgt12	0.8668***	0.0138	0.0142	0.8441***	0.0137	0.0142
OJE	0.0279***	0.0011	0.0012	0.0278***	0.0011	0.0012
OJEsq	-0.0005***	0.0000	0.0000	-0.0005***	0.0000	0.0000
Black	-0.1099***	0.0081	0.0081	-0.1047***	0.0080	0.0081
Male	0.3205***	0.0093	0.0098	0.3170***	0.0092	0.0097
Dir	0.2238***	0.0123	0.0129	0.2177***	0.0122	0.0128
SP	0.0987***	0.0136	0.0139	0.0958***	0.0135	0.0138
Mid	0.1208***	0.0132	0.0132	0.1167***	0.0131	0.0131
Ser	0.1759***	0.0112	0.0121	0.16899***	0.0111	0.0120
Oper	0.1062***	0.0142	0.0131	0.1068***	0.0141	0.0131
EO	-0.1324***	0.0127	0.0114	-0.1330***	0.0125	0.0114
Popdens	-0.0059***	0.0014	0.0012	-0.0060***	0.0014	0.0013
Banks	-0.0571***	0.0180	0.0163	-0.0572***	0.0180	0.0162
Deaths	0.0040***	0.0012	0.0011	0.0040***	0.0012	0.0011
Schools	-0.0074***	0.0015	0.0014	-0.0074***	0.0015	0.0014
Altitude	-0.0089**	0.0043	0.0040	-0.0092**	0.0043	0.0040
N	-0.5149***	0.1292	0.1263	-0.5119***	0.1290	0.1252
NE	0.6054**	0.2798	0.2643	0.6218**	0.2796	0.2621
S	0.4189***	0.1632	0.1623	0.4092***	0.1630	0.1583
MW	-0.4984***	0.1072	0.0931	-0.5037***	0.1071	0.0940
BC(Avetemp)	-2.1214	1.7719	1.7280	-2.2584	1.7706	1.6794
BC(Junerain)	-0.4628***	0.1712	0.1576	-0.4727***	0.1711	0.1560
BC(Febrain)	0.9512***	0.2320	0.2097	0.9654***	0.2318	0.2099
BC(Avetemp× Altitude)	0.1071***	0.0298	0.0268	0.1066***	0.0298	0.0266
Rho				0.2549		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.94: Results from the Rent Equation of Model 22

Model	Single Equation			SURE		
Variable	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Constant	14.3822***	2.1053	1.8857	13.6033***	2.0555	1.8905
Flusht	0.3984***	0.0323	0.0337	0.3900***	0.0313	0.0328
Filter	0.1465***	0.0256	0.0264	0.1423***	0.0248	0.0255
Br1×A	0.8576***	0.0360	0.0365	0.7813***	0.0349	0.0358
Br2×A	1.0148***	0.0364	0.0333	0.9434***	0.0353	0.0325
Br3×A	1.2797***	0.0490	0.0488	1.1654***	0.0475	0.0469
Brgt3×A	1.3605***	0.1643	0.1507	1.1894***	0.1593	0.1599
Br2×H	0.3085***	0.0288	0.0281	0.2745***	0.0279	0.0277
Br3×H	0.7022***	0.0459	0.0555	0.6252***	0.0445	0.0536
Brgt3×H	1.0811***	0.0960	0.1340	0.9774***	0.0930	0.1222
Popdens	-0.0065***	0.0015	0.0013	-0.0068***	0.0014	0.0013
Banks	-0.0384	0.0481	0.0448	-0.0404	0.0470	0.0449
Deaths	0.0012	0.0014	0.0012	0.0015	0.0014	0.0012
Schools	0.0017	0.0042	0.0029	0.0001	0.0041	0.0029
Altitude	-0.0362***	0.0109	0.0100	-0.0349***	0.0107	0.0100
N	0.3644	0.4108	0.3747	0.2120	0.4009	0.3764
NE	0.0417	0.3842	0.3583	0.0353	0.3749	0.3589
S	-1.2396***	0.3696	0.2591	-1.0554***	0.3599	0.2619
MW	-0.0498	0.1873	0.1671	-0.1119	0.1828	0.1679
Avetemp	-0.4108***	0.0791	0.0667	-0.3724***	0.0771	0.0669
Augrain	-0.0014	0.0017	0.0016	-0.0014	0.0016	0.0016
Marrain	0.0029***	0.0005	0.0005	0.0029***	0.0005	0.0005
Avetemp× Altitude	0.0011	0.0005	0.0004	0.0011***	0.0005	0.0004

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.95: Results from the Wage Equation of Model 22

Model	Single Equation			SURE		
	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Constant	7.2490***	1.1347	1.1781	7.3759***	1.1339	1.1913
Ed5to8	0.2114***	0.0182	0.0167	0.2062***	0.0181	0.0167
Ed9to12	0.6214***	0.0184	0.0179	0.6047***	0.0182	0.0178
Edgt12	1.4535***	0.0227	0.0237	1.4185***	0.0226	0.0237
OJE	0.0456***	0.0019	0.0020	0.0455***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001	-0.0008***	0.0001	0.0001
Black	-0.1815***	0.0134	0.0133	-0.1731***	0.0133	0.0133
Male	0.5188***	0.0153	0.0158	0.5137***	0.0152	0.0157
Dir	0.3797***	0.0203	0.0213	0.3703***	0.0201	0.0212
SP	0.1622***	0.0225	0.0233	0.1570***	0.0223	0.0231
Mid	0.1933***	0.0219	0.0219	0.1866***	0.0217	0.0217
Ser	0.3077***	0.0185	0.0201	0.2972***	0.0184	0.0200
Oper	0.1712***	0.0235	0.0213	0.1720***	0.0233	0.0212
EO	-0.1981***	0.0209	0.0180	-0.1985***	0.0207	0.0179
Popdens	-0.0060***	0.0008	0.0008	-0.0061***	0.0008	0.0008
Banks	-0.0025	0.0269	0.0283	-0.0045	0.0269	0.0289
Deaths	0.0016***	0.0007	0.0006	0.0017***	0.0007	0.0007
Schools	-0.0076***	0.0018	0.0017	-0.0075***	0.0018	0.0017
Altitude	-0.0126**	0.0063	0.0065	-0.0130**	0.0063	0.0066
N	-0.1558	0.2167	0.2235	-0.1797	0.2165	0.2281
NE	0.3337	0.1987	0.2065	0.3105	0.1986	0.2098
S	-0.0558	0.1613	0.1516	-0.0585	0.1611	0.1518
MW	-0.3448***	0.0958	0.0913	-0.3465***	0.0957	0.0918
Avetemp	-0.0811**	0.0408	0.0415	-0.0847**	0.0407	0.0417
Augrain	-0.0023***	0.0008	0.0008	-0.0022***	0.0008	0.0008
Marrain	0.0018***	0.0003	0.0003	0.0018***	0.0003	0.0003
Avetemp× Altitude	0.0006**	0.0003	0.0003	0.0006**	0.0003	0.0003
Rho				0.2482		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.96: Results from the Rent Equation of Model 23

Model	Single Equation			SURE		
Variable	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Constant	32.1063***	5.6221	5.4883	29.5593***	5.4890	5.4917
Flusht	0.3985***	0.0323	0.0338	0.3901***	0.0313	0.0328
Filter	0.1462***	0.0256	0.0263	0.1420***	0.0248	0.0255
Br1×A	0.8575***	0.0360	0.0364	0.7811***	0.0349	0.0358
Br2×A	1.0147***	0.0364	0.0333	0.9432***	0.0353	0.0325
Br3×A	1.2794***	0.0490	0.0489	1.1650***	0.0475	0.0469
Brgt3×A	1.3597***	0.1643	0.1505	1.1887***	0.1592	0.1597
Br2×H	0.3085***	0.0288	0.0281	0.2745***	0.0279	0.0277
Br3×H	0.7021***	0.0459	0.0555	0.6251***	0.0445	0.0536
Brgt3×H	1.0807***	0.0959	0.1339	0.9771***	0.0930	0.1221
Popdens	-0.0053**	0.0027	0.0024	-0.0056**	0.0026	0.0024
Banks	-0.1135**	0.0056	0.0508	-0.1129**	0.0543	0.0512
Deaths	0.0006	0.0012	0.0010	0.0008	0.0012	0.0011
Schools	0.0039	0.0050	0.0035	0.0023	0.0049	0.0035
Altitude	-0.1698***	0.0472	0.0429	-0.1632***	0.0461	0.0432
N	-0.4979	0.6286	0.5791	-0.6129	0.6136	0.5828
NE	-0.7233	0.6595	0.5780	-0.7043	0.6433	0.5826
S	-0.9421**	0.4918	0.4555	-0.7697*	0.4800	0.4574
MW	-0.0848	0.1421	0.1289	-0.1390	0.1389	0.1303
Ln(Avetemp)	-9.6243***	1.6189	1.5775	-8.7854***	1.5808	1.5800
Ln(Augrain)	0.1419	0.2418	0.2136	0.1344	0.2357	0.2150
Ln(Marrain)	0.7486***	0.1176	0.1094	0.7547***	0.1149	0.1090
Ln(Avetemp)× Altitude	0.0516***	0.0167	0.0151	0.0499***	0.0163	0.0152

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.97: Results from the Wage Equation of Model 23

Model	Single Equation			SURE		
	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Constant	17.6651***	3.0330	3.0355	17.5947***	3.0308	3.0719
Ed5to8	0.2112***	0.0182	0.0167	0.2060***	0.0181	0.0167
Ed9to12	0.6213***	0.0184	0.0179	0.6046***	0.0183	0.0178
Edgt12	1.4533***	0.0227	0.0237	1.4182***	0.0226	0.0237
OJE	0.0455***	0.0019	0.0020	0.0455***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001	-0.0008***	0.0001	0.0001
Black	-0.1815***	0.0134	0.0133	-0.1732***	0.0133	0.0133
Male	0.5186***	0.0153	0.0158	0.5135***	0.0152	0.0157
Dir	0.3796***	0.0203	0.0213	0.3702***	0.0202	0.0212
SP	0.1622***	0.0225	0.0233	0.1570***	0.0223	0.0231
Mid	0.1933***	0.0219	0.0219	0.1866***	0.0217	0.0217
Ser	0.3077***	0.0185	0.0201	0.2971***	0.0184	0.0200
Oper	0.1712***	0.0235	0.0213	0.1720***	0.0233	0.0212
EO	-0.1983***	0.0209	0.0180	-0.1987***	0.0207	0.0179
Popdens	-0.0069***	0.0014	0.0013	-0.0069***	0.0014	0.0013
Banks	-0.0294	0.0311	0.0329	-0.0324	0.0311	0.0337
Deaths	0.0010*	0.0006	0.0006	0.0010*	0.0006	0.0006
Schools	-0.0072***	0.0022	0.0021	-0.0071***	0.0022	0.0021
Altitude	-0.0456*	0.0260	0.0273	-0.0482*	0.0260	0.0280
N	-0.2864	0.3344	0.3532	-0.3286	0.3342	0.3608
NE	0.2126	0.3351	0.3449	0.1723	0.3349	0.3514
S	-0.3650	0.2582	0.2662	-0.3444	0.2580	0.2719
MW	-0.2062**	0.0850	0.0859	-0.2142***	0.0849	0.0876
Ln(Avetemp)	-4.2351***	0.8844	0.8788	-4.2222***	0.8838	0.8911
Ln(Augrain)	-0.1519	0.1175	0.1195	-0.1411	0.1174	0.1213
Ln(Marrain)	0.4733***	0.0652	0.0660	0.4811***	0.0652	0.0667
Ln(Avetemp)× Altitude	0.0127	0.0091	0.0095	0.0136	0.0091	0.0098
Rho				0.2483		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.98: Results from the Rent Equation of Model 24

Model	Single Equation			SURE		
Variable	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Lambda	0.1273			0.1273		
Constant	76.0729***	9.9197	9.0667	70.5474***	9.6911	9.0443
Flusht	0.7280***	0.0621	0.0625	0.7091***	0.0601	0.0607
Filter	0.2859***	0.0492	0.0502	0.2790***	0.0476	0.0485
Br1×A	1.6798***	0.0691	0.0709	1.5271***	0.0670	0.0697
Br2×A	1.9825***	0.0699	0.0651	1.8380***	0.0677	0.0634
Br3×A	2.5575***	0.0940	0.0999	2.3383***	0.0911	0.0961
Brgt3×A	2.7252***	0.3156	0.3154	2.4107***	0.3055	0.3294
Br2×H	0.5850***	0.0553	0.0519	0.5156***	0.0535	0.0511
Br3×H	1.3875***	0.0882	0.1060	1.2380***	0.0853	0.1024
Brgt3×H	2.1597***	0.1843	0.2785	1.9602***	0.1784	0.2562
Popdens	-0.0257***	0.0042	0.0036	-0.0255***	0.0041	0.0036
Banks	0.2563***	0.0555	0.0523	0.2388***	0.0540	0.0523
Deaths	-0.0018	0.0025	0.0023	-0.0012	0.0025	0.0023
Schools	-0.0105**	0.0078	0.0054	-0.0129**	0.0076	0.0054
Altitude	-0.0392***	0.0057	0.0056	-0.0358***	0.0055	0.0056
N	4.6212***	0.8240	0.7792	4.1652***	0.8044	0.7728
NE	3.9732***	0.8336	0.7621	3.7795***	0.8134	0.7626
S	-5.4477***	0.8288	0.6900	-4.9454***	0.8080	0.6906
MW	0.3537	0.2556	0.2425	0.2299	0.2495	0.2434
BC(Avetemp)	-17.9553***	2.4220	2.1883	-16.5136***	2.3653	2.1853
BC(Augrain)	-0.7589***	0.1718	0.1516	-0.7292***	0.1677	0.1522
BC(Marrain)	0.4248***	0.0922	0.0856	0.4389***	0.0901	0.0846
BC(Avetemp× Altitude)	-0.1608***	0.0525	0.0495	-0.1517***	0.0512	0.0493

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table A.99: Results from the Wage Equation of Model 24

Model	Single Equation			SURE		
	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Lambda	-0.0798			-0.0798		
Constant	18.3850***	3.6266	3.6697	18.7429***	3.6234	3.6944
Ed5to8	0.1366***	0.0110	0.0106	0.1337***	0.0109	0.0106
Ed9to12	0.3879***	0.0111	0.0112	0.3779***	0.0111	0.0112
Edgt12	0.8677***	0.0138	0.0142	0.8450***	0.0137	0.0143
OJE	0.0279***	0.0011	0.0012	0.0279***	0.0011	0.0012
OJEsq	-0.0005***	0.0000	0.0000	-0.0005***	0.0000	0.0000
Black	-0.1097***	0.0081	0.0082	-0.1046***	0.0080	0.0081
Male	0.3210***	0.0093	0.0098	0.3175***	0.0092	0.0097
Dir	0.2242***	0.0123	0.0129	0.2181***	0.0122	0.0128
SP	0.0988***	0.0136	0.0139	0.0959***	0.0135	0.0138
Mid	0.1207***	0.0133	0.0132	0.1167***	0.0131	0.0131
Ser	0.1764***	0.0112	0.0121	0.1695***	0.0111	0.0120
Oper	0.1067***	0.0142	0.0131	0.1072***	0.0141	0.0131
EO	-0.1328***	0.0127	0.0114	-0.1333***	0.0126	0.0114
Popdens	-0.0057***	0.0009	0.0008	-0.0058***	0.0009	0.0009
Banks	0.0121	0.0084	0.0085	0.0130	0.0084	0.0087
Deaths	0.0005	0.0004	0.0004	0.0005	0.0004	0.0004
Schools	-0.0058***	0.0011	0.0010	-0.0059***	0.0011	0.0010
Altitude	-0.0079***	0.0017	0.0017	-0.0080***	0.0017	0.0017
N	0.2514	0.1630	0.1667	0.2615	0.1629	0.1672
NE	0.5385***	0.1611	0.1627	0.5492***	0.1609	0.1653
S	-0.6222***	0.1767	0.1779	-0.6389***	0.1766	0.1789
MW	-0.0516	0.0467	0.0453	-0.0519	0.0466	0.0452
BC(Avetemp)	-5.1393***	1.2000	1.2108	-5.2583***	1.1989	1.2207
BC(Augrain)	-0.3218***	0.0811	0.0803	-0.3280***	0.0810	0.0813
BC(Marrain)	0.4074***	0.0539	0.0518	0.4109***	0.0538	0.0512
BC(Avetemp× Altitude)	-0.0213	0.0219	0.0230	-0.0239	0.0219	0.0233
Rho				0.2543		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Appendix B

More Empirical Results

B.1 System of Seemingly Unrelated Rent and Wage Equations (Continued)

Table B.1: Results from the Rent Equation of Model 25

Model	Single Equation			SURE		
	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Constant	7.6427***	1.5552	1.3878	6.7462***	1.5195	1.3669
Flusht	0.3980***	0.0323	0.0338	0.3895***	0.0314	0.0328
Filter	0.1455***	0.0255	0.0262	0.1416***	0.0248	0.0254
Br1×A	0.8573***	0.0360	0.0364	0.7807***	0.0349	0.0358
Br2×A	1.0142***	0.0364	0.0333	0.9426***	0.0353	0.0325
Br3×A	1.2789***	0.0490	0.0488	1.1643***	0.0475	0.0470
Brgt3×A	1.3585***	0.1643	0.1501	1.1878***	0.1592	0.1595
Br2×H	0.3089***	0.0288	0.0281	0.2748***	0.0279	0.0277
Br3×H	0.7023***	0.0459	0.0555	0.6252***	0.0445	0.0536
Brgt3×H	1.0802***	0.0959	0.1337	0.9767***	0.0930	0.1220
Popdens	-0.0087***	0.0022	0.0017	-0.0086***	0.0022	0.0017
Banks	0.0771*	0.0537	0.0439	0.0672	0.0525	0.0445
Deaths	0.0017**	0.0009	0.0008	0.0020***	0.0009	0.0008
Schools	-0.0031	0.0047	0.0034	-0.0044	0.0046	0.0034
Altitude	-0.0029	0.0030	0.0027	-0.0011	0.0030	0.0026
N	1.3178**	0.6342	0.5424	1.0684**	0.6203	0.5438
NE	1.6602**	0.9037	0.7193	1.5299**	0.8825	0.7266
S	-1.8050***	0.7750	0.6751	-1.7648***	0.7571	0.6829
MW	-0.3687***	0.1595	0.1386	-0.4348***	0.1560	0.1389
Avetemp	-0.1772***	0.0692	0.0612	-0.1311**	0.0677	0.0602
Junerain	-0.0036***	0.0016	0.0013	-0.0034***	0.0015	0.0013
Febrain	0.0014***	0.0004	0.0004	0.0014***	0.0004	0.0004
Avetemp×S	0.0496	0.0550	0.0479	0.0607	0.0538	0.0484

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table B.2: Results from the Wage Equation of Model 25

Model	Single Equation			SURE		
	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Constant	4.0012***	0.8813	0.8954	3.9912***	0.8807	0.8814
Ed5to8	0.2107***	0.0182	0.0167	0.2055***	0.0181	0.0167
Ed9to12	0.6203***	0.0184	0.0179	0.6036***	0.0182	0.0178
Edgt12	1.4518***	0.0227	0.0236	1.4167***	0.0226	0.0237
OJE	0.0455***	0.0019	0.0020	0.0455***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001	-0.0008***	0.0001	0.0001
Black	-0.1821***	0.0134	0.0133	-0.1737***	0.0133	0.0133
Male	0.5181***	0.0153	0.0158	0.5130***	0.0152	0.0157
Dir	0.3797***	0.0203	0.0213	0.3702***	0.0202	0.0212
SP	0.1618***	0.0225	0.0233	0.1566***	0.0223	0.0231
Mid	0.1926***	0.0219	0.0219	0.1859***	0.0217	0.0217
Ser	0.3071***	0.0185	0.0201	0.2965***	0.0184	0.0200
Oper	0.1709***	0.0235	0.0213	0.1717***	0.0233	0.0212
EO	-0.1995***	0.0209	0.0180	-0.1999***	0.0207	0.0179
Popdens	-0.0068***	0.0013	0.0011	-0.0069***	0.0013	0.0011
Banks	0.0499*	0.0309	0.0289	0.0487*	0.0309	0.0294
Deaths	0.0014***	0.0005	0.0005	0.0015***	0.0005	0.0005
Schools	-0.0090***	0.0021	0.0019	-0.0090***	0.0021	0.0019
Altitude	0.0048***	0.0017	0.0017	0.0049***	0.0017	0.0017
N	0.3224	0.3823	0.3676	0.2969	0.3820	0.3687
NE	1.1955***	0.4963	0.4472	1.17710***	0.4959	0.4505
S	-0.3855	0.4344	0.4396	-0.4071	0.4341	0.4504
MW	-0.4806***	0.0960	0.0942	-0.4903***	0.0959	0.0946
Avetemp	0.0309	0.0401	0.0411	0.0327	0.0401	0.0404
Junerain	-0.0025***	0.0009	0.0008	-0.0025***	0.0009	0.0008
Febrain	0.0009***	0.0003	0.0003	0.0009***	0.0003	0.0003
Avetemp×S	0.0258	0.0324	0.0327	0.0278	0.0324	0.0333
Rho				0.2486		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table B.3: Results from the Rent Equation of Model 26

Model	Single Equation			SURE		
	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Constant	16.7106	11.9027	11.7318	11.0789	11.5982	11.5654
Flusht	0.3932***	0.0322	0.0336	0.3859***	0.0312	0.0326
Filter	0.1445***	0.0256	0.0264	0.1409***	0.0248	0.0255
Br1×A	0.8578***	0.0360	0.0364	0.7809***	0.0349	0.0358
Br2×A	1.0130***	0.0364	0.0333	0.9415***	0.0353	0.0325
Br3×A	1.2780***	0.0490	0.0488	1.1635***	0.0475	0.0470
Brgt3×A	1.3595***	0.1644	0.1496	1.1883***	0.1593	0.1592
Br2×H	0.3106***	0.0288	0.0281	0.2760***	0.0279	0.0277
Br3×H	0.7039***	0.0459	0.0555	0.6264***	0.0445	0.0536
Brgt3×H	1.0814***	0.0960	0.1341	0.9775***	0.0930	0.1223
Popdens	-0.0061*	0.0032	0.0032	-0.0057*	0.0031	0.0031
Banks	-0.026	0.0252	0.0222	-0.0321	0.0246	0.0223
Deaths	0.0015	0.0012	0.0011	0.0018	0.0011	0.0011
Schools	0.0020	0.0034	0.0032	0.00038	0.0033	0.0032
Altitude	-0.0070	0.0089	0.0090	-0.0034	0.0087	0.0089
N	0.1121	0.4979	0.4892	-0.1613	0.4855	0.4822
NE	0.0317	0.8717	0.9213	-0.1397	0.8483	0.9115
S	-8.8570***	2.0457	1.9658	-8.5125***	1.9970	1.9690
MW	-0.2655*	0.1599	0.1494	-0.3376**	0.1564	0.1492
Ln(Avetemp)	-4.5199	3.7844	3.7195	-2.7157	3.6871	3.6675
Ln(Junerain)	-0.0929	0.2617	0.2745	-0.0449	0.2547	0.2714
Ln(Febrain)	0.5231*	0.2603	0.2745	0.5021*	0.2533	0.2714
Ln(Avetemp)×S	2.8448***	0.8045	0.7709	2.8500***	0.7848	0.7715

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table B.4: Results from the Wage Equation of Model 26

Model	Single Equation			SURE		
Variable	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Constant	-8.9559	5.5795	5.7925	-8.7236	5.5757	5.7118
Ed5to8	0.2115***	0.0182	0.0167	0.2062***	0.0181	0.0167
Ed9to12	0.6200***	0.0184	0.0179	0.6033***	0.0182	0.0178
Edgt12	1.4522***	0.0227	0.0237	1.4170***	0.0226	0.0237
OJE	0.0457***	0.0019	0.0020	0.0456***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001	-0.0008***	0.0001	0.0001
Black	-0.1829***	0.0134	0.0133	-0.1745***	0.0133	0.0133
Male	0.5193***	0.0153	0.0158	0.5142***	0.0152	0.0157
Dir	0.3804***	0.0203	0.0213	0.3708***	0.0202	0.0212
SP	0.1609***	0.0225	0.0233	0.1556***	0.0223	0.0231
Mid	0.1919***	0.0219	0.0219	0.1853***	0.0217	0.0217
Ser	0.3071***	0.0185	0.0201	0.2965***	0.0184	0.0200
Oper	0.1704***	0.0235	0.0213	0.1712***	0.0233	0.0212
EO	-0.1990***	0.0209	0.0180	0.1995***	0.0207	0.0179
Popdens	-0.0023	0.0014	0.0014	-0.0024*	0.0014	0.0014
Banks	-0.0333**	0.0136	0.0141	-0.0342**	0.0135	0.0144
Deaths	0.0008	0.0006	0.0006	0.0009	0.0006	0.0006
Schools	-0.0048***	0.0015	0.0015	-0.0048***	0.0015	0.0015
Altitude	0.0104***	0.0040	0.0041	0.01021**	0.0040	0.0041
N	-0.9997***	0.2443	0.2528	-1.0086***	0.2441	0.2516
NE	-0.7227*	0.3583	0.3769	-0.7104*	0.3581	0.3778
S	-3.6392***	1.1011	1.1487	-3.6803***	1.1004	1.1725
MW	-0.3904***	0.0959	0.0976	-0.4020***	0.0958	0.0982
Ln(Avetemp)	4.0689**	1.7514	1.8159	3.9978**	1.7502	1.7919
Ln(Junerain)	0.1705	0.1091	0.1145	0.1628	0.1091	0.1147
Ln(Febrain)	0.1977*	0.1074	0.1127	0.2100*	0.1074	0.1135
Ln(Avetemp)×S	1.5691***	0.4135	0.4310	1.5841***	0.4132	0.4401
Rho				0.2491		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table B.5: Results from the Rent Equation of Model 27

Model	Single Equation			SURE		
	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Constant	11.4776***	1.9798	1.6386	10.6465***	1.9297	1.6470
Flusht	0.3976***	0.0323	0.0337	0.3894***	0.0313	0.0328
Filter	0.1469***	0.0256	0.0264	0.1426***	0.0248	0.0255
Br1×A	0.8570***	0.0360	0.0364	0.7806***	0.0349	0.0358
Br2×A	1.0142***	0.0364	0.0333	0.9427***	0.0353	0.0325
Br3×A	1.2793***	0.0490	0.0489	1.1649***	0.0475	0.0470
Brgt3×A	1.3618***	0.1643	0.1506	1.1905***	0.1592	0.1598
Br2×H	0.3089***	0.0288	0.0281	0.2748***	0.0279	0.0277
Br3×H	0.7027***	0.0459	0.0555	0.6256***	0.0445	0.0536
Brgt3×H	1.0821***	0.0959	0.1342	0.9782***	0.0930	0.1224
Popdens	-0.0070***	0.0015	0.0014	-0.0072***	0.0015	0.0013
Banks	0.01958	0.0305	0.0286	0.0172	0.0298	0.0287
Deaths	0.0011	0.0014	0.0012	0.0013	0.0014	0.0013
Schools	-0.0000	0.0044	0.0030	-0.0017	0.0043	0.0030
Altitude	-0.0099***	0.0035	0.0029	-0.0082***	0.0034	0.0029
N	0.7525***	0.2874	0.2694	0.5905**	0.2805	0.2701
NE	0.4057	0.3415	0.3012	0.3985	0.3328	0.3023
S	-2.9058***	0.6304	0.5721	-2.7843***	0.6161	0.5771
MW	-0.0830	0.1931	0.1766	-0.1486	0.1884	0.1768
Avetemp	-0.3118***	0.0819	0.0642	-0.2709***	0.0798	0.0646
Augrain	-0.0027*	0.0017	0.0015	-0.0027*	0.0016	0.0015
Marrain	0.0023***	0.0004	0.0004	0.0023***	0.0004	0.0004
Avetemp×S	0.0908***	0.0405	0.0358	0.0948***	0.0396	0.0361

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table B.6: Results from the Wage Equation of Model 27

Model	Single Equation			SURE		
	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Constant	5.7712***	0.9413	0.9233	5.8612***	0.9406	0.9266
Ed5to8	0.2115***	0.0182	0.0167	0.2063***	0.0181	0.0167
Ed9to12	0.6214***	0.0184	0.0179	0.6047***	0.0182	0.0178
Edgt12	1.4534***	0.0227	0.0237	1.4183***	0.0226	0.0237
OJE	0.0456***	0.0019	0.0020	0.0456***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001	-0.0008***	0.0001	0.0001
Black	-0.1816***	0.0134	0.0133	-0.1732***	0.0133	0.0133
Male	0.5190***	0.0153	0.0158	0.5139***	0.0152	0.0157
Dir	0.3799***	0.0203	0.0213	0.3704***	0.0201	0.0212
SP	0.1619***	0.0225	0.0233	0.1567***	0.0223	0.0231
Mid	0.1930***	0.0219	0.0219	0.1864***	0.0217	0.0217
Ser	0.3077***	0.0185	0.0201	0.2971***	0.0184	0.0200
Oper	0.1711***	0.0235	0.0213	0.1719***	0.0233	0.0212
EO	-0.1981***	0.0209	0.0180	-0.1986***	0.0207	0.0179
Popdens	-0.0062***	0.0008	0.0008	-0.0063***	0.0008	0.0008
Banks	0.0241	0.0165	0.0173	0.0228	0.0165	0.0176
Deaths	0.0015***	0.0006	0.0006	0.0015***	0.0006	0.0006
Schools	-0.0085***	0.0019	0.0018	-0.0085***	0.0019	0.0017
Altitude	0.0013	0.0017	0.0016	0.0012	0.0017	0.0016
N	-0.0002	0.1523	0.1591	-0.0198	0.1522	0.1618
NE	0.4961***	0.1614	0.1617	0.4772***	0.1613	0.1637
S	-1.0087***	0.3634	0.3783	-1.0341***	0.3632	0.3880
MW	-0.3628***	0.0972	0.0948	-0.3648***	0.0972	0.0951
Avetemp	-0.0293	0.0380	0.0367	-0.0317	0.0380	0.0367
Augrain	-0.0028***	0.0007	0.0007	-0.0027***	0.0007	0.0007
Marrain	0.0015***	0.0002	0.0002	0.0015***	0.0002	0.0002
Avetemp× S	0.0527**	0.0224	0.0231	0.0540**	0.0224	0.0237
Rho				0.2483		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table B.7: Results from the Rent Equation of Model 28

Model	Single Equation			SURE		
	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Constant	32.6142***	5.5374	5.3227	29.8793***	5.4086	5.3315
Flusht	0.3979***	0.0323	0.0338	0.3895***	0.0313	0.0328
Filter	0.1469***	0.0256	0.0263	0.1426***	0.0248	0.0255
Br1×A	0.8570***	0.0360	0.0364	0.7806***	0.0349	0.0358
Br2×A	1.01426***	0.0364	0.0333	0.9428***	0.0353	0.0325
Br3×A	1.2794***	0.0490	0.0489	1.1649***	0.0475	0.0470
Brgt3×A	1.3616***	0.1643	0.1505	1.1903***	0.1592	0.1597
Br2×H	0.3088***	0.0288	0.0281	0.2747***	0.0279	0.0277
Br3×H	0.7026***	0.0459	0.0555	0.6255***	0.0445	0.0536
Brgt3×H	1.0819***	0.0959	0.1341	0.9782***	0.0930	0.1223
Popdens	-0.0083***	0.0022	0.0018	-0.0084***	0.0021	0.0018
Banks	-0.0059	0.0242	0.0218	-0.0099	0.0237	0.0220
Deaths	0.0004	0.0012	0.0010	0.0006	0.0012	0.0011
Schools	-0.0007	0.0043	0.0028	-0.0020	0.0042	0.0028
Altitude	-0.0167***	0.0043	0.0040	-0.0150***	0.0042	0.0041
N	0.5764**	0.3227	0.2985	0.4102	0.3152	0.2993
NE	0.3108	0.3789	0.3115	0.2802	0.3695	0.3154
S	-9.4460***	2.3461	2.0560	-9.1110***	2.2922	2.0808
MW	0.0550	0.1253	0.1159	-0.0056	0.1225	0.1167
Ln(Avetemp)	-9.4086***	1.6424	1.5762	-8.5292***	1.6043	1.5806
Ln(Augrain)	-0.1970	0.1608	0.1355	-0.1874	0.1568	0.1366
Ln(Marrain)	0.5688***	0.0995	0.0904	0.5818***	0.0972	0.0899
Ln(Avetemp)×S	2.6823***	0.8542	0.7556	2.6382***	0.8346	0.7645

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

Table B.8: Results from the Wage Equation of Model 28

Model	Single Equation			SURE		
	Coeff.	Std. Error	Robust Std. Error	Coeff.	Std. Error	Robust Std. Error
Constant	17.1541***	3.0743	3.0618	17.0751***	3.0721	3.0966
Ed5to8	0.2113***	0.0182	0.0167	0.2061***	0.0181	0.0167
Ed9to12	0.6213***	0.0184	0.0179	0.6046***	0.0182	0.0178
Edgt12	1.4531***	0.0227	0.0237	1.4180***	0.0226	0.0237
OJE	0.0456***	0.0019	0.0020	0.0455***	0.0019	0.0020
OJEsq	-0.0008***	0.0001	0.0001	-0.0008***	0.0001	0.0001
Black	-0.1815***	0.0134	0.0133	-0.1732***	0.0133	0.0133
Male	0.5187***	0.0153	0.0158	0.5136***	0.0152	0.0157
Dir	0.3797***	0.0203	0.0213	0.3703***	0.0201	0.0212
SP	0.1620***	0.0225	0.0233	0.1568***	0.0223	0.0231
Mid	0.1931***	0.0219	0.0219	0.1864***	0.0217	0.0217
Ser	0.3077***	0.0185	0.0201	0.2971***	0.0184	0.0200
Oper	0.1712***	0.0235	0.0213	0.1720***	0.0233	0.0212
EO	-0.1984***	0.0209	0.0180	-0.1988***	0.0207	0.0179
Popdens	-0.0074***	0.0012	0.0010	-0.0074***	0.0012	0.0011
Banks	-0.0065	0.0137	0.0144	-0.0076	0.0137	0.0148
Deaths	0.0009	0.0006	0.0006	0.0009	0.0006	0.0006
Schools	-0.0081***	0.0018	0.0017	-0.0081***	0.0018	0.0017
Altitude	-0.0073***	0.0023	0.0023	-0.0072***	0.0023	0.0023
N	-0.0781	0.1790	0.1879	-0.1022	0.1789	0.1906
NE	0.4128**	0.1896	0.1854	0.3901**	0.1895	0.1885
S	-2.8929**	1.3241	1.3779	-3.0206**	1.3232	1.4138
MW	-0.1778**	0.0749	0.0743	-0.1832**	0.0748	0.0753
Ln(Avetemp)	-4.0044***	0.9137	0.9059	-3.9830***	0.9131	0.9184
Ln(Augrain)	-0.2142***	0.0783	0.0759	-0.2089***	0.0782	0.0767
Ln(Marrain)	0.4327***	0.0553	0.0542	0.4375***	0.0552	0.0539
Ln(Avetemp)×S	0.8234*	0.4837	0.5041	0.8704*	0.4833	0.5175
Rho				0.2483		

Note: ***, **, and * indicate that the parameter is significantly different from zero at the 1, 5, and 10 percent critical levels. The t statistics are calculated using the heteroskedasticity-robust standard errors.

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