ABSTRACT

Title of dissertation:	ESSAYS ON ASSET PURCHASES AND SALES: THEORY AND EMPIRICAL EVIDENCE
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This dissertation consists of a theory essay and an empirical essay that investigate a firm's decision to buy or sell corporate assets. It seeks to answer the following research questions: (1) why do firms choose to buy or sell assets? (2) what makes assets in an industry more likely to be traded than assets in other industries? and (3) within an industry, why asset sales come in waves and tend to cluster over a certain time period?

In my theory essay, "The Real Determinants of Asset Sales", I develop a dynamic equilibrium model that jointly analyzes firms' decisions to buy or sell assets and the activity of asset sales in the industry. In my model, a firm maximizes its value by making two inter-related decisions: how much to invest in new assets and whether to buy or sell existing assets. These decisions are made under both firm- and industry-level productivity shocks. By modeling equilibrium asset prices, I am able to make predictions about an industry with a well-defined panel of firms. The model is solved through simulations and it is calibrated using the plant-level data from Longitudinal Research database. I show that most of the empirical evidence documented in the literature on asset sales is consistent with value-maximizing behavior. My model also provides testable implications for the cross-industry and time-series variations in asset sales.

In my empirical essay, "What Drives Asset Sales - The Empirical Evidence", I test the model's predictions using the plant-level data from Longitudinal Research Database on manufacturing firms in the period of 1973 to 2000. The patterns of transactions (firm-level purchase/sale decisions, and the cross-industry and the time-series variation in asset sales activities) are consistent with my theoretical model. Specifically, I show that: (1) asset purchases are more likely when firms' existing plants experience increases in productivity, and asset sales are more likely when firms have decreases in productivity ("rising buys falling"); (2) shock attributes such as persistence and dispersion help to explain the cross-industry variation in asset sales - industries with less persistent and more widely dispersed productivity shocks, on average, have higher rates of assets sales; and (3) within an industry, periods with more uncertainty regarding firms' relative productivity positions are associated with more frequent trades of existing assets. This essay is based on the ongoing joint work with Vojislav Maksimovic and Gordon Phillips.

ESSAYS ON ASSET PURCHASES AND SALES:
THEORY AND EMPIRICAL EVIDENCE

by

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Essay 1:

The Real Determinants of Asset Sales

Abstract

In this paper I develop a dynamic structural model in which a firm makes rational decisions to buy or sell assets in the presence of both idiosyncratic and aggregate productivity shocks. By identifying equilibrium asset prices, the model produces an industry with a well-defined panel of firms, and jointly analyzes firms' asset sales decisions and the aggregate asset sales activity in the business cycle. It suggests that changes of productivity, rather than levels, affect firms' decisions - firms with increasing productivity buy assets while firms with decreasing productivity choose to downsize. More assets are transacted in expansion years when aggregate productivity and price for existing assets are higher. The model is calibrated using the plant-level data from the U.S. Census Bureau's Longitudinal Research Database (LRD). Using the simulated panel, I show that most of the empirical evidence on asset sales is consistent with value-maximizing behavior: (1) firms which buy assets have higher valuation around the transaction, but lower long-run average – a result that was previously used to support the market-timing theory; (2) small acquirers have higher returns during the acquisition year than do large acquirers; and (3) dynamic properties of productivity shocks affect the asset sales activity in the industry: industries with less persistent and highly dispersed productivity shocks have greater asset sales.

1 Introduction

One of the puzzles in corporate finance is why asset sales and merger activities vary not only across industries, but also over time. Many researchers find similar results: assets are traded much more frequently in some industries than others; and a greater number of transactions occur in expansion years when aggregate productivity is high. But, what makes assets in one industry more likely to change hands than the assets in others? Why do asset sales coincide with the business cycle? Which firms engage in asset sales?[1]

This paper addresses these questions by providing a unified framework that jointly analyzes firms' asset sales decisions and asset sales activity in the industry. In my model, a firm maximizes its value by making two inter-related decisions: how much to invest in new assets and whether to buy or sell existing assets. These decisions are made under both firm- and industry-level productivity shocks. By modeling equilibrium asset prices, I am able to make predictions about an industry with a well-defined panel of firms. My model shows that most of the empirical evidence on asset sales is consistent with value-maximizing behavior. Firms optimally expand or downsize in response to changes in productivity that are driven by shocks. The model is calibrated using plant-level data from the Longitudinal Research Database maintained by U.S. Census.

I have four main findings. First, I show that a dynamic neoclassical model with productivity shocks generates transaction patterns that were previously viewed as support for the misvaluation theory, as documented by Rhodes-Kropf, Robinson, and Viswanathan (2004). Firms which buy assets have higher valuation around the transaction, but lower long-run valuation; while firms which sell assets have lower

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[1] In this paper, I use the term "asset sales" in a loose sense to include both asset sales and purchases.

valuation around the transaction, but higher long-run valuation. In my model, this phenomenon occurs as a result of equilibrium behavior without misvaluation. The intuition is as follows. Firms choose optimal sizes based on productivity levels. As productivity changes with shocks, firms with productivity increases will expand while firms with productivity decreases will downsize. Hence, more productive firms buy their less productive counterparts (high buys low). In addition, since shocks are mean reverting, firms are more likely to acquire assets at times when their current productivity is above the long-run average, and they are more likely to sell assets at times when current productivity is below the long-run average. As a result, controlling for current valuations, buyers have lower long-run valuation than do sellers (long-run low buys long-run high).

Second, this model considers a firm's decision on asset sales based on both size and productivity. Thus, it allows me to address recent empirical findings on the size effect in acquirer returns. Consistent with Moeller, Schlingemann, and Stulz (2004), I find that small acquirers have higher returns around the acquisition than do large acquirers. When there exist fixed transaction costs, acquisitions are more likely to be carried out when there is a major increase in productivity and the firm size is large. Both of these factors lead to a higher payoff in dollar terms. Small acquirers have a bigger increase in productivity and hence higher returns. Thus, the empirically observed size effect in acquirer returns is driven by the endogenous sample selection.

Moreover, I show that, in equilibrium, even when input prices fully adjust to industry-level shocks, the presence of fixed costs can still lead to greater asset sales in expansion years, when aggregate productivity is high. This is because the gain of transferring assets increases in industry productivity, and when aggregate productivity is high, acquisitions are more likely to occur, especially for the marginal buyers and sellers.

Finally, my model provides new and testable implications for how the dynamic properties of productivity shocks explain the cross-industry variation in asset sales. Since purchases and sales of assets result from changes in productivity due to shocks, this model predicts that industries in which firms find it more likely to have their relative productivity change over time have greater asset sales activity.

I consider two main differences in the model between investing in new assets and buying assets from other firms. First, based on time-to-build models in the economics literature,[2] I assume that it takes one period for new investments to become productive, while assets bought from other firms are available for production immediately. Given this difference in availability, decisions on new investments reflect expected future demand for capacity, and decisions on asset sales result from the current demand caused by unexpected changes in productivity. In other words, in my model, firms make new investments to account for the expected future growth, but participate in asset sales to fix current investment needs. To account for the empirical findings that asset sales are infrequent and lumpy, I assume that there exists a fixed cost for buying and selling assets.

I solve the model in a recursive equilibrium framework using simulations, taking asset prices and industry evolution as endogenous. I face two numerical challenges. First, to model the interactions among all firms in the industry, I need to incorporate industry structure, which is a joint distribution of productivity levels and capital stocks, into the decision process. But, this joint distribution is a high-dimension object and numerical solutions to dynamic programming problems become increasingly difficult as the size of state space increases. Second, I need to have a pre-specified pricing function for existing assets, which, when taken by all firms in the industry, can

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[2]The time-to-build attributes in capital investment are illustrated in Kydland and Prescott (1982) and Christiano and Todd (1996).

be implied by the optimal decisions of heterogeneous firms in that industry. I follow the methods developed in Krusell and Smith (1997, 1998) for solutions. Through simulations, I show that using a limited number of moments of the distribution as a proxy for the entire distribution leads to prices and quantities that are approximately optimal.

Other papers have also addressed the relationship between shocks and asset sales. Using a static equilibrium model, Maksimovic and Phillips (2002) predict how aggregate demand shocks affect a firm's growth pattern, based on its productivity. In their model, firm size is endogenously related to productivity and a positive demand shock can cause the more productive firms to buy assets from the less productive firms. In another paper, Jovanovic and Rousseau (2002) describe a model where decisions to buy and sell assets are driven by firm-specific contemporaneous productivity.

Although my model does incorporate features from these two models, it differs in several crucial ways. In my model, firms make dynamic investment decisions, based on the interaction of size and productivity. Since size also serves as a proxy for previous productivity, it allows me to consider not only cross-sectional, but also time-series effects of productivity shocks. By tracking a firm over time, I am able to include past as well as expected future productivity into current investment decisions. Such a dynamic setting helps to shed light on some of the puzzles that existing studies are not able to explain using static models. In addition, the dynamic equilibrium aspect of this model differs from most of the existing models on asset sales. Here, the decision of a particular firm depends on the characteristics of other firms in the industry, and industry structure evolves over time to reflect past productivity levels and sales activities. Using the simulated panel based on the model, I can also address questions about how levels of asset sales activity differ across various industries, and change over the business cycle.

The rest of the paper is organized as follows. Section 2 describes the related literature. Section 3 presents an example of two firms and three periods that illustrate the basic intuition. Section 4 describes the model and simulation method. Section 5 discusses the model's implications by using simulated moments, and Section 6 concludes.

2 Related Literature

My research is related to the literature on asset sales, mergers and acquisitions.

The cross-industry difference in asset reallocation has been documented in Mitchell and Mulherin (1996) and Maksimovic and Phillips (2001)[3]. Over time, both asset sales and merger activities are found to be procyclical: a greater number of mergers take place and more assets are traded in expansion years when aggregate productivity is high (Maksimovic and Phillips (2001), Rhodes-Kropf and Viswanathan (2004), Eisfeldt and Rampini (2005)). My theoretical model and empirical results are consistent with this literature.

Neoclassical theory views mergers and asset sales as efficiency-improving efforts that happen in response to industry shocks. The hypothesis that merger activities are driven by broad economic shocks can be traced to Gort (1969). Jovanovic and Rousseau (2002) formalize this idea in a model where firms with higher productivity acquire firms with lower productivity. Since their model builds on the constant return to scale technology, it focuses on cross-sectional contemporaneous sales, rather than on activities over time. Maksimovic and Phillips (2002) present an equilibrium model to show how firms respond differently to aggregate demand shocks based on their

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[3]Mitchell and Mulherin (1996) show that seven industries account for more than half of the total takeover activities in the sample period. Maksimovic and Phillips (2001) show that in manufacturing industries, the highest annual rate of asset sales is 4.72 percent and the lowest rate is 2.77 percent.

productivity. The relation between economic shocks and asset reallocation has been documented in empirical studies, such as Mitchell and Mulherin(1996), Andrade, Mitchell, and Stafford (2001), Andrade and Stafford (2004) and Harford (2005). My model augments this literature by generating simulated panel data which can be used to study firms' investment decisions over time.

Other recent studies focus on valuation and suggest that mergers might be driven by misvaluation. Shleifer and Vishny (2003) and Rhodes-Kropf and Viswanathan (2004) develop models where mergers are motivated by overvalued synergy. Empirical studies such as Rhodes-Kropf, Robinson, and Viswanathan (2004) and Dong, Hirshleifer, Richardson, and Teoh (2005) broadly support the misvaluation theory. Comparing a firm's market value and some metric of "fundamental value," they find that mergers cluster in overvalued industries, acquirers have higher current valuation, but lower long-run valuation, and cash acquirers are less overvalued than stock acquirers.

Quite a few papers have studied how characteristics affect asset sales decisions. Lang, Poulsen, and Stulz (1995), and Schlingemann, Stulz, and Walking (2002) relate decisions to sell assets with liquidity and financing needs. The agency explanation of asset purchases, though, can be traced back to Jensen (1986). And, a more recent paper by Gorton, Kahl, and Rosen (2005) shows that, when severe enough, agency problem can drive unprofitable defensive acquisitions. Linking asset sales with efficiency, Maksimovic and Phillips (2001) argue that firms are more likely to buy (sell) when they have higher (lower) productivity.

The evidence on market reaction to asset sales is mixed. Alexander, Benson, and Kampmeyer (1984) find positive abnormal returns for voluntary corporate sell-offs. Lang, Poulsen, and Stulz (1995) find that the returns are positive only when

the proceeds are paid out. Moeller, Schlingemann, and Stulz (2004) show that the announcement return for an acquiring firm is roughly two percent higher for smaller acquirers regardless of the form of financing and whether the acquired firm is public or private. Bradley and Sundaram (2005) argue that the most important determinant of announcement return to acquisition is organizational form, not firm size.

The equilibrium aspect of my model is in the spirit of Shleifer and Vishny (1992). These authors demonstrate that when an industry experiences a negative aggregate shock, the resale value of the asset must take a discount, as the potential buyer may also face cash constraints. The opposite can also be true, as my paper illustrates. That is, in expansions, when aggregate productivity is higher and orders for new investments cannot be completely filled in the short run, the increase in demand will lead to a premium in asset prices. My paper is also related to Eisfeldt and Rampini (2005), who study capital reallocation activity in the business cycle.

In addition, this paper joins a small, but growing, literature in corporate finance that matches the simulated panel based on structural models to recover firms' decisions (Gomes and Livdan (2004), Hennessy and Whited (2004, 2005), Strebulaev (2004), and Kyle and Meng (2005)). The structural approach provides an useful solution to the endogeneity problem embedded within most empirical studies, which, as shown by Coles, Lemmon, and Meschke (2003), is difficult to correct by using the standard econometric methods, such as control variables, fixed effects or simultaneous equations.

3 Basic Intuition: An Example

In this section, I use an example to show that (1) firms respond to changes of productivity through asset sales and purchases, (2) industries with less persistent idiosyn-

cratic shocks have more reallocation, and (3) asset reallocation is more likely when aggregate productivity is high.

3.1 Set Up

Consider an industry with only two representative firms ($i \in \{1, 2\}$), which exist for two periods ($t \in \{0, 1, 2\}$). Firms are price-takers. In any period, t, each firm is endowed with a capital stock $k_{i,t}$. After observing the industry-level, $z_{a,t}$ and firm-level productivity shocks, $z_{i,t}$, each firm makes decisions on new investments, $I_{i,t}$, and whether to buy or sell assets ($x_{i,t}$). A positive $x_{i,t}$ means a purchase and a negative $x_{i,t}$ is a sale. There is no short selling on new investments, i.e., $I_{i,t} \geq 0$.

There is a timing difference between investing in new assets and buying assets from other firms. Assets purchased from the other firm can be used for production in the current period, but it takes one period for new investment to become productive. The difference in timing reflects the time-to-build attribute of capital investments such that new machinery and structures usually take several building periods, while assets purchased from the other firm are already productive at the time of purchase.

After asset sales, the current capacity for production is a sum of initial stock and assets bought (sold), $k_{i,t} + x_{i,t}$, and the carried-over capital to the next period is equal to undepreciated capital plus the new investment $(1 - \delta)(k_{i,t} + x_{i,t}) + I_{i,t}$. In the last period, there is assumed to be no production, all capital is liquidated at a given price, and the two firms collect the proceeds. Firms make decisions on asset sales in the first two periods $\{x_{i,t=0}, x_{i,t=1}\}$, and decide on new investments only in the first period $\{I_{i,t=0}\}$.

The firm produces output using capital stock $k_{i,t}$, via an increasing and concave production function, π:

$$\pi\left(k_{i,t}, z_{a,t}, z_{i,t}\right) = \exp\left(z_{a,t} + z_{i,t}\right) k_{i,t}^{\alpha} \tag{1}$$

where $\alpha < 1$.

There are two states of the world, prosperity $(z_a > 0)$ and depression $(-z_a < 0)$. For simplicity, I assume that firm-level shocks also have two states, $\{z, -z\}$, and at any period, t, they are symmetric, i.e., $z_{1,t} = -z_{2,t}$. Both industry- and firm-level productivity follow Markov processes. I denote ρ_a and ρ_i as the transition probabilities that the same shock level continues in the next period such that[4]

$$
\begin{aligned}
\Pr\left[z_{a,t} = z_{a,t-1}\right] &= \rho_a \quad \text{and} \quad \Pr\left[z_{a,t} = -z_{a,t-1}\right] = 1 - \rho_a \\
\Pr\left[z_{i,t} = z_{i,t-1}\right] &= \rho_i \quad \text{and} \quad \Pr\left[z_{i,t} = -z_{i,t-1}\right] = 1 - \rho_i
\end{aligned}
\tag{2}
$$

Aggregate and idiosyncratic shocks are independent.

I normalize the unit price for new investment to one. The unit price for existing assets, P_t, comes from market clearing. To account for the transaction costs encountered during the process such as searching for partners, negotiating deals, and legal fee, there is a fixed cost, f, for participating in asset transfer. I write the total investment costs as:

$$C\left[I_{i,t}, x_{i,t}\right] = I_{i,t} + \left(P_t \cdot x_{i,t} + f \cdot 1_{x_{i,t} \neq 0}\right) \tag{3}$$

where $1_{x \neq 0}$ is an indicator function that equals one if the firm buys or sells assets.

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[4]To accommodate the symmetric constraint on firm-level productivity, I set up the process such that firm 1's firm-level productivity z_1, follows a Markov process with transition probability ρ_i; and after that is realized, firm 2 will have a shock level of $-z_1$.

The total cash flow at t, D_t, equals to profit, net of investment costs:

$$D_{i,t} = \pi_{i,t} - C_{i,t} \tag{4}$$

In both periods, the firm chooses the investment decisions to maximize the present value plus the sum of expected future cash flow, i.e.,

$$
\begin{aligned}
t = 0 \quad &\max_{\{x_{i,t=0}, I_{i,t=0}\}} \quad \left\{ D_{i,t=0} + E\left[\beta D_{i,t=1} + \beta^2 D_{i,t=2}\right] \right\} \\
t = 1 \quad &\max_{\{x_{i,t=1}\}} \qquad \left\{ D_{i,t=1} + \beta E\left[D_{i,t=2}\right] \right\}
\end{aligned}
\tag{5}
$$

where β is an intertemporal discount factor.

3.2 Implications

The appendix analyzes the details of the example. Here, I look at results from the special cases where (1) firms have the same initial size at time 0, i.e., $k_{1,t=0} = k_{2,t=0} \equiv k$; (2) the non-negativity constraint on new investment is not binding, and (3) there is no requirement to transfer the realized new investments across firms.[5]

Proposition 1 *Let θ denote the share of total assets that the firm with a positive shock will occupy, then $\theta = \dfrac{\exp\left(\frac{z}{1-\alpha}\right)}{\exp\left(\frac{z}{1-\alpha}\right) + \exp\left(\frac{-z}{1-\alpha}\right)} > \dfrac{1}{2}$ and it is increasing in shock magnitude, i.e. $\frac{\partial \theta}{\partial z} > 0$.*

Proof. See Appendix. ∎

Fixed cost is not binding First, assume that the fixed cost for transaction, f, in not binding (I will discuss this participation constraint later). Let $\{z_0, z_1\}$, $\{\theta_0, \theta_1\}$ and $\{x_0, x_1\}$ denote firm 1's productivity shock, share of total capital, and the amount of assets it bought (sold) in both periods, respectively.

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[5]I show in the appendix that this is true when $z(2\rho_i - 1) = (2\theta - 1)z_a(2\rho_a - 1)$.

Without loss of generality, I assume that firm 1 has a positive shock in the first period $(z_0 = z)$. Then, I have

$$\begin{cases} \theta_0 = \theta \\ x_0 = \left(\theta - \frac{1}{2}\right) 2k > 0 \end{cases} \tag{6}$$

Since firm 1 is more productive, it will buy assets from the other firm. Similarly, at $t = 1$, firm 1's decision in the second period is:

$$x_1 = (1 - \delta) (2k) (\theta_1 - \theta_0) \tag{7}$$

If firm 1 continues to receive a positive shock $(z_1 = z)$, then $\theta_1 = \theta$. No transaction is necessary, as its current share of assets is already at the equilibrium:

$$\begin{cases} \theta_1 = \theta_0 = \theta \\ x_1 = 0 \end{cases} \tag{8}$$

The transaction will occur only if firm 1 experiences a negative shock $(z_1 = -z)$ and becomes less productive, in which case, firm 1 has to sell assets to firm 2, i.e.,

$$\begin{cases} \theta_1 = (1 - \theta) \\ x_1 = (1 - \delta) (2k) (1 - 2\theta) < 0 \end{cases} \tag{9}$$

If the participation constraint is not binding in the first period, it will not be binding in the second period. This is because the efficiency gain from transferring assets is higher when the less productive firm also holds more capital, as compared to the case when two firms hold equal capital. Therefore, I can write the expected total quantity transferred in both periods, X, as the asset transfer in the first period, plus

the expected asset transfer in the second period when productivity changes:

$$E\left[X\right] = \underbrace{\left|\left(\theta - \frac{1}{2}\right)2k\right|}_{\text{transfer in the first period}} + \underbrace{\left(1 - \rho_i\right)}_{\text{probability of change}} \cdot \underbrace{\left|\left(1 - \delta\right)\left(2k\right)\left(1 - 2\theta\right)\right|}_{\text{transfer in the second period}} \tag{10}$$

Since lower persistence (ρ_i) means a higher probability of productivity change, industries with less persistent idiosyncratic shocks will have more asset sales.

With fixed cost   So far, I have only considered cases in which the fixed cost is not binding. With fixed costs, whether a transaction will occur also depends on whether the gain from transferring assets is high enough to recover the fixed cost.

I show in the appendix that controlling for fixed cost, f, and the difference in firm-level productivity, z, a transaction will take place if the aggregate shock, z_a, is greater than a threshold level, $\widetilde{z}_a$ where

$$\widetilde{z}_a = \log\left(f\right) - z - \log\left(k^\alpha\right) - \log\left[\frac{1}{\left(2\theta\right)^{1-\alpha}} + 2\theta^\alpha\left(1 - \alpha\right) - 1\right] \tag{11}$$

Consider a case in which firm 1 always experiences a positive shock and industry goes from recession to prosperity. There are three possible scenarios: (1) a transaction will occur in the first period if $-z_a \geq \widetilde{z}_a$; (2) the transaction will never occur if $z_a < \widetilde{z}_a$, and (3) a transaction will only occur in the second period if $-z_a < \widetilde{z}_a < z_a$.

The example above generates an interesting timing implication for asset sales. In the last case, although the difference in productivity has existed from the first period, a transaction will only occur when the aggregate productivity improves in prosperity. As a higher aggregate productivity magnifies the difference in total productivity between less- and more-productive firms, the gain from the transaction also increases. The increase in the potential gain makes the transaction more likely to occur, given a fixed transaction cost.

On the other hand, given the magnitude of aggregate shock, it implies that industries with lower fixed costs are more likely to experience higher asset sales activity. I formalize these predictions in the proposition below.

Proposition 2 (1) *Given the fixed cost and shock magnitude, sales are more likely to occur when aggregate productivity is high* (2) *Given the aggregate productivity, the likelihood of asset sales decreases as fixed cost increases.*

Proof. See Appendix. ∎

4   A Dynamic Equilibrium Model of Asset Sales

Although informative, the two-firm, two-period example has its limitations. There are only two firms and their shocks are symmetric, so it is very difficult to match model results to real data where there are many firms. Moreover, the two-period time frame is too short to analyze firms' decisions over time, given the fact that asset sales are infrequent and lumpy.

Therefore, in this section, I develop a dynamic equilibrium model in which the industry is comprised of a large number of firms and the time horizon is both discrete and infinite. Just as in the example, firms are perfectly competitive.

4.1   Firms

In each time period t, a firm produces output using capital stock k_t, via an increasing and concave production function, π :

$$\pi\left[k_{i,t}, z_{a,t}, z_{i,t}\right] = \exp\left(z_{a,t} + z_{i,t}\right) k_{i,t}^{\alpha} \tag{12}$$

Figure 1: Timing of Events

Shocks $(z_{a,t}, z_{i,t})$ are
revealed

Firm arrives
with (k_t)

Firm chooses
investments
(I_t, x_t)

Firm produces
with $(k_t + x_t)$

Firm has capital
$(1-\delta)(k_t + x_t) + I_t$

t $t+1$
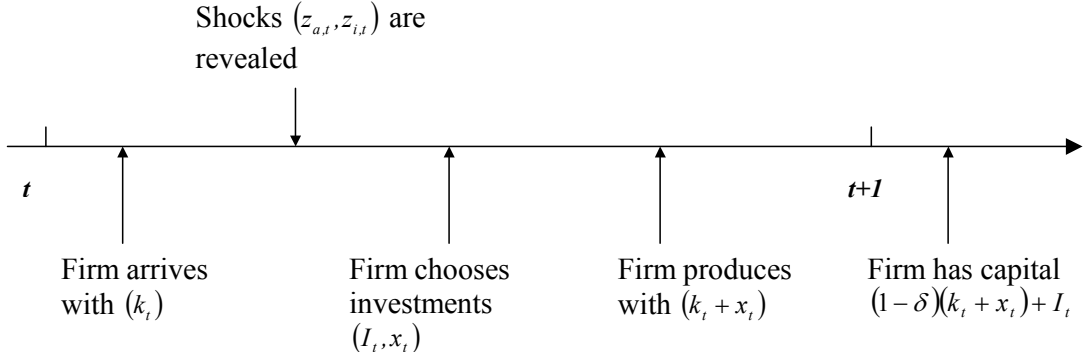
where $\alpha < 1$ and the total productivity factor consists of a common industry shock $z_{a,t}$ and a firm-specific shock $z_{i,t}$.

I assume that both industry- and firm-specific shocks follow $AR(1)$ processes:

$$z_{a,t+1} = \rho_a \cdot z_{a,t} + \varepsilon_{a,t+1} \tag{13}$$

$$z_{i,t+1} = \rho_i \cdot z_{i,t} + \varepsilon_{i,t+1}$$

where $\varepsilon_{a,t}$ and $\varepsilon_{i,t}$ are normal random variables with mean zero and variance σ_a^2 and σ_i^2, respectively. At each period, $z_{a,t}$ and $z_{i,t}$ are independent from each other and $z_{i,t}$'s are also independent across firms.

Figure 1 illustrates the timing of the decisions.

A firm arrives at period t with a level of capacity k_t. It observes the industry- and firm-level productivity shocks $\{z_{a,t}, z_{i,t}\}$ and makes two interrelated investment decisions: whether to participate in asset sales and if so, the quantity to buy or sell (x_t); and how much to invest in the new capital, $I_t{}^6$.

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[6]For simply notation, I suppress the firm index, i, from now on.

Firms cannot sell more than what they have, i.e., $k_t + x_t \geq 0$. If equality holds, there is a complete ownership transfer. New investment is non-negative and has an upper bound proportional to current capital stock, $0 \leq I_t \leq I_{\max} \times k_t$. It reflects the limited supply of new investments in the short run.[7]

I normalize the unit price of new capital to one and denote the price per unit of existing capital as P. There is a quadratic adjustment cost for investing in both types of capital:

$$\Gamma_j [k_t, j_t] = \frac{\gamma_j}{2} \left(\frac{j_t}{k_t} \right)^2 k_t \qquad where \; j \in \{I, x\} \tag{14}$$

The coefficient of adjustment costs (γ) describes how costly it is for the firm to adjust capacity. Since accommodations must be made when additional assets are either bought or sold, I assume that adjustment costs apply for both asset purchases and sales[8].

There is a fixed cost, f, for participating in asset sales. This fixed cost accounts for transaction costs encountered in asset purchases and sales, such as searching for partners, negotiating deals, and legal fee.

As in the example, assets bought from other firms will be available for production in the same period, but it takes one period for new investments to become productive. After the asset transfer, the capital available for current production equals to $(k_t + x_t)$.

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[7]See Jovanovic (1998), who discusses the supply constraint for new capacity in the short run. An alternative way to model the supply constraint in the short run is to have new capital available, but in a series of allotments that take place in several periods.

[8]For a more detailed discussion on adjustment costs, see Cooper and Haltiwanger (2003).

The firm generates the following cash flow during period t:

$$D\left[k_t, z_{i,t}; z_{a,t}, P_t\right] = \underbrace{\exp\left(z_{a,t} + z_{i,t}\right)\left(k_t + x_t\right)^{\alpha}}_{\text{production profit}} - \tag{15}$$

$$\left(\underbrace{1_{x \neq 0} f + P_t x_t + \Gamma_x\left[k_t, x_t\right]}_{\text{cost/proceeds of asset sales}} + \underbrace{\left[I_t + \Gamma_I(k_t, I_t)\right]}_{\text{cost of new investment}}\right)$$

and the capital carried over to the next period is

$$k_{t+1} = (1 - \delta)\left(k_t + x_t\right) + I_t \tag{16}$$

Consider a firm that has k units of installed capital at the beginning of period t, and a firm-specific productivity shock z_i; which also faces an industry productivity shock z_a, and a price for current assets, P. The optimization behavior of this firm can be summarized by a value function $V\left(k, z_i; z_a, P\right)$, which solves the dynamic programming problem: [9]

$$V\left[k, z_i; z_a, P\right] \tag{17}$$

$$= \max_{\substack{0 \leq I \leq I_{\max} \times k \\ x \geq -k}} \left\{ \underbrace{D\left[k, z_i; z_a, P\right]}_{\text{current cash flow}} + \underbrace{\beta E\left\{V\left[k', z_i'; z_a', P' \mid z_i; z_a, P\right]\right\}}_{\text{expected future firm value}} \right\}$$

where $0 < \beta < 1$ is the intertemporal discount factor.

The firm maximizes its current cash flow, plus the discounted expected future value.

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[9]I use the notation k', z_i', z_a', P' to denote the values of these variables at the beginning of the next period.

4.2 The Industry

Since I can describe each firm in the industry by its beginning size and current firm-level productivity shock, (k, z_i), I can completely summarize the industry structure (in addition to the aggregate productivity shock, z_a) by a measure, $F[K, Z_I]$, defined over the state space where $K = \{k_i\}$ and $Z_I = \{z_i\}$.[10]

From (17), I can write a firm's optimal asset sales decision based on state variables such that:

$$x = x[k, z_i; z_a, P] \tag{18}$$

Let X denote the net aggregate demand for existing capacity. Then market clearing requires that the equilibrium price, P, solves:

$$X[P \mid F, z_a] = \int_{k \in K, z_i \in Z_I} x[k, z_i; z_a, P] \, dF[k, z_i] = 0 \tag{19}$$

In other words, the equilibrium asset price is some function of industry structure $F[.]$ and aggregate productivity, z_a:

$$P = P[F, z_a] \tag{20}$$

I assume the law of motion for $F[.]$ as:

$$F' = H[F, z_a] \tag{21}$$

Then it follows that the law of motion for P, the equilibrium price, is:

$$P' = P[F', z'_a] = P[H[F, z_a], z'_a]$$

---

[10]Note that the marginal distribution of z_i is exogenous whereas the capital level, k_i, is endogenous.

Using (20) and (21), I can rewrite the value function of the firm as:

$$V\left[k, z_i; z_a, F\right] \tag{22}$$

$$= \max_{\substack{0 \leq I \leq I_{\max} \times k \\ x \geq -k}} \pi\left[k + x; z_i, z_a\right]$$

$$- \left(I + P\left[F, z_a\right] x + \sum_{j \in \{I,,x\}} \Gamma_j\left[k, j\right] + 1_{x \neq 0} f\right)$$

$$+ \beta \int \int V\left[k', z_i'; z_a', F'\right] N\left(dz_i' \mid z_i\right) N\left(dz_a' \mid z_a\right)$$

$$\text{where} \quad k' = (1 - \delta)(k + x) + I$$

$$F' = H\left[F, z_a\right]$$

A recursive competitive equilibrium is characterized by the following definition:

Definition 1 *(recursive competitive equilibrium) A recursive competitive equilibrium is a set of decision functions $\{x\left[.\right], I\left[.\right]\}$, a price function $P\left[.\right]$, and a law of motion $H\left[.\right]$, such that:*

(i) $V\left[k_i, z_i; z_a, F\right]$ solves a firm's optimization problem in ((22) given $H\left[.\right]$ and $P\left[.\right]$

(ii) $P\left[F, z_a\right]$ satisfies the market clearing condition in (19), such that $X\left[P \mid F, z_a\right] = 0$

(iii) $H\left[.\right]$ is generated by the decision rules implied by V

Assuming that the fixed cost condition is not binding, the first order conditions from (22) are:

$$FOC\left(x\right): \underbrace{\exp\left(z_a + z_i\right)\alpha\left(k + x\right)^{\alpha-1}}_{\text{marginal product}} = \underbrace{\left(P + \frac{\partial\Gamma_x\left[k, x\right]}{\partial x}\right)}_{\text{marginal costs}} \underbrace{-\beta\left(1 - \delta\right)\frac{\partial E\left\{V\left[k', z_i'; z_a', \overline{k}'\right]\right\}}{\partial k'}}_{\text{resale value}}$$

$$FOC\left(I\right): \underbrace{\beta\frac{\partial E\left\{V\left[k', z_i'; z_a', \overline{k}'\right]\right\}}{\partial k'}}_{\text{expected marginal value}} = \underbrace{1 + \frac{\partial\Gamma_I\left[k, I\right]}{\partial I}}_{\text{marginal costs}} - \mu_1 + \mu_2$$

$$(23)$$

where μ_1 and μ_2 are Lagrange multipliers for the non-negativity ($I \geq 0$) and upper bound ($I \leq I_{\max} \times k$)constraints of new capital, respectively.

When the participation constraint due to the fixed cost is not binding, firms trade on assets so that the marginal profit of current assets is equal to the cost (unit price plus the adjustment cost), minus the expected resale value. In the meantime, firms make decisions on new investments so that the expected marginal value of capital is equal to the marginal investment cost.

4.3   Numerical Solution

To solve for the recursive equilibrium described above, I face two numerical challenges. First, one of the state variables, industry structure F, is a high-dimension object. A numerical solution to dynamic programming problems becomes increasingly difficult as the size of state space increases. Second, I need to have an ex ante pricing function, $P = P\left[F, z_a\right]$, which, when taken by all firms in the industry, can be implied by the optimal decisions of heterogeneous firms in that industry.

I follow the methods developed in Krusell and Smith (1997, 1998). First, I assume that firms perceive asset prices as depending only on a subset of moments of F, and that the law of motion for these moments also depends only on this same set of moments. Next, I simulate the resulting investment behavior over a long period

of time. If the simulated time series of moments are very close to those perceived by the firms, then I argue that the behavior I observe very closely approximates the rational behavior implied by taking account of the entire distribution, and is therefore a candidate for an approximate equilibrium.

It turns out that just as in Krusell and Smith (1997), for my model, the first moment is sufficient to obtain only very small prediction errors.[11] The estimated equilibrium law of motion for capital has an R-square approximately 99 percent and the estimated pricing function has an R-square around 95 percent. This approximate aggregation occurs because, in the equilibrium, the mean of the distribution is sufficient to summarize the aggregate behavior, when there exists a large number of competitive firms. The prediction error between the perceived and realized law of motion of capital and the pricing function is within 1 percent. Appendix C offers a detailed description on the computational strategy.

I characterize the approximated law of motion for mean capacity and the pricing function as follows:

$$
\begin{aligned}
\log \overline{k}' &= a_0 + a_1 \log \overline{k} && if \quad z_a = z_a^L \\
\log \overline{k}' &= b_0 + b_1 \log \overline{k} && if \quad z_a = z_a^H \\
P &= c_0 + c_1 \log \overline{k} && if \quad z_a = z_a^L \\
P &= d_0 + d_1 \log \overline{k} && if \quad z_a = z_a^H
\end{aligned}
\tag{24}
$$

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[11]Since firm-level shock z_i has a zero mean, I approximate the industry structure by the mean capacity $\overline{k}$.

and rewrite the value function of the firm as

$$V\left[k, z_i; z_a, \overline{k}\right] \tag{25}$$

$$= \max_{\substack{0 \leq I \leq I_{\max} \times k \\ x \geq -k}} \pi\left[k + x, z_a, z_i\right]$$

$$- \left(I + \widehat{P}\left[\overline{k}, z_a\right] x + \sum_{j \in \{I,,x\}} \Gamma_j\left[k, j\right] + 1_{x \neq 0} f\right)$$

$$+ \beta \int \int V\left[k', z_i'; z_a', \overline{k}'\right] N\left(dz_i' \mid z_i\right) N\left(dz_a' \mid z_a\right)$$

$$where \quad k' = (1 - \delta)(k + x) + I$$

$$\overline{k}' = \widehat{H}\left[\overline{k}\right]$$

where $\widehat{H}$ and $\widehat{P}$ are identified by the set of parameters $\left(\widehat{a_0}, \widehat{a_1}, \widehat{b_0}, \widehat{b_1}\right)$ and $\left(\widehat{c_0}, \widehat{c_1}, \widehat{d_0}, \widehat{d_1}\right)$, respectively.

Proposition 3 *There exists a unique function $V\left[k, z_i; z_a, \overline{k}\right] : K \times Z_I \times Z_A \times \overline{K} \to R_+$, that solves the dynamic program in (25), and generates unique optimal policy functions $I\left[k, z_i; z_a, \overline{k}\right]$ and $x\left[k, z_i; z_a, \overline{k}\right]$.*

Proof. See Appendix ■

5 Quantitative Results

In this section, I first calibrate the model to match the summary statistics obtained from the data. Next, I discuss the derived optimal asset sales decisions and the implied aggregate activity in the business cycle. Then, using the simulated panel, I focus on two empirical issues: the relationship between valuation and asset sales decisions and the size effect in acquirer returns. Finally, through comparative statics, I show how several key values of the model affect asset sales activity.

5.1 Calibration

Since most of my data is available at an annual frequency, I assume that a time period in the model corresponds to one year. I pre-chose several parameters from the literature. Based on Cooper and Haltiwanger (2003), I use the production technology parameter $\alpha = 0.592$, and persistence and dispersion for aggregate productivity shocks $(\rho_a, \sigma_a) = (0.76, 0.05)$. I set the intertemporal discount factor, β, to be $1/1.065$, based on Gomes (2001).

Then, I chose the remaining parameters, ρ_i, σ_i, f, γ_I, γ_x so that the simulated panel generates moments consistent with the empirical evidence found in Longitudinal Research Database (LRD). Since the main results of my model are about asset sales and new investments in the business cycle, I select these parameters to match the average rate of asset sales and average rate of new investments in both expansions and recessions, as well as the average percentage of assets bought and sold in asset sales transactions. [12]

Table 1 summarizes the parameter values I use in the calibration and compares the key summary statistics generated by the model with those found in the data. Although my model calibration does not reproduce these six statistics exactly, the simulated panel is reasonably similar to its empirical counterparts.

The model also produces stylized facts, similar to empirical findings, on buyer and seller characteristics, such as size, productivity, and Tobin's q. Firms which buy assets, are slightly larger, compared to average firms, but have higher productivity and higher Tobin's q; and, firms which sell assets are much bigger than the average firms, but have lower productivity and lower Tobin's q.

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[12]The statistics on the average percentage of assets bought and sold in asset sales transactions are from Table III (column 2) in Maksimovic and Phillips (2001).

[INSERT TABLE 1 HERE]

5.2 Model Results

5.2.1 Decision on Asset Sales

Figure 2 describes the derived optimal asset sales decisions based on current capacity, k, firm productivity, z_i, and industry productivity, z_a. The decisions are shown for different size quartiles. For every quartile, I plot firm-level productivity on the X-axis and plot the rate of asset sales (x/k) on the Y-axis. The two vertical lines mark the 25th and 75th percentile of future productivity, based on firm size. The solid and dotted lines represent decisions in bad and good times, respectively.

First, I find that the expected future productivity increases with firm size. Since a firm becomes large as a result of a sequence of high firm productivity, and productivity is persistent, large firms expect a higher future productivity than do small firms. For firms of all sizes, selling assets is optimal only when realized productivity is much lower than the expected level (below the 25th percentile), and buying assets is optimal when productivity appears to be much higher than the expectation (above the 75th percentile).

Research on asset sales transactions finds that there is a significant difference in performance between buyers and sellers. For example, both Lang, Poulsen, and Stulz (1994) and Schlingemann, Stulz, and Walking (2002) find that firms with poor past performance are more likely to sell assets or divest segments. Here, my model suggests a new dimension - current size, as an additional determinant. It predicts that given the same productivity shock, small firms are more likely to buy, and large firms are more likely to sell, their assets. The intuition is as follows. Since current size serves as

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a proxy for past productivity, given the same productivity shock, the likelihood that realized productivity is below (above) the expected level is higher (lower) for large firms. This finding is consistent with Maksimovic and Phillips (2001), who show that when controlling for productivity, large single-segment firms are more likely to engage in partial firm sales than small single-segment firms.

In all cases, over time, firms are more likely to engage in asset sales in good times, when the aggregate productivity is high.

[INSERT FIGURE 2 HERE]

Figure 3 describes the dynamics of a simulated firm along several dimensions. I show how firm size (k) evolves given the realizations of firm-level productivity shocks (z_i) and I also plot out asset sales (x/k) and new investment (I/k) decisions over time. Figure 4 presents the distribution of these variables in histogram plots.

[INSERT FIGURE 3 AND 4 HERE]

Not surprisingly, firm size is related to productivity shocks. An increase in productivity is usually followed by an increase in capacity and a decrease in productivity leads to downsizing. The firm only buys assets when there is a major increase in productivity, in which case, it also invests in new assets aggressively. Meanwhile, the firm sells off existing assets when there is a deep plunge in productivity, and when that happens, it rarely invests in any new assets at the same time. New investments occur more frequently than asset sales, although they seem to be lumpy as well. There exists inactive periods when no investments are made and in other periods, investments are bounded by the short-run supply constraint.

5.2.2   Asset Sales in the Business Cycle

To investigate how asset sales activity changes in the business cycle, I simulate a stylized time path in which 20 periods of recessions are followed by 20 periods of expansions and then another 20 periods of recessions. I use the parameters specified in the calibrated model and simulate an industry with 3,000 firms. Figure 5 presents the time series of aggregate shock, mean capacity, asset price, and rate of asset sales.

[INSERT FIGURE 5 HERE]

Regardless of the initial distribution, by the end of period 20, the mean capacity, the average rate of asset sales, and the average rate of new investments all converge to some constants. This result suggests that the model is stable. At the moment when the positive shock strikes ($t = 21$), the industry's capacity is very low. To respond to the increase of aggregate productivity, investment shoots up, reaching 20 percent in the first year and 17 percent in the second year. As a result, the mean capacity in the industry rises sharply, although at a decreasing rate. The price of the existing assets also jumps up from $1.08 to $1.12 at the transition. This increase reflects the higher opportunity cost of capital, and more assets are traded within the industry. As the positive shock continues and firms expand over time, new investment starts to slow down and asset prices start to fall. Mean capacity, asset prices, and asset sales activity stabilize and converge to their long-run equilibria after about 8 periods.

When the negative productivity shock hits ($t = 41$), the industry is at its highest capacity, after a sequence of positive shocks. At the onset, new investment shrinks to 10 percent and the general demand to downsize drives asset price down from $1.09 to $1.05. As firms keep reducing their capacity, prices slowly climb. Again, it takes about 8 periods for capacity, asset prices, and asset sales activity to stabilize at their long-run equilibria.

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5.3 Reconciling Theory and Evidence

5.3.1 Valuation and Asset Sales Decisions

Recent studies suggest that mergers might be caused by misvaluation, in which case managers use overvalued equity as cheap currency to purchase assets. (Shleifer and Vishny (2003), Rhodes-Kropf and Viswanathan (2004)). To support the misvaluation theory, the empirical study by Rhodes-Kropf, Robinson, and Viswanathan (2004) shows that the probability of being an acquirer is higher when the firm has a high current market-to-book value, but low long-run average.

In the context of this model, I perform a similar analysis for the simulated panel of firms by defining market-to-book ratio as

$$MTB = V/K$$

Table 2 reports the results.

[INSERT TABLE 2 HERE]

Firms are more likely to acquire when current MTB is high but the long-run average MTB is low, and they are more likely to sell when current MTB is low but the long-run average MTB is high. This relationship is similar to evidence documented in Rhodes-Kropf, Robinson, and Viswanathan (2005). Thus, despite the fact that firms invest optimally and there is no misvaluation in my model, I am able to rationalize the effect that "long-run low buys long-run high."

The intuition is as follows. In my model, the decision to buy or sell assets depends on changes of productivity over time. Since purchasing assets is optimal when productivity increases, firms are more likely to buy at times when current productivity

is above the long-run average, and they are more likely to sell assets when current productivity is below the long-run average. Therefore, controlling for current MTB, buyers have lower long-run valuation than do sellers.

Since productivities are fully observable in the model, Table 3 reports the results from a logit model that uses productivity. Firms are more likely to buy assets when current productivity is high, and firm size is small; they are more likely to sell assets when current productivity is low, and firm size is large. In both cases, the marginal increase in the probability of buying (selling) is higher for larger firms, given an increase (decrease) in productivity, as indicated by the sign of the interaction between size and productivity. Firms are more likely to participate in sales while aggregate productivity is high.

[INSERT TABLE 3 HERE]

There is one caveat for comparing results based on the simulated panel of my model with those reported in Rhodes-Kropf, Robinson, and Viswanathan (2004). In my model, I consider only within-industry asset reallocation. Firms do not use asset purchases as a means to explore growth opportunities in other industries, neither do they sell off assets to regain focus. Therefore, my model does not, and cannot, consider mergers across industries.

5.3.2 Size Effect in Acquirer Returns

Moeller, Schlingemann, and Stulz (2004) find a striking size effect in acquirer returns. Their study shows that the announcement return for acquiring-firm shareholders is about two percent higher for smaller acquirers regardless of the form of the financing and whether the acquired firm is public or private.

Since I calibrate my model on annual frequency, it is difficult to capture the abnormal return in a three-day window around acquisition, as Moeller, Schlingemann, and Stulz have done in their paper. Nevertheless, I am able to calculate the annual return for acquirers in the transaction year by defining the return in period t:

$$r_t = \frac{V_t - V_{t-1}}{V_{t-1}}$$

Table 4 shows the returns for acquirers in different size quartiles before, around, and after the transaction. Just as in the data, small acquirers have higher returns in the transaction year. The average return for acquirers in the smallest size quartile is about 28.6 percent, compared to 18.8 percent for those in the largest size quartile. Small acquirers also tend to have higher return after the transaction.

[INSERT TABLE 4 HERE]

What causes the size effect in acquirer returns in the model, when there is no asymmetric information, no misvaluation, and firms behave rationally? Panel B presents the answer. Although small acquirers have lower productivity than large acquirers, they have much higher increases from the previous year. The average increase in productivity for small acquirers is about 2.5 times as high as that for large acquirers. This happens because in the presence of fixed costs, the likelihood of acquisition is higher when the increase in productivity is great and the firm size is large, both of which factors lead to a higher dollar payoff. To make an acquisition possible, small firms need to have a bigger increase in productivity. Therefore, ex post, small acquirers have higher increases in productivity and higher returns. The observed size effect can be caused by the endogenous sample selection.

After controlling for changes in productivity, the size effect disappears. Large acquirers have a slightly higher return, but the impact is minimal.

5.4 New Evidence on Asset Sales

The dynamic model in this paper describes an industry with time-invariant industry- and firm-level productivity shocks. In this section, I simulate the model with different parameter values to show how shock attributes affect equilibrium asset sales activity in the model.

Table 5 reports sensitivities of the simulated moments on model's parameters. For each related parameter, I simulate the model twice: once with a parameter value twenty-five percent above and once with a parameter value twenty-five percent below the baseline value. Panel A reports the moments and Panel B reports the elasticities. For each parameter, I calculate elasticity as the change of moments divided by the change in underlying parameters, multiplied by the ratio of the baseline parameter over the baseline moment. [13]

[INSERT TABLE 5 HERE]

First, I find that fixed costs (f) have a negative effect on asset sales. Higher fixed costs increase the minimum gain requirement for both buyers and sellers, and result in fewer sales. On average, firms trade less frequently, but for larger amounts. The fixed costs here may have several interpretations. For example, they can be related to the model in Rhodes-Kropf et al. (2004), as a search cost that describes how difficult it is to find a trading partner. Or they can be viewed as a technology parameter that

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[13]This method is similar to that in Hennessy and Whited (2005).

accounts for the general transaction costs encountered in asset purchases and sales, such as financing, communication costs, and legal fees.

Second, persistence and dispersion of firm-level shocks (ρ_i, σ_i) have a strong impact on asset sales. Lower persistence increases the probability that productivity may change over time, and higher dispersion leads to a greater difference between more- and less-productive firms. Since asset sales result from changes in productivity and the likelihood of a transaction occurring is higher with greater productivity differences, industries with lower persistence and higher dispersion experience more asset sales. A 25 percent decrease in ρ_i would result in a 23 percent (14 percent) increase in the amount of assets sales in good (bad) times, while a 37 percent (21 percent) increase in participation frequency in good (bad) times. A 25 percent increase in σ_i leads to a 88 percent (89 percent) increase in the amount of assets sales and almost doubles the participation frequency in good (bad) times. In the meantime, persistence also has some effect on new investments. New investments are higher when shocks are more persistent.

Finally, although not reported here, the attributes of aggregate shock (ρ_a, σ_a) have a moderate effect on new investments, but very little impact on asset sales. Higher persistence (ρ_a) makes the current state more likely to linger, and higher dispersion (σ_a) increases the difference between good and bad states, both of which factors lead to higher investments in good times and lower investments in bad times.

The predicted relationship between dynamic shock properties and asset sales activity is a novel concept that I raise in this paper. My model shows that asset sales decisions are path dependent, and, therefore, it is vital to look at them in a dynamic setting. This argument is different from the Q-theory in Jovanovic and Rousseau (2002), which considers only asset sales that are driven by cross-sectional contempo-

raneous dispersion in productivity.

6   Conclusion

In this paper, I show that an equilibrium dynamic model of asset sales, in which firms maximize value through investment decisions on new and existing capacity, generates patterns of asset sales consistent with the existing evidence, both at the firm- and at the industry-level. In my model, asset sales allow firms to adjust to changes in productivity driven by shocks. By moving resources from less to more productive firms, the activity increases efficiency in the industry.

The dynamic structure of my model enables me to examine several aspects of asset sales in a very general setting. I consider a firm's investment decisions over time and explicitly model the interaction between size, productivity, and valuation. From the equilibrium pricing, I establish a link between a firm's investment decisions and industry-level asset sales activity.

There are four main results. First, I show that some of the evidence previously used to support the misvaluation theory can be generated from a value-maximization model without any misvaluation. Firms are more likely to purchase assets at times when their current productivity is higher than the long-run average, and are more likely to sell assets when their current productivity is lower than the long-run average. The fact that shocks are mean reverting leads to the phenomenon that "long-run low buys long-run high."

Second, the size effect in acquirer returns can be explained by a sample selection problem. In the presence of fixed transaction costs, in order to carry out the transaction, small acquirers have to have bigger increases in productivity, and, therefore, ex post, realize higher returns.

Third, the dynamic properties of productivity shocks have a strong impact on aggregate asset sales activity: industries with less persistent and more volatile productivity shocks experience greater asset sales.

Finally, I show that a fixed transaction cost can generate procyclical asset sales activity, even when asset prices fully adjust to aggregate shock.

I solve the model in a recursive equilibrium framework through simulations, in which the industry structure evolves over time and asset prices are endogenously determined. The model is calibrated using plant-level data from the Longitudinal Research Database. (LRD).

The model developed in this paper can be generalized along a number of dimensions. For example, in the current model, firms are all equity-financed and there is no extra cost of issuing new equity. Adding a dimension of costly financing can bring new insights on how investment decisions interact with financing decisions. The results then, can shed light on current debate on differences between cash- and stock-financed acquisitions. Furthermore, with some modification, one can use this model to study how capital structures affect a firm's decisions to buy or sell assets. All of these fruitful areas of corporate finance demand future research.

7   Tables and Figures

Table 1: Parameter Values and Summary Statistics

This table reports the parameters of the calibrated model. Following Cooper and Halti-wanger (2003), I use the production technology parameter $\alpha = 0.592$, and serial correlation and standard deviation for industry-level productivity shocks as $(\rho_i, \sigma) = (0.76, 0.30)$. The intertemporal discount factor β is set to $1/1.065$, from Gomes (2001). I choose the remaining parameters, ρ_i, σ_i, f, γ_I, γ_x, so that the simulated panel generates moments consistent with the empirical evidence found in LRD. The moments are the average rate of asset sales and average rate of new investment in both expansions and recessions, and the average percentage of assets bought and sold in asset sales transactions. Panel C reports the characteristics of the buyer firms and seller firms. I calculate Adjusted Size as the logarithm of the average size of firms in the sample minus the average size of all firms in the industry, and Adjusted Tobin's q as the average Tobin's q in the sample divided by the average Tobin's q of all firms in the industry. Tobin's q is calculated by dividing a firm's market value (implied from the value function) to its book value (the level of its capacity).

Panel A: Parameter Values		
Parameter (Pre-chosen)		Value
Production technology	α	0.592
Discount rate	β	0.939
Aggregate shock persistence	ρ_a	0.76
Aggregate shock dispersion	σ_a	0.05
Parameter (Calibrated)		
Depreciation	δ	0.15
Idiosyncratic shock persistence	ρ_i	0.70
Idiosyncratic shock dispersion	σ_i	0.30
Adjustment cost (new capital)	γ_I	0.1
Adjustment cost (asset sales)	γ_x	0.2
Fixed cost (asset sales)	f	0.45

Panel B: Summary Statistics		
Statistics	Model	Data
Average asset sales ratio (Expansion)	4.31%	4.29%
Average asset sales ratio (Recession)	3.79%	3.86%
Average new investment ratio (Expansion)	16.95%	17.88%
Average new investment ratio (Recession)	13.51%	13.93%
Percentage of assets sold	30.45%	28.2%[a]
Percentage of assets bought	45.48%	53.8%[a]

Panel C: Asset Buyers and Asset Sellers (Model)			
	Buyer	Seller	Non-Action Firms
Adjusted Size	1.12	1.45	1
Adjusted Tobin's q	1.08	0.67	1

Table 2: Valuation and Asset Sales Decisions

The table reports the estimation results of a Logit model that uses the simulated panel based on the calibrated model. In all cases, the simulated panel consists of 3,000 firms and 200 periods. In Column (1), the dependent variable is a dummy variable that equals to one if a firm purchases assets $(x > 0)$ and equals to zero if it does not buy or sell assets $(x = 0)$. In Column (2), the dependent variable is a dummy variable that equals to one if a firm sells assets $(x < 0)$ and equals to zero if it does buy or sell assets $(x = 0)$. In Column (3), the dependent variable is a dummy variable that equals to one if a firm is an acquirer $(x > 0)$ and equals to zero if a firm is a seller $(x < 0)$. $MTB_{i,t}$ is the market-to-book ratio for firm i at time t. It is calculated as the ratio of firm value divided by its capacity. $\overline{MTB_i}$ is the average market-to-book ratio for firm i, and $\overline{MTB_t}$ is the average market-to-book ratio for all firms at time t. Standard errors are reported in parentheses.

	1 if Acquirer, 0 if No Action	1 if Seller, 0 if No Action	1 if Acquirer, 0 if Seller
	(1)	(2)	(3)
$MTB_{i,t}$	1.216***	-3.782***	7.016***
	(.005)	(.014)	(.056)
$\overline{MTB_i}$	-1.999***	2.103***	-3.696***
	(.028)	(.034)	(.092)
$\overline{MTB_t}$	-.299***	4.796***	-5.300***
	(.038)	(.047)	(.123)
Pseudo R^2	.147	.406	.812

Table 3: Productivity and Asset Sales Decision

The table reports the estimation results of a Logit model that uses the simulated panel based on the calibrated model. In all cases, the simulated panel consists of 3,000 firms and 200 periods. In Column (1), the dependent variable is a dummy variable that equals to one if a firm purchases assets $(x > 0)$ and equals to zero if it does not buy or sell assets $(x = 0)$. In Column (2), the dependent variable is a dummy variable that equals to one if a firm sells assets $(x < 0)$ and equals to zero if it does not buy or sell assets $(x = 0)$. Standard errors are reported in parentheses.

	1 if Acquirer, 0 if No Action	1 if Seller, 0 if No Action
	(1)	(2)
SIZE	-57.942***	49.710***
	(.631)	(.451)
Firm-level Shock	88.086***	-40.591***
	(1.021)	(.481)
SIZE $\times$ Firm-level Shock	10.188***	-9.989***
	(.251)	(.164)
Industry-level Shock	27.594***	11.043***
	(.342)	(.191)
Pseudo R^2	.97	.95

Table 4: Size Effect in Acquirer Returns

The table reports the estimation results on the size effect in acquirer returns that use the simulated panel based on the calibrated model. In all cases, the simulated panel consists of 3000 firms and 200 periods. Panel A shows the returns for acquirers in the transaction year as well as returns two and one year prior to the transaction and one and two year after the transaction for all size quartiles. Panel B reports the average current and lagged firm-level productivity for acquirers in all size quartiles. Panel C presents the regression results. In Column (1) and (2), I use only the subsample in which a firm has acquired assets. The dependent variable is the return of that year. Column (3) reports results using a Logit model estimation, where the dependent variable equals to one if a firm acquires and zero otherwise. In all tables, t is year when firms acquire assets. I define return as the ratio of change in value from previous period divided by the lagged value, i.e., $r_t = \frac{V_t - V_{t-1}}{V_{t-1}}$. Standard errors are reported in parentheses.

Panel A: Acquirer Return by Size					
Size Quartiles	$RET\,(t-2)$	$RET\,(t-1)$	$RET\,(t)$	$RET\,(t+1)$	$RET\,(t+2)$
1	-0.6%	6.2%	28.6%	10.5%	3.9%
2	1.6%	7.7%	24.8%	9.2%	1.6%
3	3.9%	11.7%	25.4%	9.0%	-3.2%
4	7.6%	13.7%	18.8%	5.1%	-7.8%

Panel B: Change in Productivity				
Size Quartiles	Pct. of Assets Acquired (x_t/k_t)	Productivity $(z_{i,t})$	Lagged Productivity $(z_{i,t-1})$	Change in Productivity $(z_{i,t} - z_{i,t-1})$
1	62%	0.38	-0.22	0.60
2	52%	0.54	0.08	0.47
3	56%	0.74	0.32	0.42
4	37%	0.78	0.53	0.25

Panel C: Acquirer Return and Probability of Acquisition			
	Acquirer Return (1)	Acquirer Return (2)	Prob(Acquirer) (3)
SIZE	$-.026^{***}$ (.0008)	$.005^{***}$ (.0009)	2.097^{***} (.013)
Pct. of Assets Acquired	$.291^{***}$ (.001)		
Aggregate Productivity	$.256^{***}$ (.003)	$.287^{***}$ (.003)	1.893^{***} (.043)
Change in Productivity		$.273^{***}$ (.001)	7.864^{***} (.027)
R^2	.53	.50	.38

Table 5: Sensitivity of Model Moments to Parameters

This table presents model moments when I adjust model parameters, with respect to the calibrated model. The baseline parameters are: $f = 0.5$ $\rho_a = 0.76$, $\sigma_a = 0.05$, $\rho_i = 0.70$, $\sigma_i = 0.3$. For each parameter, I simulate the model twice: once with a value of parameter of interest 25% above and once with a value 25% below the baseline value. Panel A reports the moments and Panel B reports the elasticities. For each parameter, I calculate elasticity as the change of moments divided by the change in underlying parameters multiplied by the ratio of baseline structural parameter over the baseline moment.

		Panel A: Simulated Moments					
	Base	Fixed Cost (f)		Persistence (ρ_i)		Dispersion (σ_i)	
		$+\Delta$	$-\Delta$	$+\Delta$	$-\Delta$	$+\Delta$	$-\Delta$
$\frac{X}{K}(z_a = H)$	4.31%	3.73%	5.49%	2.96%	5.28%	8.09%	1.33%
$\frac{X}{K}(z_a = L)$	3.79%	3.13%	4.60%	2.53%	4.32%	7.15%	1.04%
$\frac{I}{K}(z_a = H)$	17.0%	16.4%	17.1%	16.8%	13.4%	16.7%	16.8%
$\frac{I}{K}(z_a = L)$	13.5%	13.4%	13.7%	13.4%	10.3%	13.5%	13.2%
Freq $(x > 0, H)$	7.74%	6.42%	10.32%	5.84%	10.57%	12.63%	2.98%
Freq $(x > 0, L)$	6.79%	6.18%	8.83%	4.58%	8.23%	11.50%	2.54%
$E(x \mid x > 0)$	45.5%	47.4%	42.2%	41.3%	41.4%	51.3%	39.1%
$E(x \mid x < 0)$	-30.5%	-31.6%	-29.6%	-23.4%	-29.8%	-33.3%	-25.3%

	Panel B: Elasticity of Model Parameters		
	Fixed Cost (f)	Persistence (ρ_i)	Dispersion (σ_i)
$\frac{X}{K}(z_a = H)$	-0.682	-0.988	3.137
$\frac{X}{K}(z_a = L)$	-0.765	-0.807	3.224
$\frac{I}{K}(z_a = H)$	-0.005	0.336	-0.017
$\frac{I}{K}(z_a = L)$	0.012	0.398	0.047
Freq $(x > 0, H)$	-0.829	-1.093	2.494
Freq $(x > 0, L)$	-0.916	-0.969	2.639
$E(x \mid x > 0)$	0.376	-0.012	0.540
$E(x \mid x < 0)$	0.250	-0.369	0.521

Figure 2: Optimal Decision Rule of Asset Sales

This figure illustrates the derived optimal decision rules on asset sales, given a firm's current capacity (k) and the firm-level productivity shock (z_i). Decisions are shown in four size quartiles. For each size quartile, I plot the firm-level productivity shocks on the X-axis and the rate of asset sales (x/k) on the Y-axis. The two vertical lines mark the 25th and 75th percentile of the expected shock level, based on beginning capacity. The solid and dotted lines represent decisions in bad and good times, respectively.
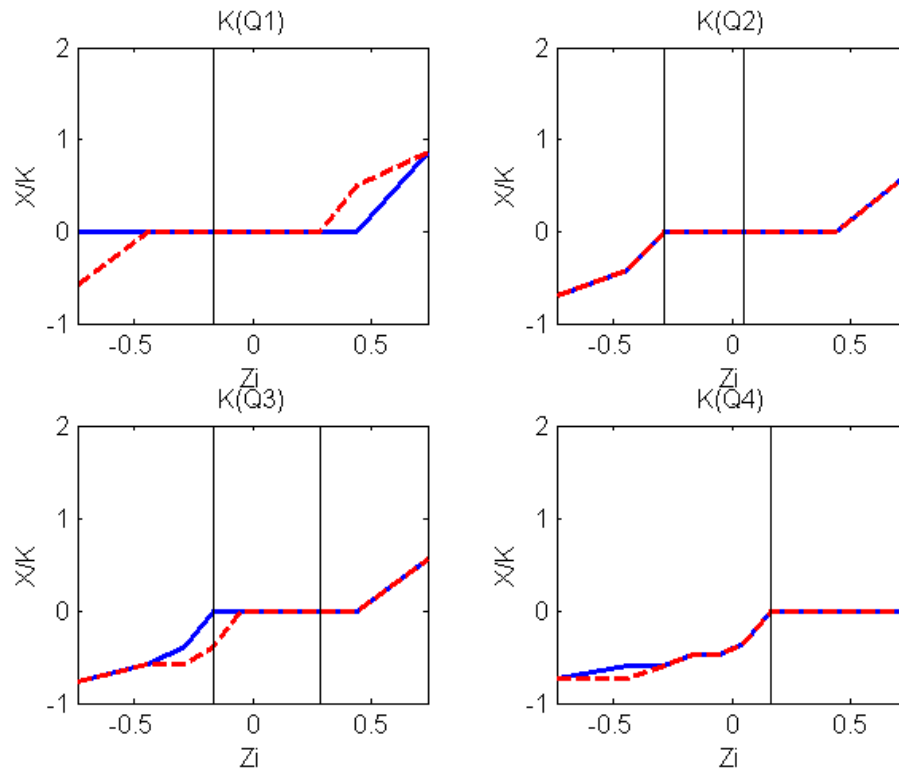
Figure 3: Time Path of A Simulated Firm

This figure illustrates a time path of a simulated firm. I plot the beginning capacity (k), firm-level productivity shock (z_i), percentage of assets bought (sold) (x/k) and new investments (I/k). For each plot, time is on the X-axis. The simulation is based on the calibrated baseline model.
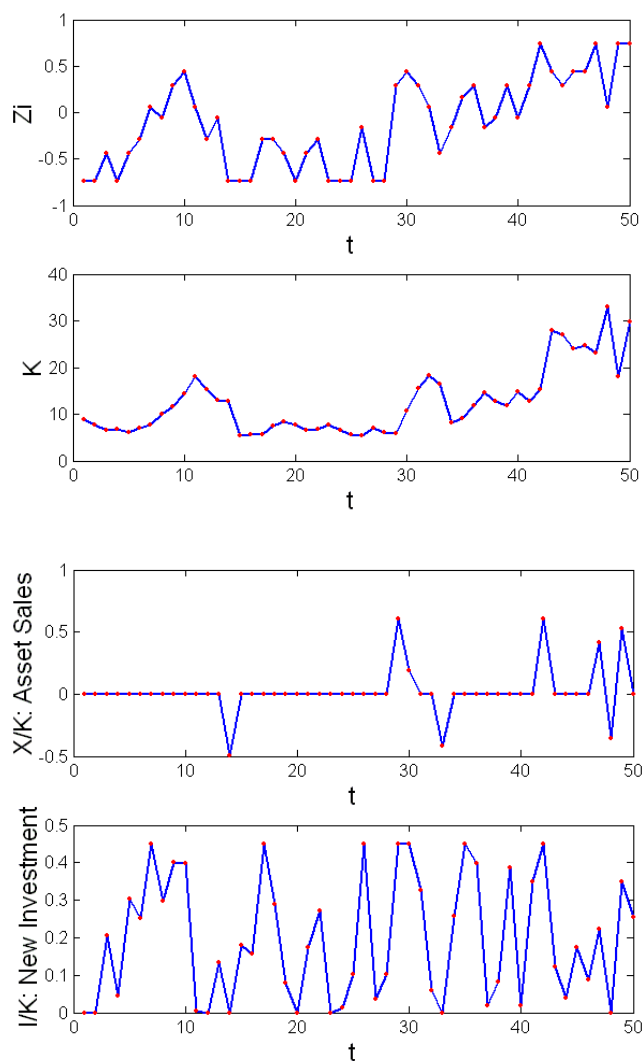
Figure 4: Histogram of Size, Shocks, Asset Sales and New Investments
This figure illustrates the distribution of the capacity (k), firm-level productivity shock (z_i), percentage of assets bought (sold) (x/k) and new investments (I/k) over time for a simulated firm using histogram plots. The simulation is based on the calibrated baseline model.
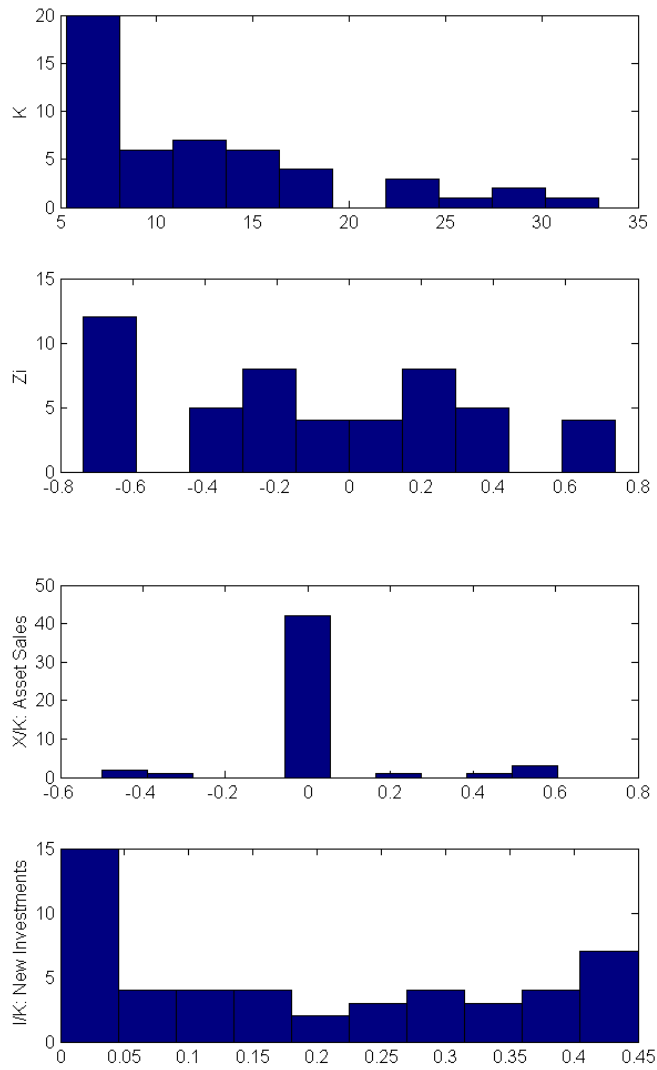
Figure 5: Asset Sales in the Business Cycle

This figure illustrates asset sales activity in the business cycle through a simulated panel. Four subplots show the time series of industry-level shock, average capacity, price of existing assets, and asset sales activity, respectively. I base the simulation on the benchmark model of 3,000 firms, in which I set aggregate productivity shocks such that 20 consecutive negative shocks are followed by 20 positive shocks and then finished with 20 negative shocks.
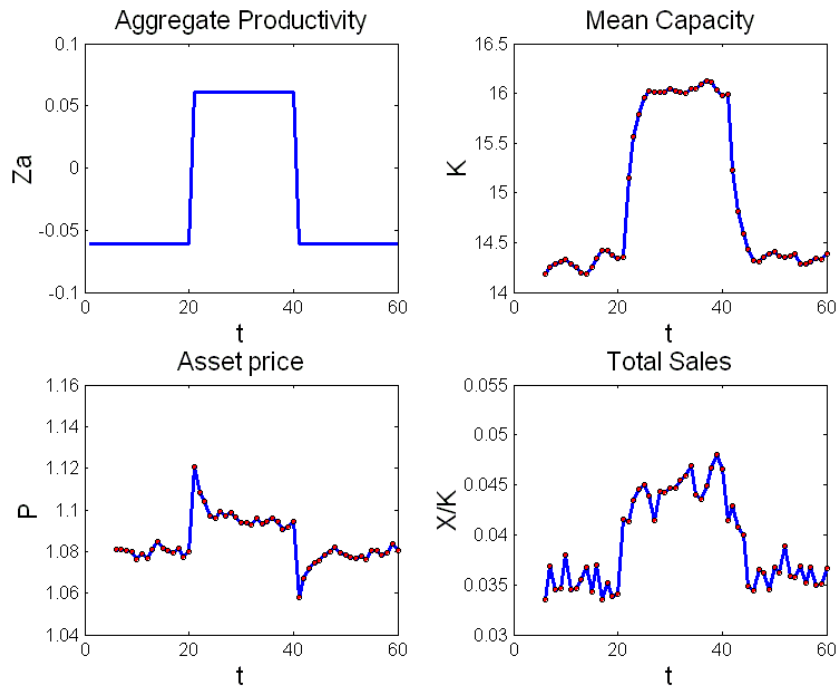
Essay 2:

What Drives Asset Sales - The Empirical Evidence

Abstract

In this paper, we analyze how changes in productivity affect firms' decision to trade assets, and what this implies for the industry-level asset sales activity over time. We find that the patterns of transactions (firm-level purchase/sale decisions, and the cross-industry and the time-series variation in asset sales activities) are consistent with the model developed in Yang(2005).

Using the plant-level data from Longitudinal Research Database on manufacturing firms in the period of 1973 to 2000, we show that: (1) asset purchases are more likely when firms' existing plants experience increases in productivity, and asset sales are more likely when firms have decreases in productivity ("rising buys falling"); (2) shock attributes such as persistence and dispersion help to explain the cross-industry variation in asset sales - industries with less persistent and more widely dispersed productivity shocks, on average, have higher rates of assets sales; and (3) within an industry, periods with more uncertainty regarding firms' relative productivity positions are associated with more frequent trades of existing assets.

1 Introduction

There exists a large and active market where firms trade their operational assets. In manufacturing industries, about 4 percent of the total existing assets change ownership every year in the period of 1974 - 2000. The intensity of asset sales varies significantly by industry. In our sample period, the average rate of plants that change ownership ranges from 1.87 percent to 6.26 percent. What makes assets in an industry more likely to be traded than assets in other industries? Are there any intrinsic industry characteristics that make assets more liquid in an industry? The activity of asset sales also differs over time. Within the same industry, the percentage of plants traded in an active period can be five times as high as that in an inactive period. What explains the time-clustering in asset sales?

This paper addresses these questions by examining the fundamental forces that motivate firms to trade their assets, and by investigating the implications it has for the asset reallocation activity in the industry over time. We show that firms optimally adjust their capacity to respond to changes in productivity brought by shocks. Shock attributes such as persistence and dispersion explain the cross-industry differences in asset sales - more transactions occur in industries with less persistent and widely dispersed shocks. Over time, firms are more likely to trade in years when uncertainty regarding their relative positions within the industry is higher.

Why do firms trade and which firms participate in asset sales? Neoclassical theory suggests that assets will be transferred from less- to more-productive firms to gain efficiency, a pattern identified as "high buys low". Stemmed from the efficiency argument, several papers have studied the relationship between the dispersion of productivity and the activity of capital reallocation. Jovanovic and Rousseau (2001) suggest that industries with wider productivity distribution should have more trans-

actions, as gains from transferring assets are higher in those industries. Studying the productivity dispersion and the transaction flow in the business cycle, Eisfeldt and Rampini (2005) argue that the costs of reallocating assets (liquidity costs) have to be counter-cyclical to generate the observed lower trading volume in recessions, at which times, productivity is more dispersed across firms. Meanwhile, Rhodes-Kropf, Robinson and Viswanathan (2004) develop a model of mergers based on searching costs. Using the transaction data of M&As, they find that buyers have similar Tobin's q as sellers do, a phenomenon they call "like buys like". Since the cost of finding a merger partner is lower when firms are similar rather than far apart, their theory implies that industries with less dispersion in productivity should have more transactions.

Yang (2005) proposes a different view. It develops a dynamic equilibrium model to show that firms optimally adjust their capacity to respond to changes in productivity brought by productivity shocks. Firms, which have increases in productivity, choose to purchase assets, and firms, which experience decreases in productivity, sell off existing assets to downsize ("rising buys falling"). The shuffling of firms' relative productivity positions, rather than their productivity levels, drives the decisions of asset purchases and sales. In other words, there is no fixed rule on the productivity levels between the buyer and the seller. In a value maximizing transaction, the buyer can have lower or higher productivity than the seller. Since asset sales are driven by uncertainty in productivity over time, on the aggregate level, the model predicts that industries with more shuffling in productivity would experience greater asset sales.

In this paper, using the plant-level data from the Longitudinal Research Database, we empirically test the model predictions of Yang (2005). We find that the patterns of transactions (firm-level purchase/sale decisions, and cross-industry and time-series variation in industry-level asset sales activity) are consistent with the model predictions.

We have three main findings. First, asset purchases are more likely when firms' existing plants experience increases in productivity, and asset sales are more likely when firms have decreases in productivity ("rising buys falling"). Buyers and sellers of existing assets tend to be diversified firms which produce in more than one three-digit SIC industries. Firms are more likely to buy assets if the increase in productivity happens in the main segments. The probability of selling off existing assets is higher when the decrease in productivity occurs in the peripheral segments. These findings are consistent with those in Maksimovic and Phillips (2001).

Second, shock attributes such as persistence and dispersion help to explain the cross-industry variation in asset sales - industries with less persistent and more widely dispersed productivity shocks, on average, have higher rates of assets sales. Together, the persistence and dispersion of productivity shocks explain about 16 percent of the industry-fixed-effect of asset sales in our sample period. Industries with lower asset turnover ratios and higher profit margins also have more trades.

Next, within an industry, periods with more uncertainty regarding firms' relative productivity positions are associated with more frequent trading in existing assets. A xx percent increase in industry uncertainty leads to a xx percent increase in the amount of assets traded. More assets are traded in expansion periods.

Our paper primarily relates to the literature on asset sales and the literature on mergers.

The hypothesis that merger activities are driven by broad economic shocks can be traced to Gort (1969). Jovanovic and Rousseau (2002) propose a model in which firms with higher productivity acquire firms with lower productivity. Since their model builds on the constant return to scale technology, it focuses on cross-sectional contemporaneous sales, rather than on activities over time. Maksimovic and Phillips (2002)

present an equilibrium model to show how firms respond differently to aggregate demand shocks based on their productivity. The relation between economic shocks and asset reallocation has been documented in empirical studies, such as Mitchell and Mulherin(1996), Andrade, Mitchell, and Stafford (2001), Andrade and Stafford (2004) and Harford (2005). Our paper contributes to this literature by providing an explanation on how economic shocks affect the trading of existing assets. We argue that economic shocks increase the probability of firms' relative positions shuffling over time and firms optimally respond to the changes by trading more frequently.

Our study also contributes to the debate on why firms trade and which firms participate in asset sales. Contrary to the neoclassical theory, which suggests that buyers can utilize assets more efficiently than sellers do, Rhodes-Kropf, Robinson and Viswanathan (2004) present the evidence that buyers and sellers have similar Tobin's q. They argue that in reality, it is "like buys like" rather than "high buys low". In this paper, we bring to the debate a new perspective. Instead of measuring the level of productivity between buyers and sellers, we examine how changes in productivity affect firms' decisions to trade assets. Our study suggests that when firms make a series of investment decisions over time under uncertainty, changes in productivity may be more important than the level itself.

Furthermore, this paper extends our understanding of the relationship between productivity dispersion and the asset sales activity in the industry. We consider not only the dispersion of productivity distribution, but also how likely firms' positions shuffle within the distribution. In the equilibrium, both factors are necessary to facilitate trading over time. Without the shuffling effect, firms only trade once, and there is no need to buy or sell afterwards, even when the differences in productivity exists. Through shock attributes such as persistence and dispersion, we establish a link between the nature of the industry and the frequency that assets are traded in

the industry.

The remainder of the paper is organized as follows. We first discuss our analytical framework and the set up testable hypotheses in Section II. The data and estimation methods are discussed in Section III. Section IV presents test results and Section V concludes.

2   Analytical Framework and Hypotheses

The hypotheses that we examine in this paper are motivated by a dynamic equilibrium model of asset sales in Yang (2005). In that model, a firm maximizes its value by making two inter-related decisions: how much to invest in new assets and whether to buy or sell existing assets. These decisions are made under both firm-level and industry-level productivity shocks. The model assumes that it takes one period for new investments to become productive, while assets bought from other firms are available for production immediately. Given this difference in availability, firms make new investments to account for the expected future growth, but participate in asset sales to fix current investment needs. The price of new capital is assumed to be constant and the price of existing assets is derived from the equilibrium based on the demand and supply of current capacity. The model provides predictions on how changes in productivity affect firms' decisions to trade assets and how the reallocation of assets differs by industry and varies over time. These predictions are different from the predictions of models that focus on the level of the productivity. We describe the model and set hypotheses motivated by the model in this section.

The model focuses on how firms choose to buy or sell assets when productivity is stochastic. Firms produce based on a decreasing return to scale technology and the level of productivity affects how much output a firm can produce using one unit of

input. A more productive firm can generate more output using the same amount of input and it is larger in size. The concept of productivity can have many interpretations. For example, productivity can be a proxy for the managerial quality. A more skilled manager organizes the production process more efficiently and therefore produces more outputs. Since the managerial talent is limited and the marginal benefit of having a skilled manager decreases in the amount of assets managed, decreasing return to scale seems to be a reasonable assumption.

When the productivity of a firm increases following a positive shock, the firm demands more capacity. To expand, it can buy assets from other firms, invest in new capital, or do both. How much to buy or invest depends on the relative costs and how persistent the shocks are. An illiquid capacity market with higher transaction costs makes buying assets more costly and therefore leads to fewer trades. When shocks are not as persistent, given a positive shock, instead of investing in new assets and getting the needed capacity in the next period, firms may choose to buy assets from others to take advantage of the higher productivity at the moment. On the other hand, when a negative shock hits, it becomes inefficient for the firm to operate at the existing scale under the lower productivity, and this firm may choose to sell off its assets. Thus, the model predicts that assets flow from firms with falling productivity to firms with rising productivity. These predictions are summarized in the following hypothesis.

Hypothesis 1 *(Probability of Asset Purchases and Sales) Purchases of assets are more likely when firms have increases in productivity and sales of assets are more likely when firms have decreases in productivity.*

Lower persistence in productivity shocks means that firms do not stay at the same productivity levels for a long time and shuffling of productivity positions among firms

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is common. On the other hand, when shocks are more widely dispersed, the larger shock magnitude increases the potential gain from transferring assets, and makes transaction more likely to occur in the presence of transaction cost. Hence, the model predicts that industries with less persistent and more widely dispersed productivity shocks have more assets traded across firms.

One caveat worth mentioning here is that the impact persistence has on trades also depends on the magnitude of transaction cost. When the transaction cost is low, lower persistence leads to more shuffling in productivity, and more asset reallocation in the industry. However, if it is very costly to transfer assets and especially when firms have to pay a large fixed cost to enter into the market, a decrease in persistence may not lead to an increase in asset sales. This is because when the increase in productivity is not sustainable, it will be costly to sell off assets when productivity drops in the future. Given this consideration, firms with rising productivity may choose not to buy assets. Therefore, the amount of assets traded in an industry depends on the relative scales of shock persistence, shock magnitude and transaction costs. The existence of transaction cost will weaken the relation between shock attributes and the rate of asset reallocation in the industry.

The following hypothesis summarizes the model's prediction.

Hypothesis 2 *(Cross-industry Variation) Industries with lower persistence and higher dispersion in idiosyncratic productivity shocks have higher rate of asset sales.*

It is well documented in the literature that asset sales come in waves and the same pattern holds for both partial and complete ownership transfers. Andrade, Mitchell and Stafford (2001) show that industries that exhibit higher level of merger activity in the 1980s' are no more likely to do so in the 1990's. Harford (2005) find that

the average number of bids an industry sees in a 24-month non-wave period is 7.8, compared to 34.3 during the wave period from 1981 to 2000. Maksimovic and Phillips (2001) show that an average of 6.19 percent of manufacturing firms are involved in mergers and acquisitions and asset sales in expansion years, compared to an average of 3.89 percent over all years. Economic shocks such as deregulation, changes in input costs, capital liquidity and industry demand, are often viewed as causes for the formation of asset reallocation wave.

In this paper, we propose an explanation of how economic shocks can affect the trading of existing assets in the industry in the spirit of Yang (2005). Consider an industry that is in the midst of an economic shock through changes of technology, changes of cost of inputs, or deregulation. The uncertainty regarding firms' relative positions in the industry increases dramatically. For example, when a new technology arrives, whether a currently more-productive firm can remain at its position depends on whether the firm adopts the new technology, the percentage of other firms in the industry that choose to adopt the new technology, and the amount of uncertainty in the new technology. The increase in the uncertainty during the transition period increases the probability that firms' relative productivity may change over time, which can lead to large-scale asset reallocation in the industry. We formalize this prediction in the hypothesis below.

Hypothesis 3 *(Time-series Variation) For a given industry, time periods with more uncertainty regarding firms' relative positions are associated with higher rate of asset sales.*

3 Data and Methodology

We use data from the Longitudinal Research Database (LRD), maintained by the Center for Economic Studies at the Bureau of the Census. The LRD is a large micro database containing plant-level information for approximately 50,000 manufacturing plants in the SIC codes 2000 - 3999.[14]

There are several advantages of using the LRD for our study, relative to using data from Compustat. First, LRD covers both public and private firms in the manufacturing industry. This allows us to track down transactions that involve both public and private acquirers and targets. Second, it offers detailed information of output and input, so that we can estimate productivity on the plant level. Third, it has separate identifiers for plants and firms; hence, we can track down plants even as they change owners. This tractability is very important for this study, as it allows us to identify assets that have changed ownership. We can then identify buyers and sellers, and study the productivity of their existing/remaining plants around the transactions.

Our sample covers the period from 1972 to 2000. We aggregate plants into firm-level business segments at the three-digit SIC level and exclude segments that have less than \$1 million in the real value of shipments in 1982 dollars. The sample used here is the same as in Maksimovic and Phillips (2004).

Productivity Measures The productivity calculation follows Schoar (2002). We obtain plant productivity from estimating a log-linear Cobb-Douglas production function for each industry-year with the following specification:

$$\ln(Y_{ijt}) = a_{jt} + b_{jt} \ln(K_{ijt}) + c_{jt} \ln(L_{ijt}) + d_{jt} \ln(M_{ijt}) + z_{ijt} \tag{1}$$

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[14]See Maksimovic and Phillips (2001) for a detailed description of the LRD.

where Y_{ijt} is the total value of shipments of plant i in industry j at time t, K_{ijt}, L_{ijt} and M_{ift} represent the value of capital stock, the equivalent total production man-hours and value of inputs of plants i in industry j at time t, respectively. We calculate the value for capital stock (K) as a sum of book value of structures and equipment.[15] We adjust labor inputs (L) to reflect both production and non-production man hours. Inputs (M) are expenses for parts and intermediate goods, fuel, and energy purchased.

As pointed out by Schoar (2002), since coefficients on capital, labor and material inputs may vary by industry and by year, this specification allows for different factor intensities in different industry-years. Moreover, since the constant term (a_{jt}) varies with time, it helps to filter out the changes in industry-level productivity. This is very crucial for our study since we want to estimate the persistence and dispersion of the firm-level productivity shocks, and the uncertainty regarding the change of firms' *relative* position within the industry.

The idiosyncratic productivity is, then, the estimated residual from these regressions, which measures a plant's relative productivity in that industry-year. It measures the difference between the actual output and predicted output, given the amount of inputs the plant uses and the mean industry production technology in place. A plant that produces more than the predicted amount of the output has a greater-than-average productivity.

Rate of Asset Sales   Similar to Maksimovic and Phillips (2001), we define the rate of asset sales as the ratio of the number of plants that change ownership over the total

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[15]To account for depreciation of beginning of period capital stock, we use data from the Bureau of Economic Analysis to make depreciation adjustment for beginning period capital stock at the two-digit level. To the beginning of period capital stock, we add the real dollars (in real 1982 dollars) spent on capital expenditures for additions to the capital stock.

number of plants in the industry. [16]

$$s_{jt} = \frac{1}{n_{jt}} \sum_{i=1}^{n_{jt}} 1\left(Plant\ i\ changes\ ownership\ from\ t-1\ to\ t\right) \tag{2}$$

where $1\left(\right)$ is an indicator function which takes the value of 1 if a plant changes ownership from $t-1$ to t and n_{jt} is the total number for firms in industry j at time t.

On average, 3.7 percent of large manufacturing plants change ownership every year during the 1974 to 2000 period. The number is higher in expansion years, approaching 4.3 percent.[17]

4   Tests and Results

4.1   The Probability of Asset Purchases and Sales

In this section, we test Conjecture 1 of probability of asset purchases and sales. We calculate productivity for all firm segments at the plant level based on (1). For firms that have more than one plant in a segment, the segment productivity is calculated as the weighted average of productivity of all plants in the segment, using the predicted plant outputs as weights. We perform our analysis on the firm segment level.

4.1.1   Probability of Asset Purchases

We identify a firm segment as a buyer if it has produced outputs in the previous period and has bought at least one plant in the current period. Therefore, we do not

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[16]For robustness, I also use the ratio of the book value of assets that change ownership over the total book value of assets in the industry as a measure for the asset sales rate. The results are qualitatively the same.

[17]Using LRD data from 1974–1992, Maksimovic and Phillips (2001) document similar facts. They find an average asset sales rate of 3.89 percent and a rate of 6.89 percent for expansion years.

consider cases in which firms buy assets to enter into new industries. Research has shown that firms that choose to diversify are not as productive as firms that stay in their existing industries, controlling for sizes.[18] Since the focus here is to investigate the decisions to expand or downsize instead of the decisions to diversify or refocus, we exclude samples that are related to diversification for our analysis.

Conjecture 1 above suggests that a firm's decision to buy assets is influenced by changes in productivity. Firms, which experience increases in productivity, are more likely to buy assets from other firms. To test this effect, we run a Probit regression using an unbalanced panel. We use the changes of segment productivity in buyer's existing plants to approximate the productivity shock in the current period. We control for firm size (SIZE), organization form (whether the firm participate in multiple industries) (D_MULTI), importance of the segment (whether it is the firm's main segment) (D_MAIN),[19] capital expenditure (CAPX), and profitability (OPMARG). To take into account of the industry effect, we also control for industry characteristics such as the average rate of sales growth (D_ECON), industry average profitability (I_OPMARG), overall industry uncertainty (I_γ) and the productivity dispersion in the industry (I_DISP).

Our specification is as follows:

$$\Pr\left(D\_BUY_{ij,t}\right) = \beta_0 + \beta_1 Z_{ij,t-1} + \beta_2 \Delta \widetilde{Z_{ij,t}} + \beta_3 X_{i,t-1} + \beta_4 Y_{ij,t-1} + \varepsilon_{ij,t} \qquad (3)$$

where $D\_BUY_{ij,t}$ is a dummy variable that takes the value of 1 if firm i is a buyer in industry j at time t; $Z_{ij,t-1}$ is the lagged productivity of firm i in industry j; and

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[18]See Maksimovic and Phillips (2002).
[19]We identify a segment to be the main segment if it contributes to at least 25% of the firm's total shipment.

$\Delta \widetilde{Z_{ij,t}}$ captures the change of productivity of the *existing plants* for firm i in industry j from time $t-1$ to t. $X_{i,t-1}$ includes all lagged control variables for industry j, and $Y_{ij,t-1}$ includes all lagged control variables for firm i in industry j.

The results in Table 1 show that changes in productivity affect the probability of asset purchases. A firm is more likely to buy assets when there is an increase in productivity. This impact is significant, even after controlling for the lagged productivity level. Multi-segment firms are also more likely to purchase assets, especially for their main segments. The probability of asset purchase is higher when the firm has high profit margin, low capital expenditure and the industry in which it operates has high profit margin, more shuffling in relative positions, and more concentrated productivity distribution. A firm is also more likely to buy assets when its industry is in expansion, experiencing positive demand shock.

[INSERT TABLE 1 HERE]

4.1.2 Probability of Asset Sales

A seller is a firm segment that sells off part or all of its plants in the next period. We do not distinguish between partial and complete sell-offs.

Conjecture 1 above suggests that firms choose to sell off assets when they experience decreases in productivity. To test this effect, we run a Probit regression on the unbalanced panel. We use the changes in productivity in the current period as a proxy for productivity shock and examine how this affects a firm's decision to sell off assets in the next period. We assume that a firm observes the changes and makes decisions on whether to sell assets; and that if it decides to sell, the assets will be transferred

in the next period.[20] We control for firm size (SIZE), organization form (whether the firm participate in multiple industries) (D_MULTI), importance of the segment (whether it is the firm's main segment) (D_MAIN),[21] capital expenditure (CAPX), asset turnover (ATTURN) and profitability (OPMARG). We also control for industry characteristics such as average rate of sales growth (D_ECON), industry average profitability (I_OPMARG), overall industry uncertainty (I_γ) and the dispersion of productivity distribution (I_DISP).

Our specification is as follows:

$$\Pr\left(D\_SELL_{ijt}\right) = \beta_0 + \beta_1 Z_{ij,t-1} + \beta_2 \Delta Z_{ij,t-1} + \beta_3 X_{j,t-1} + \beta_4 Y_{ij,t-1} + \varepsilon_{ij,t} \qquad (4)$$

where D_SELL_{ijt} is a dummy variable that takes the value of 1 if firm i sells off assets in industry j at time t; $Z_{ij,t-1}$ is the lagged productivity of firm i in industry j, and $\Delta Z_{ij,t-1}$ captures the previously observed changes of productivity from $t-2$ to $t-1$. $X_{j,t-1}$ includes all lagged control variables for industry j, and $Y_{ij,t-1}$ includes all lagged control variables for firm i in industry j.

Table 2 reports the results. Changes in productivity strongly affect a firm's decision to sell its existing assets. Firms are more likely to sell assets when they experience decreases in productivity in the previous period and when the current productivity is low. Multi-segment firms are also more likely to sell assets, especially for their peripheral segments. The probability of asset sales is higher when the firm has low asset turnover ratio and when its industry has high profitability, more uncertainty in

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[20]We use the change in the previous period because when a firm exits the industry by selling off all of its assets, the information on current productivity is no long available.

[21]We identify a segment to be the main segment if it contributes to at least 25% of the firm's total shipment.

relative productivity, and more concentrated productivity distribution.

[INSERT TABLE 2 HERE]

In sum, the results in Table 1 and Table 2 conform the importance of changes in productivity on firms' decisions to buy or sell assets. Firms are more likely to buy assets when their segments have rising productivity and they are more likely to sell assets when their segments have falling productivity. Besides, consistent with Maksimovic and Phillips (2001, 2002), we also find that multi-segment firms are more likely to participate in asset purchases and sales. And, for multi-segment firms, given an increase in productivity, the probability of a purchase is higher when it is a main segment, and given a decrease in productivity, the probability of a sale is higher when the segment is peripheral.

4.2 Cross-Industry Variation in Asset Sales

In the previous section, we show how changes of productivity affect firms' decisions to buy or sell assets. In this section, we investigate the implication this effect has for the industry-level asset reallocation. If asset purchases and sales are driven by changes in productivity, do industries with more intrinsic uncertainty due to the nature of the uncertainty have more asset sales? Can attributes of productivity shocks such as persistence and dispersion explain the cross-industry variation in asset sales?

There could be many reasons why firms in some industries face more uncertainty regarding their relative positions in the industry. For example, rapid technology changes can make a firm's future position within the industry less predictable. Firms may face greater risks of remaining current positions in the industry when product

markets are differentiated and the consumers' tastes are hard to predict. Where the industry is at in the life cycle also matters to the uncertainty. Young industries in general have more risks than mature industries.

4.2.1 Estimation of Shock Persistence and Dispersion

To estimate the persistence and dispersion of idiosyncratic shocks for industry, j, we fit an $AR(1)$ process:

$$\widehat{z_{ij,t}} = \rho_j \widehat{z_{ij,t-1}} + \varepsilon_{ijt} \tag{5}$$

where $\widehat{z_{ij,t}}$ is the estimated idiosyncratic productivity of plant i in industry j at time t using (1).

We use the autoregressive coefficient ρ_j as a measure of shock persistence, and the standard deviation of the error terms as the measure of shock dispersion such that $\sigma_j = std\left(\{\varepsilon_{ijt}\}_{i=1,t=1}^{n_j \quad T}\right)$, where n_j is the total number of plants in industry j and T is the total number of years in the sample.

To have a stable time series for the AR(1) estimation, we delete industries with less than 50 plants in any given year and industries with less than five years of observation in the time series. Our final sample consists of estimates for persistence and dispersion for 112 industries.

High shock persistence implies that productivity follows a persistent trend - being more productive in the current period increases the chances of remaining more productive in the next period. Meanwhile, dispersion measures the magnitude of the noise term in productivity shocks. Firms in industries with less persistent and

more widely dispersed productivity shocks, face higher degree of uncertainty in their relative positions.

Conjecture 2 above suggests that industries with more uncertainty, i.e. less persistent and more widely dispersed productivity shocks, have more trades of existing assets. We test this pattern in two ways. First, we compare the average rate of asset sales across industries and test whether shock persistence and dispersion explain the cross-industry differences. Next, we estimate a model with industry fixed effect to control for other potential factors that are relevant to asset sales and may be time-variant.

4.2.2 Differences in Average Rate of Asset Sales

We divide industries in our sample into three groups, each with an equal number of observations based on shock persistence ρ and dispersion σ, respectively. Table 3 shows the summary statistics of each $\rho-$group and $\sigma-$groups. Industries vary significantly in persistence and dispersion. The High-ρ group has an average persistence of 0.70 and the Low-ρ group has an average persistence of 0.56. The average dispersion in High- and Low-σ groups is 0.15 and 0.30, respectively.

[INSERT TABLE 3 HERE]

We first compare the rates of asset sales between High-ρ and Low-ρ groups and between High-σ and Low-σ groups in a univariate setting. The results are shown in Table 3. On average, the High-ρ group has an asset sales rate of 3.80 percent, compared to a rate of 4.22 percent in the Low-ρ group. The High-σ group has an asset sales rate of 4.01 percent, while the Low-σ group has an asset sales rate of 3.67 percent. Both T-test and Mann-Whitney rank test reject the null hypotheses that

rates of asset sales do not differ significantly across ρ groups or σ groups. Instead, they suggest that firms in industries in Low-ρ and High-σ groups have more trades.

Table 4 reports how shock persistence and dispersion affect the average rate of asset sales in the industry in a multivariate setting, after controlling for other industry characteristics. We use the following specification:

$$\overline{s_j} = \beta_0 + \beta_1\rho_j + \beta_2\sigma_j + \gamma \cdot \overline{X_j} + \varepsilon_j \tag{6}$$

where $\overline{s_j}$ measures the average rate of asset sales in industry j; ρ_j and σ_j are shock persistence and shock dispersion, respectively, based on (5); $\overline{X_j}$ includes control variables for industry characteristics such as capital expenditure (CAPX), asset turnover(ATTURN), profitability (OPMARG) and average percent of years the industry spends in expansion (ECON).

Persistence and dispersion significantly affect how frequently firms trade assets in an industry, individually or jointly. Industries with less persistent and more dispersed productivity shocks, on average, have higher rates of asset sales ($\beta_1 < 0$ and $\beta_2 > 0$). Lower asset turnover ratio and higher profit margin are also related more active trading. Industries with higher rates of asset sales tend to have lower rates of capital expenditure, suggesting that internal growth (capital expenditure) and external growth (asset purchases) may serves as substitutes. Although the average percentage of years an industry spends in expansion has a positive effect on the rates of asset sales, the effect is not significant.

[INSERT TABLE 4 HERE]

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4.2.3 Industry Fixed Effect of Asset Sales

The amount of asset reallocation in the economy tends to vary over time and asset sales come in waves (Eisfeldt and Rampini (2005)). Industry characteristics that affect how assets transfer across firms may also change over time. In this section, we perform a two-step estimation to control for the time variant in asset sales. We first estimate the industry fixed effect of asset sales using a panel regression; then we examine how much variation in the estimated industry fixed effects can be explained by attributes of productivity shocks such as persistence and dispersion.

In the first step, we use the following specification to estimate a panel regression with industry fixed effects:

$$s_{jt} = \alpha_j + \beta \cdot X_{j,t-1} + \varepsilon_{jt} \tag{7}$$

where s_{jt} is the rate of asset sales of industry j from time $t-1$ to t and X_{jt-1} includes all lagged controlled variables for industry j.

Maksimovic and Phillips (2001, 2004) find that more assets are traded when the industry experiences positive demand shocks, and that multi-segment firms are more likely to acquire assets compared to their single-segment counterparts. Andrade and Stafford (2004) show that mergers also help to clean out excess capacity in the downturn when capital utilization rate in the industry is low. We control for capital expenditure (CAPX), asset turnover rate (ATTURN), profitability (OPMARG), industry sales growth rate (D_ECON), size distribution (HERF), and the percentage of diversified firms in the industry (MPCT).

The results are summarized in Table 5. Panel A shows how rates of asset sales differ over the years for a given industry. First, consistent with Andrade and Stafford

(2004), we find that asset sales are higher in years when new investments are low and the capital utilization rates are low. Next, similar to Maksimovic and Phillips (2001), we find that rates of asset sales are significantly higher in expansion years, when the industry experiences positive sales growth. The size distribution, measured by the Herfindahl index, has a positive effect: years with higher dispersion, or a lower Herfindahl index, have higher rates of asset sales. Profitability, on the other hand, is not a significant factor, and neither is the percentage of diversified firms in the industry. The F test that examines the group effects reject the null Conjecture that no significant fixed effect exists across industries.

In the second step, after obtaining the estimated industry fixed effects $\widehat{\alpha}_j$ from (7), which captures the pure industry effect of asset sales, we regress it on shock attributes:

$$\widehat{\alpha}_j = \beta_0 + \beta_1 \rho_j + \beta_2 \sigma_j + \varepsilon_j \tag{8}$$

Panel B shows the results from the second-step regression. Consistent with the results from the mean regression earlier, industries with less persistent and widely dispersed productivity shocks have significantly more asset transfers across firms ($\beta_1 < 0$ and $\beta_2 > 0$). Together, these factors, persistence and dispersion, explain about 16 percent of the total variation in the estimated industry fixed effects.

[INSERT TABLE 5 HERE]

To summarize, the results found in this section from univariate analysis, mean regressions and panel regressions, are consistent with Conjecture 2 that attributes of productivity shocks explain the cross-industry variation in asset sales. Industries

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with lower persistence and higher dispersion in productivity shocks have higher rates of asset reallocation.

4.3   Time-Series Variation in Asset Sales

The persistence and dispersion of productivity shocks measure the intrinsic uncertainty firms face due to the nature of the industry. Both proxies are estimated using time-series data of more than 20 years. Although they help to explain why some industries on average have more trades in existing assets, they are not able to explain how uncertainty affects asset sales over time within a given industry.

In this section, we develop a time-variant measure that approximates the contemporaneous uncertainty within the industry, and examine how it is related to rates of asset sales over time.

4.3.1   Estimation of the Uncertainty

Since our key focus here is to capture the uncertainty related to changes in firms' relative positions within the industry, we develop our proxy of uncertainty as a correlation measure using the following specification:

$$\gamma_{jt} = corr \left\{ pct \left(\widehat{z_{ij,t}} \right), pct \left(\widehat{z_{ij,t-1}} \right) \right\} \tag{9}$$

where $pct \left(\widehat{z_{ij,t}} \right)$ and $pct \left(\widehat{z_{ij,t-1}} \right)$ are the percentiles of the estimated idiosyncratic productivity of plant i in industry j at time t, and at time $t-1$, respectively. The $\widehat{z_{ij,t}}'s$ are estimated based on (1).

The uncertainty measure, γ, captures the likelihood that a plant stays at its position in the industry. A high γ corresponds to a low level of uncertainty. We use

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percentiles instead of the raw values of productivity here so that our result is not affected by changes in distribution of productivity. When calculating γ, we exclude plants that change ownership between the period of $t-1$ and t because ownership changes are exogenous events that may bring dramatic changes to a plant's productivity.[22]

Conjecture 3 above predicts that within an industry, years with more shuffling in relative positions and high uncertainty have higher rates of asset sales. We test this effect in this section.

4.3.2 Univariate Tests

Our sample has an unbalanced panel of 112 industries and 2647 industry-years based on three-digit SIC codes in the period of 1973 - 2000. The uncertainty measure γ, has a mean of 66 percent, and a standard deviation of 11 percent.

First, we divide our sample into four groups, each with an equal number of observations based on the uncertainty measure, γ. High γ means that uncertainty is low.

Table 6 Panel A shows the average rate of asset sales in all $\gamma-$groups. Panel B tests the differences in asset sales between the 1st quartile (Low-γ group) and the last quartile (High-γ group) of γ groups. The High-γ (low uncertainty) group has an asset sales rate of 3.7 percent, compared to a rate of 4.4 percent in the Low-γ (high uncertainty) group. Both T-test and the Mann-Whitney rank test suggest that uncertainty within the industry matters for asset sales - firm-years of low γ, or high uncertainty, have more frequent asset transfers.

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[22]The results are very similar when all the plants are used to calculate γ_{jt}.

4.3.3 Multivariate Tests

To find out how shuffling of productivity in an industry affects the amount of assets traded over time, we estimate a panel regression with industry fixed effects based on the following specification:

$$s_{jt} = \alpha_j + \beta_1 \gamma_{j,t} + \beta_2 X_{j,t-1} + \varepsilon_{jt} \tag{10}$$

where s_{jt} is the rate of asset sales of industry j at time t; $\gamma_{j,t}$ measures the uncertainty in industry j from time $t-1$ to time t, using (9); and X_{jt-1} includes all lagged controlled variables of industry j.

We estimate $\gamma_{j,t}$ only using plants that do not have ownership transfer to avoid potential endogeneity problems. For control variables, we include capital expenditure (CAPX), profitability (OPMARG), rate of sales (D_ECON), size distribution (HERF) and the percentage of diversified firms in the industry (MPCT). We also include the standard deviation of productivity distribution (I_DISP) as a control variable to test how productivity dispersion affects asset sales. Again, to avoid potential endogeneity problem, we only use plants that do not change ownership during the time period for our calculation of the dispersion.

This specification is different from (7) and (8). The uncertainty measure, γ, is estimated to be time-variant. While (7) and (8) focus on how intrinsic uncertainty of an industry affects the average rate of asset sales, the specification in (10) tests whether changes of uncertainty over time have an impact on asset sales activity in a given industry.

The results are shown in Table 7. There exists a significant relationship between industry uncertainty and rate of asset sales. Within an industry, years with high uncertainty (or low γ) have much higher asset sales. For example, the rate of asset sales is at xxx percent when the uncertainty is at its 90th percentile (or 10th percentile of γ), whereas it is only xxx percent when the uncertainty is at its 10th percentile (or 90th percentile of γ). Our findings here support Conjecture 3 that within an industry, time periods with more uncertainty have higher rates of asset sales.

More asset sales also occur in years when new investment is low and the capital utilization is low. Assets are more likely to be traded when demand is high and the industry is in expansion. A higher percentage of multi-segment firms in the industry contributes to a higher rate of asset sales, consistent with our earlier finding that multi-segment firms are more likely to participate in asset purchases and sales. The productivity dispersion, however, does not have a significant effect on asset sales.

[INSERT TABLE 7 HERE]

4.3.4   Uncertainty and Capital Expenditure

For firms that pursue expansion, capital expenditure and asset purchase serve as alternative means. Yang (2005) suggests that given a positive shock, firms are more likely to buy assets when shocks are transitory, and that investing in new assets is more preferable when shocks are persistent. This is because higher persistence makes the current position more likely to stay, and therefore lower the risk from getting the capacity in the next period through new investments.

Table 8 shows how uncertainty in the industry affects the rate of capital expenditure. Consistent with the model developed in Yang (2005), we find that there exists

a significant negative relationship between industry uncertainty and capital expenditure. Firms invest more in new assets in periods with less uncertainty (or high γ).

[INSERT TABLE 8 HERE]

The finding here on the relation among uncertainty, asset purchases and sales, and capital expenditure offer preliminary insights on how firms choose between internal and external growth for expansion, and how uncertainty regarding firms' relative positions may affect the investment patterns in an industry.

5   Conclusion

In this paper, we analyze how changes in productivity affect firms' decision to trade assets, and what it implies for asset sales activity in the industry over time. We find that the pattern of transactions (firm-level purchase/sale decisions, and cross-industry and time-series variation in industry-level asset sales activity) are consistent with the model developed in Yang (2005).

Using the plant-level data from Longitudinal Research Database on manufacturing firms in the period of 1973 to 2000, we find three main results:

1. Asset purchases are more likely when firms' existing plants experience increases in productivity, and asset sales are more likely when firms have decreases in productivity ("rising buys falling")

2. Shock attributes such as persistence and dispersion help to explain the cross-industry difference in asset reallocation - industries with less persistent and more widely dispersed productivity shocks have greater assets sales on average.

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Together, persistence and Dispersion explain about 16 percent of the industry fixed effect in asset sales.

3. Within the industry, periods with more shuffling regarding firms' relative position in productivity are associated with more frequent reallocation. A xx percent increase in industry uncertainty leads to a xx percent increase in the amount of assets traded.

These findings suggest that firms optimally adjust their capacity in response to productivity shocks, in patterns that are consistent with profit maximization.

6   Tables

Table 1: Probability of Asset Purchase

This table reports estimation results on the probability of asset purchases using a Probit model based on (3). The dependent variable is a binary variable that takes the value of 1 if a firm segment buys assets in the current period and 0 otherwise. Productivities are caluclated based on (1). D_MULTI is a binary variable that takes the value of 1 if the firm has more than one segment and 0 otherwise. D_MAIN is a dummy variable that takes the value of 1 if it is the main segment. CAPX is the capital expenditure ratio. OPMARG is the operational margin, measured as a ratio of earnings divided by sales. SIZE measures the total value of shipments in the segment. ATTURN is the asset turnover ratio, measured as sales divided by asset size. D_ECON is a dummy variable that equals to one if the industry-level sales increase for two consecutive years, minus one if sales decrease for two consecutive years and zero otherwise. I_OPMARG is the average industry operational margin. I_γ measures the uncertainty in the industry from (9) and I_DISP is the standard deviation of productivity distribution. All the control variables are lagged. z-statistics are reported in parentheses and *, **, *** represent significance level of 10%, 5%, and 1%, respectively.

Dependent variable: Probability of Asset Purchases								
	(1)		(2)		(3)		(4)	
Lagged Productivity	0.001				0.030		0.145	***
	(0.05)				(1.24)		(5.73)	
Change of Productivity			0.084	***	0.094	***	0.107	***
			(3.61)		(3.82)		(4.25)	
D_MULTI	0.729	***	0.742	***	0.742	***	0.746	***
	(61.78)		(62.07)		(62.01)		(59.45)	
D_MAIN	0.100	***	0.112	***	0.111	***	0.077	***
	(8.82)		(9.7)		(9.69)		(6.45)	
CAPX	-0.028		-0.022		-0.023		0.028	
	(-1.53)		(-1.19)		(-1.22)		(1.47)	
OPMARG	0.342	***	0.380	***	0.356	***	0.304	***
	(10.46)		(14.15)		(10.68)		(8.85)	
SIZE (x 10^6)	0.013	***	0.013	***	0.013	***	0.012	***
	(9.19)		(9.18)		(9.04)		(7.96)	
ATTURN							-0.010	***
							(-13.42)	
D_ECON	0.045	***	0.045	***	0.045	***	0.020	***
	(6.86)		(6.78)		(6.80)		(2.77)	
L_OPMARG	1.017	***	0.961	***	0.989	***	2.086	***
	(13.86)		(13.51)		(13.26)		(9.99)	
L_γ							-0.310	***
							(-4.85)	
L_DISP							0.277	***
							(3.06)	
Constant	-2.709	***	-2.741	***	-2.740	***	-2.198	***
	(-176.56)		(-176.10)		(-175.99)		(-39.62)	
							w/ fixed effect	
Psedo R-square	7.9%		8.1%		8.1%		10.3%	
Number of Obs.	485,717		485,427		485,427		485,427	

Table 2: Probability of Asset Sales

This table reports estimation results on the probability of asset sales using a Probit model based on (4). The dependent variable is a binary variable that takes the value of 1 if a firm segment sells assets in the next period and 0 otherwise. Productivities are caluclated based on (1). D_MULTI is a binary variable that takes the value of 1 if the firm has more than one segment and 0 otherwise. D_MAIN is a dummy variable that takes the value of 1 if it is the main segment. CAPX is the capital expenditure ratio. OPMARG is the operational margin, measured as a ratio of earnings divided by sales. SIZE measures the total value of shipments in the segment. ATTURN is the asset turnover ratio, measured as sales divided by asset size. D_ECON is a dummy variable that equals to one if the industry-level sales increase for two consecutive years, minus one if sales decrease for two consecutive years and zero otherwise. I_OPMARG is the average industry operational margin. I_γ measures the uncertainty in the industry from (9) and I_DISP is the standard deviation of productivity distribution. All the control variables are lagged. z-statistics are reported in parentheses and *, **, *** represent significance level of 10%, 5%, and 1%, respectively.

Dependent variable: Probability of Asset Sales								
	(1)		(2)		(3)		(4)	
Current Productivity	-0.048	***						
	(−3.52)							
Change of Productivity			-0.040	***	-0.064	***	-0.072	***
			(−3.01)		(−3.95)		(−4.34)	
Lagged Productivity					-0.038	***	-0.049	***
					(−2.6)		(−3.24)	
D_MULTI	0.336	***	0.335	***	0.336	***	0.321	***
	(40.75)		(40.70)		(40.77)		(37.63)	
D_MAIN	-0.146	***	-0.148	***	-0.147	***	-0.161	***
	(−16.54)		(−16.68)		(−16.64)		(−17.77)	
ATTURN	-0.001	***	-0.001	***	-0.001	***	-0.001	***
	(−7.07)		(−7.23)		(−6.85)		(−4.97)	
CAPX	-0.182	***	-0.187	***	-0.186	***	-0.166	***
	(−15.28)		(−15.59)		(−15.44)		(−13.57)	
OPMARG	0.107	***	0.081	***	0.108	***	0.120	***
	(5.66)		(5.11)		(5.69)		(6.12)	
SIZE (x 10^6)	0.006	***	0.005	***	0.006	***	0.009	***
	(5.07)		(4.86)		(5.01)		(5.65)	
D_ECON	0.012	***	0.012	***	0.012	***	-0.001	
	(2.8)		(2.85)		(2.81)		(−0.11)	
L_OPMARG	0.692	***	0.725	***	0.692	***	1.705	***
	(14.79)		(16.01)		(14.72)		(12.82)	
L_γ							-0.465	***
							(−11.99)	
L_DISP							0.047	
							(0.81)	
Constant	-1.812	***	-1.809	***	-1.810	***	-1.420	***
	-173.53		-173.14		-173		-(40.05)	
							w/ fixed effect	
Pseudo R-square	3.26%		3.28%		3.29%		3.79%	
Number of Obs.	625,933		622,601		622,601		597,508	

Table 3: Shock Persistence, Dispersion and Asset Sales

This table reports the test results from comparing average assets sales between High-ρ and Low-ρ industries, and between High-σ and Low-σ industries, respectively. We form groups such that the High-group consists of observations in the top 33 percentile, the Low-group consists of observations in the bottom 33 percentile and the Medium-group consists of all observations in between. For each year, we measure the asset sales rate as the number of plants that change ownership divided by the total number of the plants in the industry. p-values are reported in parentheses.

Panel A: Shock Persistence (ρ) and Asset Sales				
	# of Obs	Mean(ρ)	Mean	Std. Dev.
Low - ρ	38	0.56	4.22%	0.90%
High - ρ	37	0.70	3.80%	0.83%
T Test			2.11	(3.81)
Signed Rank Test			1.62	(10%)
Spearman Correlation			−0.20	(8%)
Kendall's Tau			−0.15	(6%)

Panel B: Shock Volatility (σ) and Asset Sales				
	# of Obs	Mean(σ)	Mean	Std. Dev.
Low - σ	38	0.15	3.67%	0.78%
High- σ	37	0.30	4.01%	0.88%
T Test			−1.78	(8%)
Signed Rank Test			−1.66	(10%)
Spearman Correlation			0.24	(4%)
Kendall's Tau			0.15	(5%)

Table 4: Persistence, Dispersion and Asset Sales: Mean Regression

This table reports regression results on the average asset sales rate based on (6). For each year, we measure the asset sales rate as the number of plants that change ownership dividing by the total number of plants in the industry. CAPX is the average capital expenditure ratio. ATTURN is the average asset turnover ratio, measured as a ratio of total sales divided by total assets. OPMARG is the average operational margin, measured as a ratio of earnings divided by sales. ECON measures the percentage of expansion years over the total industry years. We define a year as an expansion year if it has positive sales growth rates for two consecutive years. t-statistics are reported in parentheses and *, **, *** represent significance level of 10%, 5%, and 1%, respectively.

	Dependent Variable: Average Asset Sales Rate (in percentage)		
	(1)	(2)	(3)
Shock Persistence (ρ)	-3.26***		-2.31***
	(-2.94)		(-2.01)
Shock Dispersion (σ)		3.69***	2.91***
		(3.30)	(2.49)
CAPX	-2.50	-7.80*	-5.77*
	(-0.62)	(-1.89)	(-1.38)
ATTURN	-0.55***	-0.47***	-0.51***
	(-2.93)	(-2.53)	(-2.78)
OPMARG	4.25***	3.91***	4.23***
	(3.94)	(3.70)	(4.02)
ECON	0.60*	0.49	0.55
	(1.53)	(1.27)	(1.43)
CONS	6.86***	4.82***	6.13***
	(8.16)	(8.21)	(7.03)
# of Obs.	112	112	112
Adj. R^2	25%	26%	28%

Table 5: Persistence, Dispersion and Industry Fixed Effect of Asset Sales

This table reports the regression results on industry's fixed effects of asset sales based on (7) and (8). Panel A shows estimation results of a fixed-effect model in which the dependent variable is the annual asset sales rate in an industry. For each year, the asset sales rate is measured as a ratio of the number of plants that change ownership divided by the total number of plants. CAPX is the capital expenditure ratio. ATTURN is the asset turnover ratio, measured as a ratio of total sales divided by total assets. OPMARG is the operational margin, measured as a ratio of earnings divided by sales. D_ECON is a dummy variable that equals to one if the industry-level sales increase for two consecutive years, minus one if sales decrease for two consecutive years and zero otherwise. HERF is the Herfindahl Index based on sizes. MPCT is the percentage of plants in the industry that are owned by multi-segment firms. All explanatory variables are lagged. Panel B shows the regression results using the estimated industry fixed effect of asset sales as the dependent variable. In both panels, t-statistics are reported in parentheses and *, **, *** represent a significance level of 10%, 5%, and 1%, respectively.

Panel A: Panel Regression	
Dependent Variable: Asset Sales Rate (in percentage)	
CAPX	-6.18^{***}
	(-4.71)
ATTURN	-0.99^{***}
	(-4.43)
D_ECON	0.24^{***}
	(3.09)
HERF	-8.00^{****}
	(-3.36)
OPMARG	2.23
	(1.23)
MPCT	-0.96
	(-1.41)
CONS	7.46^{***}
	(18.08)
R^2 (overall)	4%
F-stat (all $\alpha_i = 0$)	24.68

Table 5: Continued

Panel B	
Dependent Variable: Industry Fixed-effects of Asset Sales	
Shock Persistence (ρ)	-1.93***
	(-7.07)
Shock Dispersion (σ)	5.39***
	(19.76)
CONS	0.02
	(0.12)
# of Obs.	112
R^2	16.35%

Table 6: Uncertainty and Asset Sales: Univariate Analysis

This table reports the test results from comparing average assets sales between High- and Low-γ industry-years. Uncertainty measure, γ, is estimated using (9). We form four groups based on γ such that each group has the same number of observations. Group 1 contains the industry-years with the lowest γ, and Group 4 includes industry-years with the highest γ. Panel A reports the mean of γ and the average rate of asset sales in each γ-group. Panel B reports the test results when comparing the rate of asset sales between group 1 and group 4. For each year, we measure the asset sales rate as the number of plants that change ownership divided by the total number of the plants in the industry. p-values are reported in parentheses.

Panel A: Uncertainty and Asset Sales			
Quartiles based on γ	# of Obs	Mean (γ)	Mean (Asset Sales Rate)
1 (low γ)	753	0.528	4.41%
2	753	0.646	4.02%
3	753	0.707	3.91%
4 (high γ)	752	0.781	3.71%

Panel B: Compare Rate of Asset Sales between Groups		
	# of Obs	Mean (Asset Sales Rate)
Low - γ	753	4.41%
High - γ	752	3.71%
T Test		$t = 4.7519$
		$(p = 0.00\%)$
Rank Test		$z = 4.644$
		$(p = 0.00\%)$

Table 7: Uncertainty and Asset Sales - Panel Regression

This table reports the regression results using the panel data based on (10). The dependent variable is the annual rate of asset sales in an industry. For each year, the asset sales rate is measured as a ratio of the number of plants that change ownership divided by the total number of plants. I_γ measures the uncertainty in the industry based on (9) and I_DISP is the standard deviation of productivity distribution. CAPX is the capital expenditure ratio. OPMARG is the operational margin, measured as a ratio of earnings divided by sales. HERF is the Herfindahl Index based on sizes. MPCT is the percentage of plants in the industry that are owned by multisegment firms. D_ECON is a dummy variable that equals to one if the industry-level sales increase for two consecutive years, minus one if sales decrease for two consecutive years and zero otherwise. All explanatory variables are lagged. t-statistics are reported in parentheses and *, **, *** represent a significance level of 10%, 5%, and 1%, respectively.

Dependent variable: Rate of Asset Sales (in percentage)

	(1)		(2)	
I_γ	−3.120	***	−3.196	***
	(−5.49)		(−5.51)	
I_DISP			0.672	
			(0.66)	
CAPX	−9.520	***	−9.551	***
	(−9.29)		(−9.31)	
OPMARG	2.988		2.681	
	(1.63)		(1.41)	
HERF	−7.099	**	−7.472	**
	(−2.21)		(−2.29)	
MPCT	−1.276	*	−1.312	*
	(−1.85)		(−1.89)	
D_ECON	0.222	**	0.225	**
	(2.53)		(2.56)	
I_γ * D_ECON	0.064		0.063	
	(0.50)		(0.50)	
Constant	8.370	***	8.284	***
	(16.62)		(15.92)	
F-stat	2.48		2.47	
Adjust R-square	13%		13%	
Number of Obs	2674		2674	

Table 8: Uncertainty and Capital Expenditure: Panel Regression

This table reports the regression results using the panel data. The dependent variable is the annual rate of capital expenditure in an industry. For each year, the asset sales rate is measured as a ratio of the number of plants that change ownership divided by the total number of plants. I_γ measures the uncertainty in the industry based on (9) and I_DISP is the standard deviation of productivity distribution. CAPX is the capital expenditure ratio. OPMARG is the operational margin, measured as a ratio of earnings divided by sales. HERF is the Herfindahl Index based on sizes. MPCT is the percentage of plants in the industry that are owned by multisegment firms. D_ECON is a dummy variable that equals to one if the industry-level sales increase for two consecutive years, minus one if sales decrease for two consecutive years and zero otherwise. All explanatory variables are lagged. t-statistics are reported in parentheses and *, **, *** represent a significance level of 10%, 5%, and 1%, respectively.

Dependent variable: Rate of Capital Expenditure (in percentage)

	(1)		(2)	
I_γ	5.048	***	4.591	***
	(4.85)		(4.32)	
I_DISP			3.921	**
			(2.14)	
Asset Sales	−33.111	***	−33.193	***
	(−9.17)		(−9.19)	
OPMARG	36.228	***	34.417	***
	(11.03)		(10.16)	
HERF	−12.825	**	−14.956	**
	(−2.24)		(−2.57)	
MPCT	4.267	***	4.031	***
	(3.50)		(3.30)	
D_ECON	0.264	*	0.281	*
	(1.70)		(1.81)	
I_γ * D_ECON	1.356	***	1.353	***
	(5.99)		(5.98)	
Constant	10.424	***	9.918	***
	(11.00)		(10.16)	
F-stat	5.67		5.47	
Adjust R-square	0.2859		0.2869	
Number of Obs	2674		2674	

Appendix of Essay 1

Appendix 1: Two-Firm Example

I solve the model from backwards.

- At t=1

Firm i wishes to maximize the following value function:

$$V\left(k_i^1, z_a^1, z_i^1\right) = \max_{x_i^1 \geq -k_i^1} \pi\left(k_i^1 + x_i^1, A_i^1\right) - P^1 x_i^1 - f + \beta\left(1 - \delta\right)\left(k_i^1 + x_i^1\right) \quad \text{(A1)}$$

FOC(x_i^1) :

$$A_i^1 \alpha \left(k_i^1 + x_i^1\right)^{\alpha-1} - P^1 + \beta\left(1 - \delta\right) = 0$$

With the market clearing condition $x_1^1\left(P^1\right) + x_2^1\left(P^1\right) = 0$, we can solve for $\left(P^1, \{x_i^1\}_{i=1}^2\right)$ such that

$$
\begin{aligned}
x_1^1 &= -x_2^1 = \theta^1\left(k_1^1 + k_2^1\right) - k_1^1 & if & \quad f \leq G^1 \\
x_1^1 &= -x_2^1 = 0 & if & \quad f > G^1
\end{aligned}
\quad \text{(A2)}
$$

$$P^1 = \alpha \exp\left(z_a^1\right)\left(\frac{\exp\left(\frac{z^1}{1-\alpha}\right) + \exp\left(\frac{-z^1}{1-\alpha}\right)}{\left(k_1^1 + k_2^1\right)}\right)^{1-\alpha} + \beta\left(1 - \delta\right) \quad \text{(A3)}$$

$$if \quad x_1^1 \neq 0$$

$where$ $\quad \theta^1 \equiv \frac{\exp\left(\frac{z^1}{1-\alpha}\right)}{\exp\left(\frac{z^1}{1-\alpha}\right) + \exp\left(\frac{-z^1}{1-\alpha}\right)}$ is the share of total capital for firm 1 and $G^1 = $ $\min\left\{\left[\pi\left(k_i^1 + x_i^1, A_i^1\right) - \pi\left(k_i^1, A_i^1\right)\right] - \left[P^1 - \beta\left(1 - \delta\right)\right] x_1^1\right\}_{i=1}^2$ is the minimum gain from transaction across two firms.

- At t=0

Using $(A1)$, firm i wishes to maximize the following value function:

$$V\left(k_i^0, z_a^0, z_i^0\right) = \max_{\substack{x_i^0 \geq -k_i^0 \\ 0 \leq I_i}} \pi\left(k_i^0 + x_i^0, A_i^0\right) - \left(P_x^0 x_i^0 + f + I_i\right) + \beta E V^1\left(k_i^1, z_a^1, z_i^1\right) \quad \text{(A4)}$$

where $\quad k_i^1 = (1 - \delta)(k_i^0 + I_i^0)$

$$\text{FOC }(x_i^0) \quad : \quad A_i^0 \alpha (k_i^0 + x_i^1)^{\alpha-1} - P^0 + \beta (1 - \delta) \frac{\partial EV^1}{\partial k_i^1} = 0 \qquad \text{(A5)}$$

$$\text{FOC }(I_i) \quad : \quad -1 = \beta \frac{\partial EV_i^1}{\partial k_i^1}$$

With market clearing condition $x_1^0(P^0) + x_2^0(P^0) = 0$, we can solve for optimal asset transfer $\left(\{x_i^0\}_{i=1}^2\right)$ new investment $\left((\{I_i\}_{i=1}^2)\right)$ and equilibrium price (P^0).

$$
\begin{aligned}
x_1^0 &= -x_2^0 = \theta^0 \left(k_1^0 + k_2^0\right) - k_1^0 & if \quad f \leq G^0 & \qquad \text{(A6)} \\
x_1^0 &= -x_2^0 = 0 & if \quad f > G^0 &
\end{aligned}
$$

$$I_i = \left(\frac{\alpha}{\frac{1}{\beta} - \beta(1-\delta)}\right)^{\frac{1}{1-\alpha}} \left[z_a^0(2\pi_a - 1) + z_i^0(2\pi_i - 1)\right] - (1 - \delta)\left(k_i^0 + x_i^0\right) \qquad \text{(A7)}$$

$$P^0 = \alpha \exp\left(z_a^0\right) \left(\frac{\exp\left(\frac{z^0}{1-\alpha}\right) + \exp\left(\frac{-z^0}{1-\alpha}\right)}{\left(k_1^0 + k_2^0\right)}\right)^{1-\alpha} + (1-\delta)\beta EP^{1*} \qquad \text{(A8)}$$

$$if \quad x_1^0 \neq 0$$

where $\quad \theta^0 \equiv \frac{\exp\left(\frac{z^0}{1-\alpha}\right)}{\exp\left(\frac{z^0}{1-\alpha}\right) + \exp\left(\frac{-z^0}{1-\alpha}\right)}$ is the total share of existing capital for firm 1 and $G^0 = \min\left\{\left[\pi\left(k_i^0 + x_i^0, A_i^0\right) - \pi\left(k_i^0, A_i^0\right)\right] - \left[P^0 - \beta(1-\delta)\right]x_1^0\right\}_{i=1}^2$ is the minimum gain from transaction across two firms.

The expected future price for existing asset depends on current aggregate productivity and whether the constraints on investment are binding

$$
\begin{aligned}
\beta EP^1 &= 1 - \mu_1 & if \quad I_i = 0 & \qquad \text{(A9)} \\
&= 1 & if \quad I_i > 0 &
\end{aligned}
$$

where μ_1 is the Lagrangian multipliers for the non-negativity restriction that $I_i \geq 0$.

Plug in $(A6)$ into $(A2)$

$$
\begin{aligned}
x_1^1 &= \theta^1 \left(k_1^1 + k_2^1 \right) - k_1^1 \qquad\qquad\qquad\qquad\qquad\qquad (A10)\\
&= \theta^1 \left[(1 - \delta) \left(k_1^0 + k_2^0 \right) + (I_1 + I_2) \right] - \left[(1 - \delta) \theta^0 \left(k_1^0 + k_2^0 \right) + I_1^0 \right]\\
&= (1 - \delta) \left(k_1^0 + k_2^0 \right) \left(\theta^1 - \theta^0 \right) + \left(\theta^1 - \frac{I_1}{I_1 + I_2} \right) (I_1 + I_2)
\end{aligned}
$$

Without loss of generality, assume that $z_1^0 = z > 0$, then $\theta^0 \equiv \dfrac{\exp\left(\frac{z}{1-\alpha}\right)}{\exp\left(\frac{z}{1-\alpha}\right) + \exp\left(\frac{-z}{1-\alpha}\right)} > \frac{1}{2}$

Note that

$$
\begin{aligned}
\frac{I_1}{I_1 + I_2} &= \theta^0 \frac{\left(\frac{\alpha}{\frac{1}{\beta} - \beta(1-\delta)} \right)^{\frac{1}{1-\alpha}} \left[\frac{z_a^0 (2\pi_a - 1) + z(2\pi_i - 1)}{\theta^0} \right] - (1 - \delta) \left(k_1^0 + k_2^0 \right)}{\left(\frac{\alpha}{\frac{1}{\beta} - \beta(1-\delta)} \right)^{\frac{1}{1-\alpha}} \left[2z_a^0 (2\pi_a - 1) \right] - (1 - \delta) \left(k_1^0 + k_2^0 \right)} \qquad (A11)\\[2mm]
&\implies \frac{I_1}{I_1 + I_2} = \theta^0 \qquad if \qquad z (2\pi_i - 1) = \left(2\theta^0 - 1 \right) z_a (2\pi_a - 1)
\end{aligned}
$$

Appendix 2: Proofs of Proporsitions

Proposition 1   Let θ denote the share of total assets that the firm with a positive shock will occupy, then $\theta = \frac{\exp\left(\frac{z}{1-\alpha}\right)}{\exp\left(\frac{z}{1-\alpha}\right)+\exp\left(\frac{-z}{1-\alpha}\right)} > \frac{1}{2}$ and is increasing in shock magnitude such that $\frac{\partial\theta}{\partial z} > 0$.

Proof. From the derivation above

$$\theta^0\left(z^0 = z\right) = \frac{\exp\left(\frac{z^0}{1-\alpha}\right)}{\exp\left(\frac{z^0}{1-\alpha}\right)+\exp\left(\frac{-z^0}{1-\alpha}\right)} = \frac{\exp\left(\frac{z}{1-\alpha}\right)}{\exp\left(\frac{z}{1-\alpha}\right)+\exp\left(\frac{-z}{1-\alpha}\right)} = \theta \quad (A12)$$

$$\theta^1\left(z^1 = z\right) = \frac{\exp\left(\frac{z^1}{1-\alpha}\right)}{\exp\left(\frac{z^1}{1-\alpha}\right)+\exp\left(\frac{-z^1}{1-\alpha}\right)} = \frac{\exp\left(\frac{z}{1-\alpha}\right)}{\exp\left(\frac{z}{1-\alpha}\right)+\exp\left(\frac{-z}{1-\alpha}\right)} = \theta \quad (A13)$$

Since $z > 0 > -z$, $\theta > \frac{1}{2}$

Let $\exp\left(\frac{z}{1-\alpha}\right) = c$

$$\theta = \frac{c}{\frac{1}{c}+c} = \frac{c^2}{1+c^2} = 1 - \frac{1}{1+c^2} \quad (A14)$$

$$\frac{\partial\theta}{\partial c} = \frac{2C}{\left(1+c^2\right)^2} > 0$$

$$\frac{\partial c}{\partial z} = \frac{1}{1-\alpha}\exp\left(\frac{z}{1-\alpha}\right) > 0$$

$$\frac{\partial\theta}{\partial z} = \frac{\partial\theta}{\partial c} \times \frac{\partial c}{\partial z} > 0$$

Q.E.D. ∎

Proposition 2   (1) Given the fixed cost and shock magnitude, sales are more likely to occur when aggregate productivity is high. (2) Given the aggregate productivity, the likelihood of asset sales decreases as fixed cost increases.

Proof. Assume that firms start with equal sizes, $k_1^0 = k_2^0 = k$. Without loss of generality, assume that $z^0 = z > 0$, i.e., Firm 1 has the higher idiosyncratic productivity at $t = 0$. From $(A6)$, the adjusted capacity (after asset transfer) for both firms are:

$$\left(k + x_1^0\right) = \theta \cdot 2k - k \quad (A15)$$

$$\left(k + x_2^0\right) = (1-\theta)\, 2k$$

Sales will occur if the minimum gain from the transaction, G^0, if greater than the fixed transaction cost, f. Therefore, the probability of having sales occur increases in G^0.

From the derivation, $G^0 = \min \{[\pi (k_i^0 + x_i^0, A_i^0) - \pi (k_i^0, A_i^0)] - [P^0 - \beta (1 - \delta)] x_1^0\}_{i=1}^2$

Using $(A6)$ and $(A8)$, the gain from the transfer for both firms are:

$$G_1^0 = \underbrace{\exp \left(z_a^0 + z\right) [(2\theta k)^\alpha - k^\alpha]}_{\text{marginal increase in production}} - \underbrace{\alpha \exp \left(z_a^0 + z\right) \left(\frac{1}{2\theta k}\right)^{1-\alpha} (2\theta k - k)}_{\text{cost of the purchase (net of resale value)}}$$

$$G_2^0 = \underbrace{\exp \left(z_a^0 - z^0\right) [(k)^\alpha - (2 (1 - \theta) k)^\alpha]}_{\text{marginal decrease in production}} + \underbrace{\alpha \exp \left(z_a^0 + z\right) \left(\frac{1}{2\theta k}\right)^{1-\alpha} (2\theta k - k)}_{\text{proceeds from the sale (net of resale value)}}$$

Since $0 < G_1^0 < G_2^0$, we have $G^0 = \min \{G_1^0, G_2^0\} = G_1^0$

Rearrange terms in G^0

$$G^0 = \exp \left(z_a^0 + z\right) k^\alpha \left[(2\theta)^\alpha (1 - \alpha) - 1 + \frac{\alpha}{(2\theta)^{1-\alpha}}\right]$$

$$\frac{\partial G^0}{\partial z_a} = \exp \left(z_a^0 + z\right) k^\alpha \left[(2\theta)^\alpha (1 - \alpha) - 1 + \frac{\alpha}{(2\theta)^{1-\alpha}}\right] = G^0 > 0 \quad (A16)$$

i.e., sales are more likely to occur when aggregate productivity (z_a) is high.

The threshold level of aggregate shock, $\overline{z_a}$ satisfies $G^0 (\overline{z_a}) = f$:

$$\widetilde{z_a} = \log (f) - z - \alpha \log (k) - \log \left[(2\theta)^\alpha (1 - \alpha) - 1 + \frac{\alpha}{(2\theta)^{1-\alpha}}\right] \quad (A17)$$

$$\frac{\partial \widetilde{z_a}}{\partial f_x} = \frac{1}{f_x} > 0$$

i.e., given the aggregate shock (z_a), sales are more likely when fixed cost is low.

Q.E.D. ∎

Proposition 3   There exists a unique function $V (k, z_i; z_a, \overline{k}) : K \times Z_I \times Z_A \times \overline{K} \to R_+$, that solves the dynamic program in (18), and generates unique optimal policy functions $I(k, z_i; z_a, \overline{k})$ and $x(k, z_i; z_a, \overline{k})$.

Proof. Assume that both shocks are bounded such that $z_a \in \left[\overline{z_a}, \underline{z_a}\right]$ and $z_i \in \left[\overline{z_i}, \underline{z_i}\right]$

Since both shocks follow $AR(1)$ process and $0 < \rho_a < 1$ and $0 < \rho_i < 1$, shocks are monotone.

The maximum allowable capital stock $k_{\max}$ is then determined by

$$
\begin{aligned}
\exp(\overline{z_a} + \overline{z_i})\pi'(k_{\max}) - \delta &= 0 \\
\Rightarrow \quad k_{\max} &= \left[\frac{\exp(\overline{z_a} + \overline{z_i})\alpha}{\delta} \right]^{\frac{1}{1-\alpha}}
\end{aligned}
$$

Since $k > \overline{k}$ is not economically profit, let

$$
K \equiv [0, k_{\max}]
$$

By definition, K is compact and non-empty. Therefore, the set for mean of k, $\overline{K}$ is also compact and non-empty, $\overline{K} \equiv [0, k_{\max}]$. The production function $\pi(.)$ is continuous and concave such that $\pi' > 0$ and $\pi'' < 0$ The discount rate, $0 < \beta < 1$

Therefore, it satisfies the condition (1) - (3) in Adda and Cooper (2004), and by Theorem 3 in Cooper and Russell (2004), there exists a unique continuous function V: $K \times Z_I \times Z_A \times \overline{K} \to R_+$ that solves (18) and there exists stationary policy functions $I(k, z_i; z_a, \overline{k})$ and $x(k, z_i; z_a, \overline{k})$.

Q.E.D. ∎

Appendix 3: Computation of Approximate Equilibrium

The steps below outline my computation strategy for approximate equilibrium:

- Step1

  Guess an initial law of motion H_0 with coefficients $\{a_0, a_1, b_0, b_1\}$ and initial pricing function identified as $\{c_0, c_1, d_0, d_1\}$ Solve problem (25), for value function $V(k_i, z_i; z_a, \overline{k})$, and decision rules $x(k_i, z_i; z_a, \overline{k})$ and $I(k_i, z_i; z_a, \overline{k})$

- Step 2

  Use value function derived from Step 1 and a given price grid, P, to solve the following problem:

$$\widetilde{V}(k_i, z_i; z_a, \overline{k}, P) = \max_{\substack{0 \leq I_i \leq \overline{I} \times k_i \\ q_i \geq -k_i}} \pi(k_i + x_i, A_i) - \left[I_i + P_x x_i + \sum_{j \in \{I,,x\}} \Gamma^j(k_i, j_i) + f_x \right]$$
$$+ \beta EV\left(k_i', z_i'; z_a', \overline{k}' | z_i; z_a, \overline{k} \right)$$

  Assume that future price will evolve based on the perceived pricing function. Derive for value function $\widetilde{V}(k, z_i; z_a, \overline{k}, P)$ and decision rules $\widetilde{x}(k_i, z_i; z_a, \overline{k}, P)$ and $\widetilde{I}(k_i, z_i; z_a, \overline{k}, P)$.

- Step 3

  (i) Fix an initial capacity/idiosyncratic shock distribution for a large number of firms $F^0 = \{k_i^0, z_i^0\}_{i=1}^N$, and pick an initial aggregate shock level $\{z_a^0\}$. Simulate firms' decisions using the decision rules derived in Step 2. Find the price level (P^0), at which market clears.

  (ii) Derive the optimal decisions on asset sales x_i^0 and new investment, I_i^0 using the price P^0 and the decision rules $\widetilde{x}(k_i, z_i; z_a, \overline{k}, P)$ and $\widetilde{I}(k_i, z_i; z_a, \overline{k}, P)$.

  (iii) Capacity in the next period $\{k_i^1\}_{i=1}^N$ can be calculated using $k_i^1 = (1 - \delta)(k_i^0 + x_i^0) + I_i^0$, and mean capacity is: $\overline{k}^1 = \sum_{i=1}^N k_i^1 / N$

- Step 4

  Generate idiosyncratic and aggregate shocks for the next period, following AR(1) using $(\rho_a, \sigma_a, \rho_i, \sigma_i)$

Repeat a large number of times to obtain a time series of price and mean capacity $\left\{P^t, \overline{k}^t\right\}_{t=1}^T$

- Step 5

    Use the stable part of the obtained time series to regress $\left\{\log\left(\overline{k}_{t+1}\right)\right\}$ and $\in \{P_t\}$ on constants and $\left\{\log\left(\overline{k}_t\right)\right\}$ for each value of z_a to get the realized law of motion $\widehat{H}$ and realized pricing function $\widehat{P}$ Compare the *perceived* law of motion H_0 and perceived pricing function P^0 with the *realized* law of motion $\widehat{H}$ and realized pricing function $\widehat{P}$. If different, use new coefficients $\left(\widehat{a_0}, \widehat{a_1}, \widehat{b_0}, \widehat{b_1}, \widehat{c_0}, \widehat{c_1}, \widehat{d_0}, \widehat{d_1}\right)$ to construct initial guess, return to Step1, and iterate until convergence.[23]

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[23]Convergence is achieved if the norm of the difference in coefficients divided by the norm of the initial coefficients is less than 1%.

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