ABSTRACT

Title of Dissertation: ESSAYS ON LABOR ECONOMICS

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The modern work landscape is undergoing a period of significant transformation. In this dissertation, I delve into three distinct, yet interconnected, themes that shed light on the complex interplay between abilities, tasks, and well-being within this changing environment.

In Chapter 1, I explore the mental health implications of a recent and dramatic shift in work arrangements: the rise of Work From Home (WFH) during the COVID-19 pandemic. Specifically, the chapter evaluates the impact of working from home (WFH) on mental health, relative to other forms of workplace arrangements during the pandemic. Leveraging the longitudinal structure of the data from the British Cohort Study, the paper explores two novel dimensions that potentially influence the mental health effects of WFH, early-age cognitive and social abilities. To account for self-selection, the identification relies on a Roy selection model with correlated factors and cost-shifters. The findings suggest that WFH has negative mental health effects compared to a workplace arrangement (WP), but positive effects compared to not working (NW). Additionally, WFH has the largest detrimental impact on the mental health of individuals with

lower social abilities relative to WP, and it confers the most substantial benefits on those with higher cognitive abilities compared to NW. Finally, the model predicts that investments in cognitive and social ability mitigate the cost and amplify the benefits associated with WFH.

Next, in Chapter 2, I shift the focus to a contentious education policy that has recently received much attention, affirmative action in education. In this chapter, I examine the impacts of an education affirmative action policy on not only education outcomes, but also later labor market outcomes, in the context of Vietnam. In particular, the policy in this study provides nationwide direct high school admissions to ethnic minority students, exempting them from taking a high-stakes high school entrance exam. Using the joint variation in the student's ethnicity and birth year in a difference-in-differences framework, I show that the policy improves the probability of entering high school for ethnic minorities. Further, leveraging this policy-induced variation as an instrument, I explore the policy's long-term effects on labor market outcomes. The results indicate that ethnic minority students who were encouraged to enter high school by the policy are more likely to participate in the labor force, obtain employment, and hold salaried positions. The analysis of occupation-specific skill distributions and task intensity suggests that these effects are likely attributable to the human capital channel rather than education signaling. Despite its overall benefits, the policy's impacts are not equally distributed across the gender line and wealth levels: Male and wealthy ethnic minority students benefit more from the policy. Using a random forest model to identify the compliers' characteristics confirms that future family concerns among females and financial constraints are major frictions for ethnic minorities to benefit from the policy. Overall, these results suggest that while affirmative action positively impacts education and labor outcomes for ethnic minorities, targeted policies are vital for equitable distribution, addressing gender and financial barriers.

Finally, Chapter 3 closes the discussion on the topic of tasks and skills at the critical early career stages. The early stages of one's career are a dynamic period of exploration and skill development not only from formal training but also through on-the-job tasks. Therefore, the paper explores the pivotal relationship between abilities and tasks during this time. Specifically, it investigates how cognitive, social, and manual abilities are rewarded in this crucial period, while also emphasizing the role of abilities in sorting individuals across task-based occupations. The paper employs the British Cohort Study 1970 in a Roy selection model with correlated factors. In this context, the Roy model allows the analysis to focus not only on the returns to abilities, but also on the sorting process within the context of occupations categorized by their task composition. The results reveal a task-specific nature in the returns to abilities during early career stages, emphasizing the importance of aligning abilities with the specific task requirements of chosen occupations for optimal rewards. Additionally, the paper also highlights the role of abilities in early career sorting, showing that individuals with high cognitive and social abilities tend to gravitate towards knowledge-based occupations - occupations that are characterized by intensive cognitive tasks or intensive social tasks. These findings offer valuable insights for both young individuals navigating their career paths and policymakers crafting programs aimed at facilitating informed decision-making and enhancing success in the early career landscape.

ESSAYS ON LABOR ECONOMICS

by

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Dedication

To Piero Gregori,

Nicole Gregori,

and our families.

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List of Abbreviations

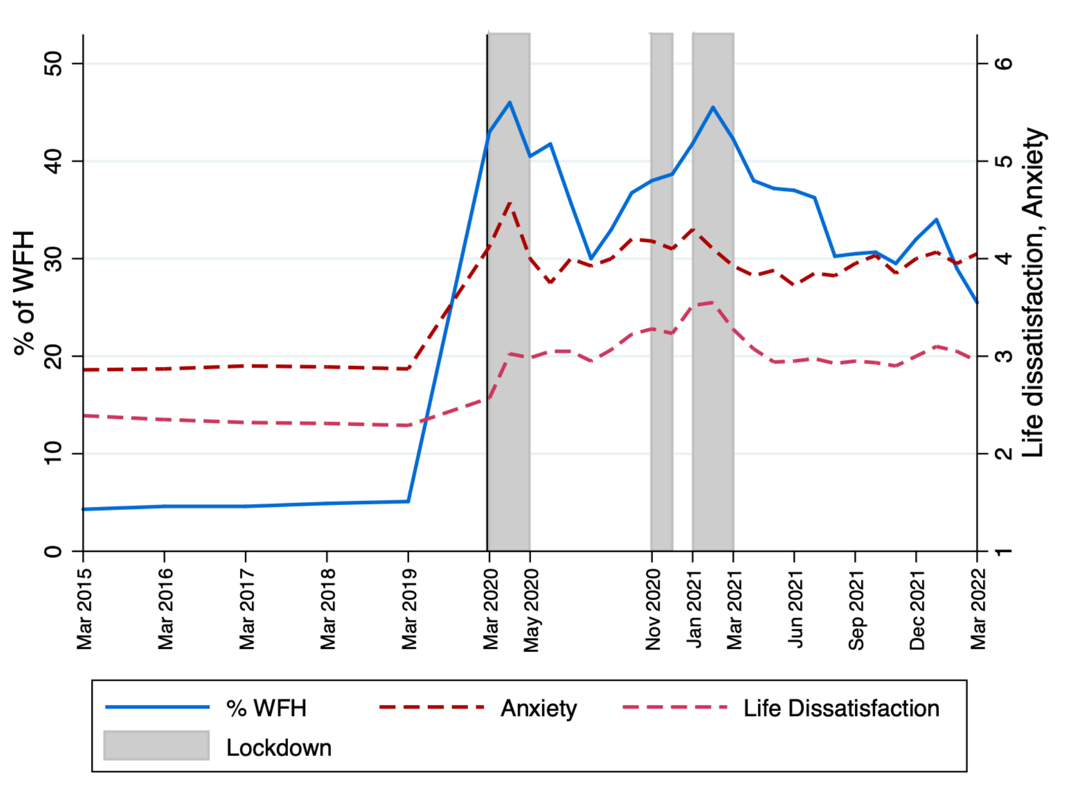
ATE	Average Treatment Effect
ATT	Average Treatment Effect on the Treated
BCS	British Cohort Study
CLS	Centre for Longitudinal Studies
DID	Difference-in-Differences
IPUMS	Integrated Public Use Microdata Series
IV	Instrumental Variable
LATE	Local Average Treatment Effect
LF	Labor Force
LFP	Labor Force Participation
MCS	Millennium Cohort Study
MNP	Multinomial Probit
MoET	Ministry of Education and Training
MTE	Marginal Treatment Effect
NCDS	National Child Development Study
NHS	National Health Service
NW	Not Working
NS	Next Step
ONS	Office for National Statistics
O*NET	Occupational Information Network
SES	Socioeconomic Status
STEP	Skills towards Employment and Productivity
TT	Treatment on the Treated
WFH	Work from Home
WP	Workplace
WVS	World Values Survey

Chapter 1: Working From Home and Mental Health During COVID-19

1.1 Introduction

The COVID-19 pandemic has brought about a seismic shift in the labor market landscape, with many corporations swiftly embracing working from home (WFH) as the new normal. In the UK, the adoption of WFH underwent an unprecedented transformation, skyrocketing from a mere 5% to over 40% since March 2020, and this trend has endured beyond the pandemic, as highlighted in Figure 1.1. Alongside this significant change, there has been a remarkable development outside the labor market — a substantial increase in mental health deterioration. Particularly in the UK, as WFH became more prevalent, anxiety and life dissatisfaction levels surged, especially during the pandemic's early stages, as also depicted in Figure 1.1. These concurrent trends prompt the question of whether the introduction of WFH during the pandemic has had an impact on the mental well-being of workers.

Figure 1.1: Percentage of WFH and Average Mental
in the UK



Note: Figure 1.1 shows the percentage of workers working from home in the UK between 2015 and 2020. *Source*: Office for National Statistics

Unlike the ongoing discussions about the productivity and innovation effects of WFH, where the mental health of workers is often overlooked, pandemic-era WFH had unique characteristics that played a crucial role in shaping workers' mental health [1]. Pandemic-era WFH began with a sudden shift to an unstructured work schedule, offering flexibility but blurring the lines between work and personal life due to the constant expectation of availability and productivity. Additionally, pandemic-induced WFH emphasized structured virtual meetings, alleviating COVID-related concerns but diminishing non-verbal communication, which, in turn, led to feel-

[1]A growing body of literature has focused on the impact of WFH on productivity during and especially after the pandemic (Aksoy et al. 2022; Barrero, Bloom, and S. J. Davis 2023). There is also another strand of literature looking at whether and how WFH during the pandemic changes workers' preferences for WFH nowadays (Barrero, Bloom, and S. J. Davis 2021; Bloom, Han, and Liang 2022; Lewandowski, Lipowska, and Smoter 2022; Y. Chen et al. 2023)

ings of isolation, especially among those valuing social connections. Furthermore, WFH during the pandemic redefined opportunity costs associated with work, amplifying the trade-offs between work, personal life, and job security. While WFH reduced fears of job loss, it also required individuals to sacrifice personal and family time for adapting to new technologies and management styles, often resulting in fatigue and heightened stress levels.

This paper evaluates the effects of WFH on mental health during the COVID-19 pandemic in the UK. The paper addresses three specific questions. First, the paper quantifies the extent to which WFH affects mental health relative to other conventional forms of work arrangement: Workplace (WP) and Not Working (NW). Second, the paper looks into whether workers with different abilities internalize the mental health costs and benefits of WFH differently [2]. Finally, through a simulation exercise, it suggests that improving abilities at an early age can improve mental health later in life, particularly in response to the COVID pandemic shock. To comprehensively assess the nuances of mental health dimensions affected, three measures of mental health are considered: loneliness, depression, and life satisfaction. While loneliness and depression are affective measure, life satisfaction is an evaluative one [3].

The analysis draws upon data from the British Cohort Study 1970 (BCS). The longitudinal structure of the data enables me to account for an individual's historical information, which may influence the individual's workplace arrangements and mental health during the pandemic. Moreover, since participants have been surveyed since birth, the data allows me to construct

[2] Abilities refer to a set of innate attributes that individuals possess, representing a fixed stock of skills that are established early in life. They are assessed during the formative years of childhood and adolescence, capturing fundamental capabilities such as learning, problem-solving, and social interaction throughout one's lifetime. These early measurements of abilities serve as foundational indicators of potential for skills development later on.

[3] Affective measures are constructed based on the frequency that the respondents encounter positive or negative feelings. Evaluative measures require the respondents to form self-assessment of overall life quality (Schimmack 2008; Lindqvist, Östling, and Cesarini 2020)

comprehensive production functions of cognitive and social abilities at an early age as well as to link these early age abilities with the pandemic' work activities and mental health experience during the COVID-19 pandemic. This exploration aims to underscore the significance of these two dimensions of abilities.

The lack of geographical variation in the lockdown timing poses several empirical challenges in the context of the UK [4]. The first empirical challenge to identify the effects of WFH on mental health stems from pre-COVID occupational constraints. The nature of the tasks bundled in an occupation impacts the feasibility of shifting the location of work to home. A pre-COVID occupation composed of unteleworkable tasks may not contain WFH as a feasible option. Consequently, the sorting process of workers with unteleworkable pre-COVID occupations differs from those with teleworkable pre-COVID occupations. While the sorting of those in unteleworkable occupations encompasses a combination of occupational constraints and subjective utility derived from the costs and benefits of WFH relative to other options, the sorting process of teleworkable workers reflects only the latter. To mitigate this first concern, based on the worker's pre-COVID occupation core tasks, the sample is restricted to include only workers whose pre-COVID occupations can reasonably be performed at home. It is important to consider that these individuals often have stronger cognitive abilities, social abilities, and higher baseline mental well-being before the pandemic. Therefore, the effects of WFH on mental health observed from this sample might capture the lower bound of the negative effects. In other words, the overall impact on the general population may not be externalized from this sample.

Second, among workers whose option sets contain WFH as a feasible option, the subjective

[4]The three lockdowns in the UK were nationwide; they were uniformly implemented across the country. Although Scotland, Wales, and Northern Ireland experienced different timing, their representation is limited, leading to insufficient variation for the analysis.

net benefits of mental health linked to different forms of work arrangement spur self-selection. To overcome this problem, I estimate a Roy selection model with three options of work arrangement: WFH, WP, and NW. Within each option, the option-specific cost shifters are added to strengthen the identification. In the estimation, WP is normalized. The cost shifters for WFH and NW are "*Distance to Work*" and "*Past Unemployment Spells*," respectively.

Last and related to the previous point, during the pandemic, systematic differences in the observed characteristics of workers in WFH versus others have been widely recognized (Adams-Prassl et al. 2020; Angelucci et al. 2020; Dingel and Neiman 2020; Bick, Blandin, Mertens, et al. 2020; Hensvik, Le Barbanchon, and Rathelot 2020; Mongey and Weinberg 2020; Alon et al. 2020; among others). However, little is known about how unobserved abilities affect the costs and benefits of these work arrangement options. Different levels of unobserved abilities define the net gain of each option in terms of smoothing out changes due to WFH during the pandemic. For instance, the ability to learn new technologies, to separate family from work responsibilities, or to maintain social interactions. These differences affect workers' net benefit across work arrangement options as well as workers' mental health responses within each option. Thus, workers' unobserved abilities are a source of variation that potentially affects the sorting into each work arrangement option. I address this concern by extending the model with two dimensions of unobserved abilities, cognitive and social abilities. Regarding social abilities, my specific focus centers on one dimension: emotion regulation. Importantly, to correct for measurement errors and family bias in the formation of these abilities at an early age, I proxy these abilities through a measurement system of test scores instead of directly using test scores as controls. Both unobserved abilities are measured through test scores taken at a young age, before the worker makes any schooling decisions or enters the labor market. Using early-age test scores guarantees the measures of two dimensions of unobserved abilities not being influenced by education or labor market experience.

I first show that during the pandemic, WFH negatively affects mental health relative to WP but not to NW. Relative to WP, the average treatment effects of WFH on mental health aggregate deterioration is 0.087 standard deviations, mostly driven by loneliness. In contrast, when comparing WFH with NW, WFH improves the mental health aggregate deterioration by 0.174 standard deviations. The effect is attributable to both the reduction in loneliness and an improvement in life satisfaction.

Next, to shed light on how workers with different levels of unobserved abilities internalize the costs and benefits of WFH, I turn to the contributions of the unobserved cognitive and social abilities to the average treatment effects of WFH. Specifically, I look at changes in the treatment effects across deciles of cognitive and social abilities. In comparison to WP, the negative mental health effects of WFH are relatively consistent across the cognitive deciles, but these negative effects decrease as we move up the social deciles. Conversely, when compared to NW, the mental health benefits of WFH are most pronounced among those with high cognitive abilities, while there is less variability in the benefits across the social deciles.

Finally, given the importance of cognitive and social abilities in explaining the heterogeneity of the mental health effects of WFH, I carry out a simulated exercise to understand the extent to which the average treatment effect of WFH can be changed by improving cognitive and social abilities. The results show that a 0.5 standard deviation increase in social abilities leads to a fraction of 0.205 of compliers from the WP margin switching to WFH. For these compliers, WFH improves overall mental health by 0.034 standard deviations relative to WP. The magnitude of this improvement is roughly equivalent to alleviating one-third of the adverse effects of WFH compared to WP from the baseline average treatment effect. There is no effect when comparing WFH with NW. Regarding the simulated increase in cognitive abilities, a 0.2 standard deviation increase in cognitive abilities improves the mental health deterioration by 0.063 standard deviations relative to NW, representing an additional improvement in mental health of approximately one-third of the baseline average treatment effect. The simulation has no effect on the mental health effect of WFH relative to WP.

My paper makes two main contributions to the literature. First, it directly relates to the strand of literature about WFH and mental health during the pandemic. Given the constraint of data collection and available variation, many of the studies looking at WFH during the pandemic specifically are descriptive rather than causal (Galanti et al. 2021; Beland et al. 2022). Whereas, for those works that provide a causal interpretation, the method usually relies on geographical variation of lockdown policies (Brodeur et al. 2021; Hamermesh 2020; Bertoni et al. 2022; Adams-Prassl et al. 2022; Altindag, Erten, and Keskin 2022). This approach restricted the interpretation of the effects to lockdown policies, rather than to WFH. By using the Roy model, I provide an estimate of the mental health effect of WFH specifically. Moreover, I contrast these effects with two different alternative options. The divergent directions of the average treatment effects highlight the importance of choosing the reference group when analyzing WFH's consequences.

My paper also speaks to the unequal effects of the pandemic across workers with different levels of abilities. Cumulative evidence shows that cognitive and social abilities at an early age predict labor market outcomes as well as other life outcomes (Feinstein 2000; J. J. Heckman, Stixrud, and Urzua 2006; J. Heckman, Pinto, and Savelyev 2013; Sarzosa and Urzúa 2021; D. J. Deming 2017). However, little is known about the role of these abilities during an economic downturn. A parallel strand of literature highlights the unequal negative effects of economic shocks on vulnerable individuals in terms of demographic characteristics, but overlooks whether individuals with lower early age abilities are more severely affected. Specific to the COVID pandemic, despite the growing body of literature showing that remote work exemplifies some of the pre-existing inequalities in the labor market across gender, race, or educational levels (Adams-Prassl et al. 2020; Angelucci et al. 2020; Chetty, Friedman, Stepner, et al. 2020; Farré et al. 2022; Oreffice and Quintana-Domeque 2021; Alon et al. 2020; Finkelstein et al. 2022; Stantcheva 2022), little is known about whether the mental health effects of WFH are the same across workers with different abilities. I connect these two streams of works by showing that workers with lower abilities are disproportionately affected by WFH in terms of mental health. This result reiterates the importance of early age abilities by showing their benefits during a period when the economy temporarily deteriorates.

The paper is organized as follows. Section 2 provides the institutional information of the UK during the pandemic. Section 3 describes the data in the analysis. Section 4 lays out the empirical model, while Section 5 discusses the identification and estimation of the empirical model. Section 6 shows the main results. Section 7 describes the simulation and the results. Section 8 provides a discussion about the main results. Section 9 checks the model performance. Section 10 concludes.

1.2 Context

1.2.1 COVID Cases

The impact of the COVID-19 pandemic in the UK has been far-reaching, affecting public health, society, and the economy on multiple fronts. The initial reported cases of COVID-19 in the UK emerged on January 31, 2020, marking the onset of a rapidly evolving situation. Throughout the subsequent months, the virus gained momentum, culminating in a full-blown outbreak by March, 2020. In response to the escalating crisis and in an effort to safeguard the integrity of the healthcare system, the government implemented a series of containment measures. These measures encompassed crucial strategies such as social distancing, the closure of pubs and restaurants, and advisories for individuals to embrace remote work arrangements (Sherrington 2022).

By April 2020, the situation reached a critical point, with daily cases surging to an alarming peak of 10,000 and weekly deaths over 1,000. The overwhelming influx of severe COVID-19 cases placed unprecedented strain on the National Health Service (NHS), prompting the establishment of field hospitals to expand capacity and care for patients (Denis Campbell and Booth 2021). These measures played a pivotal role in curbing the rapid spread of the virus, leading to a gradual decline in infection rates from around mid-May. During this period, the government introduced a robust “test and trace” system to proactively monitor and isolate newly identified cases. As restrictions began to ease in June and July, the number of daily cases began to surge once more in September 2020. By November, the country experienced a staggering spike in cases, with daily counts surpassing 30,000 (UK 2023a). This resurgence posed significant challenges, necessitating a swift and coordinated response from public health officials and policymakers.

1.2.2 Working From Home During the Pandemic

In this context of the pandemic, there was a notable acceleration of the previously gradual and steadily increasing trend toward homeworking in the UK [5]. The widespread adoption of WFH started on 16 March 2020, when Prime Minister Boris Johnson announced the Coronavirus statement requiring *"people to start working from home where they possibly can."* The fraction of homeworkers in the workforce remained high even after the lockdown was relaxed in May. Specifically, the percentage of homeworkers stayed about 30% between May and September 2020, which was after the first lockdown and before the second social restriction. Figure A.1 summarizes the key dates of the lockdown and other policies that could potentially relate to the adoption of WFH in the country.

Despite the spike in WFH in the country, a high fraction of workers continued to carry out their jobs at the workplace (Reuschke and Felstead 2020). According to the Office for National Statistics (ONS), at the peak of the pandemic, in April 2020, there were 38.50% of homeworkers in the workforce, conditional on being the workforce, Figure A.4. Whereas, the percentage of workers who did not WFH constitutes about 46.77% percent. Other forms of hybrid WFH were not common during this period. Moreover, relative to other age groups, workers in the age range

[5]While 2020 has turned homeworking from an unconventional labor market option into a norm, this practice is not a new concept. Since the 1970s, homeworking was seen as the solution to growing dependency on fossil fuels and long commuting times (McCarthy 2020). However, several concerns were associated with detaching workers from the office space. Traditional employers appeared reluctant in light of potential effects on productivity and collaboration. Trade unionists, by contrast, feared the crumbling of long fought for workers' rights and safety standards (Equality and Commission 2020). Most recently, the low level of homeworkers, except among self-employment, was often explained as a result of managerial styles, data protection concerns (such as GDPR), or a lack of broadband connectivity. Consequently, the small and selective fraction of homeworkers up until now made homeworking a workplace amenities when available, rather than a common option to enter the labor force. This, in turn, provided limited insights into what effects homeworking constitutes in the workforce at large as a labor force participation option during the pandemic.

between 50-62 constituted the second lowest fraction of homeworkers, 42% as in Figure A.4. Some important variations in the fraction of homeworkers emerged across regions as well as occupations. For instance, the highest fraction of homeworkers were reported in densely populated area (e.g. in London 57.2%) in occupations requiring higher qualifications, and for individuals over 25 years of age (Cameron 2020).

1.2.3 Government Financial Support During the Pandemic

The UK government offers two key programs: one for the newly unemployed and another specifically for furloughed workers. The existing Universal Credit system provided support for housing and childcare, while the Jobseeker's Allowance (JSA) offered an additional £75 per week for up to 182 days to those who recently lost their jobs (UK 2023b). This financial assistance likely cushioned the blow of unemployment for some, potentially making it easier to withdraw from the labor market temporarily.

For furloughed workers, the Coronavirus Job Retention Scheme (CJRS) was essential. While many European states ramped up their Short Term Work (STW) schemes in response to the 2008-2010 economic crisis, the UK did not have such a plan in place at the beginning of the COVID-19 pandemic (Eurofound 2020). In response, in March 2020, the government announced the Coronavirus Job Retention Scheme (CJRS) to cover 80% (up to £2,500/month/employee) of the salary due to furloughed workers. Subsequent iterations of the program encountered different government and employer sharing of the owed 80% wages as well as minimum number of allowable weekly work hours - including part time after July 2020 (Clark 2021). From a peak of 9 million furlough workers in April 2020, the number reduced to 1 million in September 2021 when the plan came to an end (Revenue and Customs 2021). As a result, many workers could remain connected to their employers while experiencing a reduced income.

The existence of these programs is significant because they may have offered individuals the opportunity to withdraw from the labor market without facing a dramatic drop in income. This has two potential implications for the empirical model in the next section. First, the financial support offered by these programs may have actively encouraged some workers to withdraw from the labor market. This stands in contrast to a scenario where job loss is solely a consequence of company actions, such as layoffs. The presence of financial support programs creates a situation where leaving the workforce becomes a more voluntary decision for some individuals. Second, the financial security provided by these programs might downplay the role of financial worries in explaining the observed differences in mental health between those who left the workforce and those who stayed employed. This allows the model to isolate the potential impact of WFH on mental well-being, rather than attributing it to financial concerns.

1.2.4 Mental Health and Health Care System in the UK

The UK runs a decentralized "comprehensive, universal and free at point of delivery" healthcare (Health and Care 2012). The NHS of England, Welsh and Scotland, and the Northern Ireland Health and Care System are the bodies responsible for running the system aimed at offering best-in-class service regardless of one's ability to pay with a commitment to provide the best value for taxpayers' money (Health and Care 2012). Regardless of citizenship or employment, anyone who is legally residing in the country is entitled to NHS assistance free of charge (Health Improvement and Disparities 2014). Thus, a change in employment status would not jeopardize access to the health care system. Put differently, it is unlikely that changes in mental health well-being are caused by changes in having access to the health care system.

However, the NHS has often been criticized for its poor management of its mental health care program. Critics have highlighted a lack of resources leading to 6% of patients waiting over a year and up to 13 years in extreme cases (D. Campbell 2018). In 2018, the Royal College of Psychiatrists found that most of the surveyed patients waited over 3 months to access mental health services [6]. Specific to the NHS' mental health service during the pandemic, in the financial year 2020-2021, 5% (2.803 million) of the UK population took advantage of mental health services with 97,103 who spent time in hospital. For the age group of individuals over 50 years old, 895,122 individuals (44% male and 56% female) contacted NHS mental services during the same period (NHS 2021).

1.3 Data

I conduct the main analysis with the British Cohort Study 1970 (BCS). In addition, I use information from the O*NET database to construct an index of teleworkable occupations. Further details about the data are described below.

[6]Unfavorable findings coupled with deteriorating general conditions during the COVID-19 pandemic urged the NHS to reprioritize mental health care, which is now considered at equal footing to physical care. The renewed commitment will include an annual £2.3 billion in funding for 2023/24 - out of the 190 billion NHS budget (Fund 2023).

1.3.1 British Cohort Study 1970 (BCS)

1.3.1.1 Overview

BCS is one of the cohort studies from the National Longitudinal Cohort Studies, administered by the Centre for Longitudinal Studies (CLS). The BCS started on a large and nationally representative cohort of individuals at birth and contains rich information about the work and lives of all the respondents until now [7]. All members of the BCS were born in 1970, so they reached the age of 50 when the pandemic struck the UK.

In terms of external validity, several characteristics shed light on the interpretations of the mental health effect of WFH during the pandemic for this cohort. First, when comparing the BCS with other cohorts, the BCS experienced fewer mental health disruptions during the pandemic. However, when looking at the mental health trend of the BCS themselves, it is shown that the pandemic might have triggered a "second mid-life crisis" among them. There was a significant spike in mental health deterioration among BCS members during the pandemic, akin to the magnitude of mental health decline observed when they experienced their mid-life crisis around the age of 40 (Henderson et al. 2020; Moreno-Agostino et al. 2023). In comparison with other cohorts, members of the BCS actually had fewer family concerns during the pandemic. They maintained a more stable household composition, meaning they were less likely to experience changes such as children moving in or separating from their partners. Additionally, the BCS were less prone to intrahousehold conflicts, a common concern during the pandemic (Zilanawala et al. 2020). Along the same line, in contrast to other cohorts where family-related concerns took

[7] There are four cohort studies from the National Longitudinal Cohort Studies: 1958 National Child Development Study (NCDS), 1970 British Cohort Study (BCS), Next Step (NS), and Millennium Cohort Study (MCS). To focus on the effect of WFH at a specific stage of one's career, I leave out other cohorts.

center stage during the pandemic, the BCS placed a relatively greater emphasis on work-related issues. Specifically, when asked about their pandemic experiences, the BCS frequently mentioned the word "work" in their responses, while for other cohort members, the word "family" was more prevalent (Carpentieri et al. 2020).

1.3.1.2 Cohort Study at Age 5 and Age 10

Cognitive Test Scores: Participants of the BCS took part in a number of face-to-face cognitive assessment tests at age 10. To construct the cognitive unobserved ability, I use three of the cognitive assessment tests: reading, mathematics, and pattern recognition. Multiple cognitive processes overlap to achieve the test scores of these three dimensions such as recognizing symbolic information, working memory or attention (Ashkenazi et al. 2013; Kidd et al. 2014; Purpura and Ganley 2014; Chu, VanMarle, and Geary 2016). Therefore, the use of these three test scores can well capture a single latent cognitive ability at an early age.

Social Test Scores: I focus on one facet of social abilities, emotion regulation. Parents of the BCS participants were invited to answer self-reported questions based on the Rutter scale. The items included in the Rutter scale span three dimensions of emotion regulations: hyperactivity, externalizing behaviors, and internalizing behaviors (McGee, Williams, and Silva 1985; Kumpulainen, Räsänen, and Henttonen 1999). Hyperactivity relates to excessive physical movement and poor attention span. Externalizing behaviors capture the degree of negative acting to the *external* environments such as hostility toward adults and peers; whereas internalizing behaviors reflect the *internal* psychological environment, including symptoms of being withdrawal, fearful or anxious (Achenbach 1978; Hinshaw 1987; S. B. Campbell, Shaw, and Gilliom 2000;

Eisenberg et al. 2001). I use these three measures as a proxy for the underlying social factor in terms of emotion regulation.

Other Early Age Information: Apart from the test scores, the survey at age 10 also contains information about family characteristics at the time the tests were taken. Additionally, to reflect parental investment before the tests were taken, I combined information from the survey at age 5. All these additional variables aim at capturing the fact that family factors are shown to influence the formation of cognitive and social abilities at an early age (Shaw and Winslow 1997; Guo and Harris 2000; Richards and Wadsworth 2004). Thus, to capture family influences on the observed test scores, I include the following variables: gender, regions of residence, social-economic status, number of days that parents read to their child, and autonomous parenting styles.

The summary statistics of variables from this wave (age 10) of the survey are reported in Panel C of Table 2.1.

Table 1.1: Descriptive Statistics
of Teleworkable and Non-Teleworkable Occupations

	Teleworkable		Non-Teleworkable	
	Mean	SD	Mean	SD
During COVID				
Work arrangement				
WFH	0.546	0.498	0.157	0.364
WP	0.365	0.482	0.722	0.448
NW	0.088	0.284	0.121	0.326
Mental health				
Loneliness	-0.018	0.998	-0.005	0.975
Depression	-0.021	0.997	-0.014	0.971
Life satisfaction	0.012	0.988	0.001	1.014
Financial Condition				
Comfortable	0.504	0.500	0.388	0.488
Difficult	0.107	0.309	0.158	0.365
Before COVID				
Female	0.575	0.494	0.516	0.500
Having a partner	0.820	0.384	0.757	0.429
Having children	0.666	0.472	0.594	0.491
Mental health				
Loneliness	-0.041	0.974	0.087	1.035
Depression	-0.023	1.005	0.015	0.989
Life satisfaction	0.027	0.954	-0.053	1.100
Financial Condition				
Comfortable	0.437	0.496	0.344	0.475
Difficult	0.149	0.356	0.201	0.401
Distance to work (in mile)	15.693	52.401	13.345	37.369
Cumulative unemployment spells (in month)	176.629	97.280	185.729	98.888

Note: Table 1.1 shows the mean and standard deviation of teleworkable and non-teleworkable occupations. COVID variables were collected in two waves: the first one was in May, 2020, and the second one was in September-October, 2020. Pre-COVID mental health outcomes are aggregated from mental health measures across waves since age 34. *Financial Status* and *Distance to work* come from the latest survey wave just before the pandemic (Age 46). *Unemployment Spells* are constructed from historical unemployment spells across waves since age 26.

1.3.1.3 Cohort Study between Age 26 and Age 46

Other Information: Several characteristics can potentially define the underlying mechanisms of the sorting and the mental health effects. To better represent the costs and benefits of each work arrangement based on the available information, I bring together information from survey data between age 26 and age 46. This extensive 20-year window of information provides me with historical employment background, family composition, and mental health conditions before the pandemic for each individual.

Cost-shifters: The two cost-shifters are also constructed using data from the survey waves between the age of 16 and the age of 46. Specifically, the distance to work measures the number of miles from one's home to the workplace. Whereas, the cumulative duration of unemployment spells measures the number of months that an individual experienced unemployment between the age of 16 and the age of 46.

Panel B of Table 2.1 show the descriptive statistics of these variables.

Table 1.2: Descriptive Statistics of the Analytical Sample

	WFH		WP		NW	
	Mean	SD	Mean	SD	Mean	SD
A. COVID Survey Variables (Age 50)						
Mental Health Outcomes						
Mental Health Aggregated Deterioration	-0.014	1.004	-0.051	0.955	0.251	1.095
Loneliness	0.009	1.005	-0.069	0.978	0.194	1.026
Depression	-0.026	1.012	-0.009	0.961	0.163	1.062
Life satisfaction	0.017	0.999	0.044	0.956	-0.243	1.122
B. Pre-COVID Survey Variables (Age 26 - Age 46)						
Mental Health Outcomes						
Mental Health Aggregated Deterioration	-0.007	0.987	0.009	1.012	0.006	1.026
Loneliness	-0.026	0.990	0.032	1.002	0.022	1.042
Depression	-0.032	0.999	-0.004	0.966	0.181	1.105
Life Satisfaction	-0.008	0.990	0.003	1.011	0.029	1.013
Work and Finance Characteristics						
Financial Status	1.557	0.667	1.659	0.679	1.706	0.744
Distance to Work (Mile)	17.855	54.016	10.270	30.928	20.607	78.247
Unemployment Spells (Month)	168.166	96.992	185.456	98.130	198.405	90.476
Family Composition						
Having a partner	0.818	0.386	0.826	0.379	0.799	0.402
Having children	0.665	0.472	0.662	0.473	0.634	0.483
C. Age 10 Variables						
Test Scores						
Reading	0.557	0.793	0.289	0.881	0.324	0.850
Math	0.561	0.858	0.199	0.896	0.314	0.821
Pattern Recognition	0.449	0.893	0.207	0.908	0.255	0.890
Externalizing	0.213	0.890	0.222	0.810	0.116	0.984
Internalizing	0.091	0.918	0.079	0.954	-0.004	1.028
Hyerpactivity	0.238	0.867	0.148	0.896	0.118	0.943
Derived Aggregated Test Scores						
Cognitive	0.607	0.805	0.268	0.869	0.346	0.832
Social	0.240	0.878	0.200	0.859	0.110	1.007
SES	3.977	1.280	3.774	1.243	3.839	1.213
Female	0.531	0.499	0.637	0.481	0.696	0.461

Note: Table 2.1 shows the mean and standard deviation by work arrangement options during COVID. COVID variables were collected in two waves: the first one was in May, 2020, and the second one was in September-October, 2020. Pre-COVID mental health outcomes are aggregated from mental health measures across waves since age 34. *Financial Status* and *Distance to work* come from the latest survey wave just before the pandemic (Age 46). *Unemployment Spells* are constructed from historical unemployment spells across waves since age 26. *Derived Aggregated Test Scores* are constructed by factor analysis of the observed test scores, retaining one factor for each dimension.

1.3.1.4 CLS COVID-19 Surveys

Aiming at shedding light on how the pandemic has affected life and the labor market outcomes of individuals nationwide, CLS invited participants in the BCS and other cohort studies to fill in an online COVID-19 survey [8]. The COVID-19 survey asked questions about the individual's economic and educational activities before and during the pandemic. The first wave of the survey was rolled out and completed in May 2020, whereas, the second wave of the survey was rolled out and completed between September and October 2020.

Loneliness: To measure loneliness, three items from the UCLA measure are used. These items are based on the twenty-item UCLA-LS3 developed by Russell, Peplau, and Ferguson 1978. Several adoptions of the UCLA-LS3 have been adjusted and applied to different contexts (Australia: Elphinstone 2018; Turkey: Durak and Senol-Durak 2010; Northern Ireland: Shevlin, S. Murphy, and J. Murphy 2015; Italy: Boffo, Mannarini, and Munari 2012; and Japan: Masuda et al. 2012). In the UK, these items are commonly used as a standard measure of loneliness (Hawkley et al. 2020). Participants in the CLS COVID-19 survey are asked about their emotional state of longing for human contacts. Not only is loneliness prevalent among the older population, ranging between 18% and 29% in the UK (Hawkley et al. 2020), but it also associates with early mortality (Holt-Lunstad et al. 2015). To construct an aggregated measure of loneliness, I use factor analysis, retaining one factor.

Depression: Depression is a common mental disorder that relates to excessive sadness and loss of interest in activities. Nine symptoms of depression from the Malaise Inventory by

[8] Although targeting nationally representative participants, due to the online nature of the surveys, these surveys were only able to reach out to participants with a valid email address. Table A.1 reports the initial sample, issued sample, target population, and corresponding responding rate.

Rodgers et al. 1999 are asked in the CLS COVID-19. Depression is a highly recurrent mental health disorder (Burcusa and Iacono 2007) that leads to several deleterious outcomes such as cognitive impairment, and cardiovascular diseases (De Nooij et al. 2019; Harshfield et al. 2020). In addition to demographic features such as gender or age status (Salk, Hyde, and Abramson 2017), depression is also shown to be tightly linked with economic downturn (Frasquilho et al. 2015). Similar to the construction of loneliness, I aggregate responses from the nine questions by factor analysis to obtain a single index of depression[9].

Life Satisfaction: The broadest measure of mental health to be considered is life satisfaction, which indicates an overall subjective measure of mental well-being (Stiglitz, Sen, Fitoussi, et al. 2009). Life satisfaction exhibits a strong negative association with both loneliness (Szcześniak et al. 2020) and depression (Rissanen et al. 2011; Lombardo et al. 2018). In the CLS COVID-19 survey, life satisfaction is measured on a scale of ten. Participants were asked to specify the level of their overall life satisfaction. In the analysis, I directly use this single question as a measure of life satisfaction. Table A.3 shows the question items used for each mental health measure.

Panel A of Table 2.1 displays the summary statistics of the mental health variables from the CLS COVID surveys.

1.3.2 O*NET

To classify pre-COVID occupations into teleworkable versus non-teleworkable types, I use the latest version of the O*NET database, which was released in July, 2020. I merge information

[9] I also constructed an average score of the items for both loneliness and depression, as opposed to factor analysis. The results hold up to this alternative aggregation.

in O*NET with workers' occupations pre-COVID based on O*NET SOC and UK SOC at the three-digit level. Using the information in the Work Context and Generalized Work Activities survey, I follow Dingel and Neiman 2020 to construct an indicator of whether an occupation is teleworkable or not. These items mostly focus on two dimensions of an occupation, the degree of physical activities and the degree of social interactions.

1.3.3 Sample Restriction

To obtain the analytical sample, I impose two sample restrictions. First, to focus on the effects of WFH relative to other work arrangement options, the sample excludes individuals who were not in the labor market before COVID. Second, I restrict the sample to include only workers whose pre-COVID occupations are classified as teleworkable based on the teleworkable indicator by Dingel and Neiman 2020. Overall, the sample restrictions aim at retaining workers with comparable sorting processes. The remaining analytical sample includes 2,161 observations.

In comparison with the national statistics, the analytical sample over-represents the percentage of homeworkers in the workforce, 55.45% versus 46.60% as in Figure 1.1. This is expected as teleworkable workers are more likely to WFH. Table 1.1 compares the characteristics of BCS workers with teleworkable and those with non-teleworkable occupations. It is noticeable that teleworkable workers are more likely to WFH. In addition, teleworkable workers also score better in terms of mental health well-being before as well as during COVID. These two features imply that the effects on the teleworkable sample are likely to be at a lower bound compared to the effects of an overall population.

Another important note on the sample is that although the BCS was designed to sample as a representative of the national population, attrition to the later waves, especially during the pandemic, limits the representativeness of the sample. A discussion about the potential effects of attrition is presented in the later section.

1.4 Empirical Model

The empirical model in this section aims at addressing the empirical challenge of self-selection that arises from observed characteristics as well as unobserved abilities. The model also allows for the possibility that unobserved abilities are only partially reflected on test scores due to influences from family background and measurement errors.

One limitation of the model lies in its omission of explicit considerations for constraints imposed by the firm. Specific company policies might curtail a worker's flexibility in sorting into one of the three work arrangement options. Consequently, the sorting process can be perceived as a collective decision, involving the worker's preferences and the productivity criteria set by the firm with which the worker was employed just prior to the pandemic.

1.4.1 Sorting Process

A worker i whose occupation is teleworkable is presented with three options of work arrangement: *"Not Working (NW)"*, *"Working From Home (WFH)"*, and *"Working in the Workplace (WP)"*. The sorting into one of the three options for a worker i is a collective decision between the worker's optimization problem in terms of his or her mental health, and the firm's workplace arrangement policies during the pandemic. To maximize their total happiness incorporating both mental health and monetary components, each worker forms a latent utility that represents their costs and benefits in terms of mental health for each work arrangement option k, I_i^k. The option with the highest level of latent utility determines the final sorting of worker i. That is, let D_i indicate the observed option of worker i. Then, D_i takes the following form of multinomial probability:

$$D_i = \underset{k \in \{\text{WP, WFH, NW}\}}{\text{argmax}} \{I_i^k\} \tag{1.1}$$

Although I_i^k cannot be directly observed in the data, its values can be estimated based on the worker's characteristics and abilities. First, compared to WFH, while workers in the NW option spend zero hours in labor market activity, workers in the WP option are required to follow a structured work schedule to balance work and non-work commitments. For instance, workers with children are more likely to bear more mental health costs from family and work conflicts (Alon et al. 2020; H.-A. H. Dang and Nguyen 2021). Another demographic factor is gender. In certain contexts, apart from childcare responsibilities, women often shoulder a disproportionately higher share of household duties compared to men, leading to a heightened mental health burden (Del Boca et al. 2020; Jiao, Qi, and Z. Chen 2023). Second, another key feature that distinguishes WFH from other work arrangements is the changes in the quantity and the way social interactions are carried out. While WFH provides the opportunity of working with lower concern for COVID infection, it limits in-person interactions with non-household members. These effects vary across individuals with different degrees of fear of COVID infection (García-Fernández et al. 2022; Szcześniak et al. 2020) and the composition of household members with whom they interact (Beland et al. 2022; Hamermesh 2020; Archibong and Annan 2023). Finally, WFH provides workers with relief from the stress of potential job loss [10]. However, this positive effect can be offset by other mental health costs coming from additional time needed being substituted away from taking care of families, or of oneself to adapt to remote technologies or management styles [11]. These trade-offs can vary by individual's financial status or mental health conditions before the pandemic (Angelucci et al. 2020; Holingue et al. 2020; McGinty et al. 2020; Baird et al. 2022). The firm can intervene in the costs and benefits of these three mechanisms. For instance, depending on a worker's function, the firm may grant different degrees of autonomy in time flexibility or the opportunity for job continuity during the pandemic.

Based on these motivations, equation (1.2) characterizes the structure of the latent utility for a worker i for a work arrangement k, I_i^k.

$$I_i^k = X_i^I \beta^{k,I} + \eta_i^{k,I}, \tag{1.2}$$

$$\text{for } k \in K$$

$$K \equiv \{\mathit{NW, WFH, WP}\}$$

In equation (1.2), I_i^k is assumed to be linearly dependent on the observed characteristics of the individual, and the unobserved components [12]. Specifically, X_i^I is the observed characteristics, and $\eta_i^{k,I}$ is the unobservable components. The observed characteristics included are the individual's

[10]Prior to the pandemic, involuntary job loss has been shown to negatively affect mental health, including increases in depressive symptoms, or reduction in life satisfaction (Burgard and Kalousova 2015; Kuhn, Lalive, and Zweimüller 2009; Michaud, Crimmins, and Hurd 2016).

[11]A reduction in the opportunity cost of time, which encourages individuals to partake in healthier activities like increased exercise, more restful sleep, and regular medical check-ups, may potentially contribute to improved mental health during an economic downturn (Ruhm 2000; Ruhm 2005). Moreover, there can be health improvements resulting from job loss if the workplace entails hazardous working conditions and physical exertion (Fryer and Mckenna 1987; Fineman 1983; Fineman 1987; Theodossiou 1998; T. S. Dee 2001; Ruhm 2000; Ruhm 2005)

[12]Ideally, I_i^k should include also the firm's characteristics. However, due to data limitations on the information of the firm, the firm's characteristics are not included.

gender, family composition, financial status, and mental health condition before the pandemic. Additionally, since work arrangement variation differs across regions and occupations, as shown in section 2.2, dummies for the regions of residence and one-digit occupation are also included. In addition to the observable characteristics motivated by the previous discussion, the latent utility is also influenced by the certain costs that the worker attaches to each work arrangement option. Therefore, the observable component in equation (1.2) includes the worker's observed characteristics as well as the option-specific cost shifters. The motivation of the cost shifters is discussed in detail in the next section, and the structure of the unobservable component is explained in the last part of this section.

1.4.2 Potential Outcomes

Depending on the option of work arrangement, the worker's mental health is defined based on his or her characteristics as follows.

$$H_i^k = X_i^H \beta^{k,H} + \eta_i^{k,H}, \quad \text{for } k \in K \tag{1.3}$$

where X_i^H includes worker i's observables. Similar to the sorting equation, X_i^H includes gender, family composition, financial status, mental health condition before the pandemic, regions of residence, and one-digit occupations. For exclusion restriction, X_i^H does not include the option-specific instruments. The full list of variables included in X_i^H is reported in Table A.4. $\eta_i^{k,H}$ is worker i's unobservables that affect the outcomes in consideration.

1.4.3 Structure of Unobservables

Motivated by the psychology literature, two dimensions of unobserved abilities, cognitive and social abilities, are assumed to affect the sorting into one of the three work arrangement options and mental health. Workers with different levels of cognitive and or social abilities face different costs and benefits regarding each option in terms of mental health. Cognitive abilities allow workers to have effective coping through optimal attention, planning, or memory function (Diamond 2005). Whereas, a higher level of social abilities associates with better emotional adaptation, and a higher degree of motivation to form social interactions (Rajappa, Gallagher, and Miranda 2012; S. K. Davis and Humphrey 2014). Through these functions of cognitive and social abilities, workers with higher levels of these abilities are better at learning new ways or avoiding work-life conflicts (Kinnunen et al. 2003; Rantanen et al. 2008). Therefore, they are better motivated to sort into WFH. Equation (1.4) and (1.5) are the structure of the unobserved component in the choice equation (1.1) and the outcome equation (1.3), respectively.

$$\eta_i^{k,I} = \theta_i^C \lambda_C^{k,I} + \theta_i^S \lambda_S^{k,I} + \varepsilon_i^{k,I}, \quad \text{for } k \in K \tag{1.4}$$

$$\eta_i^{k,H} = \theta_i^C \lambda_C^{k,H} + \theta_i^S \lambda_S^{k,H} + \varepsilon_i^{k,H}, \quad \text{for } k \in K \tag{1.5}$$

$\{\lambda_C^{k,I}, \lambda_S^{k,I}, \lambda_C^{k,H}, \lambda_S^{k,H}\}$ are the factor loadings of each ability in the corresponding equation. In equation (1.4), $\{\lambda_C^{k,I}, \lambda_S^{k,I}\}$ are the influences of the unobserved abilities on the worker's work arrangement. Whereas, in equations (1.5), $\{\lambda_C^{k,H}, \lambda_S^{k,H}\}$ indicate the effects of unobserved abilities on mental health. $\{\varepsilon_i^{k,I}, \varepsilon_i^{k,H}\}$ are the error terms that are assumed to be orthogonal to X_i^I and X_i^H as well as θ_i^C, and θ_i^S. Further, $\{\varepsilon_i^{k,I}, \varepsilon_i^{k,H}\}$ are independent from one another, and they are both mutually independent across choices. Finally, the error terms are normally distributed with mean zero:

$$\varepsilon_i^{k,I} \sim N(0, \sigma_{\varepsilon_{k,I}})$$
$$\varepsilon_i^{k,H} \sim N(0, \sigma_{\varepsilon_{k,H}})$$

1.4.4 Measurement System

The unobserved abilities are assumed to be known by the workers, and their sorting hinges on their private knowledge about these abilities. However, these abilities are not fully discernible in the data. The most reliable proxies for these abilities are the recorded test scores in the data. Nevertheless, test scores can be imprecise measures of abilities due to factors such as random variation, or structural influences such as family background, education, or labor market experience (Hansen, J. J. Heckman, and Mullen 2004; J. J. Heckman, Stixrud, and Urzua 2006; Cunha and J. Heckman 2007). In this model, to isolate the effects of education and labor market experience on test scores, I utilize test scores assessed at an early age. The remaining concerns associated with these early-age test scores include random measurement error and family influence. To derive more precise insights into the workers' true abilities, I employ a measurement system comprising two sets of test scores: cognitive and social. Cognitive test scores encompass reading, mathematics, and pattern recognition, while social test scores encompass internalizing, externalizing, and hyperactivity behaviors. The unobserved cognitive abilities only affect the observed cognitive test scores, whereas unobserved social abilities influence both social and cognitive test scores, capturing the complementary nature of these two dimensions of abilities (Cunha and J. Heckman 2007). The structure of the measurement system is displayed in equation (1.6) and equation (1.7).

$$C_{j,i} = X_i^{j,C}\beta^{j,C} + \theta_i^C\lambda^{j,C} + \theta_i^S\lambda^{l,S} + \varepsilon_i^{j,C}, \tag{1.6}$$

$$\text{for } j = 1, ..., J$$

$$S_{l,i} = X_i^{l,S}\beta^{l,S} + \theta_i^S\lambda^{l,S} + \varepsilon_i^{l,S}, \tag{1.7}$$

$$\text{for } l = 1, ..., L$$

To control for family influences on test scores, in addition to observed individual characteristics, I allow family background at the time and before the tests were taken to affect the observed test scores. Specifically, $X_i^{j,C}$ and $X_i^{l,S}$ include gender, regions of residence, parental socio-economic status, and parental investments, which include the number of days reading to the child, or the degree of autonomy in the parenting style. $C_{j,i}$ is worker i's cognitive test score j; $S_{l,i}$ is worker i's social test score l. $\{\varepsilon_i^{j,C}$, $\varepsilon_i^{l,S}$ $\}$ are the idiosyncratic shocks that are independent across test scores.

Instead of imposing normality, I assume that $\{\varepsilon_i^{j,C}$, $\varepsilon_i^{n,S}$ $\}$ follow a mixed normal distribution with two mixtures.

$$\varepsilon^{j,C} \sim p_1^{j,C} N(\mu_1^{j,C}, \sigma_1^{j,C}) + p_2^{j,C}(\mu_2^{j,C}, \sigma_2^{j,C})$$

$$\varepsilon^{l,S} \sim p_1^{l,S} N(\mu_1^{l,S}, \sigma_1^{l,S}) + p_2^{l,S}(\mu_2^{l,S}, \sigma_2^{l,S})$$

$$p_1 + p_2 = 1$$

4.5. Effects of WFH on Mental Health

To obtain the effects of WFH on mental health, I consider the ATE between WFH and a reference option $\bar{k}$, defined by equation (3.21) below.

$$\begin{aligned} \text{ATE}_{\text{WFH},\bar{k}} &= \mathbf{E}[H_i^{\text{WFH}} - H_i^{\bar{k}}] \\ &= \int \cdots \int (H_i^{\text{WFH}} - H_i^{\bar{k}}) dF(X_i^H, \theta_i^C, \theta_i^S, \varepsilon_i) \\ &\text{for } k \neq \bar{k} \end{aligned} \tag{1.8}$$

where $\mathbf{E}[.]$ is the expectation operator with respect to $\{X_i, \theta_i^C, \theta_i^S, \varepsilon_i^{k,H}\}$. $F(X_i^H, \theta_i^C, \theta_i^S, \varepsilon_i)$ is the cumulative joint distribution. Using the estimated parameters, I simulate the mental health outcomes for each worker i across all options of work arrangements, then compare the average values across potential outcomes. Based on the previous assumptions on selection on observables, and selection on unobserved abilities, $H_i(k) \perp\!\!\!\perp D_i(k)|(X_i, \theta_i^C, \theta_i^S)$, the ATE recovers the effect of WFH relative to a normalized state $\bar{k}$ on mental health.

1.5 Identification and Estimation

Following the approach of extended matching with unobserved dimensions (Carneiro, Hansen, and J. J. Heckman 2003a; J. J. Heckman, Stixrud, and Urzua 2006), I combine several sources of variation for the identification. The parameters in the sorting process are identified by the variation in the worker's observable characteristics, unobserved abilities, functional form, and cost shifters. To estimate the potential mental health outcomes, I use variations coming from the observable characteristics as well as the unobserved abilities while conditioning on sorting. Finally, while the unobserved abilities are crucial in the identification of the sorting and the potential mental health outcomes, on their own, the distributions of unobserved abilities are identified based on the cross-covariance of early age test scores.

1.5.1 Exclusion Restriction of Option-Specific Instruments

As in other discrete choice models, the identification of the empirical model in the previous section relies on the conditional independence assumption. That is, the sorting process into different forms of work arrangements and the mental health outcomes are independent, conditional on the observed characteristics and the unobserved abilities. The inclusion of option-specific cost shifters strengthens the identification in several ways. First, the inclusion of the cost shifters allows the effect to be identified at the infinity (J. J. Heckman and Pinto 2018). Second, since unobserved abilities distributions, as a part of the unobserved component, are non-parametrically identified, the option-specific cost shifters separate the effects of unobserved ability on the sorting versus on the mental health outcomes (J. J. Heckman and Honore 1990; J. Heckman and Navarro-Lozano 2004). Lastly, in addition to the set of individual observables, there exist other variables that change the costs of sorting into a specific option but do not impose direct effects on the potential mental health outcomes. Therefore, the inclusion of these variables helps better represent the individual's problem.

The option WP is perceived as the *status quo*, thus, in the estimation, it is normalized. Each cost shifter is assumed to affect the sorting in the corresponding option but does not affect the sorting in other options or alter the individual's outcomes. Specifically, for option WFH, the cost shifter is the *"distance to work"*, measured in miles before the pandemic. Using information before the pandemic ensures that changes in location during the pandemic do not affect the decision of WFH [13]. A longer distance to work increases the commuting cost, negatively affecting a worker's preference for WP. Therefore, workers who live further from their workplace are more likely to sort into WFH relative to WP, holding other factors constant. For option NW, the *"cumulative duration of unemployment spells"* before the pandemic is used as the cost-shifter. A higher cumulative unemployment spells reduce labor market attachment, leading to a higher incentive to withdraw from the labor market.

Table 1.3 shows the effects of the two cost shifters on the probability of WFH relative to WP and the probability of NW relative to WP. Columns (1) and (2) show the effect of the "distance to work" cost shifter on the two probabilities. While the "distance to work" statistically predicts the probability of WFH, it has no effect on the probability of NW. On the other hand, columns (3) and (4) show that the *"cumulative duration of unemployment spells"* increases the probability of NW, but it has no effect on the probability of WFH. These results affirm that the two cost shifters only affect the margin of choice that they are included in.

[13] An extended literature shows that the pandemic and WFH induce household relocation, and shift the demand for housing to different locations, mostly moving away from the center (Brueckner, M. E. Kahn, and Lin 2023; Haslag and Weagley 2022; Ramani and Bloom 2021)

Table 1.3: First Stage of Cost-Shifters

	Prob. WFH (1) OLS	Prob. NW (2) OLS	Prob. WFH (3) OLS	Prob. NW (4) OLS
Distance to Work (Mile)	0.006***	0.001		
	(0.001)	(0.001)		
Past Unemployment Spells (Months)			0.000	0.000**
			(0.000)	(0.000)
Individual controls	✓	✓	✓	✓
Observations	1,877	1,334	1,877	1,334
R-squared	0.187	0.205	0.168	0.208

Note: Table 1.3 shows the effect of *Distance to Work* and *Past Unemployment Spells* on the probability of WFH relative to other alternative options, and on the probability of NW relative to other alternative options. Indivdual controls are the same as those included in the MNP, see table A.4 for the full list of variables. Standard errors are in parenthesis. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

1.5.2 Distributions of Unobserved Abilities

The empirical model in the previous section postulates unobserved abilities as a source of omitted variables bias that obscures the sorting effects into work arrangements on mental health. The model assumes that conditional on the observables, unobserved abilities spur the remaining dependence across states and outcomes. Some previous works approach the problem of unobserved abilities with random coefficients, which integrates out the endogenous unobserved component (Keane and Wolpin 1997; Rust 1994; Adda and R. Cooper 2002; and Blevins 2014). In this paper, I follow an alternative path to link this source of unobserved abilities to two sets of test scores, allowing the unobserved component to be multidimensional with interpretable meaning for each dimension (J. J. Heckman, Stixrud, and Urzua 2006; J. J. Heckman, Humphries, and Veramendi 2018; Sarzosa and Urzúa 2021). Importantly, the model is also flexible for the possibility that the two dimensions of abilities are measured imprecisely. Although test scores capture a wealth of variations in the two abilities, they are noisily measured.

In particular, to characterize the distributions of the two unobserved abilities, the model relies on the system of measurement structure as in Section 4.4, where the unobserved abilities are linked to the corresponding test scores. The remaining measurement errors, which are orthogonal to the test scores and the covariates, are integrated out. Thus, for each dimension of abilities, the model requires two conditions. First, there exist at least three test scores being recorded for each dimension. Second, the correlations of test scores are sufficiently high. To these conditions, Table A.5 shows that within each ability dimension, the correlations of test scores are high. The correlations of test scores within cognitive ability are 0.580, 0.587, and 0.739. The correlations of test scores within social ability are equally high: 0.379, 0.408, and 0.560. Across dimensions, test scores also correlate with one another, however, with a lower degree. The estimation relies on the linearity in the measurement structure and the observed covariance across the recorded test scores. Appendix C describes in detail the required normalization to identify the distribution of each unobserved ability dimension.

1.5.3 Estimation

The empirical model implies the following sample likelihood:

$$\mathbf{L}(\Theta|.) = \prod_{i=1}^{N} \left\{ \int_{\boldsymbol{\theta}} \prod_{j \in J} f_C(C_{i,j}|X_i^{j,C}, \boldsymbol{\theta}) \prod_{l \in L} f_S(S_{l,i}|X_i^{l,S}, \boldsymbol{\theta}) \varphi(H_i|X_i^I, X_i^H, \boldsymbol{\theta}) dF(\boldsymbol{\theta}) \right\} \tag{1.9}$$

where Θ is the set of parameters to be estimated; $\boldsymbol{\theta}$ contains both latent factors, $\boldsymbol{\theta} \equiv \{\theta^C, \theta^S\}$; $F(\boldsymbol{\theta})$ is the cumulative density functions of the latent factors; $f_C(.)$ and $f_S(.)$ are the density of the cognitive and social test scores, respectively. The linear structure and variables included in $f_C(.)$ and $f_S(.)$ are defined as in the measurement system equation (1.6) and equation (1.7). $\varphi(.)$ is the multinomial probit estimation function with the structure defined in equation (1.1). Specifically, $\varphi(.)$ is defined as follows:

$$\varphi(H_i|X_i^I, X_i^H, \boldsymbol{\theta}) = \prod_{q \in K} \left\{ f(H_i(q)|X_i^H, \boldsymbol{\theta}) Pr(I_i^q \geq 0|X_i^I, \boldsymbol{\theta}) \right\}^{\mathbf{1}\{q=k\}} \tag{1.10}$$

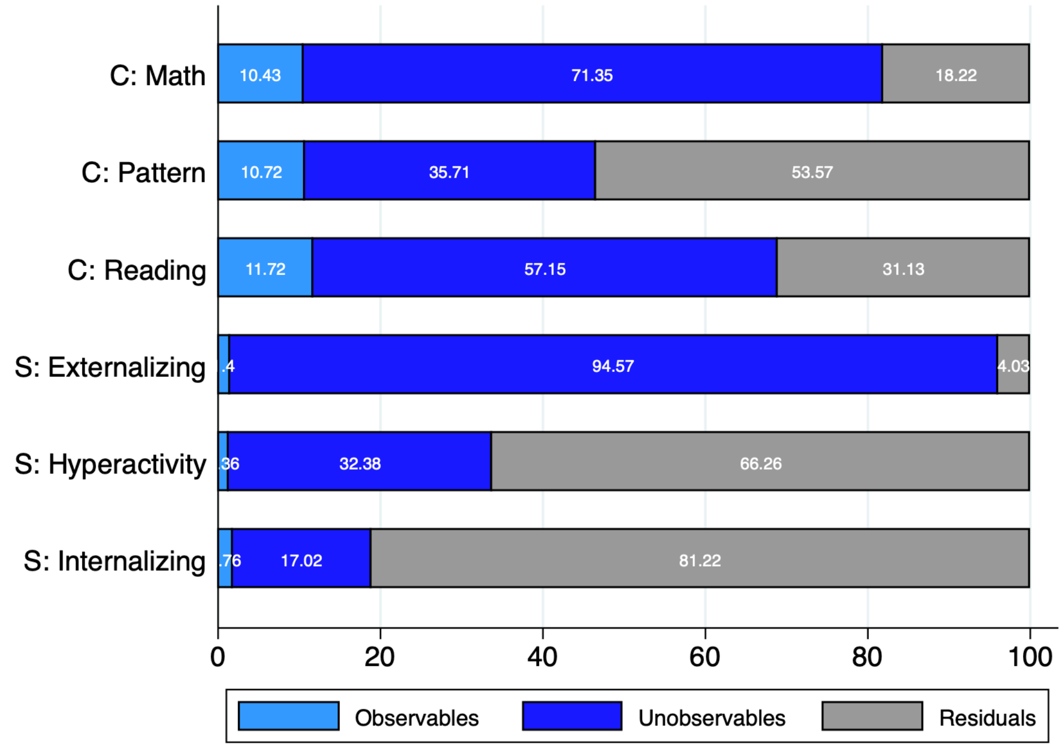
I use Markov Chain Monte Carlo to estimate the likelihood function (1.9). The estimated parameters are derived from the average of 2,000 draws from the posterior distributions. The reported standard errors are the standard deviation of the 2,000 draws.

1.6 Results

1.6.1 Effects of Unobserved Abilities on Sorting

To understand the importance of unobserved abilities to the observed test scores, I apply ANOVA to decompose the variance of the observed test scores into three components: unobserved abilities, observed characteristics, and random noise. Figure 3.5 shows the results. In the figure, test scores are measured with a high degree of noise, varying between 4.03% and 81.22%. Moreover, both latent factors explain a good fraction of the test scores, varying between 17.02% and 94.57%. Whereas, observed characteristics explain much less. Altogether, these results suggest that a direct use of these test scores can lead to a high degree of measurement errors.

Figure 1.2: Variance Decomposition



Note: Figure 3.5 shows the contribution of the observables, unobserved abilities (factors), and the residuals to the variance of the observed test scores. The decomposition uses the simulated sample from the empirical model. The observables include the total variance contribution of: gender, family SES, parental investments, and regions of residence. Finally, the residuals represent the share of the variance in each observed measure explained by the remained unobserved idiosyncratic errors.

Table 1.4 shows the marginal effects of unobserved abilities from the sorting equation. Each column corresponds to one work arrangement option in the multinomial probit. WP is considered the normalized option. A one standard deviation increase in cognitive ability increases the probability of sorting into WFH by 0.214, reduces the probability of sorting into WP by 0.224, and increases the probability of NW by 0.011. Whereas, a one standard deviation increase in social ability decreases the probability of NW by 0.003, and it has no effect on the other two options. Figure A.7 in the Appendix graphically shows evidence of sorting on unobserved cognitive and social abilities.

Table 1.4: Marginal Effects of Observed Characteristics, Unobserved Abilities, and Cost Shifters on Sorting

	WFH (1) MNP	WP (2) MNP	NW (3) MNP
Observed Abilities			
Female	0.026	-0.224***	-0.019
	(0.026)	(0.002)	(0.027)
Partner	-0.009	0.005	0.004
	(0.025)	(0.026)	(0.003)
Child	-0.025	0.031	-0.005*
	(0.031)	(0.032)	(0.003)
Bad Finance	-0.004	0.002	0.002
	(0.034)	(0.032)	(0.035)
Good Finance	0.024	-0.031	0.006**
	(0.033)	(0.035)	(0.003)
Unobserved Abilities			
Cognitive	0.214***	-0.224***	0.011***
	(0.000)	(0.002)	(0.002)
Social	0.008	-0.004	-0.003***
	(0.012)	(0.019)	(0.001)
Cost Shifters			
Distance to Work (Mile)	0.027*	-	-
	(0.014)		
Past Unemployment Spells (Month)	-	-	0.001***
			(0.000)

Note: Table 1.4 shows the marginal effects on the probability of sorting into WFH, WP, and NW. The table reports the marginal effects calculated from the estimated parameters in equation (1.2). The full list variables included in the MNP is in Table (A.4). Standard errors are in parenthesis. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Overall, this first set of results shows that unobserved abilities are an important dimension of sorting into different work arrangements. Further, the sorting on abilities into WFH is sharply different from WP, although both of these options indicate an active status in the labor force during the pandemic. The results also highlight the importance of social ability in the probability of remaining in the labor force: individuals with high cognitive ability alone are more likely to withdraw from the labor market, whereas those with high cognitive as well as social abilities remain in the labor force and sort into WFH or WP.

The Table also shows the effect of each cost shifter on the corresponding option. The "*Distance to work*" cost shifter increases the probability of WFH, and the "*Past Unemployment Spells*" increases the probability of NW. Both of these results are as expected.

1.6.2 Estimated Effects of WFH on Mental Health

This section shows the effects of WFH on mental health, conditioning on observed characteristics as well as unobserved abilities. The results in Table 1.5 are calculated from the ATE defined in equation (3.21). To provide an initial overview of the impact of WFH on mental health, Column (1) shows the effect of WFH on an aggregated measure of mental health deterioration. This measure is derived from the average of loneliness, depression, and life satisfaction (reverse). When considering all three dimensions of mental health together, WFH causes a 0.087 standard deviation increase in the overall measure of mental health deterioration compared to WP. Conversely, when compared to the NW option, WFH leads to a 0.174 standard deviation decrease in the overall measure of mental health deterioration. It is essential to acknowledge that these effects pertain to the analytical sample during the initial phase of the pandemic. Beyond this context, the nature of WFH may vary significantly, potentially resulting in different impacts on mental health. For example, unlike WFH during the pandemic, which often involved a binary choice between fully remote work or full-time office attendance, contemporary WFH arrangements often embrace a hybrid model. This hybrid structure offers workers the flexibility to manage their schedules while still retaining opportunities for in-person interactions with colleagues.

Columns (2) to (4) delve into specific dimensions of mental health that are influenced by

WFH, offering a closer examination of their individual effects. One of the concerns associated with WFH during the pandemic is the potential disruption in the worker's social network. Compared to on-site workers, individuals who work from home experience a transformation in their social support from in-person interactions to virtual interactions with colleagues. Moreover, during the early months of the pandemic, this transition in social interaction is abrupt, an experience unfamiliar to many individuals. On the other hand, in comparison to non-working individuals, those in WFH still maintain some level of social interactions with colleagues. As social ties among co-workers play a crucial role in the mental health of workers themselves (Rockmann and Pratt 2015), the displacement of this social network may contribute to a higher level of loneliness. Column (2) focuses on examining the effect of WFH on loneliness. When compared to WP, WFH increases loneliness by 0.118 standard deviation. On the contrary, in comparison to NW, WFH leads to a reduction in loneliness by -0.158 standard deviation. Column (3) looks into a more severe condition of mental health deterioration, depression. Different from loneliness, there is no statistically significant effect of WFH on depression when compared with either alternative option. One possible explanation for the lack of significant effects on depression is that depression often arises from longer-term exposure to more severe stressors. While WFH during the pandemic may impact mental well-being, it might not be a severe enough shock to trigger depression.

The last dimension of mental health to consider is life satisfaction. Different from the measures of loneliness and depression, life satisfaction is an evaluative measure, which requires the respondent to form a self-assessment of their overall quality of life as a whole. Studying life satisfaction is crucial because previous research has indicated that a positive income shock enhances the evaluation of life quality, although it may not necessarily improve emotional well-being (Kahneman and Deaton 2010; Lindqvist, Östling, and Cesarini 2020). Column (4) shows no effect of WFH on life satisfaction relative to WP, but a consistent improvement in mental health of WFH relative to NW.

Overall, the results in Table 1.5 demonstrate that WFH during the initial months of the pandemic affects mental health. However, the direction of this effect depends significantly on the alternative option with which WFH is compared. Furthermore, the results underscore the importance of considering alternative options when analyzing the effect of WFH on different mental health measures. Specifically, while WFH affects emotional well-being only when compared to WP, it influences both emotional well-being and life evaluation when compared to NW during this time.

Table 1.5: Latent Model: Effects of WFH on Mental Health

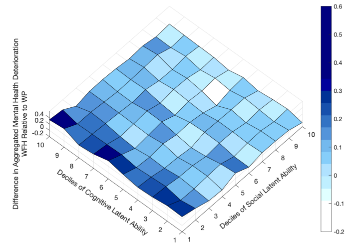
	Mental Health Aggregated Deterioration	Loneliness	Depression	Life Satisfaction
	(1)	(2)	(3)	(4)
	ATE	ATE	ATE	ATE
WFH - WP	0.087**	0.118***	0.051	-0.070
	(0.042)	(0.047)	(0.037)	(0.044)
WFH - NW	-0.174**	-0.158**	0.003	0.190**
	(0.077)	(0.081)	(0.071)	(0.082)

Note: Table 1.5 shows the effects of WFH on mental health relative to NW or WP. The ATE is calculated based on equation (3.21). The full list of variables in the potential outcomes is in Table (A.4). Standard errors are in parenthesis. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

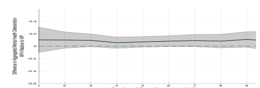
1.6.3 Effects of Unobserved Abilities on the Treatment Effects

Despite the growing body of literature about the heterogeneous effects of remote work during the COVID pandemic across sub-demographic groups (Adams-Prassl et al. 2020; Angelucci et al. 2020; Dingel and Neiman 2020; Bick, Blandin, Mertens, et al. 2020; Hensvik, Le Barbanchon, and Rathelot 2020; Mongey and Weinberg 2020; Adams-Prassl et al. 2020; among others), there is scant evidence on whether different levels of cognitive and social abilities enable workers to better cope with changes in their work arrangements. The empirical model in the previous section allows to decompose the effects of unobserved abilities not only on the sorting into WFH versus other options, but also to shed light on the extent to which cognitive and social abilities influence the treatment effects of WFH on mental health.

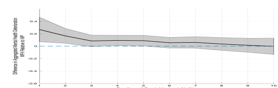
Figure 1.3: Effects of Unobserved Cognitive and Social Abilities of the Treatment Effects - WFH relative to WP



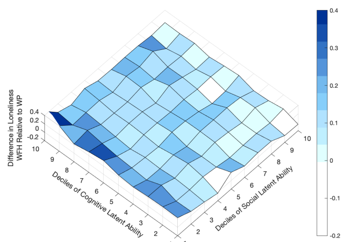
(a) Aggregated Mental Health: Cognitive - Social



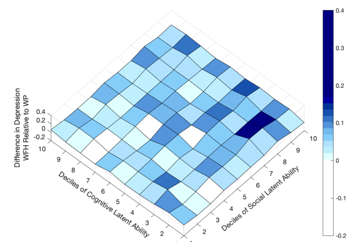
(a-i) Cognitive



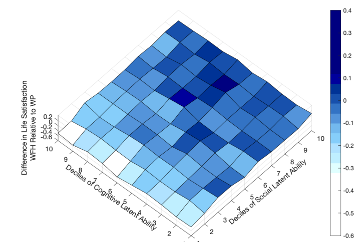
(a-ii) Social



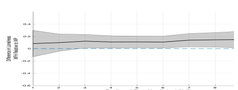
(b) Loneliness: Cognitive - Social



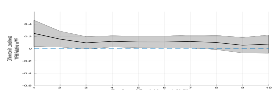
(c) Depression: Cognitive - Social



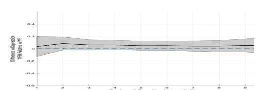
(d) Life Satisfaction: Cognitive - Social



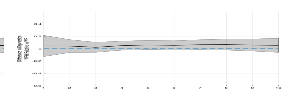
(b-i) Cognitive



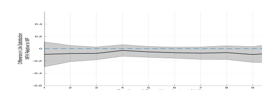
(b-ii) Social



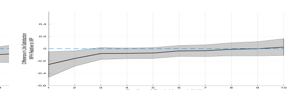
(c-i) Cognitive



(c-ii) Social



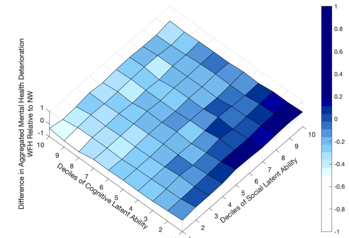
(d-i) Cognitive



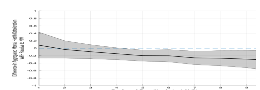
(d-ii) Social

Note: Figure 1.3 shows the difference in mental health between WFH and WP, along the deciles of cognitive and social abilities. Higher deciles are associated with higher values of the unobserved abilities. The color bar indicates the value of mental health. The solid line shows the mean of corresponding mental health measure within each unobserved abilities deciles; the shaded area shows the 95% confidence interval.

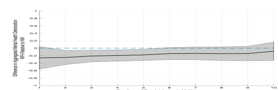
Figure 1.4: Effects of Unobserved Cognitive and Social Abilities of the Treatment Effects - WFH relative to NW



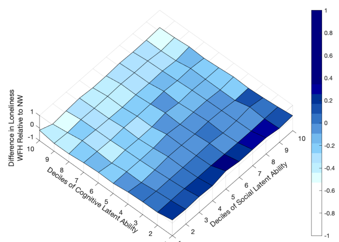
(a) Aggregated Mental Health: Cognitive - Social



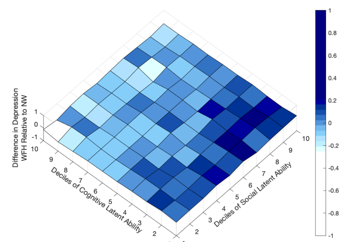
(a-i) Cognitive



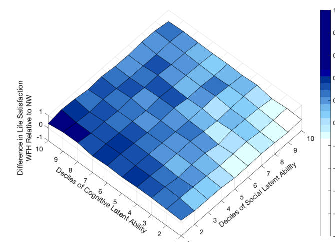
(a-ii) Social



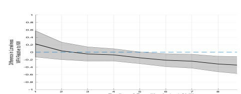
(b) Loneliness: Cognitive - Social



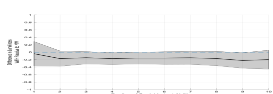
(c) Depression: Cognitive - Social



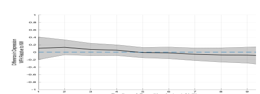
(d) Life Satisfaction: Cognitive - Social



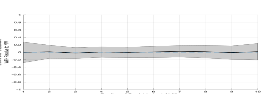
(b-i) Cognitive



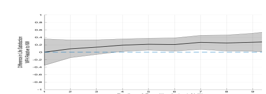
(b-ii) Social



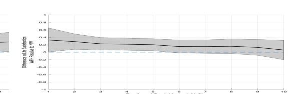
(c-i) Cognitive



(c-ii) Social



(d-i) Cognitive



(d-ii) Social

Note: Figure 1.4 shows the difference in mental health between WFH and NW, along the deciles of cognitive and social abilities. Higher deciles are associated with higher values of the unobserved abilities. The color bar indicates the value of mental health. The solid line shows the mean of corresponding mental health measure within each unobserved abilities deciles; the shaded area shows the 95% confidence interval.

Figure 1.3 shows the contribution of cognitive and social abilities to the estimated treatment effect of WFH relative to WP on mental health. Two remarks emerge from the figure. First, the treatment effects of WFH compared to WP are contingent on both cognitive and social abilities. The contribution of cognitive and social abilities varies significantly across all mental health measures. Second, when considering the heterogeneous mental health effects of WFH relative to WP, social abilities play a more pivotal role compared to cognitive abilities. The negative impact of WFH on mental health is predominantly concentrated among individuals with lower deciles of social abilities. Whereas, the changes in mental health effects across deciles remain fairly constant for cognitive abilities.

Similarly, figure 1.4 shows the contribution of cognitive and social abilities to the estimated treatment effect of WFH relative to NW on mental health. Although cognitive as well as social abilities continue to contribute to the variation in the treatment effect of WFH, cognitive abilities become more crucial when compared to the NW option. Most of the benefits of the mental health effect of WFH relative to NW are observed among individuals at the higher deciles of cognitive abilities.

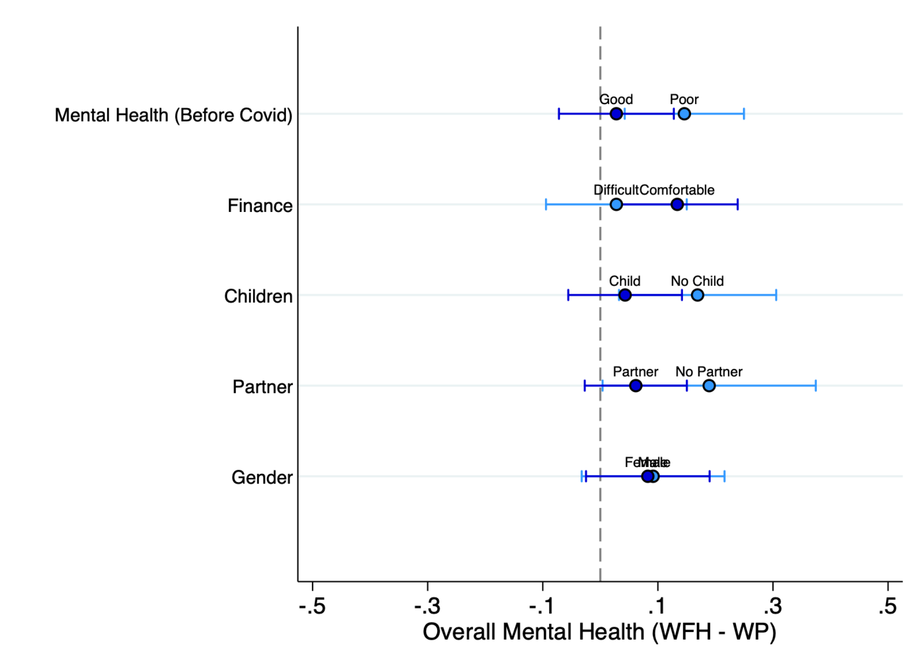
Overall, these results highlight the importance of cognitive and social abilities on mental health as well as the multi-dimensionality of abilities. An aggregated measure of worker ability would not be able to capture the contrasting responses across the two dimensions.

1.6.4 Effects of Observed Characteristics on the Treatment Effects

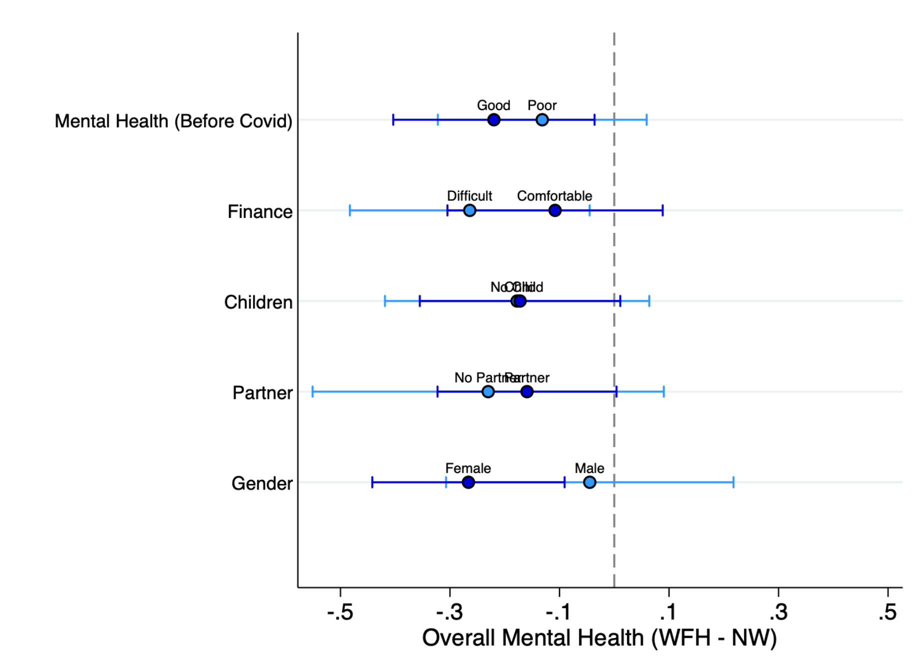
In addition to the variation in the ATE across the two dimensions of unobserved abilities, another important question is whether the ATE varies across observed characteristics. Figure 1.5a and Figure 1.5b show the differences in the ATE across observable dimensions when comparing WFH with WP, and with NW.

When comparing WFH to WP, individuals who had poor mental health conditions prior to the pandemic, faced financial difficulties, had no children, and no partner tended to experience a more pronounced decline in mental health. Gender did not exhibit significant differences in this context. Likewise, when comparing WFH to NW, individuals with worse mental health conditions before the pandemic, financial constraints, and no partner derived fewer mental health benefits from WFH in comparison to NW. Notably, females experienced greater mental health benefits when WFH was compared to NW, and there was no discernible difference between those with or without children.

Figure 1.5: Effects of Observable Characteristics of the Treatment Effects



(a) WFH - WP



(b) WFH - NW

Note: Figure 1.5 shows the difference in mental health between WFH and WP or NW by the observed characteristics. The 95% confidence intervals are included.

One possible reason why gender or family composition in terms of partnership or children show less variation in the ATE is the relatively stable family situation experienced by the BCS cohort during the pandemic, as previously discussed. For instance, Figure A.6a illustrates that the BCS cohort's children have an average or median age of around 16 years. This implies that, on average, BCS members were less likely to face the challenges associated with caring for very young children. Furthermore, Figure A.6b indicates that during the pandemic, only a small percentage of BCS members lived with additional household members beyond their partners or children, suggesting that concerns related to extended family arrangements were less prominent for the BCS cohort.

1.7 Marginal Effects of Increasing Unobserved Abilities

Given that the mental health effects of WFH vary substantially across the cognitive and social abilities deciles, this section addresses what would happen to the mental health effect of WFH during this unprecedented period if the levels of cognitive and social abilities were improved. Although in this section, the increases in cognitive and social abilities come from simulations, in practice, cumulative evidence suggests that cognitive and social abilities are amenable to change through early-age interventions, due to the levels of brain plasticity and neurogenesis (Black et al. 2017; S. Grantham-McGregor et al. 2007). These interventions can range from simple parent-child interactions such as playing, reading, or singing (Attanasio, Kozhimannil, and Kjerulff 2018; S. M. Grantham-McGregor et al. 1991; Hamadani et al. 2019) to more structured curricula. Notably, two major early childhood interventions in the US are Head Start and Perry Preschool. Building on the findings from prior research, the simulation exercise entails a 0.2

standard deviation increase in cognitive abilities and a 0.5 standard deviation increase in social abilities.

The effects of the marginal effects are calculated as follows

$$\text{Marginal Effect} = \frac{E[Y|\text{Simulated Intervention}] - E[Y^*|\text{Baseline}]}{E[D|\text{Simulated Intervention}] - E[D^*|\text{Baseline}]} \tag{1.11}$$

Table 1.6 shows the effects of the two simulations on the compliers, always-takers, and never-takers. First, regarding the simulated increase in social abilities, an increase of 0.5 standard deviations reduces the mental health effects of WFH relative to WP by 0.034 standard deviations. This magnitude accounts for a third of the negative mental health effects of WFH relative to WP from the baseline results. There is no effect from this simulation on the mental health effect of WFH relative to WP. Second, in terms of simulating an increase of 0.2 standard deviations in cognitive abilities, the results show an improvement in mental health by 0.063, approximating a third of the mental health benefits when comparing WFH with NW. As before, the result is option-specific, there is no effect when comparing WFH with WP.

Table 1.6: Latent Model: Marginal Effects of Increasing Cognitive and Social Abilities on Mental Health

Overall Mental Health	Total Effect (1)	Compliers (2)	Always-Takers (3)	Never-Takers (4)
Increase Social: by 0.5 sd				
WP-Margin	-0.034*	-0.014**	-0.028*	0.008
	(0.020)	(0.006)	(0.016)	(0.013)
NW-Margin	-0.024	-0.007*	-0.016	-0.000
	(0.027)	(0.004)	(0.024)	(0.000)
Share WP-Margin	-	0.205	0.461	0.1578
Share NW-Margin	-	0.069	0.461	0.001
Increase Cognitive: by 0.2 sd				
WP-Margin	0.008	-0.004	-0.005	0.0168
	(0.011)	(0.005)	(0.015)	(0.012)
NW-Margin	-0.063***	-0.013***	-0.050***	-0.001
	(0.026)	(0.004)	(0.023)	(0.001)
Share WP-Margin	-	0.225	0.482	0.137
Share NW-Margin	-	0.073	0.482	0.001

Note: Table 1.6 shows the effects of increasing the share of WFH on mental health relative to NW or WP among the compliers, always-takers, and never-takers. The results from both waves are presented. The Marginal Effect is calculated based on equation (1.11). The full list of variables in the potential outcomes is in Table (A.4). Standard errors are in parenthesis. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Another noteworthy aspect of the findings is that both sets of results are primarily influenced by the always-takers, constituting approximately 80% of the total effects. These individuals would opt for WFH irrespective of the increases in social or cognitive abilities. Conversely, the remaining effects come from the compliers. This suggests that increasing social or cognitive abilities alters the mental health impact of WFH primarily at the intensive margins, with relatively minor shifts in the costs and benefits associated with switching between options.

1.8 Discussions

1.8.1 Effect Size Compared to Existing Literature

A meaningful way to contextualize the magnitude of the effects is to compare the effect size with similar studies on mental health during the pandemic. As previously mentioned, the majority of empirical works on mental health during the pandemic center around lockdown policies as the treatment of interest, as opposed to the direct impact of WFH. Therefore, this section draws comparisons with studies that examine the effects of lockdown measures on mental health during the pandemic, rather than WFH and mental health.

Overall, the effects from the ATE in the previous section fall within the range of the estimates from previous studies, which vary between 0.05 standard deviation and 1.5 standard deviation. For example, in a study about the age-specific curfew on the older population in Turkey, the authors show that the lockdown leads to a 0.2 standard deviation in mental health distress among the affected group (Altindag, Erten, and Keskin 2022). Two potential explanations to explain for the estimates from this study being larger than mine. First, lockdown represents a more stringent form of social interactions than WFH. While lockdowns forbid any type of interactions, WFH mostly limits interactions with colleagues. Moreover, lockdowns may signal more infection fears than WFH, which causes more mental health distress. Second, the age group affected in Altindag, Erten, and Keskin 2022 is older than the BCS cohort. Older individuals may have a heightened concern about COVID infection and changes in their lives due to the lockdowns, which could result in more pronounced negative effects on their mental health.

Specific to the context of the UK, Wang et al. 2022 find that involuntary furlough associates with an increase in mental health deterioration by 1.32 standard deviation. The magnitude of this effect is significantly larger because of their focus on involuntary job loss. Whereas, in my sample, those in the NW option include not only individuals who were on furlough but also voluntarily withdrew from the labor market. It is important to recall that a shortcoming of the empirical model is its incapability to distinguish between a worker's choice and a firm choice. The sorting process is a collective decision of the individual and of the firm.

1.8.2 Long-term Effects

This section investigates the extent to which the effects observed in 2020 persist over the long term. On one hand, the abrupt shift to WFH, along with rapid policy changes during the initial months of the pandemic, may result in short-lived effects on mental health. Conversely, the prolonged duration of WFH can intensify mental health issues of this work arrangement since mental health effects tend to persist (Burcusa and Iacono 2007).

In this section, I leverage the latest COVID survey that was administered in September, 2021. I applied the same empirical model as in the previous section on the new data. I first apply the treatment status in 2021 on outcome in 2021. This aims at aligning the treatment status and outcomes to be consistent in the same recorded time frame. Table 1.7 presents the findings. Compared with the main results, the negative effects of WFH in 2021 are larger. Relative to WP, WFH in 2021 increases mental health deterioration by 0.115 standard deviation instead of 0.087 standard deviation. Relative to NW, WFH in 2021 reduces mental health deterioration by 0.134 standard deviation instead of 0.174 standard deviation.

Table 1.7: Latent Model: Effects of 2020-WFH on Mental Health Later Wave in 2021

	Mental Health Aggregated Deterioration	Loneliness	Depression	Life Satisfaction
	(1)	(2)	(3)	(4)
	ATE	ATE	ATE	ATE
WFH - WP	0.115***	0.166***	0.079**	-0.087*
	(0.046)	(0.047)	(0.040)	(0.046)
WFH - NW	-0.134**	-0.142**	0.027	0.152***
	(0.068)	(0.073)	(0.056)	(0.067)

Note: Table 1.7 shows the effects of WFH on mental health relative to NW or WP in 2021. The ATE is calculated based on equation (3.21). The full list of variables in the potential outcomes is in Table (A.4). Standard errors are in parenthesis. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

While the majority of individuals do not change their workplace arrangement between 2020 and 2021, a smaller fraction switches their arrangements, especially those previously in the NW margin. Table A.7 shows the percentage of individuals switching workplace arrangments between 2020 and 2021. As a consequence, the effects of the WFH status in 2021 on the outcome in 2021 are a weighted aggregation of two sources: (i) the persistent effects of WFH in 2020 on outcomes in 2021, and (ii) the new assignment effects of WFH in 2021 on outcomes in 2021. To better understand if the larger negative effects of WFH come from the persistent channel or the new assignment channel, I next run the model on outcomes recorded in 2021, however, the treatment status is kept the same as during the 2020 period. Moreover, to focus exclusively on the persistent effect of WFH in 2020, I restrict the sample to include only individuals who do not change their workplace arrangements. This helps understand whether the same treatment during 2020 affects outcomes recorded in 2021. The results are shown in Table 1.8. A comparison of these results with the main findings and the findings in Table 1.7 confirms that the treatment status in 2020 exacerbates the mental health repercussions of WFH. Specifically, in comparison to WP, WFH in 2020 leads to a larger increase in aggregated mental health deterioration, a magnitude of

0.148 standard deviations, as opposed to 0.087 standard deviations. Similarly, in comparison to NW, WFH in 2020 results in a smaller, statistically insignificant decrease in aggregated mental health deterioration, a magnitude of 0.033 standard deviation. These findings imply that WFH in 2020 incurs long-term mental health costs, thereby amplifying the overall mental health burden associated with WFH relative to WP, and outweighing the mental health benefits of WFH relative to NW.

Table 1.8: Latent Model: Effects of 2021-WFH on Mental Health Later Wave in 2021

	Mental Health Aggregated Deterioration	Loneliness	Depression	Life Satisfaction
	(1)	(2)	(3)	(4)
	ATE	ATE	ATE	ATE
WFH - WP	0.148***	0.180***	0.072	-0.128***
	(0.055)	(0.056)	(0.045)	(0.057)
WFH - NW	-0.033	-0.180	0.114	0.011
	(0.113)	(0.113)	(0.087)	(0.118)

Note: Table 1.8 shows the effects of WFH on mental health relative to NW or WP in 2021. The ATE is calculated based on equation (3.21). The full list of variables in the potential outcomes is in Table (A.4). Standard errors are in parenthesis. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Aside from the persistent effect of WFH in 2020, another consideration that potentially accounts for the recorded mental health in 2021 is the difference in the way WFH is implemented in 2021 compared to in 2020. Compared to 2020, WFH in 2021 receives more support, such as technological, or communication training. These differences in WFH implementation can affect both those who already working from home in 2020 as well as those starting to work from home in 2021. Therefore, these factors cannot be completely ruled out in the exercises above.

1.8.3 Sensitivity to mental health pre-COVID control

To check the importance of controlling for the mental health conditions before the pandemic, this section applies the same model without controlling for pre-COVID mental health conditions. The results are reported in Table 1.9. Compared with the main results, without controlling for pre-COVID mental health shows a larger magnitudes in the results. These differences can be attributed to the fact that the latter result is a combination effects of the WFH mental health effects and pre-conditions of the worker's mental health.

Table 1.9: Latent Model: Effects of WFH on Mental Health Without Controlling for Pre-COVID Mental Health Conditions

	Mental Health Aggregated Deterioration	Loneliness	Depression	Life Satisfaction
	(1)	(2)	(3)	(4)
	ATE	ATE	ATE	ATE
WFH - WP	0.348***	0.299***	0.199***	-0.333***
	(0.091)	(0.085)	(0.083)	(0.091)
WFH - NW	-0.304	-0.362***	-0.165	0.267
	(0.208)	(0.152)	(0.153)	(0.212)

Note: Table 1.9 shows the effects of WFH on mental health relative to NW or WP, without controlling for pre-COVID mental health conditions. The ATE is calculated based on equation (3.21). The full list of variables in the potential outcomes is in Table (A.4). Standard errors are in parenthesis. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

A closer look at the estimated parameters in the outcome equations part of the empirical model shows that when the mental health before COVID is not controlled for, the contributions of the unobserved abilities are larger. Table 1.10 shows the estimated parameters of the unobserved abilities, cognitive and social abilities, from the outcome equations. In all outcomes, and across both dimensions, when pre-COVID mental health conditions are not added to the set of controls, the contributions of the unobserved abilities are larger. This suggests that when the mental health conditions before COVID are added, they absorb some effects of the unobserved abilities on the mental health outcomes during the pandemic.

Overall, controlling for mental health conditions before the pandemic is a more conservative approach. Comparing the results from the models with and without the before COVID mental health control shows that the model with the control for before COVID mental health captures a lower bound of the negative mental health effects of WFH. Although controlling for mental health conditions before the pandemic cannot completely rule out the possibility of reverse causation, meaning that mental health before COVID affects the sorting into workplace arrangements during COVID, the comparable results of two models with and without the pre-COVID mental health conditions suggest that reverse causation may not completely uphold the results.

Table 1.10: Latent Model: Effects of Unobserved Abilities on Mental Health With and Without Controlling for Pre-COVID Mental Health Conditions

Panel A: *With before COVID mental health*	Mental Health Aggregated Deterioration	Loneliness	Depression	Life Satisfaction
	(1)	(2)	(3)	(4)
	ATE	ATE	ATE	ATE
NW				
Cognitive	0.010	-0.012	0.022	-0.007**
	(0.030)	(0.033)	(0.026)	(0.032)
Social	0.018	0.026	-0.018	-0.016
	(0.049)	(0.053)	(0.041)	(0.051)
WP				
Cognitive	0.100***	0.046	0.019	-0.105**
	(0.038)	(0.042)	(0.034)	(0.040)
Social	-0.017	-0.007	-0.016	0.021
	(0.052)	(0.056)	(0.043)	(0.054)
WFH				
Cognitive	0.066	0.005	0.002	-0.087
	(0.072)	(0.076)	(0.066)	(0.076)
Social	-0.223*	0.327***	0.107	- 0.155
	(0.123)	(0.121)	(0.107)	(0.128)
Panel B: *Without before COVID mental health*	Mental Health Aggregated Deterioration	Lonely	Depression	Life Satisfaction
	(1)	(2)	(3)	(4)
	ATE	ATE	ATE	ATE
NW				
Cognitive	-3.603***	-2.606***	-2.312***	3.539***
	(0.149)	(0.132)	(0.131)	(0.149)
Social	1.063***	0.763***	0.583	-1.058***
	(0.079)	(0.071)	(0.069)	(0.079)
WP				
Cognitive	4.420***	3.141***	2.576***	-4.389***
	(0.175)	(0.174)	(0.170)	(0.175)
Social	-0.856***	-0.665***	-0.562***	0.826***
	(0.076)	(0.072)	(0.069)	(0.076)
WFH				
Cognitive	7.654***	4.712***	4.717***	-7.736***
	(0.655)	(0.553)	(0.54)	(0.668)
Social	-1.791***	-0.946***	-1.135***	1.848
	(0.276)	(0.214)	(0.220)	(0.279)

Note: Table 1.10 shows the effects of WFH on mental health relative to NW or WP, without controlling for pre-COVID mental health conditions. The ATE is calculated based on equation (3.21). The full list of variables in the potential outcomes is in Table (A.4). Standard errors are in parenthesis. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

1.9 Model Performance

1.9.1 Compared to the Difference-in-Differences Model

Previous studies about the mental health effects of lockdown policies rely on the before and after variations in the changes in mental health. To benchmark the results from the empirical model with the common empirical approach, this section presents the results from a difference-in-differences framework. Specifically, leveraging the panel structure of the data with information before the pandemic, the difference-in-differences model is as follows:

$$\text{Mental Health}_{it} = \beta_0 + \beta_1 \text{Post}_{it} \times \text{WFH}_{it} + \beta_2 Post_{it} + \beta_3 \text{WFH}_{it} + \beta_4 X_{it} + \varepsilon_{it} \qquad (1.12)$$

In equation (2.5), Mental Health$_{it}$ is the mental health of a worker i in period t, WFH$_{it}$ indicates whether worker i WFH or not, and $Post_{it}$ indicates whether the period is during the pandemic, X_{it} is the worker i's characteristics, including the aggregated test scores as proxies for unobserved abilities. The coefficient of interest is β_1, which captures the effects of WFH during the pandemic on mental health relative to the mental health before the pandemic for those who do not WFH.

Table 1.11 shows the results from equation (2.5). Column (1) shows the results for WFH relative to both alternative options, column (2) shows the results of WFH relative to WP only, and column (3) shows the results of WFH relative to NW only. Note that column (1) represents the composite effects from both margins in the empirical model since it does not distinguish the two options.

Table 1.11: Difference-in-Differences: Effects of WFH on Mental Health

	WFH - WP and NW (1)	WFH - WP (2)	WFH - NW (3)
WFH × COVID	0.228***	0.321***	-1.720***
	(0.081)	(0.079)	(0.132)
WFH	-0.076	-0.163**	1.696***
	(0.071)	(0.068)	(0.117)
COVID	-0.175***	-0.267***	1.798***
	(0.033)	(0.034)	(0.109)
Observations (before-after)	6,526	5,931	2,230
R-square	0.084	0.104	0.182

Note: Table 1.11 shows the effects of WFH on mental health relative to NW or WP, using a difference-in-differences framework. The reported coefficient is β_1 from equation (2.5). Standard errors are in parenthesis. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

In all three columns, the results are in the same direction as the results from the empirical model, however, the magnitudes from the difference-in-differences model are larger. A main explanation is that β_1 captures not only the WFH effect, but also the self-selection effect in the WFH work arrangement, as being addressed by the empirical model.

1.9.2 The Difference-in-Differences Model with Survey Weights

Longitudinal surveys can be susceptible to bias due to attrition. Table A.1 shows the response rate of the BCS survey during COVID. To check to which extent attrition affects the estimated results, this section shows the Difference-in-Differences estimates with the COVID survey weights. The COVID survey weights are provided in the BCS data, aiming at addressing inefficient or biased estimates arising from attrition [14]. Comparing the results between the

[14]The COVID weight essentially applies a logistic model on the information of individuals before COVID to predict the probability of responding. The reported weight is the inverse of the probability of response. The information includes gender, ethnicity, parental social class, number of rooms at home/persons per room, cognitive ability, early life mental health, voting, membership in organizations, Internet access prior to web survey, consent for biomarkers, consent for linkages, educational qualifications, economic activity, partnership status, psychological distress,

Difference-in-Differences with and without weights gauges the importance of addressing attrition in our analysis.

Table 1.12: Difference-in-Differences (with Weight): Effects of WFH on Mental Health

	WFH - WP and NW (1)	WFH - WP (2)	WFH - NW (3)
WFH × COVID	0.325***	0.406***	-1.345***
	(0.088)	(0.084)	(0.122)
WFH	-0.017	-0.138*	1.578***
	(0.076)	(0.072)	(0.107)
COVID	-0.292***	-0.378***	1.444***
	(0.034)	(0.035)	(0.093)
Observations (before-after)	6,506	5,914	2,217
R-square	0.093	0.119	0.215

Note: Table 1.12 shows the effects of WFH on mental health relative to NW or WP, using a difference-in-differences framework. Survey weights are included. The reported coefficient is β_1 from equation (2.5). Standard errors are in parenthesis. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table 1.12 shows the results. Comparing Table 1.11 and Table 1.12, the estimates are in the same direction, and have comparable magnitudes. However, in the Difference-in-Differences with weight, the negative mental health effect of WFH is slightly larger and the positive mental health effect of WFH is slightly smaller. This difference might be explained by negative selection in the response sample. Table 1.13 compares the characteristics of respondents and non-respondents. Negative selection, in this case, occurs when people who feel less strongly about the negative impact of WFH on their mental health are more likely to complete the survey.

BMI, self-rated health, smoking status, maternal mental health, social capital/social support, income, number of non-responses across all previous sweeps, response to COVID-19 Wave 1 and 2 survey

Table 1.13: Characteristics of the Response and Non-Response Samples

	(1) Full sample	(2) Response	(3) Non-Response	(4) Difference (3)-(2)
Female	0.488	0.587	0.461	-0.125***
	(0.500)	(0.493)	(0.499)	(0.012)
Child	0.627	0.661	0.590	-0.071***
	(0.484)	(0.474)	(0.492)	(0.015)
Partner	0.746	0.819	0.718	-0.101***
	(0.435)	(0.385)	(0.450)	(0.011)
Bad Finance	0.344	0.438	0.309	-0.129***
	(0.475)	(0.496)	(0.462)	(0.012)
Good Finance	0.249	0.150	0.286	0.136***
	(0.432)	(0.357)	(0.452)	(0.011)
Cognitive	-0.000	0.456	-0.121	-0.577***
	(1.000)	(0.847)	(1.003)	(0.024)
Social	0.000	0.212	-0.056	-0.268***
	1.000	0.886	1.021	0.024
Pre-COVID Mental Health	-1.085	-0.026	-1.494	-1.468***
	(1.218)	(0.971)	(1.044)	(0.026)
Observations	10,316	2,161	8,155	10,316

Note: Table 1.13 shows the before-COVID characteristics of the response and non-response samples. Column (4) shows the difference between the two samples. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Compared with the non-response sample, the response sample score higher in cognitive and social tests. They are also less likely to be female, have children, have a partner, be in a bad financial situation, or have a high aggregated before COVID mental health deterioration score. All these characteristics could potentially help the response sample to cope better with WFH, leading to a lower negative mental health effect of WFH when focusing exclusively on this group.

1.9.3 Test Two Factor Assumption

A concern of the model is that there are other unobserved elements that possibly correlate with sorting and mental health, for example, resilience. To address this concern, I provide the goodness of fit of the model. If the model is misspecified, then the simulated values will not match the observed values.

Table 3.10 displays the model fit. Column (1) shows the mean values from the observed data, Column (2) shows the mean values from the simulated data based on the model estimated parameters, and Column (3) shows the p-values from the two samples mean test. From the p-value across all outcomes, the null hypothesis fails to be rejected, meaning that the simulated mean values fit well with the observed sample mean values. This result assures that the two-factor model does not leave out confounding unobserved factors. One plausible explanation is that emotional regulation at a young age may already capture other non-cognitive dimensions that are relevant for sorting into different work arrangements and mental health.

Table 1.14: Latent Model: Goodness of Fit

	Data Mean Values (1)	Simulated Mean Values (2)	H0: Data = Simulated (p-value) (3)
Aggregated Mental Health Deterioration			
Unconditional	-0.000	-0.000	0.508
Conditional on Labor Market Choice			
WFH	-0.014	-0.015	0.509
WP	-0.051	-0.050	0.487
NW	0.251	0.246	0.524
Loneliness			
Unconditional	-0.000	0.000	0.494
Conditional on Labor Market Choice			
WFH	0.009	0.011	0.484
WP	-0.069	-0.069	0.497
NW	0.194	0.190	0.524
Depression			
Unconditional	-0.000	-0.000	0.504
Conditional on Labor Market Choice			
WFH	-0.026	-0.026	0.506
WP	-0.009	-0.009	0.502
NW	0.163	0.164	0.497
Life Satisfaction			
Unconditional	0.000	0.000	0.506
Conditional on Labor Market Choice			
WFH	0.017	0.016	0.515
WP	0.045	0.045	0.492
NW	-0.244	-0.243	0.498

Note: Table 3.10 reports the sample means from the data, from the simulated data, and the p-values of two means test. Unconditional mean is defined as $E[H_i]$. Conditional means for WFH, WP, and NW are defined as $E[H_i|k = \text{WFH}]$, $E[H_i|k = \text{WP}]$, and $E[H_i|k = \text{NW}]$, respectively. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

1.9.4 Decomposition of the Observed Outcomes

The effects of WFH can also be defined by the treatment on the treated, which is the treatment effects of WFH among those who actually worked from home. The TT is defined as in equation (1.13). To compare the ATE with the TT, from Column (1) to Column (4), Table 1.15 shows the results from the TT. In all outcomes, the TT shows better mental health effects of WFH. Specifically, in column (1), WFH induces a decrease in overall mental well-being by 0.073 standard deviations compared to WP. This decline is smaller than the baseline adverse effect of 0.087 standard deviation. On the other hand, when compared to NW, WFH enhances overall mental health by 0.225 standard deviation, surpassing the baseline effect of 0.174 standard deviation. Therefore, the results here provide evidence that there exist sorting gains on mental health in the sorting process of work arrangements.

$$TT = \mathbf{E}[H_{i,d=\text{WFH}} - H_{i,d=\bar{k}} | D_i = \text{WFH}] \tag{1.13}$$

Table 1.15: Latent Model: Effects of WFH on Mental Health For the Treated

	Mental Health Aggregated Deterioration	Loneliness	Depression	Life Satisfaction
	(1)	(2)	(3)	(4)
	TT	TT	TT	TT
WFH - WP	0.073*	0.124***	0.049	-0.055
	(0.045)	(0.050)	(0.039)	(0.046)
WFH - NW	-0.225***	-0.205***	-0.030	0.234***
	(0.082)	(0.087)	(0.078)	(0.087)

Note: Table 1.15 shows the effects of WFH on mental health relative to NW or WP for only those WFH. The ATT is calculated based on equation (1.13). The full list of variables in the potential outcomes is in Table (A.4). Standard errors are in parenthesis. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Besides the sorting gains, the observed difference can mask other sources of biases. A formal decomposition of the observed difference unfolds what observational data can or cannot explain about the link between WFH and mental health outcomes. Table 1.16 shows the results of decomposing the observed difference in mental health outcomes using the following approach:

$$\begin{aligned}\underbrace{\mathbf{E}[H_i|D_i = \text{WFH}] - \mathbf{E}[H_i|D_i = \bar{k}]}_{\text{Observed Difference}} &= \underbrace{\mathbf{E}[H_{i,d=\text{WFH}} - H_{i,d=\bar{k}}]}_{\text{ATE}_{\text{WFH},\bar{k}}} \\ &+ \underbrace{\mathbf{E}[H_{i,d=\text{WFH}} - H_{i,d=\bar{k}}|D_i = \text{WFH}] - \mathbf{E}[H_{i,d=\text{WFH}} - H_{i,d=\bar{k}}]}_{\text{Sorting on Gains}} \\ &+ \underbrace{\mathbf{E}[H_{i,d=\text{WFH}}|D_i = \text{WFH}] - \mathbf{E}[H_{i,d=\bar{k}}|D_i = \bar{k}]}_{\text{Selection Bias}} \qquad (1.14)\end{aligned}$$

Across outcomes, when comparing WFH with WP, the impact of selection based on observable characteristics is less significant. In column (4), the bias from selection on observables only constitutes 0.007 standard deviation in overall mental health. However, in column (5), the bias resulting from the selection on unobserved abilities contributes 0.057 standard deviation to overall mental health changes, indicating its greater importance in explaining the mental health effect of WFH. Different from the comparison between WFH and WP, when comparing WFH with NW, the sorting on gains provides a better explanation for the effect on mental health from WFH. In column (3), sorting on gains results in a 0.05 stand deviation in the change of overall mental health, and bias from selection on observables contributes a 0.029 standard deviation. Putting together, the decomposition suggests that while observable characteristics are important, they alone cannot fully account for the variations in mental health changes among different work arrangement options.

Table 1.16: Latent Model: Observed Difference in Mental Health Decomposition

	WFH - WP				
	Observed Difference (1)	ATE (2)	Sorting on Gains (3)	Selection Bias Observables (4)	Selection Bias Unobs. Abilities (5)
Mental Health Aggregated Deterioration	0.038	0.087**	-0.014	0.007	0.057*
	(0.045)	(0.042)	(0.018)	(0.048)	(0.031)
Loneliness	0.078*	0.118***	0.006	-0.0116	0.083***
	(0.046)	(0.047)	(0.019)	(0.051)	(0.031)
Depression	-0.017	0.052	-0.003	-0.014	0.027
	(0.045)	(0.037)	(0.015)	(0.044)	(0.027)
Life Satisfaction	-0.027	-0.070	0.015	-0.019	-0.039
	(0.045)	(0.044)	(0.018)	(0.050)	(0.032)
	WFH - NW				
	Observed Difference (1)	ATE (2)	Sorting on Gains (3)	Selection Bias Observables (4)	Selection Bias Unobs. Abilities (5)
Mental Health Aggregated Deterioration	-0.265***	-0.175***	-0.050*	-0.029	0.005
	(0.079)	(0.077)	(0.026)	(0.023)	(0.010)
Loneliness	-0.185***	-0.158**	-0.047*	-0.043	0.004
	(0.075)	(0.081)	(0.028)	(0.025)	(0.011)
Depression	-0.189***	0.003	-0.033	-0.185***	-0.001
	(0.077)	(0.071)	(0.025)	(0.021)	(0.009)
Life Satisfaction	0.260***	0.260***	0.029	0.002	-0.004
	(0.081)	(0.083)	(0.025)	(0.024)	(0.011)

Note: Table 1.16 reports the decomposition of the observed difference in mental health, following equation (1.14). Standard errors are in parenthesis. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

1.10 Conclusion

The COVID-19 pandemic created an incentive for workers and employers to experiment with new ways of working, departing from the usual dichotomy of either being in the workplace or not working at all, to a new option of WFH. Since 2022, the number of infections has been on a downward trend, and the general population slowly returned to normality with the World Health Organization announcing the end of COVID-19 as a public health emergency. However, the pandemic demonstrated that many jobs can be effectively performed remotely, challenging the traditional notion that certain roles require a physical presence. Compared to pre-2020, this adaptability has led to a broader acceptance of remote work possibilities across industries.

Despite this crucial shift due to the pandemic, little has been learned about the extent to which each work arrangement option affected the workers' mental health during this uniquely challenging time. My paper shows that WFH appears as a contributing factor to the surge in mental health deterioration in the initial months of the pandemic. I show that the impact of WFH on mental health is contingent on the specific alternative option considered, highlighting the importance of different counterfactuals used in analyzing the mental health effects of WFH in this context. Secondly, cognitive and social abilities emerge as significant factors in explaining the variations in these effects. While the effects of WFH during the pandemic can hardly be extrapolated to the current model of WFH, the variation in the treatment effects across cognitive and social abilities shows the importance of these two dimensions in analyzing the relationship between workplace arrangements and mental health. Lastly, while increases in cognitive and social abilities can yield benefits, these advantages are nuanced and apply differently to distinct groups within the workforce. Although WFH during the pandemic differs significantly from

WFH nowadays, understanding the mental health effect of WFH at its inception can provide a framework for future work on WFH.

Chapter 2: Affirmative Action, Education and Labor Market Outcomes in Vietnam

2.1 Introduction

The term “affirmative action” was first coined in the United States in 1961, but the concept of using government intervention to promote equality has a global history (Sowell 2004)[1] [2]. Despite its widespread adoption as a policy tool to promote equality and address historical disadvantages, affirmative action, especially in education, has long been a subject of controversy. Supporters argue that affirmative action policies in education are a necessary step towards rectifying systemic discrimination and ensuring equal opportunities for marginalized groups (Chan and Eyster 2003; Fryer Jr, G. Loury, and Yuret 2003; Ellison and Pathak 2021; Akhtari, Bau, and Laliberté 2020). In contrast, critics contend that affirmative action policies can perpetuate discrimination, create reverse bias, and undermine meritocracy (Evans 2003; Sander 2004; Ferman and Assunção 2005; Grau 2018). For instance, in the United States, the controversy surround-

[1] The term ”affirmative action” was first coined in 1961 by Hobart Taylor Jr., an African American governmental official and civil rights attorney who was working on President John F. Kennedy’s Committee on Equal Employment Opportunity (Richardson, Ralph, 2014, p.436). Kennedy issued Executive Order 10925, which required federal contractors to take ”affirmative action to ensure that applicants are treated equally without regard to race, color, religion, sex, or national origin.” (Sowell 2004, p.124)

[2] In India, affirmative action policies have been implemented to combat historical discrimination against lower castes. Similarly, in South Africa, affirmative action was used to address the legacy of apartheid. Brazil has employed affirmative action policies to tackle the historical impact of slavery, while Malaysia has utilized such policies to address the effects of British colonialism that favored the Malay majority over other ethnic groups

ing affirmative action emerged in the early 1970s when universities started considering race as a factor in admissions decisions [3]. These debates recently reached a pinnacle with the Supreme Court's decision to terminate nearly five decades of affirmative action jurisprudence in college admissions. Therefore, understanding the impact of affirmative action policies in the education space is crucial as they navigate a landscape of historical debates, global adoption, and varying perspectives, shaping policies that strive for equality and addressing past inequities.

More importantly, beyond assessing the immediate impact of education affirmative action policies on education itself, it is also important to examine its long-term effects on the labor market and whether it is a temporary or permanent solution. This is essential for understanding the ongoing debate over the policy's short-term implementation. For example, if affirmative action increases graduation rates for historically marginalized groups but does not improve their job prospects, its effectiveness may be questioned. Additionally, studying the long-term effects of affirmative action can reveal any unintended consequences, such as resentment and backlash against non-beneficiaries who are overlooked for school admissions.

In this paper, I evaluate the impact of an ethnicity-based affirmative action policy in Vietnam on the educational and labor market outcomes of ethnic minority individuals. Specifically, I take advantage of a policy change that enabled ethnic minority students to secure direct admission to high school without the need to take a high-stakes entrance exam. The primary objective of this policy was to narrow the historical education gap between ethnic minorities and the majority Kinh population. For example, in 1990, the General Statistics Office of Vietnam reported an illiteracy rate of 21.4% among ethnic minorities, contrasting with 5.1% for the Kinh population.

[3] In 1978, the Supreme Court ruled in the case of Regents of the University of California v. Bakke that race could be considered as one factor in admissions decisions, but that it could not be the sole factor. In 1996, California voters passed Proposition 209, which prohibited the state from considering race or ethnicity in public employment, education, or contracting.

Moreover, ethnic minorities had an average of 4.9 years of schooling, compared to 7.7 years for the Kinh population.

Enacted in 1997 and effective in 1998, the policy expanded the scope of ethnicity-based affirmative action. It allowed minority students to gain direct admission to high school based on their final-year middle school GPA, eliminating the need for the national high school entrance exam. These exams, deemed high-stakes, played a pivotal role in determining access to high school and subsequent educational levels. They necessitated extensive preparation and were associated with high levels of stress, occasionally leading to extreme cases such as suicidal attempts (Truc et al. 2015) [4].

I first evaluate whether the policy achieves its primary goal of increasing the representation of ethnic minorities in high school. To account for the overall growing trend in educational attainment in Vietnam, I employ a difference-in-differences approach to estimate the policy's impact on the probability of entering high school for ethnic minority students relative to ethnic majority students, the Kinh majority. Specifically, I use the joint variation of the student's ethnicity and birth year as the exogenous exposure to the policy. Ethnic minority students born beginning in 1983 would reach the age of being eligible for taking the entrance exam in 1998, therefore, they are affected by the policy. Ethnic minority students born before 1983 as well as the Kinh majority, born across all years are not affected. The assumption underlying the identification is that conditional on the controls, changes in the outcomes for the minorities and the Kinh majority would have been the same without the policy intervention. I show that the policy directly affects the probability of entering high school for ethnic minority students born in and after 1983. In

[4] See: https://tuoitrenews.vn/news/education/20180508/vietnamese-schoolgirl-supposedly-commits-suicide-over-poor-exam-results/45506.html

my preferred specification, which includes school district fixed effects, regional trends, and the school supply in addition to a rich set of individual controls, the policy increases the probability of entering high school for the affected ethnic minority students by 1.5 percentage points off a baseline of 18.3. A further investigation shows that these positive results in educational outcomes are driven by ethnic minority students who have strong academic potential. These are ethnic minorities who continue to finish high school, enroll in college, and subsequently earn their college degrees.

Next, in examining the policy's long-term impact, I analyze a comprehensive array of labor market results for students influenced by the policy to pursue high school education. I instrument for the effect of entering high school induced by the policy with the exogenous exposure to the policy, coming from the joint variation of the student's ethnicity and birth year. In this instrumental variable framework, the assumption is that the policy affects other long-term outcomes only through its effect on high school entrance for ethnic minority students, and not through other channels. The results show that students from ethnic minorities prompted by the policy to pursue high school education exhibit a 21.6 percentage point increase in labor force participation, a 33.2 percentage point increase in employment rates, and a 27.5 percentage point increase in holding salaried positions, conditional on being employed. Collectively, these findings indicate that while the primary focus of the policy was to enhance educational outcomes for ethnic minorities, its long-term effects have extended to the labor market. Furthermore, using task-based occupational data for students, I provide evidence that these labor market outcomes are likely influenced by the human capital channel rather than the education signaling channel. Additionally, I rule out the possibility that these results are affected by any unfavorable views toward ethnic minorities in the labor market resulting from the policy.

Throughout the analysis, I conduct an event study on the outcomes of interest to assess the parallel trend assumption of the difference-in-differences model. In all cases, prior to the policy change, there are no systematic breaks in the pre-trend outcomes between the ethnic minority and the Kinh majority students. Additionally, to evaluate whether exclusion restriction of the policy exposure as an instrument holds, I conduct a zero-first-stage test. The result of the test shows that in the sub-sample where there is no first stage effect, there is also no reduced form effect. This provides confidence for the instrument. To further examine the validity of the identification assumption, I conduct a series of sample robustness checks, and the main results hold up to different sample restrictions.

Lastly, to check if there exist alternative shocks that are specific to a student's ethnicity rather than the policy itself, I leverage the similar ethnic composition in Cambodia to conduct a placebo test that compares the outcomes of the Kinh and other ethnic groups in Cambodia, where there was no admission policy change. I carry out the placebo tests on different sample restrictions to ensure the similarity of the two countries. In all the placebo tests, there are no differences in terms of education outcomes for the cohorts born before 1983 as well as the cohorts born after. There are also no differences in any other long-term outcomes.

My paper contributes to the current debates about affirmative action policy in two main ways. First, my paper is one of the few that evaluates an affirmative action policy in education at the national level [5]. Although there exists a wealth of literature about affirmative action policies in education, the majority of these studies focus on affirmative action at an elite's college admissions (Arcidiacono 2005; Bertrand, Hanna, and Mullainathan 2010; Cestau, Epple, and Sieg 2017;

[5] Mello 2022 and Mello 2023 focus on an affirmative action policy at the national level in Brazil. However, this policy aims at targeting low-SES students, instead of focusing on race or ethnic dimension.

Ellison and Pathak 2021; Barrow, Sartain, and De la Torre 2020; Bagde, Epple, and Taylor 2016; Akhtari, Bau, and Laliberté 2020), with a few papers focusing on a broader scope at the US state level (Card and Krueger 2005; Arcidiacono et al. 2014; Bleemer 2023). This means that the scope and goals of these studies are different. They are more likely to focus on the diverse presence of the school's student body, and hardly do they address a broader question of whether affirmative action policies can close some development gaps at the national scale. Moreover, while cumulative evidence at the college level shows that affirmative action policies succeed in increasing the representation of the minority groups, the compliers groups being affected by affirmative action policies at the college level are very different, which means that these policies may not work at the national level. At the college level, the compliers group is composed of more selective individuals in terms of academic quality, and the returns to college for this selective group are higher than at the national level. At the national level, the affected groups are likely to have higher psychic costs and lower returns in education.

A second contribution of the paper is to evaluate the link between education affirmative action policies and their long-term labor market outcomes. While there exists a strand of literature that focuses on the impact of affirmative action policies in the labor market (Holzer and Neumark 1999; Marion 2017; Miller 2017; Subedi, Rafiq, and Ulker 2022), due to data limitations, most studies on affirmative action policies at the college level do not look into the long-term effect of these policies. Therefore, the long-term impact of these policies on the labor market remains largely unexplored. As for the scant evidence on education affirmative action policies on the labor market outcomes, the results are mixed. While some papers highlight the positive lasting effects (Arcidiacono 2005; Herskovic and Ramos 2017; Bleemer 2023), others show the opposite (L. D. Loury and Garman 1993; Frisancho and Krishna 2016). Exploring whether affirmative action in education has lasting impacts or serves as a temporary solution can provide valuable insights into the ongoing debate surrounding the short-term implementation of the policy.

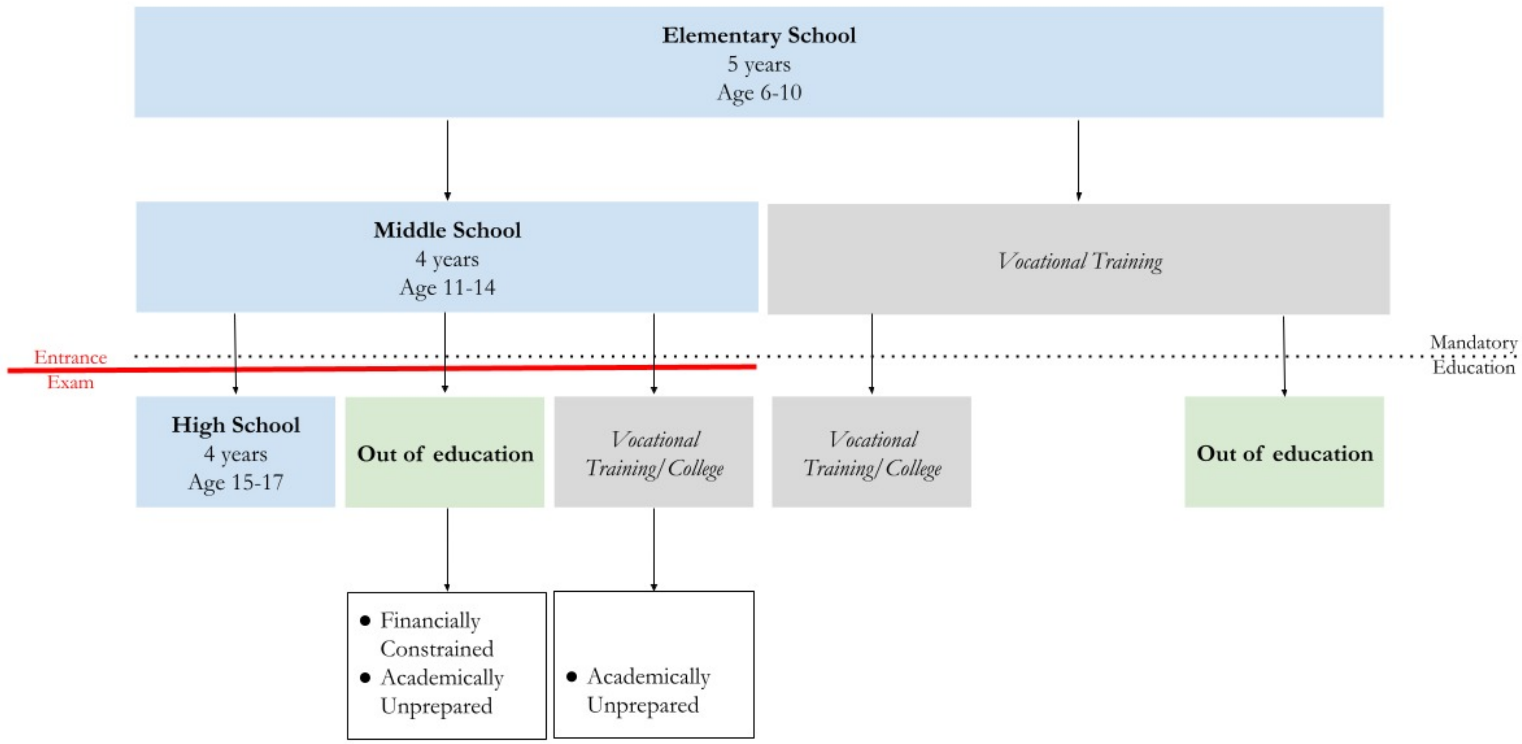
The paper is organized as follows. Section 2 provides some background on the general education system, labor market in Vietnam and contextual information about the policy change. Section 3 discusses the conceptual framework. Section 4 describes the data. Section 5 discusses the empirical strategies. Section 6 discusses the results on education, while Section 7 shows the results on labor market outcomes. Section 8 focuses on the heterogeneous effects of the policy. Section 9 shows the robustness checks and the placebo tests. Section 10 discusses policy implications. Section 11 concludes.

2.2 Context

2.2.1 The Education System in Vietnam

The Vietnamese education system is under the supervision of the Ministry of Education and Training (MoET). Education is structured in five cycles: preschool, primary school (grades 1-5), middle school (grades 6-9), high school (grades 10-12), and university. In 1991, compulsory education was established for children ages six to 14. The first level of mandatory education is primary school with an intended age group between six and 11 years old. In middle school, students have the option to enroll in either secondary education or vocational training. Only students entering secondary education are eligible for higher education admission, whereas vocational training is intended as an ending educational cycle lasting one to three years (Duggan 2001). Figure 2.1 summarizes the education system in Vietnam.

Figure 2.1: Structure of Education System in Vietnam



Note: Figure 2.1 summarizes the education structure in Vietnam

Throughout the educational system, advancement is determined by high-stakes exams. Specifically, to enter high school (upper secondary school), students aged fifteen to seventeen who complete middle school (the lower secondary cycle) are required to take a national high school entrance exam. The exam tests students' knowledge of mathematics and Vietnamese literature. A student's total score on the exam is used to determine whether and to which school the student can enroll for the high school level [6]. Several factors explain the pivotal role of this exam in the education system and the pressure that comes along with it. First, only students who perform well on this exam are eligible to enter high school, and consequently potentially continue to university. The economic incentive to pursue further education comes from the association between a degree in a higher education level and better economic opportunities. Second, Confucian culture coupled with limited access to education during the French colonial period have led to a social norm where educational advancement conveys status (H.-A. Dang 2008; H.-A. Dang 2013).

2.2.2 An Admission Policy Change in 1998

Vietnam is an ethnically diverse country with 54 ethnic groups. The majority group is called the Kinh majority, they constitute about 80% of the country's population. Other ethnic groups are considered as ethnic minorities. One of the major gaps that exist between the Kinh majority and other ethnic groups is the levels of educational attainment. For example, at the primary level, in 1992-1993, the net enrollment of the Kinh majority was about 30 percentage points higher than that of the ethnic minority. At the middle school level, the gap was about 15 percentage points,

[6] A similar examination is required for students to graduate from elementary school and enroll in the lower secondary level. However, since May 2004 this has been transitioned from a national exam into individual middle school admission tests.

and at the high school level, the gap was about 10 percentage points (H.-A. H. Dang and Glewwe 2018). Among the many reasons that could explain this gap, the literature has often pointed to the predominance of minorities in rural areas (89.6% against 66.1% of Kinh), the lower income among the minorities (41.4% lower than Kinh), a higher rate of poor households among the minorities (3.3 times higher than the national average), language barriers, discriminatory attitudes as well as lower perceived value for formal education (Thuy 2001; London 2011; DeJaeghere, Vu Dao, and Duong 2021).

Aiming at closing the ethnic-based educational gap, in November 1997, the MoET passed a law that changed the national admission policy to enter high school for ethnic minority students nationwide. Under this policy change, ethnic minority students aged fifteen to seventeen who achieve a grade of "average" in their last year of middle school [7] are exempted from taking the high school entrance exam and are granted direct admission to a high school of their choice within their school district. The policy became effective in 1998, which affects admission to high school for students who were born in 1983 onward.

Importantly, this policy was passed in the period when Vietnam experienced some major expansions in education. From 1994 to 2002, the percentage of expenditures in education in total GDP grew from 3.5% of GDP to 4.2% of GDP (Bank 2005). Between 2000 and 2006, the number of schools increased by 13.5%, from 33,300 to 37,800, with the largest proportional increase (46.2%) in high schools which registered an increase of 46.2% (Statistics (UIS) 2021). As a result, enrollments also increased, from 1 million students in 1995 to 3 million students in 2005. These expansions suggest that there is no significant capacity constraint at the national level. Consequently, it is unlikely that the affirmative action policy resulted in ethnic minorities

[7] Equivalent to a grade B in the US grading system.

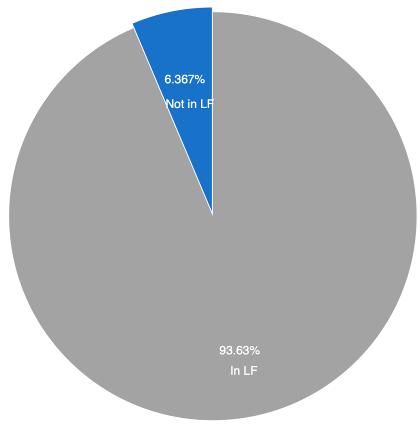
displacing the Kinh majority.

2.2.3 Labor Market in Vietnam

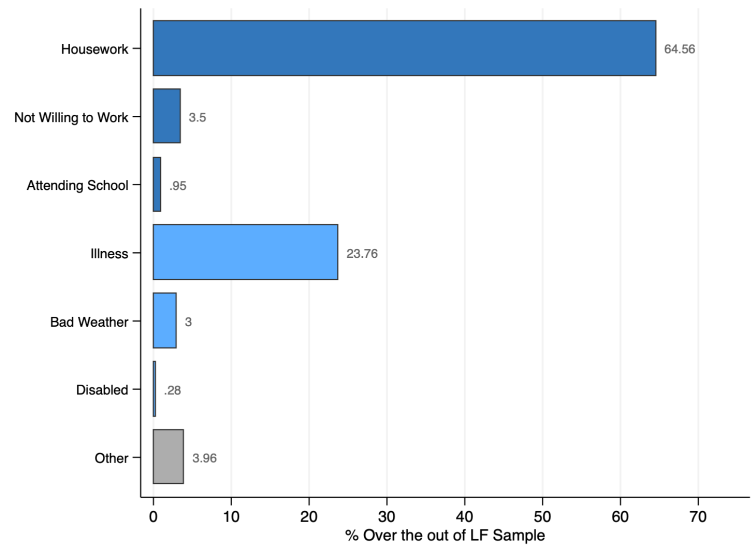
Considering the labor market conditions in Vietnam during this period, there are two significant aspects where the policy can have long-term effects. First, regarding labor force participation, despite a relatively low percentage of individuals not participating in the labor force, approximately 6% among cohorts born between 1976 and 1988, a considerable proportion within this group actively chooses to withdraw from the labor market. Notably, the primary reason for their non-participation is engaging in household chores, accounting for 64.56% of those not in the labor force within the 6% mentioned earlier, Figure 2.2. In this context, a push for more schooling can serve as a catalyst to encourage this segment of the population to re-enter the labor force. By providing educational opportunities, individuals can acquire the necessary skills, knowledge, and qualifications to enhance their employability, and expand their career options.

Second, a closer examination of the labor market reveals that among those who do participate, only a small fraction, approximately 10%, are engaged in high-skilled occupations. The majority of workers are concentrated in middle or low-skilled occupations, Figure 2.3. Therefore, an intervention in education has the potential to increase the representation of workers in high-skilled occupations. By providing individuals with the necessary skills and qualifications, there is an opportunity to enhance their employment prospects and enable them to access high-skilled job opportunities in the long run.

Figure 2.2: Percentage of LFP and Reasons for not in the LF for the Cohorts Born Before 1982



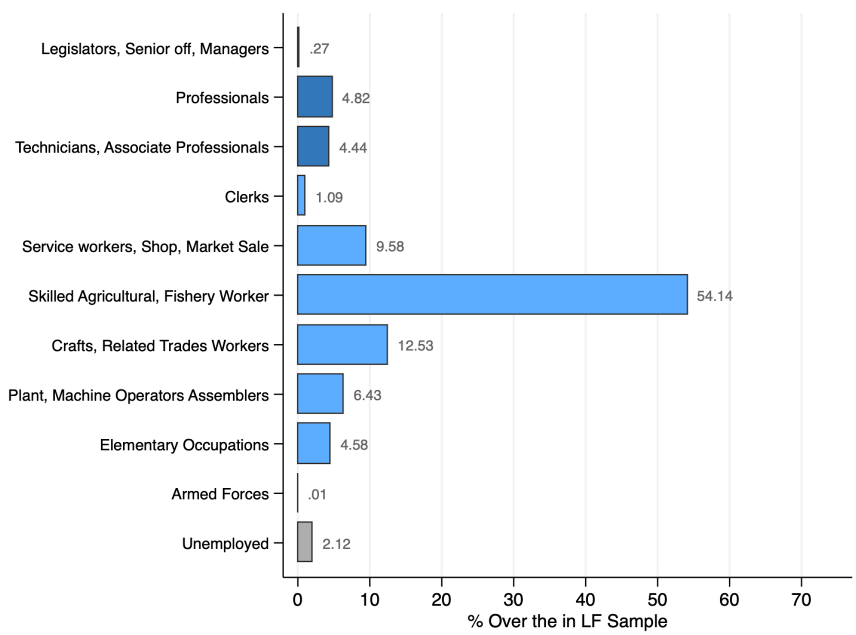
(a) Percentage of LFP



(b) Reasons for not in the labor force

Note: Figure 2.2 shows the percentage of LFP and the reasons for not participating in the labor force for the cohorts born before 1982.

Figure 2.3: Occupation Distribution for Those in the LF



Note: Figure 2.3 shows the occupations distribution for the cohorts born before 1982.

2.3 Conceptual Framework

2.3.1 Short-run Education Effects

Consider education as a means of investment, individuals decide to invest in education when the future returns exceed the present investment costs (Becker 2009). The investment costs can include financial costs such as school fees, opportunity costs such as staying in school instead of earning labor income, and effort costs. In the context of the policy change, for the Kinh majority, neither the future returns nor the investment cost was affected by the policy. Whereas, for the ethnic minorities, due to the policy change, the investment cost in education is reduced. Specifically, this cost comes from the reduction of effort cost. Other investment costs of the ethnic minorities would not be affected since the policy does not provide financial assistance. While the present costs of investing in education are reduced for ethnic minorities, the future returns to education may also be affected in a negative way if there exists discriminatory backlash triggered by the policy.

To formalize the tension of the present investment and future returns caused by the policy, consider a simple two-period framework of investing in high school. In period 1, an individual i inherits some family wealth y_i, consumes c_i^1, saves s_i, and decides whether to attend high school or not, $e_i \in \{0, 1\}$. Let c_i^2 be the consumption in the second period, the individual's utility is given as:

$$U_i = lnc_i^1 + lnc_i^2 \tag{2.1}$$

Individuals are heterogeneous in their skills gaps to continue high school, θ_i. The skills gap is defined as the skills endowed by the individual i and the required skills to enter high school. The larger θ_i, the more costly it is to continue high school. For example, the effort or material costs to increase one's skills in order to reach the required levels for passing the entrance exam to high school. In the second period, skilled individuals, those who attended high school, are employed in high-skilled jobs and receive a salary w_H with the probability $\gamma \in [0, 1]$. γ represents the labor market discriminatory behaviors towards ethnic minorities. If there is no discriminatory friction, $\gamma = 1$, individuals with high skills receive w_H with certainty. Whereas, if to the extreme that discriminatory views prevent highly skilled individuals from obtaining a skilled position, then $\gamma = 0$. This means that even obtaining more education does not help secure better future employment. For individuals who do not attend high school, they receive a salary w_L with certainty.

Suppose there are no credit market problems, so individuals can borrow today and pay the same interest rate r tomorrow. The decision to attend high school is to maximize the utility in equation (2.1) with respect to e_i, c_i^1, and c_i^2 subject to the budget constraint:

$$c_i^1 + \frac{c_i^2}{1+r} \leq \frac{w_L}{1+r} + e_i \frac{\gamma w_H - w_U}{1+r} + y_i - e_i \theta_i \tag{2.2}$$

The solution to the individual is such that the individual decides to invest in high school only if the following condition is satisfied:

$$\theta_i \leq \frac{\gamma w_H - w_L}{1+r} \tag{2.3}$$

The decision rule in equation (2.3) has two important implications in this context. First, a greater skill premium as captured by $(\gamma w_H - w_L)$ will increase the likelihood of attending high school. Second, a higher skill gap θ_i reduces the likelihood of attending high school. For the Kinh majority, neither of these two components is affected by the policy change. Whereas, for ethnic minorities, both of these components are affected.

On the one hand, by exempting ethnic minorities from the high school entrance exam, the policy reduces the skill gap required to enter high school. This, in turn, reduces the cost of investing in high school, and increases the likelihood of entering high school. On the other hand, the policy may cause some negative views about ethnic minorities to be worsen, for example, the credibility of the individual's high school attainment. Thus, for an ethnic minority affected by the policy, born after 1983, the decision to enter high school becomes:

$$\theta_i - k \leq \frac{(\gamma - q)w_H - w_L}{1 + r} \tag{2.4}$$

Compared to the Kinh majority born in all years, and the ethnic minorities in the old cohort, the ethnic minority born in the young cohort will decide to enter high school when the benefit from the policy, k, is higher than the future cost q.

2.3.2 Long-run Effects in the Labor Market

There are three potential channels through which the policy may impact the long-run outcomes of ethnic minority students. While the first two relate to the values of education, either through human capital accumulation or signaling, the last channel links to unfavorable views toward ethnic minorities.

2.3.2.1 Human Capital Accumulation

One of the primary ways in which education affects labor market outcomes is through the direct accumulation of human capital. In the context of the affirmative action policy, the removal of the entrance exam requirement for education can have significant effects on ethnic minorities. By eliminating this requirement, the policy reduces the costs associated with investing in education for ethnic minorities, including both effort and material costs. As a result, the policy encourages higher levels of human capital investment among ethnic minorities. This increased investment in education narrows the skill gaps between ethnic minority groups and the Kinh majority. Consequently, the marginal product of labor, which measures the additional output generated by each additional unit of labor input, becomes more comparable between the two groups.

The narrowing of the marginal product of labor has positive implications for labor market outcomes. With increased human capital investment, ethnic minorities experience better labor market prospects, such as an increased likelihood of employment and a higher probability of securing high-skilled occupations. In essence, the policy's impact operates through the first channel mentioned above, resulting in long-term improvements in labor market outcomes for ethnic minorities relative to the Kinh majority. By lowering the investment costs in education, the policy facilitates greater human capital accumulation, leading to a more equitable and inclusive labor market for ethnic minority groups.

2.3.2.2 Education Signaling

Different from the human capital accumulation channel, suppose that entering high school does not provide students with productive skills. Rather, being admitted to a high school helps send the signal about a student's unobserved skills to a potential employer in the labor market. Before the policy was implemented, low-type students, regardless of their ethnicity, were less likely to enter higher school due to the higher cost of taking the exam. Now with the policy, low-type ethnic minority students face a lower cost of entering high school, leading to a higher likelihood of entering high school. In the labor market, both low-type and high-type ethnic minority students will send the same signal to the potential employer. This can have two opposite consequences on the labor market outcomes of the ethnic minority student, depending on the employer's knowledge about the policy.

In the first scenario, suppose the potential employer is not aware of the policy, then on average, there is an improvement in the labor market outcomes of ethnic minority students. This is because the low-type ethnic minority students also send a good signal in the labor market, leading to better labor market outcomes for them. Without knowing the type of ethnic minorities, on average, what can be observed is an improvement in labor market outcomes for ethnic minorities relative to the Kinh majority. In the second scenario, the employer is aware of the policy and presumes that ethnic minorities did not receive qualified training in school, thus they should not be hired. In this case, the average labor market outcomes for ethnic minorities across types would be worse off compared to the Kinh majority.

Overall, if education signaling is the main mechanism, then the policy effect is ambiguous, depending on the employer's knowledge about the policy. An important aspect that makes this mechanism of education signaling work in Vietnam is that while entering high school is a difficult barrier to continuing education, graduating from high school is a less challenging step. Therefore, being admitted to high school sends a more informative signal about an individual's type than finishing high school.

2.3.2.3 Labor Market Unfavorable Views Toward Ethnic Minorities

In addition to its educational effects, the policy may have a significant impact on long-term labor market outcomes through the lens of negative views against ethnic minorities. One potential consequence is that the policy could intensify prejudice against hiring ethnic minorities if employers perceive it as unfair within the educational context. If such a perception exists, it could lead to negative repercussions for the labor market outcomes of ethnic minorities.

If employers hold the belief that the policy grants preferential treatment to ethnic minorities in education, they may develop a sense of unfairness or resentment. This perception could be rooted in the belief that ethnic minorities are gaining advantages over other candidates solely based on their ethnicity, rather than on merit or qualifications. Consequently, employers may develop a bias against hiring ethnic minorities, resulting in discriminatory practices during the selection and hiring processes. As a result, the labor market outcomes for ethnic minorities could be adversely affected. They may face reduced opportunities, lower chances of being employed, or limited access to higher-skilled positions compared to the majority population.

2.4 Data

I bring together several sources of data. The main dataset is from the census extracted from IPUMS International (Ruggles et al. 2009). This dataset provides key variables for the analysis, including the student's ethnicity, birth year, and some characteristics of the student and his or her household. In addition to the census, to shed light on the education mechanism on labor market outcomes, I use task-based information at the occupation level from STEP, and diversity view information from the World Value Survey. Throughout different specifications, to control the supply side of education. I constructed a dataset of the number of schools for every district in Vietnam for each year. The details of the datasets are as below.

2.4.1 IPUMS Census

In this paper, for the main analysis, I use the census micro-data from the Integrated Public Use Micro-data Series (IPUMS) - International for Vietnam. The data represent 15% of the Population and Housing Census (2009) administered by the General Statistics Office in Vietnam. Three major sample restrictions are imposed to obtain the final analytical sample. First, I restrict the sample to include only individuals who were born between 1976 and 1988. This ensures that everyone in the sample was born after the reunification in 1975 and is old enough to have completed their high school education by the time of the survey year. Second, I exclude individuals who are not in the general education system due to disability or illiteracy. Finally, I exclude individuals whose district of residence changed over the past five years. This restriction is motivated by the fact that school districts, which overlap with residence districts (London 2011), are an important determinant of educational attainment (H.-A. H. Dang and Glewwe 2018).

Table 2.1 shows the mean and standard deviation of the analytical sample. After the sample restrictions mentioned above, the sample includes 2,660,938 observations. Ethnic minorities constitute 13.6% of the sample. 27.2% of the sample enters high school. Fewer ethnic minorities enter high school than the Kinh majority (17.8% versus 28.7%). Regarding the long-term labor market outcomes, although ethnic minorities have a higher rate of labor force participation and employment, they have lower rates of holding salaried positions (16.2% of ethnic minorities and 38.3% of Kinh).

Table 2.1: Descriptive Statistics

	Full Sample		Kinh Majority		Ethnic Minorities	
	Mean	SD	Mean	SD	Mean	SD
Ethnic Minorities	0.136	0.343	-	-	-	-
Outcomes						
Entering High School	0.272	0.445	0.287	0.452	0.178	0.382
LFP	0.922	0.269	0.915	0.279	0.963	0.189
Employed	0.900	0.300	0.892	0.311	0.954	0.210
Salaried Workers	0.353	0.478	0.383	0.486	0.162	0.368
Individual Characteristics						
Female	0.491	0.500	0.498	0.500	0.449	0.497
Religious	0.178	0.382	0.181	0.385	0.154	0.361
Marital Status						
Single	0.311	0.463	0.318	0.466	0.263	0.440
Married	0.671	0.470	0.663	0.473	0.720	0.449
Separated	0.013	0.113	0.013	0.115	0.011	0.102
Widowed	0.005	0.072	0.005	0.070	0.006	0.079
HH Characteristics						
HH Size	4.556	1.793	4.499	1.761	4.914	1.944
Nb. Females in HH	2.270	1.204	2.240	1.189	2.460	1.285
Female HH head	0.217	0.412	0.230	0.421	0.138	0.345
Home Ownership	0.954	0.210	0.950	0.218	0.975	0.155
Nb. Appliances	2.120	1.385	2.214	1.404	1.526	1.087
Electricity	0.028	0.164	0.015	0.123	0.106	0.308
Indoors Tap Water Status	3.884	2.400	3.744	2.442	4.771	1.880
Wall Material						
Brick, Stone, Concrete	0.730	0.444	0.788	0.408	0.363	0.481
Concrete	0.009	0.092	0.009	0.096	0.004	0.060
Wood, Earth Adobe	0.056	0.230	0.034	0.182	0.196	0.397
Netted Bamboo	0.029	0.168	0.017	0.130	0.106	0.308
Mixed Material	0.106	0.308	0.082	0.275	0.257	0.437
Other	0.069	0.254	0.068	0.253	0.075	0.263
Roof Material						
Concrete, Cement	0.149	0.356	0.165	0.371	0.046	0.210
Reinforced Concrete	0.461	0.498	0.462	0.499	0.451	0.498
Tile	0.331	0.470	0.328	0.469	0.348	0.476
Cane, Wood, Straw	0.058	0.234	0.044	0.204	0.150	0.357
Other	0.002	0.040	0.001	0.034	0.004	0.067
Urban Status	5.182	1.580	5.098	1.640	5.714	0.970

Note: Table 2.1 shows the mean and standard deviation of the overall sample and by ethnic groups. The analytical sample includes 2,660,938 individuals. Survey weights are applied.

2.4.2 Supplementary Data

2.4.2.1 STEP

The STEP Skills Measurement Program is a World Bank initiative designed to offer policy-relevant low and middle-income countries data aimed at understanding skill demands within the labor market, the methods by which skills are attained, and the connections between skills and economic results. This program encompasses household and employer surveys, gathering data on a wide array of skills, including reading proficiency, personality, behavior, time and risk preferences, and job-relevant competencies.

In the analysis of mechanisms, I use information about the intensity of communication tasks, analytical tasks, physical tasks, and routine tasks bundled in an occupation. I also use information about the spread of cognitive skills and social skills measured by the standard deviation of an occupation.

2.4.2.2 World Value Survey

The World Values Survey (WVS) is a comprehensive global research endeavor focused on investigating the values and beliefs held by individuals, how these values evolve over time, and the resulting social and political implications. Conducted in nearly 100 countries since its inception in 1981, the WVS yields valuable insights that inform the decisions of policymakers, scholars, and various stakeholders. These findings are instrumental in tackling pressing global issues like inequality, climate change, diversity, discrimination, and family and political instability.

In order to understand whether discriminatory view affects the labor market outcomes of ethnic minorities, I use information about diversity views at the provincial level.

2.4.2.3 Scraped Data on School Construction

To control the supply side of education, I constructed a dataset of the number of schools for every district in Vietnam for each year. To construct this dataset, I scraped local online newspapers, and major websites of school rankings to identify the district and the founding year of each high school. Appendix C describes in detail the procedure to collect this dataset.

2.5 Empirical Model

2.5.1 Difference-in-Differences

To evaluate the effects of the policy change in 1998 on the probability of entering high school for ethnic minority students, I employ a difference-in-differences (DID) approach that is similar to the identification in La Ferrara and Milazzo 2017. Specifically, I compare the outcomes of ethnic minority and Kinh majority students who were born before and after 1983. Unlike students from the ethnic minority, the Kinh majority students are not affected by the policy change. Variation in the education outcomes from the Kinh majority mainly helps to isolate the overall growth rate of high school enrollment from the policy effect. The underlying assumption of this DID approach implies that the trends in the outcomes for students born before 1983, thus exceeding the age of taking the high school entrance exams, are similar between ethnic minority students and the Kinh majority students. The estimating equation is:

$$E_{itd} = \beta_0 + \beta_1(\text{Minority}_i \times \text{Post}_{it}) + \beta_2\text{Minority}_i + \beta_3\text{Post}_{it} + \beta_4\mathbf{X}_{itd} + \beta_5(\mathbf{X}_{itd} \times \text{Post}_{it}) + \mu_r \times t + \mu_r \times t^2 + \delta_t + \delta_d + \varepsilon_{itd} \quad (2.5)$$

where E_{itd} is the probability of entering or finishing high school for an individual i, born in year t, and living in district d. Minority_i is equal to 1 if the individual belongs to a minority group. Post_{it} is equal to 1 if the individual was born in 1983 or after - The individual is young enough to be exposed to the policy change. $\mathbf{X}_{itd}$ contains the individual and household characteristics at the time of the census survey (2009). These include gender, following a religion or not, marital status, homeownership, number of females in the household, and the overall household size. To account for the differential effects of these controls on education after the policy change, the interactions of these controls, $\mathbf{X}_{itd}$, and the dummy Post_{it} are included. The region-specific linear time trends, $\mu_r \times t$, and quadratic time trends, $\mu_r \times t^2$, are included to account for the macro changes at the regional level that can affect high school outcomes, for example, for example, changes in population, or local poverty level. δ_t is the birth year fixed effects, which capture the cohort-specific effects on the high school outcomes. δ_d is the district of residence fixed effects. Since the districts of residence overlap with the school districts, δ_d also captures the school quality in the district. ε_{itd} is the error term. I estimate equation (2.5) using a linear probability model with survey weights. The standard errors are clustered at the district level. Estimating the model without the survey weights also shows similar results. The policy effect is captured by β_1, which is the coefficient of the interaction between Minority_i and Post_{it}. β_1 is identified under the assumption that conditional on the controls, changes in outcomes for the minorities and the Kinh majority would have been the same without the policy intervention.

To evaluate the validity of the parallel trend assumption, I evaluate an event study specification of equation (2.5). Instead of interacting Minority_i with Post_{it}, I interact Minority_i with a set of birth year dummies as follows:

$$E_{itd} = \beta_0 + \sum_{j=1976}^{1988} \beta_{1j}(\text{Minority}_i \times \text{Year}_{ij}) + \beta_2 \text{Minority}_i + \beta_3 \text{Post}_{it}$$
$$+ \beta_4 \mathbf{X}_{itd} + \beta_5(\mathbf{X}_{itd} \times \text{Post}_{it}) + \mu_r \times t + \mu_r \times t^2 + \delta_t + \delta_d + \varepsilon_{itd} \qquad (2.6)$$

where Year_{ij} is the set of birth year dummies, each of which is equal to one if the individual i is born in year j. The coefficients β_{1j}'s capture the difference in outcomes between the ethnic minority and the Kinh majority students for each birth year cohort. Conditional on the set of of controls, the policy should have no effects on individuals whose age exceeds the age limit to take the exam, that is those who were born before 1983. This implies that for $j < 1983$, β_{1j}'s are hypothesized to be close to zero and statistically insignificant.

2.5.2 Long-Term Outcomes

Since the policy's targeted outcome is high school enrollment, the policy effects on other long-term outcomes are fundamentally triggered by the policy's effect on attending high school. Thus, to investigate whether the policy changes other long-term outcomes, I evaluate the effects of going to high school induced by the policy in an instrumental variable framework. The instrument is the exposure to the policy, which comes from the joint variation between a student's ethnicity and birth year. The system of equations is as follows:

$$\begin{aligned} E_{itd} &= \beta_0 + \beta_1(\text{Minority}_i \times \text{Post}_{it}) + \beta_2\text{Minority}_i + \beta_3\text{Post}_{it} \\ &\quad + \beta_4\mathbf{X}_{itd} + \beta_5(\mathbf{X}_{itd} \times \text{Post}_{it}) + \eta_1\text{exp}_i + \eta_2\text{exp}_i^2 + \mu_r \times t + \mu_r \times t^2 + \delta_d + \delta_t + \varepsilon_{itd} \quad (2.7) \\ Y_{itd} &= \pi_0 + \pi_1\hat{E}_{itd} + \pi_2\text{Minority}_i + \pi_3\text{Post}_{it} \\ &\quad + \pi_4\mathbf{X}_{itd} + \pi_5(\mathbf{X}_{itd} \times \text{Post}_{it}) + \phi_1\text{exp}_i + \phi_2\text{exp}_i^2 + \mu_r \times t + \mu_r \times t^2 + \gamma_d + \gamma_t + \nu_{itd} \quad (2.8) \end{aligned}$$

Equation (2.7) is the first-stage equation, capturing the direct effects of the policy on entering high school as in equation (2.5). The reasons to focus on the probability of entering high school rather than the probability of completing high school are twofold. First, high school enrollment is the primary goal of the policy, and completing high school is an outcome related to starting high school. Second, the probability of entering high school is a more responsive margin relative to the probability of completing high school. Equation (2.8) is the outcome equation. Y_{itd} is the long-term outcome of interest. The probability of entering high school, $\hat{E}_{ijt}$, is instrumented by the exposure to the policy. exp_i and exp_i^2 capture the effects on the long-term outcomes due to the duration of being in the mainstream education system. exp_i is defined as the difference between age and the number of schooling years. All other controls are defined as in equation (2.5). The coefficient of interest is π_1, which captures the effects of entering high school induced by the policy change. The identification relies on the assumption that the policy affects the long-term outcomes only through the policy effects on entering high school, and not through other mechanisms. Since the intended target of the policy is to improve high school outcomes of ethnic minority students, the policy effects on long-term outcomes are unlikely driven by other confounding causes. I estimate the model by 2SLS, using the sample weights, and clustering the standard errors at the district level. The results are robust without using the sample weights.

In terms of long-term labor market outcomes, I consider the probability of participating in the labor market, the probability of being employed, and the probability of holding salaried positions conditional on being employed. All three outcomes can be affected by high school enrollment (Card 1999; Gallipoli, Meghir, and Violante 2005; J. J. Heckman, Stixrud, and Urzua 2006).

A structural approach: The choice of the reduced-form instrumental variable (IV) framework here is intended to tackle the question regarding the labor market outcomes of ethnic minorities students whose high school enrollment is directly influenced by the policy. Another approach to examining the long-term impacts of the policy is to adopt a structural instrumental variable model. However, the breadth of the structural model exceeds the scope of the current question. To illustrate this, consider a Heckman-style latent index model, wherein labor market outcomes are contingent on high school enrollment, denoted as U_i. Specifically, the labor market outcomes can be formulated as follows:

$$Y_i = \alpha + \beta U_i + \varepsilon_i \tag{2.9}$$

In this framework, the decision to enter high school is, in turn, a function of the instrument, Z_i, which is the exposure to the policy ($Ethnicity_i \times Post_{it}$).

$$U_i^* = \pi_0 + \pi_1 Z_i + \eta_i \tag{2.10}$$

The latent utility U_i* represents the difference in net gain from entering high school, versus not entering high school, with the observed high school enrollment equal to:

$$U_i = \begin{cases} 1 & \text{if } U_i^* > 0 \\ 0 & \text{if } U_i^* \leq 0 \end{cases} \tag{2.11}$$

In this context, one of the underlying preferences can be academic motivation, which can be captured by the unobserved component η_i. Such academic motivation determines whether an ethnic minority student born in the younger cohort opts to not enter high school despite exposure to the policy. In particular, individuals with low academic motivation $\eta_i < \pi_0 - \pi_1$ would not enter high school even if they are eligible for the direct admissions (never-takers); individuals with $-\pi_0 - \pi_1 \leq \eta_i < -\pi_0$ (compliers) would enter high schools if they belong to the young cohorts of ethnic minorities; and individuals with $\pi_0 \leq \eta_i$ (alwaystakers) would always enter high school.

Different from the reduced-form approach, the strengths that are commonly found in the structural approach are twofold. First, the structural approach is powerful in providing an *average treatment effect* (ATE) for the population, which can be computed as a weighted average of the *marginal treatment effects* (MTE) (J. J. Heckman and Vytlacil 2005). Whereas, the estimate from the reduced form is restricted to a *local average treatment effect* (LATE). The identification of an ATE is crucial in several contexts, it is nevertheless not informative about an affirmative action policy that affects only the minorities group. The question of interest in this section is to understand the labor market effects for the ethnic minorities students who are triggered by the policy to enter high school. In this sense, the section does not address the broader concern of the labor market effects of high schools on the overall population. Rather, the focus is on the ethnic minorities students who would have not entered high school if it were not for the policy. Therefore, the extrapolation of the LATE through a structural model is not necessary in this context..

Second, based on the choice model, the structural framework provides insights into preferences underlying the choice of taking advantage of the policy (J. J. Heckman and Urzua 2010). An extension of the previous simplified model is when the benefits of high school are not constant. That is:

$$Y_i = \alpha + (\beta + \mu_i)U_i + \varepsilon_i \tag{2.12}$$

For example, this is the case when individuals are endowed with different abilities. In this case, the structural approach allows for the identification of sorting on gains, which cannot be grounded in the reduced-form IV approach. While this is an interesting question on its own, it goes beyond the scope of this paper. The primary focus of this section in the paper is to understand whether the policy has long-lasting impacts on the labor market, rather than delving into the preference parameters of the beneficiaries. Further, due to data limitations, an attempt to estimate the preference parameters would not be possible. To identify the preference parameters, data on individual preferences such as a direct measure of academic motivation must be available.

Overall, although the structural approach holds potential for various benefits, the questions it addresses diverge from the focus of this section. Consequently, the findings presented in the next section are derived from the reduced-form approach.

2.6 Education Results

2.6.1 Effect on Entering High School

Table 2.2 shows the effects of the policy on the probability of entering high school. The table reports the estimates of β_1 in equation (2.5). The standard errors are clustered at the district level. The survey weights are applied [8]. Column (1) shows the result of a baseline difference-in-differences specification, in which only the birth year fixed effect and district fixed effects are included. The positive and statistically significant coefficient implies that compared with the Kinh majority students, ethnic minority students eligible for the policy change experienced an increase in the probability of entering high school by 1.8 percentage points, *ceteris paribus*. From columns (2) to (5), more controls are added to the specification. The coefficients remain statistically significant and stable when controlling for individual characteristics, household composition, variation in the fraction of ethnic minorities at the district-year level, regional time trends, and importantly, the supply of schools.

[8] Table B.1 shows the results without using the survey weights.

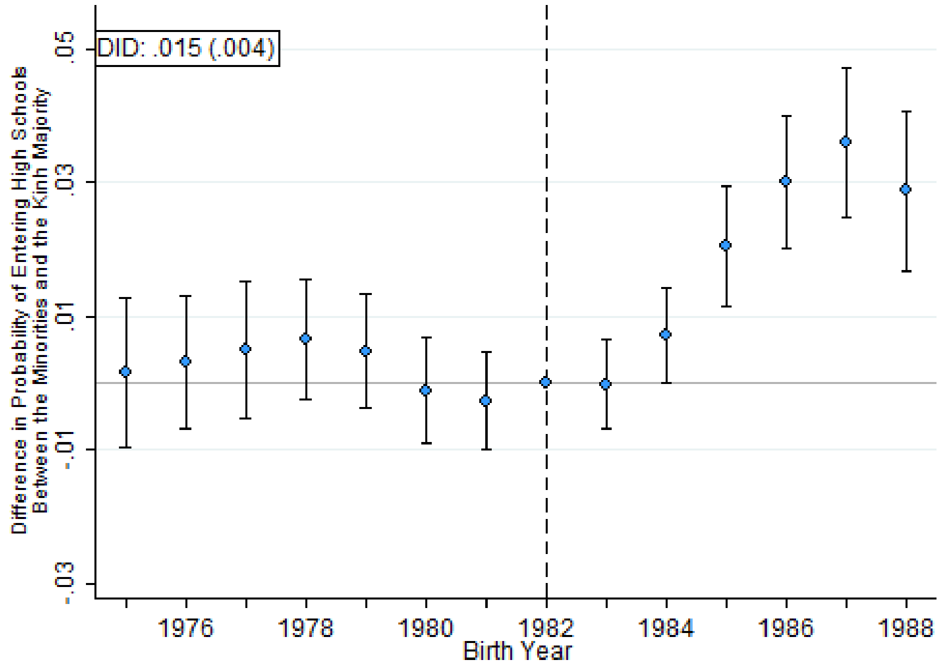
Table 2.2: Effects on Probability of Entering and Completing High School

Dependent Variable	Prob. Entering High School				
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS
Minority × Post	0.018*** (0.006)	0.019*** (0.004)	0.018*** (0.004)	0.015*** (0.004)	0.015*** (0.004)
Observations	2,660,938	2,660,938	2,660,938	2,660,938	2,660,938
Nb. Clusters	674	674	674	674	674
Dependent Mean	0.271	0.271	0.271	0.271	0.271
R-squared	0.103	0.182	0.182	0.182	0.182
Birth Year FE	✓	✓	✓	✓	✓
District FE	✓	✓	✓	✓	✓
Indv and HH Controls		✓	✓	✓	✓
Fraction of Ethnic Minorities			✓	✓	✓
Region × Linear, Quadratic Trend				✓	✓
Number of High Schools					✓

Note: Table 2.2 shows the effects of the policy on the probability of entering and completing high school. The estimated coefficient is β_1 in equation (2.5). Survey weights are applied. Standard errors are clustered at the district level. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

To validate the parallel trends assumption, Figure 2.4 shows the estimates of $\beta_1 j$'s in equation (2.6) and the 95 percent confidence bands. In the figure, all the interactions from the cohorts that were born before 1983 are close to zero and statistically insignificant. This confirms the assumption that ethnic minority and Kinh majority students shared parallel trends in the outcomes before the policy change. In contrast, for the cohorts born after 1983, the figures show a clear increase in the outcomes, which is consistent with the positive effects of the policy as shown in Table 2.2.

Figure 2.4: Difference in the Probability of Entering High School Between Ethnic Minority and Kinh Majority Students



Note: Figure 2.4 shows the difference in the probability of entering high school between Kinh and ethnic minority students. Each point shows the estimated coefficient β_{1j} from equation (2.6) and its associated 95% confidence interval. Survey weights are applied. The normalized birth year is 1982.

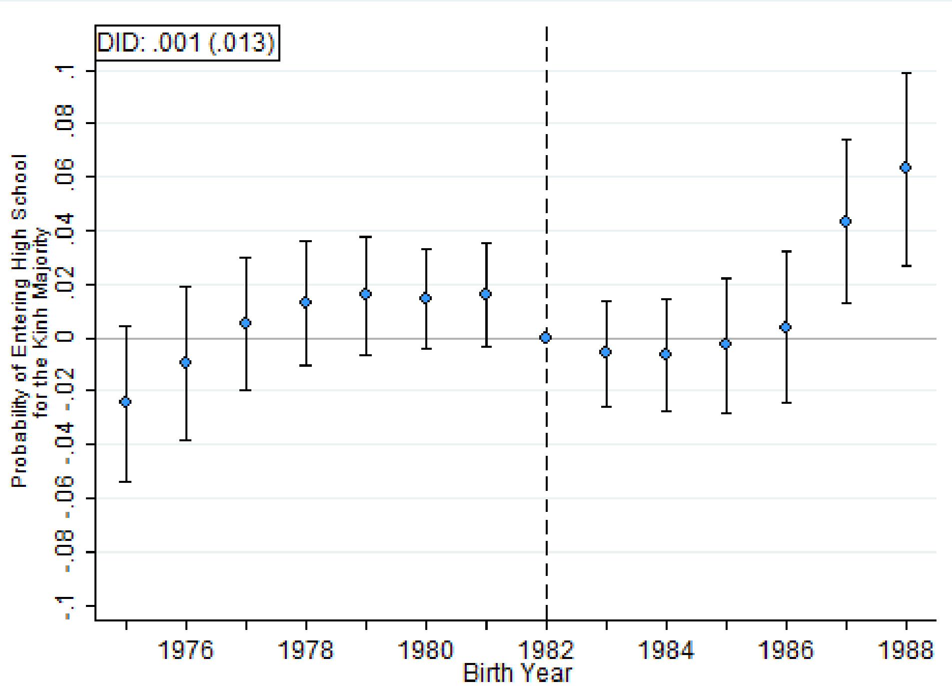
2.6.2 Displacement

Another validity concern pertains to whether the policy's enhancement of the probability of ethnic minority students entering high school comes at the expense of reduced high school enrollment among the Kinh majority students. That is, whether the policy triggers a reduction in the high school enrollment among the Kinh majority rather than increasing the enrollment among the ethnic minorities. Figure B.2 shows the raw trend in the average probability of entering high school for the Kinh majority and other ethnic minority groups, in which the reference cohort is 1975. Similarly, Figure B.2b, shows the trend in the average probability of entering high school for the two groups, controlling for individual characteristics, with the reference cohort in 1982. In both figures, For the cohorts born before 1983, the trends are similar between the Kinh and other ethnic groups. For the cohorts born after 1983, while the trend increases for other ethnic groups, there is no decline for the Kinh majority. This suggests that the policy does not have a negative impact on the probability of entering high school for the Kinh majority.

A more formal approach to assessing displacement involves examining the likelihood of Kinh majority students entering high school in regions with differing concentrations of ethnic minorities. If displacement occurs, it would be expected that the probability of Kinh majority students entering high school to decrease in areas with high ethnic minority populations following the policy implementation. To conduct this analysis, I employ a methodology akin to that outlined in equations (2.5) and (2.6). However, I limit the sample to include only Kinh majority individuals, with particular focus on the coefficients relating to interactions between the fraction of ethnic minorities in a district and the post-policy period, or between the fraction of ethnic minorities in a district and birth year. Figure 2.5 summarizes the results.

In Figure 2.5, the difference-in-differences estimate is close to zero and statistically insignificant. Moreover, before and after the policy the coefficients on the interactions between ethnic minorities fraction and birth year are also close to zero and statistically insignificant. The exceptions are for the last two cohorts, born in 1987 and 1988; however, for these two cohorts, the coefficients are positive instead of negative.

Figure 2.5: Difference in the Probability of Entering High School for the Kinh Majority in Areas with Varying Ethnic Minorities Fraction



Note: Figure 2.5 shows the difference in the probability of entering high school for the Kinh sample in areas with different fractions of ethnic minorities. Each point shows the estimated coefficient β_{1j} from equation (2.6) and its associated 95% confidence interval. Survey weights are applied. The normalized birth year is 1982.

A possible explanation for this is the change in the school supply side. As part of the comprehensive reforms initiated in 1986, known as Doi Moi, education played a pivotal role based on the principle that *"Investing in education is investing for development."* In 1991, the Central Committee devised a 10-year plan to achieve universal primary education with the support of the UN and UNESCO. By 1995, as 12% of the national budget was allocated to education, external multilateral investors, such as The World Bank and Asian Development Bank, were sought to help achieve the ambitious goal within the designated time frame. The school expansion during this period provides a sufficient number of slots for the stabilized enrollment rate among the Kinh majority students as well as the increasing enrollment rate among ethnic minorities.

To gain a better understanding of the school supply during this period, using the number of new schools being constructed, Figure B.3 shows that at the national level, the number of new high schools being constructed has increased significantly, starting from 1997. Moreover, the number of high school aged students per school has also gone down, suggesting that capacity constraint has been less of a concern. Importantly, the new constructions spread across the whole country rather than concentrated in the areas with high fractions of ethnic minorities, Figure B.4 and Figure B.5. Thus, while the school capacity has increased, it does not appear to be a focus on targeting ethnic minorities.

2.6.3 Types of Ethnic Minorities Triggered to Enter High School

A prevailing concern regarding affirmative action policies is whether such policies diminish the caliber of admitted students within the education system (Ballou, Sanders, and Wright 2004; Rothstein and Yoon 2008; Light and Strayer 2000; Arcidiacono et al. 2014; Bleemer 2023). To evaluate whether the policy creates mismatches in the academic capabilities for high school enrollment, Table 2.3 shows the outcomes derived from equation (2.5) concerning education achievements beyond high school. Column (1) first focuses on the probability of completing high school. If the policy had caused ethnic minorities to attend high schools for which they were academically unprepared, it would likely result in a reduced probability of completing high school. In contrast to this hypothesis, column (1) shows the opposite effect. On average, ethnic minorities in the younger cohort experience a 0.6 percentage point increase in the probability of high school completion.

Table 2.3: Effects on Students Quality

	Academic Ability			Academic Motivation
	Completed High School OLS (1)	Some College OLS (2)	Completed College OLS (3)	High School vs Vocational OLS (4)
Minority × Post	0.006*	0.007***	0.008***	0.049***
	(0.003)	(0.001)	(0.001)	(0.004)
Observations	2,660,938	2,660,938	2,660,938	840,311
Nb. Clusters	674	674	674	674
Dependent Mean	0.220	0.082	0.060	0.799
R-squared	0.194	0.215	0.217	0.055
Birth Year FE	✓	✓	✓	✓
District FE	✓	✓	✓	✓
Indv and HH Controls	✓	✓	✓	✓
Fraction of Ethnic Minorities	✓	✓	✓	✓
Region × Linear, Quadratic Trend	✓	✓	✓	✓
Number of High Schools	✓	✓	✓	✓

Note: Table 2.3 shows the effects of the policy on the probability of completing high school, obtaining some college and completing college. The estimated coefficient is β_1 in equation (2.5). Survey weights are applied. Standard errors are clustered at the district level. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

As the literature has noted, the variation in match quality may differ based on the selectivity of institutions (Bound, Lovenheim, and Turner 2010; Arcidiacono et al. 2014). Although the result in column (1) indicates a positive outcome at the national level, it is possible that the match quality at less selective high schools outweighs any potential over-match of ethnic minorities at more selective institutions, resulting in a positive effect on graduation rates. To examine the extent to which there exist mismatches at more selective high schools, columns (2) and (3) turn to college outcomes. The hypothesis is that if the low level of mismatches at the national level is due to most ethnic minorities graduating from lower-quality high schools, this would make them less likely to pursue higher education. However, the results in columns (2) and (3) reveal that eligible ethnic minorities are more likely to enroll in college by 0.7 percentage points and graduate from college by 0.8 percentage points.

The absence of evidence indicating policy-induced mismatch can be attributed to the policy's eligibility criteria, mandating that young ethnic minorities attain at least a grade B in their final year of high school. This implies that those propelled into high school through the policy already possess a certain level of academic readiness. Then what prevented these students from entering high school in the absence of the policy? A potential explanation is the high-stakes nature of the high school entrance exams. In addition to the preparation costs, high-stakes exams may have a disproportionate impact on stress levels (Azmat, Calsamiglia, and Iriberri 2016; Cai et al. 2019; Heissel et al. 2021) or potentially lead to "stereotype threats" among minority students (Steele 1997; Steele and Aronson 1998; Spencer, Steele, and Quinn 1999; T. Dee and Jacob 2006). All of which can discourage ethnic minorities from attempting to enter high school.

To test whether the presence of high-stakes entrance exams demotivates ethnic minorities from entering high schools, column (4) focuses on the probability of entering high school within a restricted sample, which includes only two options: high schools and vocational schools. Both high schools and vocational schools involve comparable material and time investments, but the key difference is that students entering vocational schools are not required to take the entrance exams. Column (4) reveals that within this restricted choice set, ethnic minorities in the young cohorts are more likely to enter high schools than vocational schools by 4.9 percentage points. Taken together, the results from columns (1) to (4) suggest that the ethnic minorities influenced by the policy may belong to a group that is marginally academically prepared but has lower academic motivation to enroll in high school.

2.7 Long-Term Results

2.7.1 Effects on Labor Market Outcomes

To address the question of whether the policy's effects are transient and lack a lasting impact, Table 2.4 shows the effects of going to high school triggered by the policy on a set of long-term outcomes in the labor market. The table reports the results of the 2SLS estimates of π_1 in equation (2.8). The standard errors are clustered at the district level. The survey weights are applied [9][10]. Across outcomes, the reported F-statistics are above the conventional threshold of 10. In particular, the F-statistics is 108.823 for the outcome of labor force participation and being employed, and it is 106.103 for the outcome of holding a salaried position. In terms of the main effects, in Column (1), going to high school increases the probability of participating in the labor force by 21.6 percentage points for the ethnic minority affected by the policy. In Column (2), going to high school increases the probability of being employed by 33.2 percentage points. The last dimension of labor market outcomes to consider is the quality of the occupation. The result in Column (3) shows that entering high school leads to an increase in the likelihood of being salaried workers, conditional on being employed, by 27.5 percentage points. Overall, across the three measures of labor market outcomes, ethnic minority students triggered to enter high school by the policy benefit from the policy in the labor market years later.

[9] Table B.2 shows the results without using the survey weights.
[10] The reduced form results for the three outcomes are summarized in Figure B.6

Table 2.4: Long Term Effects on Labor Market Outcomes

Dependent:	LFP (1) IV	Employed (2) IV	Salaried Worker (3) IV
Entering High School	0.216***	0.332***	0.275***
	(0.028)	(0.034)	(0.082)
Observations	2,643,894	2,643,894	2,400,539
Nb. Clusters	674	674	674
Dependent Mean	0.921	0.900	0.392
F-Statistics	108.823	108.823	106.103
Birth Year FE	✓	✓	✓
District FE	✓	✓	✓
Indv and HH Controls	✓	✓	✓
Fraction of Ethnic Minorities	✓	✓	✓
Region × Linear, Quadratic Trend	✓	✓	✓
Number of High Schools	✓	✓	✓
Experience	✓	✓	✓

Note: Table 2.4 shows the effects of the policy on labor market outcomes. The estimated coefficient is π_1 in equation (2.8). Survey weights are applied. Column (3) is conditional on being employed. Standard errors are clustered at the district level. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

2.7.2 Zero-First-Stage Test

Despite incorporating several controls for regional trends and school supply trends, there remains a concern that unobserved trends may be correlated with high school entrance rates and labor market outcomes. To address this concern, I carried out a zero-first-stage test, which aims at evaluating the effects of the reduced form for a subpopulation where there is no first stage effect (Bound and Jaeger 1996, Bound and Jaeger 2000, Altonji, Elder, and Taber 2005, Angrist, Lavy, and Schlosser 2010). If the first stage effect is zero, then the result for the reduced form should be zero as well if the exclusion restriction holds. Although the zero-first-stage test cannot verify the exclusion restriction, it provides confidence that the exclusion restriction is satisfied.

In particular, in this context, I estimate reduced-form effects in a sub-sample where the policy has no discernible impact on high school entrance. This sub-sample includes districts with a low percentage of ethnic minorities of less than 1%. Columns (4) and (5) of Table 2.5 present the first-stage results for this sub-sample, showing statistically insignificant first-stage effects, indicating minimal effects from the policy within these districts. Columns (1) to (3) report the reduced-form effects on three labor market outcomes, and in all cases, the coefficients are statistically insignificant. Overall, the results in Table 2.5 confirm that in the sub-sample where there is no first-stage effect, there is also no reduced-form effect.

Table 2.5: Reduced-Form and First-Stage Effects for the Sub-sample of Districts with Less Than 1% of Ethnic Minorities

	Reduced Form			First Stage	
	LFP	Employed	Salaried Worker	Entering High School	Entering High School
	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	OLS
Minority × Post	0.080	0.091	0.105	0.045	0.041
	(0.179)	(0.174)	(0.155)	(0.157)	(0.159)
Observations	29,517	29,517	25,937	29,517	25,937
Nb. Clusters	6	6	6	6	6
Dependent Mean	0.916	0.890	0.434	0.340	0.334
R-squared	0.069	0.070	0.274	0.614	0.622
Birth Year FE	✓	✓	✓	✓	✓
District FE	✓	✓	✓	✓	✓
Indv and HH Controls	✓	✓	✓	✓	✓
Fraction of Ethnic Minorities	✓	✓	✓	✓	✓
Region × Linear, Quadratic Trend	✓	✓	✓	✓	✓
Number of High Schools	✓	✓	✓	✓	✓
Experience	✓	✓	✓	✓	✓

Note: Table 2.5 shows the reduced-form and first stage effects of the policy in the sub-sample of districts with less than 1% of ethnic minorities. The estimated coefficient is π_1 in equation (2.5). Survey weights are applied. Column (3) and (5) are conditional on being employed. Standard errors are clustered at the district level. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

2.7.3 Mechanisms of long-term effects

As mentioned in the previous section, the policy affects labor market outcomes primarily through two main educational channels: human capital accumulation and signaling. Leveraging the variation in task intensities of occupations, this section offers suggestive evidence regarding the channels that establish a connection between the policy's impact on labor market outcomes through education. In addition, using data on diversity views at the regional level, the section also aims at providing insight into whether unfavorable views toward ethnic minorities are a driving factor behind the observed labor market effects.

Table 2.6: Effects on Task Intensity

	Task Intensity				Skill Distribution Spread	
	Communication	Analytical	Physical	Routine	Cognitive	Social
	(1)	(2)	(3)	(4)	(5)	(6)
	IV	IV	IV	IV	IV	IV
Entering High School	1.075***	1.926***	-0.976***	-0.109	0.917***	0.248***
	(0.151)	(0.207)	(0.065)	(0.159)	(0.102)	(0.055)
Observations	2,371,047	2,371,047	2,371,047	2,371,047	2,357,449	2,361,220
Nb. Clusters	674	674	674	674	674	674
Dependent Mean	0.067	0.068	0.008	0.031	0.561	0.312
F-Statistics	111.384	111.384	111.384	111.384	93.235	93.885
Birth Year FE	✓	✓	✓	✓	✓	✓
District FE	✓	✓	✓	✓	✓	✓
Indv and HH Controls	✓	✓	✓	✓	✓	✓
Fraction of Ethnic Minorities	✓	✓	✓	✓	✓	✓
Region $\times$ Linear, Quadratic Trend	✓	✓	✓	✓	✓	✓
Number of High Schools	✓	✓	✓	✓	✓	✓
Experience	✓	✓	✓	✓	✓	✓

Note: Table 2.6 shows the effects of the policy on task intensity and skill distributions spread. The estimated coefficient is π_1 in equation (2.8). Survey weights are applied. Tasks intensity is normalized to have mean zero and unit standard error. Columns (1) - (6) are conditional on being employed. Standard errors are clustered at the district level. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

2.7.3.1 Human Capital

Through the human capital accumulation channel, a higher level of education indicates a higher level of training to learn complex tasks such as analytical tasks. Another dimension of productive skills that can be enhanced through schooling is social skills. Therefore, if the policy's impact on labor market outcomes is channeled through human capital, it should manifest in a rise of ethnic minorities' employment within professions involving intricate or social tasks. Table 2.6 shows the task intensity in the occupations of ethnic minorities relative to the Kinh majority. Columns (1) and (2) show that ethnic minorities in the young cohorts that went to high school through the policy are more likely to be employed in occupations with a higher degree of communication as well as analytical tasks. Specifically, in column (1), high school increased the communication task intensity by 1.075 standard deviations for the affected ethnic minorities, and in column (2), the effect is 1.926 standard deviations for analytical tasks. Columns (3) and (4) look at tasks that do not require training in education: physical tasks, and routine tasks. In contrast with communication and analytical task intensity, going to high school reduces the intensity of physical tasks in occupations by 0.976 standard deviation in column (3), and there is no effect on the routineness of tasks in column (4).

2.7.3.2 Education Signalling

To check whether a part of the observed long-term labor market outcomes result from education signaling, columns (5) and (6) look at the effect of going to high school on being employed in occupations with different degrees of skill spread. A wider spread of skill distribution within an occupation indicates that the signal conveyed by a potential employee is more difficult for employers to interpret accurately. Consequently, employers might be less inclined to trust the signal from the potential employee in such occupations. In this context, if policy-induced high school attendance leads to employment in an occupation characterized by a larger spread of skill distribution, it suggests that the credibility of the high school signal is diminished, and vice versa. Column (5) reveals that entering high school amplifies the spread of cognitive skills distribution within the occupations of affected ethnic minorities by 0.917 standard deviations. Similarly, column (6) indicates that high school entry escalates the spread of social skills distribution by 0.248 standard deviations. These outcomes imply that the ethnic minorities prompted to attend high school through the policy ended up in occupations where their educational signal carries less weight. As a result, the labor market effects found in the previous section are less likely driven by signaling mechanisms.

It is crucial to acknowledge that the findings regarding the signaling mechanism are suggestive rather than conclusive, primarily due to the potential presence of general equilibrium effects associated with signaling. Although I refrain from directly considering these equilibrium effects, it is important to recognize that they may indeed influence the analysis concerning education signaling. However, choosing to sidestep the general equilibrium effects in this context is justified. Despite the policy being implemented at the national level, its impact effectively targets a small subset of the population relative to the broader economy. Consequently, the likelihood of it generating significant equilibrium effects is relatively low.

2.7.3.3 Unfavorable Views Toward Ethnic Minorities

In addition to education, the presence of labor market stigma or negative bias toward ethnic minorities might potentially mitigate the impact of high school entry on employment. To investigate the influence of such negative prejudice on labor market outcomes, Table 2.7 analyzes whether the effects of high school entry differ for three labor market outcomes in regions with varying perspectives on ethnic diversity. If negative views are at play, the effects of high school entry in regions with less support for ethnic diversity might be lower. From column (1) to column (3), across all three measures of labor market outcomes, the interaction terms between high school entry and the ethnic diversity view indicator are statistically insignificant. This suggests that negative views do not appear to exert an effect on labor market outcomes.

Table 2.8 examines whether negative views similarly affect the effects of the policy on task intensity and the spread of skill distributions, in order to verify if the policy's impact via these channels is influenced by negative views. Similar to the findings in Table 2.7, none of the interaction terms in Table 2.8 demonstrate statistical significance, thus confirming that neither of the education channels is influenced by negative views. In a different context, Aryal, Bhuller, and Lange 2022 use hidden versus transparent to quantify the effects of human capital versus signaling, in which the authors also sidestep from general equilibrium effects due to the small scale of the affected population.

Table 2.7: Difference in Long Term Effects on Labor Market Outcomes by Ethnic Diversity Views

Dependent:	LFP (1) IV	Employed (2) IV	Salaried Worker (3) IV
Entering High School × Diversity View	-0.085 (0.063)	0.045 (0.058)	-0.121 (0.125)
Observations	991,142	991,142	903,985
Nb. Clusters	255	255	255
Dependent Mean			.903
F-Statistics	8.129	7.663	7.959
Birth Year FE	✓	✓	✓
District FE	✓	✓	✓
Indv and HH Controls	✓	✓	✓
Fraction of Ethnic Minorities	✓	✓	✓
Region × Linear, Quadratic Trend	✓	✓	✓
Number of High Schools	✓	✓	✓
Experience	✓	✓	✓

Note: Table 2.7 shows the effects of the policy on labor market outcomes. The estimated coefficient is the interaction of π_1 in equation (2.8) and Diversity View ($\pi_1 \times$ Diversity Views). Diversity View is measured at the provincial level. Survey weights are applied. Column (3) is conditional on being employed. Standard errors are clustered at the district level. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table 2.8: Difference in Long Term Effects on Labor Market Outcomes by Ethnic Diversity Views

	Task Intensity				Skill Distribution Spread	
	Communication	Analytical	Physical	Routine	Cognitive	Social
	(1)	(2)	(3)	(4)	(5)	(6)
	IV	IV	IV	IV	IV	IV
Entering High School × Diversity View	-0.235	-0.473	-0.393	0.284	0.021	-0.251*
	(0.301)	(0.320)	(0.244)	(0.237)	(0.227)	(0.129)
Observations	891,773	891,773	891,773	891,773	886,181	887,417
Nb. Clusters	255	255	255	255	255	255
Dependent Mean						
F-Statistics	7.356	7.356	7.356	7.356	7.839	7.826
Birth Year FE	✓	✓	✓	✓	✓	✓
District FE	✓	✓	✓	✓	✓	✓
Indv and HH Controls	✓	✓	✓	✓	✓	✓
Fraction of Ethnic Minorities	✓	✓	✓	✓	✓	✓
Region × Linear, Quadratic Trend	✓	✓	✓	✓	✓	✓
Number of High Schools	✓	✓	✓	✓	✓	✓
Experience	✓	✓	✓	✓	✓	✓

Note: Table 2.8 shows the effects of the policy on task intensity and the skill distributions spread. The estimated coefficient is the interaction of π_1 in equation (2.8) and Diversity View (π_1 × Diversity Views). Diversity View is measured at the provincial level. Survey weights are applied. Columns (1) - (6) are conditional on being employed. Standard errors are clustered at the district level. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

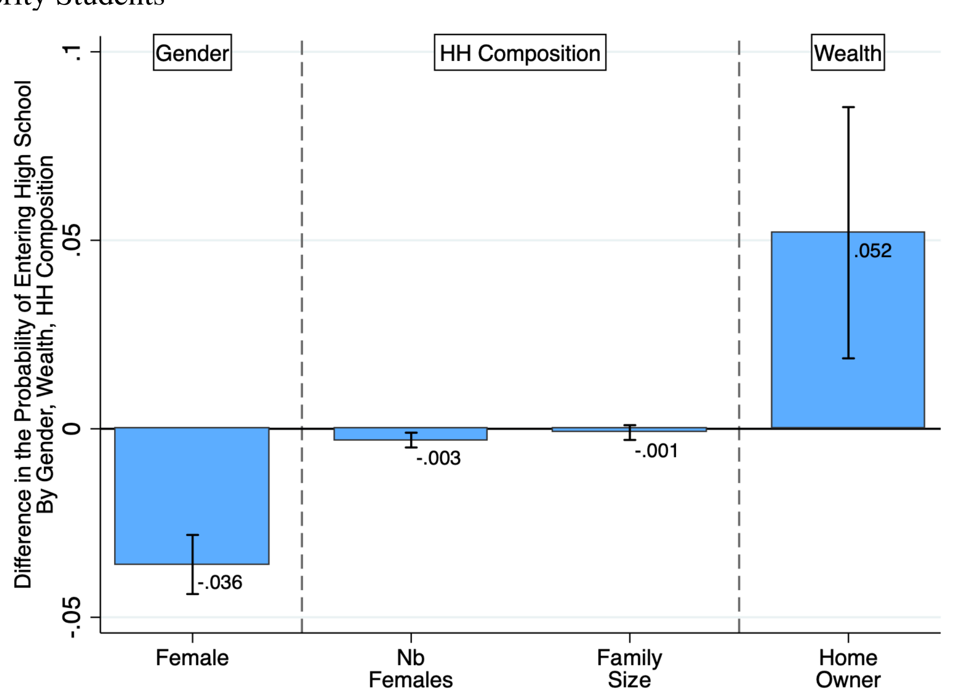
2.8 Heterogeneous Effects

2.8.1 Heterogeneous Effects of Entering High School

I next analyze the possibility that the policy effects on education may differ along the dimensions of gender, household composition, and wealth. Household composition is measured by the number of females in the family, and the family size. Family wealth is proxied by home ownership and the number of appliances. In terms of gender, culture and social norms may lead to males and females having different educational aspirations (Bian, Leslie, and Cimpian 2017; Bordalo et al. 2019; Cassan 2019). Affirmative action policies may align more closely with the aspirations of one gender, leading to differing effects. Secondly, regarding household composition, in families with multiple female members, there may be competition for limited resources, such as financial support for education (Stafford 1987; Dayioğlu, Kirdar, and Tansel 2009; Parish and Willis 1993). Affirmative action policies may intensify this competition or lead to a reallocation of resources within the family, potentially impacting educational outcomes. Lastly, given that the policy solely intervenes at the admissions stage without offering financial assistance, wealthier households are more inclined to facilitate their children's access to the policy's benefits.

Figure 2.6 summarizes the heterogeneous effects of the policy along these three dimensions. Each bar in the figure represents the interaction coefficient between the policy exposure and the associating dimension ($\text{Ethnic}_i \times \text{Post}_{it} \times \text{Dimension}$). I find that the positive policy effect on education is least pronounced among females and most significant among wealthier households. The policy differential effects vary less with respect to household composition. Specifically, in terms of gender, the effect of the policy on high school enrollment is 3.6 percentage points lower for female ethnic minorities born in the young cohort compared to their male counterparts. In terms of household composition, for both dimensions number of females in the households and the family size, the differential effects are small in magnitude, close to zero. Lastly, concerning wealth, both wealth measures indicate that the policy exhibits its most potent positive effect among wealthier ethnic minorities. Specifically, a higher number of appliances and home ownership increase the policy's effect by 1.1 percentage points and 5.2 percentage points, respectively.

Figure 2.6: Difference in the Probability of Entering High School Between Ethnic Minority and Kinh Majority Students



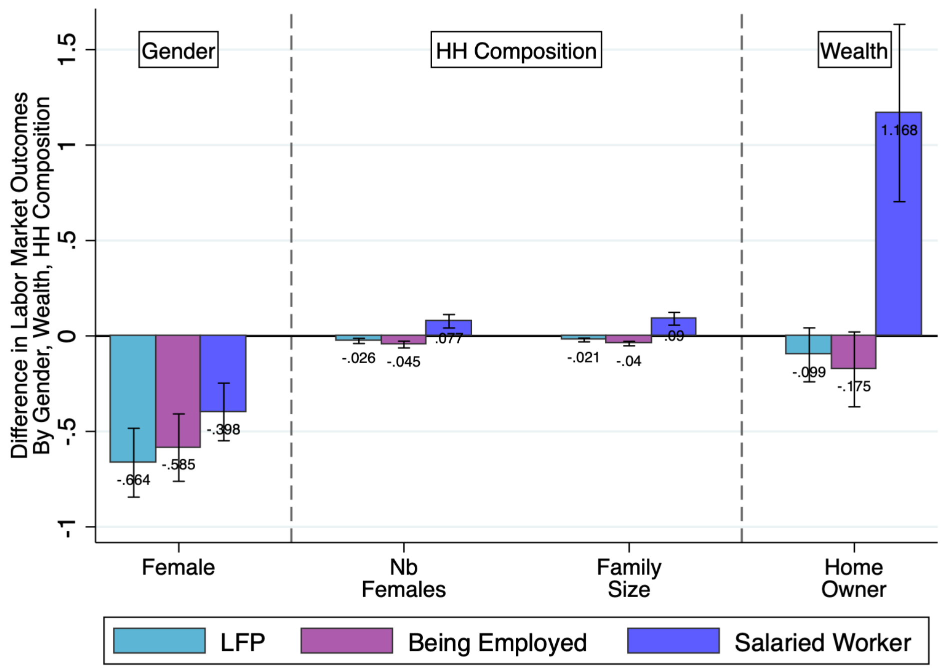
Note: Figure 2.6 shows the difference in the probability of entering high school between Kinh and ethnic minority students, by gender, wealth, and household composition. Each bar shows the interaction between estimated coefficient β_1 from equation (2.5) the corresponding dimension ($\beta_1 \times$ Dimension). The associated 95% confidence interval is shown in the figure. Survey weights are applied. The normalized birth year is 1982.

The above findings carry significant policy implications, as they reveal a limitation of affirmative action policies. While these policies positively impact education, they might not distribute their benefits uniformly across all segments of the population.

2.8.2 Heterogeneous Effects of Labor Market Outcomes

This section carries out a similar heterogeneous analysis for the labor market outcomes. Figure 2.7 shows the differences in the policy effects on labor force participation, being employed, and being a salaried worker for the three dimensions: gender, household composition, and wealth.

Figure 2.7: Difference in Labor Market Outcomes Between Ethnic Minority and Kinh Majority Students



Note: Figure 2.7 shows the difference in the probability of participating in the labor force, being employed, and being a salaried worker between Kinh and ethnic minority students, by gender, wealth, and household composition. Each bar shows the interaction between estimated coefficient β_1 from equation (2.5) the corresponding dimension ($\beta_1 \times$ Dimension). The associated 95% confidence interval is shown in the figure. Survey weights are applied. The normalized birth year is 1982.

The figure shows a similar pattern as in the case for education. Specifically, aligning with the heterogeneous impact of the policy on education, the positive policy effects on labor market outcomes are diminished for female ethnic minorities born in the young cohorts. This trend is consistent across all three labor market outcomes. Similarly, variations in policy effects are less pronounced concerning household composition. Regarding wealth, while wealth does not influence the policy effects on labor force participation or employment status, it does enhance the policy effect on the probability of becoming salaried workers.

2.8.3 Compliers

The heterogeneity in the treatment effects highlights the subgroups that benefit more from the policy change. A more direct approach to discerning those who benefit most from the policy is by examining the characteristics of the compliers. However, identifying the compliers in a quasi-experimental design poses a challenge due to the need to differentiate them from the always-treated individuals in the treated group, as well as the never-treated individuals in the control group. This overlap of groups is illustrated in Figure B.7. Within this context, the compliers are ethnic minority students born after 1983, who would not have entered high school without the policy change.

The identification of compliers is accomplished using a random forest classification algorithm, following a three-step procedure. First, the model is trained using 70% of the data from the pre-treated cohorts. Then, for model validation, the remaining 30% of the pre-treated cohorts are used to predict the probability of high school enrollment. The chosen model exhibits a precision rate of 97%. Lastly, the selected model is applied to the post-treated cohorts to predict their likelihood of entering high school. Compliers are individuals for whom the predicted outcome of high school entry is null, despite their actual outcome being positive. The idea is that the model utilizes individual information to predict whether they would enroll in high school when there was no policy change. Comparing this prediction with the observed data, when the policy is in place, shows who change their decision.

Table 2.9 presents the attributes of the compliers, juxtaposing their characteristics with those of the always-treated and the never-treated. In contrast to the always-takers, compliers tend to originate from larger families with a higher number of female family members. Conversely, when compared to the never-takers, the families of compliers are relatively smaller and have fewer female members. Regarding gender and financial status, compliers demonstrate a reduced likelihood of being female compared to both always-takers and never-takers. Moreover, they exhibit a greater propensity for homeownership. The observed characteristics of the compliers suggest that the policy change, which led to the shift in high school enrollment decisions, predominantly impacted male individuals and those from more financially privileged ethnic minority backgrounds.

Table 2.9: Characteristics of the Treated Compliers, Always-Takers, and Never-Takers

	Never-Takers Mean (1)	Compliers Mean (2)	Always-Takers Mean (3)	Diff (2) - (1) (4)	Diff (2) - (3) (5)
Household size	5.200	5.095	4.506	-0.106***	0.588***
				(0.010)	(0.053)
Nb. Female in HH	2.588	2.513	2.315	-0.075***	0.198***
				(0.006)	(0.035)
Female	0.466	0.419	0.497	-0.046***	-0.078***
				(0.002)	(0.013)
Home owner	0.981	0.984	0.752	0.003***	0.232***
				(0.001)	(0.004)
Religious	0.133	0.090	0.071	-0.043***	0.019**
				(0.001)	(0.008)
Having children	0.546	0.327	0.089	-0.219***	0.237***
				(0.002)	(0.012)
Marital Status					
Single	0.334	0.532	0.693	0.198***	-0.161***
				(0.002)	(0.013)
Married	0.653	0.462	0.307	-0.191***	0.155***
				(0.002)	(0.013)
Separated	0.003	0.002	0.000	-0.001***	0.002
				(0.000)	(0.001)
Divorced	0.006	0.002	0.000	-0.003***	0.002*
				(0.000)	(0.001)
Widowed	0.004	0.002	0.000	-0.003***	0.002
				(0.000)	(0.001)
Observations	221,942	62,356	1,480		
Percent	77.66	21.82%	0.52%		

Note: Table 2.9 shows the characteristics of the compliers, always-takers, and never-takers. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

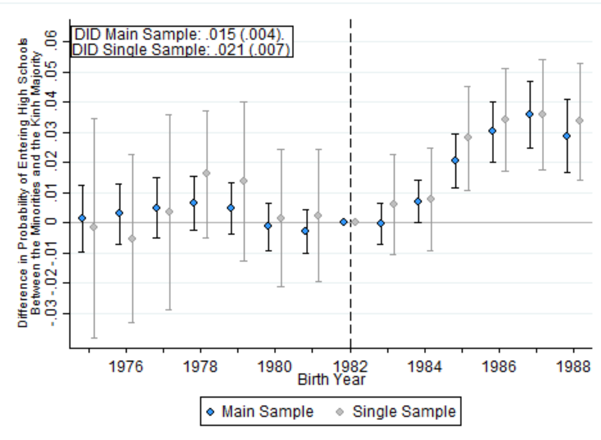
A closer look at other characteristics in Table 2.9 uncovers that in comparison to the never-takers, compliers exhibit a lower likelihood of having children and being married. Conversely, in contrast to the always-takers, compliers show a heightened propensity for both having children and being married. These findings collectively suggest that while the policy aids in leveling the playing field for ethnic minorities, its effects do not fully mitigate two common challenges faced by ethnic minorities: financial constraints and family-related concerns, particularly among female ethnic minorities.

2.9 Robustness Checks

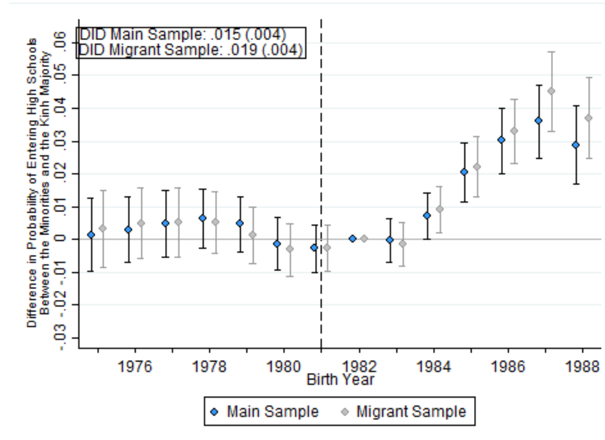
2.9.1 Sample Robustness Checks

This subsection shows the robustness of the results with different sample restrictions. Figure 2.8 shows the results from four sample restrictions. One of the important cultural differences between the Kinh majority and other ethnic groups is marital practices. In comparison with the Kinh majority, child marriage is more commonly practiced among other ethnic minority groups (UNFPA 2018). Different marriage customs can affect the incentives to invest in education (Ashraf et al. 2020). Thus, unobserved changes in the trend of child marriage if happen in the same year as the policy change can confound the policy effects on education. To check whether there exist relative changes in marital practices between the two groups, in the first sample robustness check, I exclude individuals who are married by the time they are observed in the census survey. Figure 2.8 shows that the results from excluding married individuals are similar to the main results. There are no differences in the probability of entering high school for the cohorts born before 1983, and there is a sharp increase for the ethnic minority students relative to the Kinh majority students born after 1983. This result assures that changes in marital practices are not a potential confounding effect.

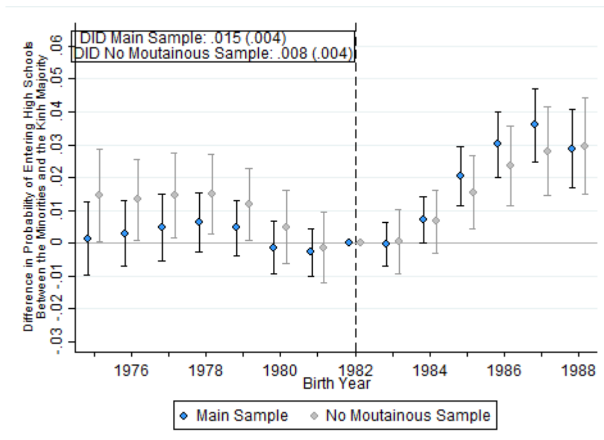
Figure 2.8: Sample Robustness Checks



(A) Single Sample



(B) Migrant Sample



(C) No Mountainous Sample

Note: Figure 2.8 shows the difference in the probability of entering high school between ethnic minority and Kinh majority students across three different sample restrictions. The sample restrictions are defined in the text. Each point shows the estimated coefficient β_{1j} from equation (2.6) and its associated 95% confidence interval. Survey weights are applied. The normalized year is 1982, the year just before the policy implementation. The blue points are estimated from the main analytical sample; the gray points are estimated from the restricted sample.

In the preferred specification, the fixed effects of the district of residence are added to capture difference in school quality, due to the overlapping between the district of residence and the school district (London 2011). However, since I only observe the district of residence at the time of the survey rather than at the time that the individual attends high school, any migration that happens between the high school years and the survey year cannot be captured by the district-fixed effects. In the main analysis, I address this concern by excluding individuals whose district of residence was five years before the survey changed. This restriction reduces only a small fraction of the data - fewer than than 8% of the individuals in the final sample reporting changing districts. To further assess how sensitive the main results are to migration, I relax this restriction to include also individuals who have lived in a different district. The results from this sample restriction are shown in Figure 2.8. In the figure, the results from the extended sample are very close to the main results.

Prior to the policy change in 1998, a small subset of ethnic minority students living in the mountainous areas have been exposed to a similar affirmative action policy. Starting in 1986, ethnic minorities living in the mountainous areas are exempted from the high-school entrance exam, conditional on their performance in the last year of middle school. The policy change in 1998 differs from this early scheme as it expands the affirmative action to cover all ethnic minority students nationwide. To check whether the main results are driven by the subset of ethnic minorities in the mountainous areas, I carry out the same analysis on a restricted sample excluding the mountainous areas. The results from this sample restriction are also similar to the results from the main sample.

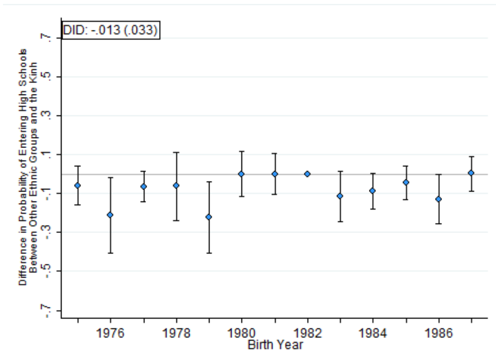
2.9.2 Placebo Tests

Apart from changes in terms of marital practices or migration, there may exist some other shocks that are specific to the ethnic minorities that drive the main results. To further assess whether this is the case, I carry out a set of placebo tests, leveraging the similarities in the ethnic composition between Vietnam and Cambodia. Bordered with the south of Vietnam, Cambodia is a neighboring country that shares a similar culture (Environment and Division 2002). Several ethnic groups are present in both Vietnam and Cambodia, including the Kinh majority. Table B.3 in the Appendix displays the summary statistics of the analytical sample from the Cambodia census data obtained from IPUMS. Similar sample restrictions as described in Section 3 are applied to obtain the final analytical sample.

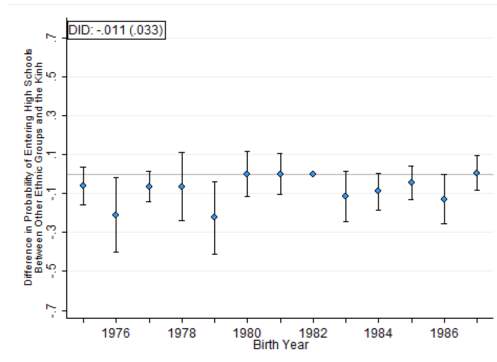
Since all the ethnic groups in Cambodia do not experience the affirmative action change in 1998, the outcomes of other ethnic groups relative to the Kinh ethnic group in Cambodia should not be affected. I perform the same analysis as in the main analysis but using the population census of Cambodia in 2008. In this analysis, the placebo-treated group includes all the ethnic groups apart from the Kinh that were born in or after 1983. Several sample restrictions are performed to test the validity of the placebo results. In the first sample, I include all ethnic groups. Second, I include only the ethnic groups that are present in Vietnam and Cambodia. Third, I include only individuals living in districts with at least 5% of residence belonging to the Kinh ethnic group. Finally, I include only individuals living in districts with at least 1% of residence belonging to the Kinh ethnic group.

Figure 2.9 shows the estimates of β_{1j}'s in equation (2.6), using the Cambodia census data. The estimates of β_1 from the DID equation (2.5) are also reported in the figures. Different from the main results, in all the sample restrictions of the placebo tests, there is no statistically significant difference in either the probability of entering high school or completing high school between other ethnic groups and the Kinh ethnic group. Across all cohorts, born before and after 1983, the coefficients are statistically insignificant. Importantly, there is no sharp increase in the outcome for the cohorts that were born after 1983.

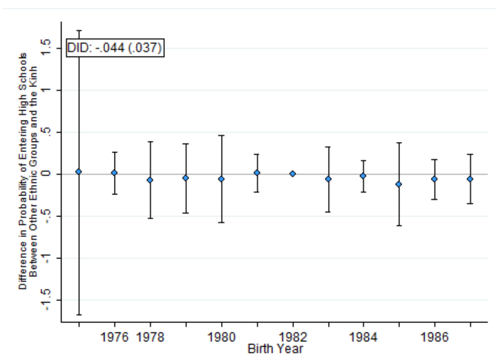
Figure 2.9: Placebo Tests: Comparing the Probability of Entering Between Other Ethnic Groups and the Kinh in Cambodia



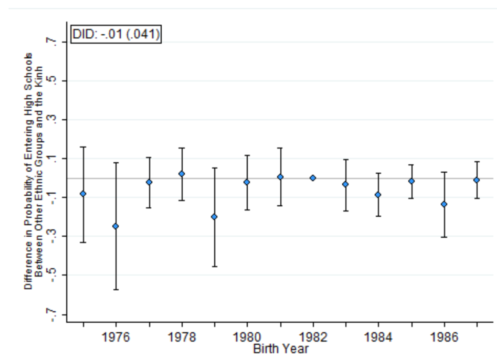
(A) All Ethnic Groups



(B) Ethnic Groups in Both Countries



(C) High Kinh Fraction (5%)



(D) High Kinh Fraction (1%)

Note: Figure 2.9 shows the difference in the probability of entering high school between other ethnic groups and Kinh students in Cambodia. Survey weights are applied. The sample restrictions are defined in the text. Each point shows the estimated coefficient β_{1j} from equation (2.6) and its associated 95% confidence interval. The normalized year is 1982, the year just before the policy implementation.

Table 2.10 continues the placebo test for the long-term outcomes. The table reports the coefficient π_1 from equation (2.8) for the Cambodia sample for the four sample restrictions. No consistent pattern of significant effects of attending high school, as triggered by the placebo program, is observed across various sample restrictions and outcomes.

Table 2.10: Placebo Test: Long Term Effects on Labor Market and Non-Labor Outcomes Cambodia Sample

	Labor Outcomes		
	LFP (1) IV	Employed (2) IV	Salaried Worker (3) IV
All Ethnic Groups			
Entering High School	0.057	0.169**	-0.089
	(0.073)	(0.067)	(0.097)
Ethnic Groups in Both Countries			
Entering High School	0.062	0.185***	-0.094
	(0.073)	(0.067)	(0.116)
High Kinh Fraction (5%)			
Entering High School	0.765	0.777	0.768
	(1.184)	(1.571)	(1.031)
High Kinh Fraction (1%)			
Entering High School	-0.093	0.070	-0.363*
	(0.124)	(0.092)	(0.199)
Birth Year FE	✓	✓	✓
District FE	✓	✓	✓
Indv and HH Controls	✓	✓	✓
Region × Linear, Quadratic Trend	✓	✓	✓
Experience	✓	✓	✓

Note: Table 2.10 shows the *placebo* effects of the policy on labor long-term outcomes, using the Cambodia sample. The estimated coefficient is π_1 in equation (2.8). Survey weights are applied. Column (2) is conditional on participating in the labor force, Column (3) is conditional on being employed. Standard errors are clustered at the district level. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

2.10 Policy Implications

Several policy implications can be drawn from the results. Firstly, the key findings highlight the positive impact of a nationwide affirmative action policy in incentivizing educational investment among ethnic minority students, ultimately resulting in improved long-term labor market outcomes. Crucially, this policy's success is closely tied to its implementation during a period of educational capacity expansion. By ensuring that the education benefits of the majority are not compromised, the policy generates enduring advantages for the minority without triggering negative reactions in the labor market. It is essential to recognize that the effectiveness of an affirmative action policy can be more contentious in a different context, especially when there are capacity constraints in the education system (Eibach and Keegan 2006; Norton and Sommers 2011). To enhance the viability of such policies in various settings, concrete measures to address capacity limitations and potential backlash should be considered in the formulation and implementation of affirmative action policies.

Concerning labor market outcomes, the finding that the observed impacts are more likely linked to the human capital channel than education signaling suggests that the challenges faced by ethnic minorities may originate from insufficient productive skills. Consequently, policies geared toward enhancing human capital development—such as targeted skills training, mentorship programs, and improved access to vocational education—hold the potential to yield substantial and sustainable improvements in labor market outcomes for ethnic minorities. Policymakers should consider strategies focusing on skill-building and practical experience to align more effectively with the observed benefits driven by human capital, ensuring a smoother transition from education to the labor market for individuals from diverse backgrounds. Notably, proven job training programs (Card, Ibarrarán, et al. 2011; Diaz and Rosas 2016; Field et al. 2019) can be specifically directed toward ethnic minorities who may have missed out on high school enrollment.

Another noteworthy implication comes from the results that the benefits of the policy are disproportionately concentrated among males and wealthier members of ethnic minorities. This concentration highlights the need for complementary initiatives to ensure equal opportunities across the entire spectrum of ethnic minorities. To amplify the effectiveness of the policy, additional measures can be considered. For instance, alongside financial aid packages, it is imperative to implement strategies that provide positive role models for ethnic minority students.

The inclusion of mentors, particularly teachers, who can inspire and guide students from minority backgrounds, has been identified as a catalyst for positive outcomes (Carrell, Page, and West 2010; Muralidharan and Sheth 2016; Egalite and Kisida 2018; Card, Domnisoru, et al. 2022). Moreover, showcasing instances of success despite societal barriers can be particularly impactful. Sharing stories of individuals who have overcome challenges and achieved success, especially those that resonate with the experiences of ethnic minority female students, can foster a sense of empowerment and motivation (Beaman et al. 2009; Lafortune, Riutort, and Tessada 2018).

2.11 Conclusion

Access to high school education represents a critical juncture in an individual's educational journey and has far-reaching implications for future life outcomes. Therefore, investigating whether a commonly practiced admission policy perpetuates existing socioeconomic disparities among different ethnic groups is of paramount importance for shaping effective education and labor market policies. In this paper, I evaluate the effects of an ethnic-based affirmative action policy in Vietnam. I rely on variation in the student's ethnicity combined with their birth year in a difference-in-differences framework to assess the policy effects.

The findings underscore tangible benefits accruing to ethnic minority students from the policy, both immediately and over time. Notably, the policy markedly increases the likelihood of ethnic minority students gaining admission to high schools, a critical step in their educational progression. These effects primarily manifest among ethnic minorities possessing adequate academic quality but exhibiting low motivation to undertake high-stakes entrance exams for high schools. Moreover, those students who are propelled into high school through this policy subsequently enjoy enhanced labor market outcomes. They are more likely to participate in the workforce, secure employment, and hold salaried positions. These labor market effects are likely attributable to the human capital channel rather than the education signaling channel. These results hold to various robustness checks and a placebo test. In the context of Vietnam, these results suggest that the affirmative action policy effectively improves the educational and labor market outcomes of ethnic minority students.

Nonetheless, it is essential to acknowledge that certain limitations exist within the policy's scope. Notably, the benefits appear to be disproportionately concentrated among male and wealthier ethnic minority students, highlighting that gender and wealth-related disparities persist. These findings underscore the importance of considering these additional dimensions of disadvantage when designing and implementing affirmative action policies. While affirmative action policies represent meaningful tools to level the playing field for marginalized groups, it is crucial to address these supplementary challenges to ensure that the policies effectively fulfill their intended purpose. Ultimately, this study contributes to the ongoing discourse surrounding the efficacy and equity of affirmative action policies in the Vietnamese context. It sheds light on the complexities inherent in promoting equal opportunities in education and the labor market, paving the way for a more nuanced understanding of the multifaceted nature of affirmative action's impact.

Chapter 3: The Returns to Cognitive, Social, and Manual Abilities in Early Occupations

3.1 Introduction

Occupations are comprised of various tasks that necessitate workers to utilize their skills (Acemoglu and D. Autor 2011) [1]. Tasks, therefore, are the building blocks to unpack the market values of a worker's skills. However, the prevalence of high job mobility during the early career stages (Topel and Ward 1992; Gathmann and Schönberg 2010) prompts an important question: do workers' skills align with the tasks required by their early occupations, and are these alignments rewarded appropriately? While previous studies have explored the complex relationship between skills and tasks, they often focus on outcomes during stable career stages rather than earlier in individuals' career paths (Weinberger 2014; Beaudry, Green, and Sand 2016; D. J. Deming 2017; D. Deming and L. B. Kahn 2018). Alternatively, some works conceptualize skills-tasks matching as a cumulative process rather than explicitly investigating it during the initial phases of careers (Guvenen et al. 2020; Lise and Postel-Vinay 2020). As a result, there remains a gap in understanding the mechanisms underlying skills-tasks matching and the varied returns to skills

[1] In Acemoglu and D. Autor 2011, the concepts of tasks and skills are defined to capture different notions of work. "*A task is a unit of work activity that produces output (goods and services). In contrast, a skill is a worker's endowment of capabilities for performing various tasks.*". In this paper, I follow this distinction between tasks and skills.

across task-based occupations, especially for individuals in the early stages of their careers.

In this paper, building on previous works, I investigate how workers with different abilities, which are the fixed stocks of skills, sort into different initial task-based occupation paths, and subsequently how this sorting pattern affects the returns to their abilities. I first apply a K-means algorithm to classify occupations into three categories based on the tasks required: intensive social tasks occupations, intensive cognitive tasks occupations, and intensive manual tasks occupations. Different from previous methods used to classify occupations, the K-means algorithm allows the grouping of occupations to take into consideration unexplored patterns in a broader number of tasks, instead of solely relying on the pre-determined grouping rule from the core tasks (D. H. Autor, Levy, and Murnane 2003). Prior research investigating the returns to skills within the Roy-type framework often encounters a significant obstacle: the computational burden associated with incorporating a large number of occupations. This limitation arises because each occupation necessitates the estimation of additional parameters for the returns to skills, leading to a rapid expansion in model complexity [2] [3]. Consequently, previous studies have been constrained to include a limited subset of occupations, neglecting the potential heterogeneity within broadly defined occupational categories. Empirical evidence from the Department of Labor's Dictionary of Occupational Titles (DOT) underscores this point, revealing substantial variations in task requirements across three-digit census occupations classified under the same one-digit category. K-means clustering offers a compelling solution to this challenge. By employing K-means, I

[2] The issue is further compounded when operationalizing skills through occupation-specific experiences (as implemented in Keane and Wolpin 1997). In such cases, the number of state variables within the dynamic programming problem also increases proportionally with the number of occupations included. Unfortunately, the computational complexity of solving dynamic programming problems rises exponentially with the number of state variables.

[3] An alternative approach, as suggested by Yamaguchi 2012, involves the application of the Kalman filter. However, this method primarily emphasizes the complexity of occupations and may not adequately capture the distinct requirements associated with various types of tasks.

can strategically group occupations into a smaller, optimal number of clusters based on their task composition. This data-driven approach allows me to capture the essential heterogeneity within broadly defined occupations without encountering the computational limitations associated with a vast number of parameters. In essence, K-means clustering unlocks the potential to incorporate the heterogeneity in tasks compositions of occupations while maintaining computational tractability.

After defining the three distinct groups of task-based occupations, using the British Cohort Study 1970 (Brown 2014), I estimate the returns to abilities and occupation choice parameters from an empirical Roy model that exploits the variations in task-based occupation choices and wages, conditional on observable characteristics and unobserved latent abilities. To be comprehensive with the three groups of occupations, I incorporate three dimensions of latent abilities in the model: cognitive, social, and manual abilities. In my framework, an individual's occupation choice and wages are driven by the individual's observed characteristics as well as the fixed stock of unobserved latent abilities. The incorporation of self-selection across task-based occupations allows me to evaluate the heterogeneous returns to abilities while overcoming the common selection biases.

The first finding of the paper underscores the pivotal role of abilities in guiding individuals into their initial task-based occupations. I first show evidence from the reduced form, which suggests that sorting into different task-based occupations based on abilities exists. Next, I formally estimate the contributions of abilities to the sorting by estimating a Roy model, in which a worker's choice set includes the three task-based occupation groups. Contrary to expectations of matching specific abilities to tasks, the results reveal that cognitive and social abilities jointly influence the sorting process, while manual ability does not emerge as a determining factor. Specifically, individuals with higher cognitive and social abilities tend to gravitate towards knowledge-based occupations - occupations characterized by intensive cognitive or social tasks - with cognitive-intensive occupations placing a stronger emphasis on both abilities dimensions. Additionally, while neither social nor manual abilities determine sorting into occupations with intensive manual tasks, individuals with higher cognitive abilities exhibit a decreased likelihood of sorting into such occupations. Overall, the findings highlight the importance of both cognitive and social abilities for initial occupation placements, while also suggesting that high cognitive abilities alone might influence individuals towards non-manual occupations.

The second set of results underscores the nuanced value of different abilities in the labor market. While all three dimensions of abilities are rewarded to some extent, the highest returns are observed in occupations that align closely with the corresponding abilities. This highlights the task-specific nature of abilities valuation in the labor market, emphasizing the importance of abilities-task alignment for maximizing returns. In essence, the findings suggest that simply possessing high levels of abilities does not guarantee optimal returns; rather, it is the effective application of these abilities in tasks that drives the highest rewards. Specifically, the returns to cognitive abilities are most pronounced in occupations requiring intensive cognitive tasks, while social abilities yield the highest returns in occupations emphasizing intensive social tasks. Similarly, manual abilities exhibit the greatest rewards in occupations centered around intensive manual tasks. These findings underscore the significance of abilities-task matching in maximizing individual earning potential and highlight the importance of strategic career planning based on one's set of abilities.

Understanding occupational premiums, and the early career pay difference between job types, reveals valuable insights. The final set of results shows that at the early career stage while there is no occupation premium between the two knowledge-based occupation groups, intensive social tasks, and intensive cognitive tasks occupations, occupation premiums emerge greatly between knowledge-based occupations and manual occupations. Unpacking the variations underlying these average differences shows that the highest occupation premium between intensive social tasks and intensive cognitive tasks concentrates among those with low abilities. Comparing intensive social tasks and manual tasks, the occupation premium is relatively unequal across all deciles of the three dimensions. Lastly, comparing intensive cognitive tasks and intensive manual tasks occupations, the premiums are among those with high social ability, the variations along the cognitive and manual abilities are fairly minimal.

These results make three main contributions. First, these results offer insights into early career choices. Among others, macroeconomic conditions play a significant role. Evidence suggests recessions negatively impact initial job placement, with these effects lingering throughout careers. Factors like the quality of a first employer (Oreopoulos, Von Wachter, and Heisz 2012) and the shares of task contents in newly formed jobs (Summerfield 2022) contribute to this long-term impact. Asides from macroeconomic conditions, the transition from education to work is also crucial. Student debt, for example, can influence career paths. Previous studies show it can push graduates towards high-paying but potentially limited-growth fields (Minicozzi 2005) and away from lower-paid yet impactful public service jobs (Rothstein and Rouse 2011). More importantly, skills, particularly non-cognitive skills, significantly influence career choices and early career financial returns (Antecol and Cobb-Clark 2013; Kottelenberg and Lehrer 2019). Beyond non-cognitive skills, while some research explores the role of cognitive skills and risk tolerance in specific fields, like teaching (Lang and Palacios 2018), a broader understanding across various occupations remains limited. My findings add to this conversation, revealing that abilities do play a significant role, but not all equally. Cognitive and social abilities have a clear impact on career sorting, while manual abilities have a lesser influence.

Secondly, the findings regarding the returns to abilities contribute to the existing literature on the heterogeneous returns to skills. While much of the literature delves into this concept within the context of educational sorting (Carneiro, Hansen, and J. J. Heckman 2003b; J. J. Heckman, Stixrud, and Urzua 2006; Prada and Urzúa 2017), scant evidence exists regarding the impact of endogenous sorting into specific task-based occupations during early careers. Conversely, the significance of tasks in elucidating wage structure primarily arises in works surrounding technological advancements, with substantial evidence indicating technological evolution as a pivotal catalyst for changes in wage structures (D. H. Autor, Levy, and Murnane 2003; Goos and Manning 2007; D. H. Autor and Handel 2013; D. H. Autor and Dorn 2013; Acemoglu and Restrepo 2022). However, within this line of work, skills are typically perceived as a singular measure based on educational attainment, resulting in a limited understanding of their multidimensionality. My findings bridge these two strands of literature by demonstrating that abilities are rewarded differently across various task-based occupations. Furthermore, the differences in returns between pairs of occupation groups vary across deciles of abilities, offering a more nuanced comprehension of how abilities are remunerated throughout the early stages of workers' careers across different task-based occupations.

Lastly, this paper contributes to the literature on skills and task matching. Previous studies have highlighted the importance of examining skills and task matching as multidimensional concepts to understand the returns to skills (Gathmann and Schönberg 2010; Yamaguchi 2012; Lindenlaub 2014; Lise and Postel-Vinay 2020; Guvenen et al. 2020)[4]. Although this paper does

[4]Expanding the range of potential mappings between tasks and skills, Yamaguchi 2012 employs a Kalman filter

not specifically focus on mismatches, and the various metrics used to quantify them, it advances this literature in three main ways. First, prior studies have often assumed fixed skill-specific prices across occupations, attributing changes in skill returns to the accumulation of task-specific human capital over one's career path rather than variations in value across different occupations. This paper diverges by considering the possibility of different skill values across occupations, offering a more nuanced understanding of skill returns in different task-based occupation groups. Second, while previous research has predominantly focused on the returns to skills accumulation over time, there remains a gap in understanding skill-task matching at the early career stage. For instance, Guvenen et al. 2020 discuss skills and task mismatches to be higher at the latter career stage than at an early one due to cumulative mismatches. This paper addresses this by exploring the relationship of skill-task alignment during individuals' formative career years. Third, existing studies often assume that skills are observed and incorporated into models through pre-defined measures, with limited discussions about the inherent noise in these observed test scores. By employing unobserved abilities as a more precise measure of skills, this paper underscores the significant role that abilities play in shaping the early trajectory of workers' careers.

The paper is organized as follows. Section 2 presents the conceptual framework. Section 3 provides a description of the data I use in the analysis. Section 4 shows motivating patterns in the data. Section 5 describes the empirical model. Section 6 shows the main results, while Section 7 shows the robustness checks. Section 8 concludes.

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framework to estimate task-specific human capital accumulation and occupation choices based on cognitive and motor skills. Yamaguchi's approach captures the complexity of tasks influencing the returns to task-specific human capital accumulation; however, occupational sorting is determined exogenously by job offer arrivals. Introducing search frictions, Lise and Postel-Vinay 2020 emphasize the significance of skills mismatches in the return to task-specific on-the-job experience. In a similar vein of mismatches due to search frictions, Guvenen et al. 2020 provide evidence that not only do current mismatches negatively impact wages, but past accumulated mismatches also leave a lasting effect on wages.

3.2 Conceptual Framework

The following stylized framework conceptualizes the connections between unobserved abilities, task-based occupations, and labor income. The individual maximizes his income from the first job by choosing a task-based occupation in the form of a bundle of tasks $\{T_k\}_{k \in K}$, taking as given his pre-market unobserved abilities $\boldsymbol{\theta}$, and preferences $\boldsymbol{\eta}$.[5] Let ρ be the discount rate, then the individual faces the present discounted value of lifetime earnings as below:

$$\int_0^T exp(-\rho t) Y(x(t); \boldsymbol{\eta}) dt \tag{3.1}$$

$Y(.)$ is the individual's income at time t, which is a function of task wages $W(\{T_k(t)\}_{k \in K}, t)$ and the individual's efficiency in producing tasks $x(\{T_k(t)\}_{k \in K}, t)$. Imposing a linear functional form,[6] $Y(.)$ is defined as:

$$Y(t) = W(\{T_k(t)\}_{k \in K}, t) x(\{T_k(t)\}_{k \in K}, t) \tag{3.2}$$

From equation (2), the bundle of tasks $\{T_k(t)\}_{k \in K}$ governs the labor income through both wages and individual efficiency. This reflects the fact that the productive inputs of an occupation are the intensity of different task units (D. H. Autor and Handel 2013). Further, in a competitive environment, although task wages vary across occupations, they are the same across individuals,

[5]The assumption that the stock of skills is fixed prior to the labor market reflects the view that skills are durable investments as in J. Mincer 1958 and J. A. Mincer 1974. The point at which individuals cease to invest in skills captures the equalization between the investment costs and the present value of skill investment gains. The investment costs in skills post-education can vary from the non-productive time to carry out job training, to the undertaking sub-optimal occupation matches in certain skills dimension to enhance the skills through learning-by-doing.

[6]The linearity in $Y(.)$ assumes that individuals are risk-neutral, thus stochastic effects play no role in the choice of the task bundles.

conditional on the individual's productivity in producing tasks. Put differently, what drives the differences in the individual's labor income within the same task-based occupation is his efficiency in producing tasks. This efficiency in turn is defined through the process of latent skills and tasks matching $M(t)$. Allowing the matching process to engine the productivity gain encapsulates the productive link between skills and tasks through the multi-dimensional skills-tasks matching (Guvenen et al. 2020; Lise and Postel-Vinay 2020). The better the match between the skills and tasks, the more productivity gain materializes.

$$\dot{x}(t) = g(x(t), M(t)) \tag{3.3}$$

$$M(t) = m(\{T_k(t)\}_{k \in K}, \boldsymbol{\theta}) \tag{3.4}$$

An example of the functional form of $M(t)$ is the max operation:

$$M(t) = \max\left\{\sum_j \sum_k (\theta_j - T_k(t)), 0\right\} \tag{3.5}$$

Equation (5) implies that for a given match, the more abilities θ_j the individual possesses relative to the requirement of skills θ_j to perform task T_k, the higher rate of productivity the individual gains from the match. On the other hand, if the individual's abilities θ_j is below $T_k(t)$, then his abilities θ_j do not contribute to the task productivity gain from the match.

From equations (3), (4), and (5), $Y(.)$ depends on the unobserved abilities, the tasks bundle, and the abilities-tasks match.

$$Y(t) = Y\left(\{T_k(t)\}_{k \in K}, x(\{T_k(t)\}_{k \in K}, t), M\left(\{T_k(t)\}_{k \in K}, \boldsymbol{\theta}, t\right); \boldsymbol{\eta}\right) \tag{3.6}$$

So far, the effect of the unobserved abilities operates through the matching process. Additionally, the unobserved abilities affect also the initial level of productivity, the discount rate ρ, and the preferences $\boldsymbol{\eta}$ (J. J. Heckman, Stixrud, and Urzua 2006).

$$x(0) = x(\boldsymbol{\theta}, 0) \tag{3.7}$$

$$\rho = \rho(\boldsymbol{\theta}) \tag{3.8}$$

$$\boldsymbol{\eta} = \boldsymbol{\eta}(\boldsymbol{\theta}) \tag{3.9}$$

Allowing for the unobserved abilities to determine the initial condition, the discount rate, and the preferences relaxes the assumption that individuals are homogeneous in every aspect. Thus, such heterogeneity contributes to the differences in individuals' choices of occupation task bundles $\{T_k(t)\}_{k \in K}$.

Overall, this framework suggests that unobserved abilities $\boldsymbol{\theta}$ influence the choice of the tasks bundle as well as labor income through several channels. First, unobserved abilities affect the preferences and discount rate parameters, leading to different choices of task bundles. Second, the productivity of producing tasks depends on unobserved abilities through the initial condition and the matching function, both of which eventually affect labor income.[7]

On the technical side, considering abilities $\boldsymbol{\theta}$ as individual unobserved heterogeneity, this framework features the prevalence of accounting for individual unobserved heterogeneity in estimating the returns to skills in a task-based framework. Without incorporating self-selection, individual unobserved heterogeneity plagues the estimation of the returns to skills due to three problems: self-selection into occupations on the unobserved dimensions across individuals, measure-

[7] Although tax rates and interest rates are important in the individual's decision (J. J. Heckman, Lochner, and Todd 2008), for simplicity, this framework is abstract from these elements.

ment errors, and potential self-selection into occupations on the unobserved dimensions within individuals over time.

The first issue is the endogeneity of self-selection into occupations across individuals at each period. Similar to other work on self-selection based on the Roy model,[8] self-selection into task-based occupations is analogous to a missing data problem where for each individual only the wage from the chosen occupation can be observed. This self-selection problem causes biases to the coefficients of interests in an OLS setting (Dolton, Makepeace, and Van der Klaauw 1989). One common path to address this problem is to include the occupation dummies as in D. J. Deming 2017. However, if the occupation choices and observed wages are both functions of unobserved latent skills, as in this setting from equations (6) to (9), then the inclusion of the occupation dummies does not resolve the self-selection bias. In fact, the coefficients on skills and the occupation dummies are both biased.[9]

A second concern arises in the common approach which assumes that all the individual unobserved heterogeneity that enters the occupation choice decision is captured by the pre-market abilities measures. The problems of this approach are twofold. First, pre-market test scores are noisy measures of latent abilities. If the measurement errors contained in the test scores are classical, such measurement errors cause an attenuation bias in the estimates of the returns to abilities, leading to a downward bias toward zero for these coefficients. Second, test scores reflect not only the individual's abilities but also other observed characteristics such as family background, giving rise to the bias in the abilities coefficients. However, the directions of this

[8]Some examples of self-selection based on the Roy model: female labor force participation: Gronau 1974, J. Heckman 1974; choice of schooling: Willis and Rosen 1979, J. J. Heckman, Stixrud, and Urzua 2006; training program participation: Ashenfelter and Card 1984, Ham and LaLonde 1996, Rodríguez, Saltiel, and Urzúa 2022; choice of the industry: J. J. Heckman and Sedlacek 1990

[9]The biases in the skills coefficients and the occupation dummies are shown in Appendix A2.

bias cannot be pinned down (J. J. Heckman, Stixrud, and Urzua 2006; Cunha and J. J. Heckman 2008).

3.3 Data

I use two data sets for the analysis. The main data set is the BCS70, which I use to construct the individual's abilities and occupation-related variables. I then match the BCS70 with the task content data set constructed from O*NET to classify an individual's occupations into different task-based categories. The matching relies on the occupation 2-digit conversion from the UK SOC system to the O*NET SOC. The detailed descriptions of the two data sets are explained below.

3.3.1 O*NET and occupation classification

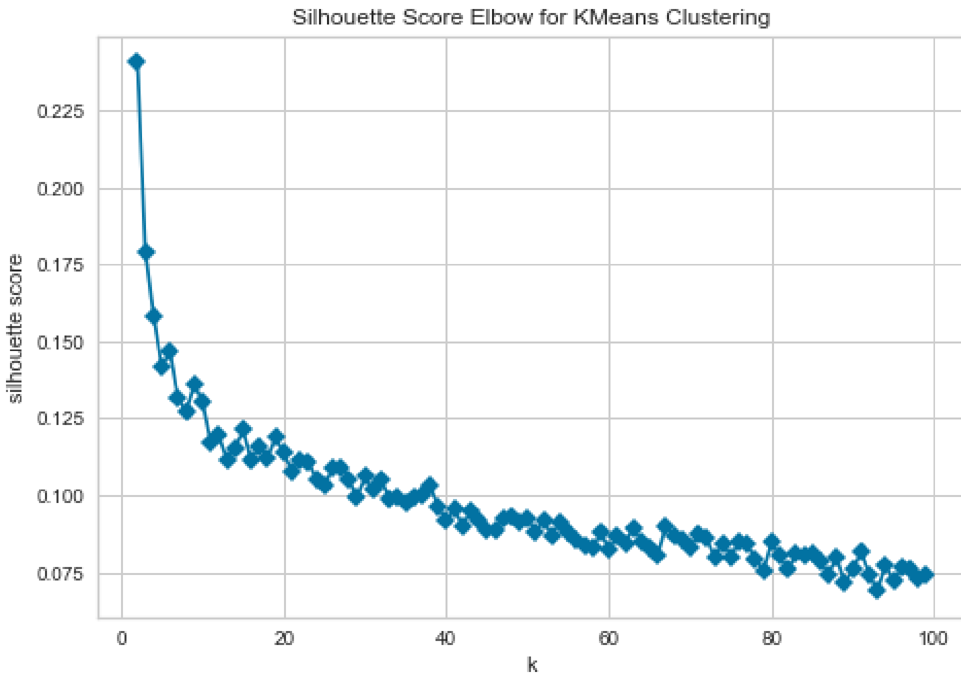
The O*NET database contains detailed information about almost 1,000 occupations covering the entire U.S. economy. For each occupation, the O*NET comprises surveyed responses about the abilities, skills, knowledge, and "*Work Activities*". The responses are collected on an ordinal scale. For the analysis, O*NET scores on "*Work Activities*" are used.

To group occupations into different categories, I leverage a clustering technique called the *k-means* algorithm. K-means is well-suited for this task because it efficiently identifies distinct groups based on a single, continuous variable, in this case, task intensity. Occupations with similar task intensity scores are grouped together. This data-driven method avoids the need for pre-defined rules about which occupations belong to each category, relying instead on the inherent structure of the task intensity data to establish the groupings.

1. Normalize the score of tasks: Each O*NET constituent score is first created by collapsing the O*NET-SOC occupational classification scheme into SOC occupations. Each task score is then standardized to have a mean zero and a standard deviation one.

2. Determine the number of occupation groups: The number of occupation groups is determined based on the scree plot, which provides the within-group variance (sum of squared distances) as a function of the number of groups. While the within-group variation always decreases as the number of groups increases since smaller and more specific groups are created, the rate of decrease slows down. The optimal number of groups is typically identified as the "elbow" of the curve, the point where the decrease in variation starts to level off. At this point, adding more groups no longer significantly reduces variation within each group. In this context, the variance in the task scores of each occupation is used to identify the number of occupation groups. Figure 3.1 shows the results of the scree plot for the data from O*NET with 41 tasks from 968 occupations. In the figure, the variance starts to level off in three groups. Therefore, three is chosen as the optimal number of occupation groups.

Figure 3.1: Diagnosis of the number of Occupation groups



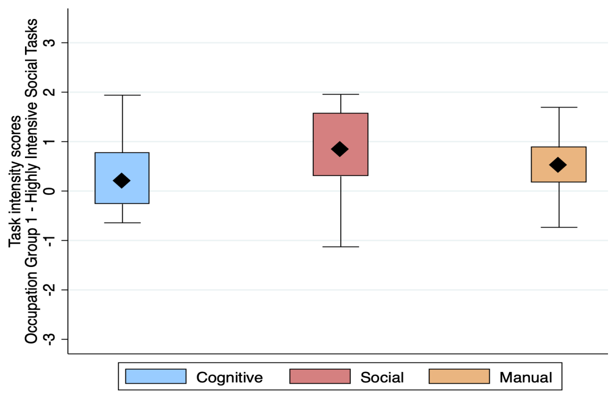
Note: Figure 3.1 shows the scree plot after the factor analysis of all occupation tasks items. The items come from O*NET "*Work Activities*" file. In total, there are 41 items for 968 occupations.

3. Apply the k-mean algorithm to group occupations into three groups: The algorithm starts by randomly selecting three data points, which are occupations in this case, as initial centroids. These centroids represent the "centers" of each potential group. Each occupation in the dataset is then assigned to the closest centroid based on its task intensity score. The Euclidean distance is used to determine closeness. Once all occupations are assigned, the centroids are recalculated by averaging the task intensity scores of the occupations assigned to each group. These steps are repeated iteratively. In each iteration, occupations are reassigned to the closest centroid based on the updated positions. This process continues until the centroids no longer significantly change, indicating convergence.

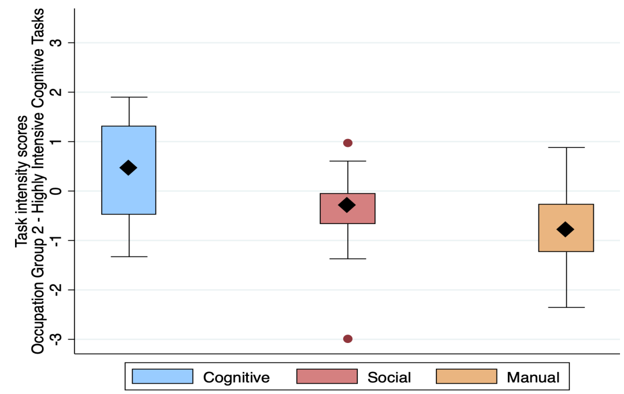
Unlike other pre-defined grouping approaches, K-means does not assign labels to the clusters *ex-ante*. However, analyzing the task composition of occupations within each group provides insights into the characteristics of each occupation group. Figure 3.2 illustrates this point. It shows the average scores for cognitive tasks, social tasks, and manual tasks across occupations within each group [10]. From the figure, the first group has the highest average score for social tasks, the second group excels in cognitive tasks, and the third group exhibits the highest average score for manual tasks.

[10] To define the three task dimensions (cognitive, social, and manual), the factor analysis, which is also a data exploration method, is applied. This method analyzes the relationships between all the task intensity scores and identifies underlying patterns. In this case, factor analysis reveals three distinct factors. Tasks with strong loadings exceeding 0.7 on a specific factor are then assigned to the corresponding dimension (cognitive, social, or manual).

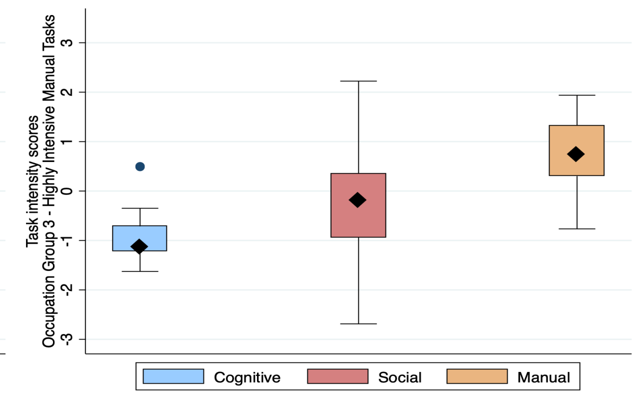
Figure 3.2: Task Intensity within Occupation Groups



(a) Highly Intensive Social Task Group



(b) Highly Intensive Cognitive Task Group



(c) Highly Intensive Manual Task Group

Note: Figure 3.2 shows the distributions of the tasks intensity scores within an occupation for the three occupation groups.

3.3.2 British Cohort Survey 1970

The British Cohort Survey (1970) (BCS70) conducted by the Center for Longitudinal Studies (CLS) first surveyed 17,000 individuals born in England, Scotland, and Wales in 1970. The survey subsequently followed up these individuals in eight sweeps: in 1975 (when members were aged five years), 1980 (age 10), 1986 (age 16), 1996 (age 26), 1999-2000 (age 29-30), 2004-2005 (age 34-35), 2008-2009 (age 38-39), 2012 (age 42) and 2016 (age 46). The information contained in each follow-up sweep varies from medication condition, educational attainment, cognitive test scores, and social activities to employment history. From the BCS70, I use the test scores measures at age 10, occupations, wages, and other additional individual controls at age 26.

To capture the latent factors of an individual's cognitive, social, and manual abilities, I draw on three sets of test scores at age 10, each includes three measures. For the cognitive latent abilities, I use three measures included in the British Ability Scales (BAS): Word Definitions (37 items), Word Similarities (42 items), and Recall of Digits (34 items). For the social latent abilities, the three measures come from the Rutter scale, which focuses on emotions regulation. These include hyperactivity, internalizing, and externalizing. Hyperactivity refers to excessive physical movements and poor attention span. Internalizing focuses on a child's internal psychological environment, such as symptoms of fear or anxiety. Whereas, externalizing relates to negative acting behaviors with external actors, such as parents, teachers, or peers. When considering manual abilities, three key measures are examined: gross motor skills, fine motor skills, and coordination skills. Gross motor skills pertain to movements involving large muscle groups, such as running or jumping rope, primarily in the legs and arms. Fine motor skills, on the other hand, involve movements of smaller muscle groups, like those found in the hand and wrist, for activities such as holding pens or using utensils. Coordination skills focus on balance and synchronization between the limbs and eyes, as demonstrated in tasks like throwing and catching a ball, walking backward, or standing on one leg.

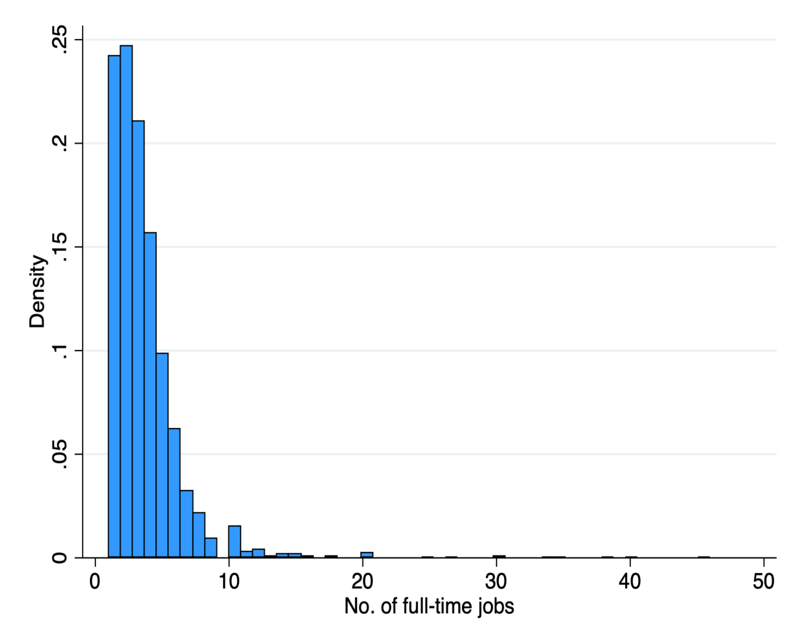
In addition to the test scores measures, from the BCS70, I use weekly wages and occupations collected at age 26. Wages are converted to dollar values as in the year 2013. Self-employed individuals are excluded from all the analysis. I use the two-digit occupation code from the UK SOC90 to merge with the O*NET data set.

3.4 Patterns in the data

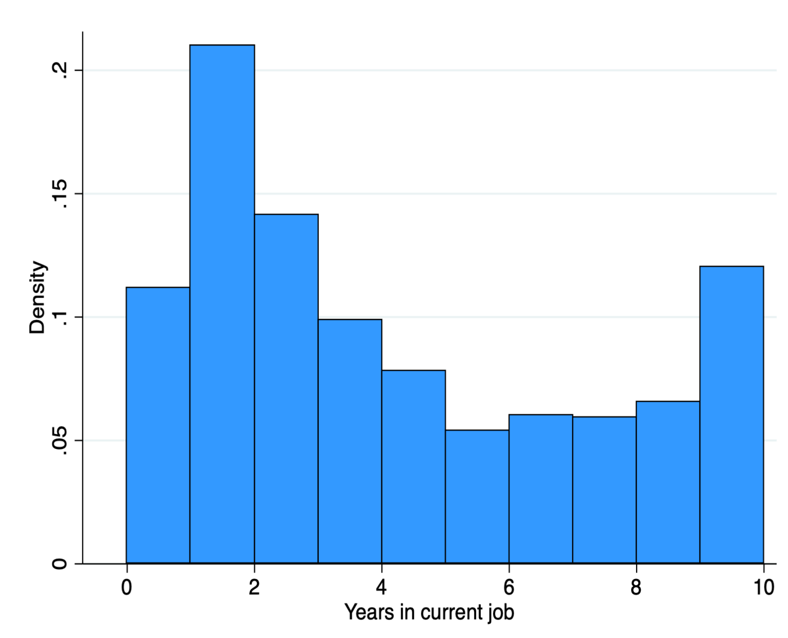
3.4.1 Data summary

At 26 years old, members of the BCS are in the nascent phase of their careers. 72.83% of the cohort are in full-time positions. Figure 3.3a sheds light on the limited full-time working experience typical of this early career phase. The majority of BCS members with full-time jobs have held fewer than 5 positions by the time of the interview, with the largest portion having only one or two full-time jobs. This limited job history aligns with the patterns on seniority. Most BCS members within the cohort report having only one to two years at their current job, Figure 3.3b. This trend mirrors the phase typical of early career stages, where individuals either have not yet entered the job market or frequently change positions. During this period, individuals may explore various roles, experiment with different career paths, and develop their abilities. Regarding those not in full-time positions, Figure 3.4 shows that the majority of them are in part-time positions, 29.03%, and are out of the labor market to take care of family, 28.21%. A smaller number of these individuals are unemployed, 15.70% or in education, 10.59%, or sick, 6.09%.

Figure 3.3: Career characteristics of BCS members at age 26



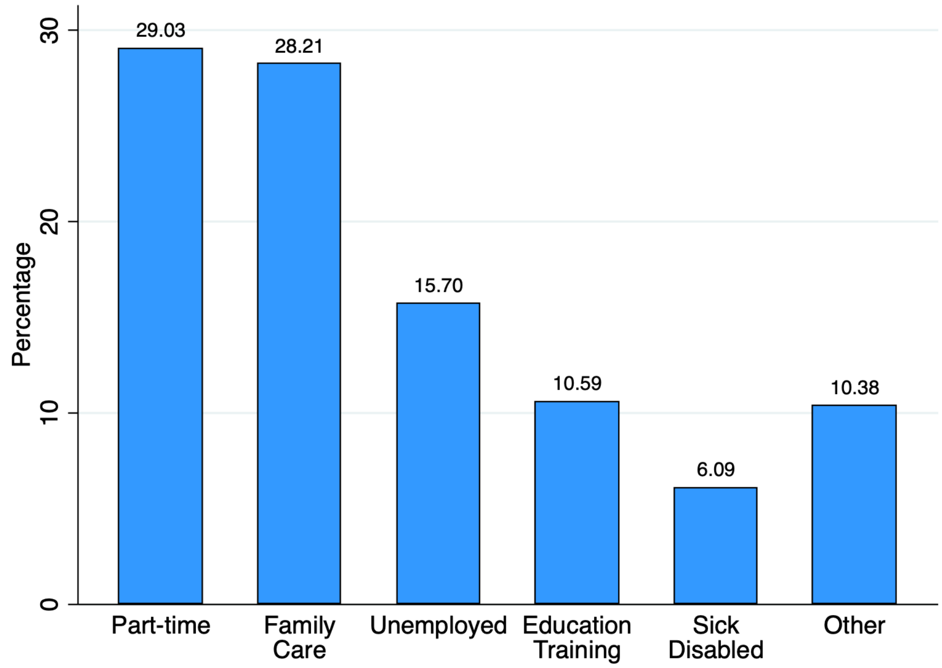
(a) Number of full-time jobs



(b) Years in current job

Note: Figure 3.3 shows the occupations characteristics of BCS members at age 26. Figure 3.3a shows the distribution of the number of full-time jobs for the BCS members at age 26. Figure 3.3b shows the distribution of the number of years in the current job for the BCS members at age 26.

Figure 3.4: Distributions of not working individuals



Note: Figure 3.4 shows the activities of not working individuals at age 26 in the BCS sample. Not working is defined as individuals that do not hold full-time positions.

To have a more comprehensive picture of the members of the BCS, Table 3.1 displays the descriptive statistics of the main variables for the whole sample. Among the BCS at age 26, the distribution of gender is relatively equal, there are 46% males. Most of the individuals in the sample are not married and do not have children, 30.9% are married and 17.0% have children. Few of the individuals have parents with a college degree, 2.6% have mothers with a college degree, and 11.5% have fathers with a college degree.

Table 3.1: Summary statistics - Whole sample

	Mean	SD
Variables at age 26		
Weekly income (in log)	5.912	0.324
Married	0.309	0.462
Children	0.170	0.375
Variables at age 10		
Male	0.465	0.499
Mom with a degree	0.026	0.159
Dad with a degree	0.115	0.319
Reading test score	0.000	1.000
Math test score	0.000	1.000
Pattern test score	-0.000	1.000
Internalizing test score	0.000	1.000
Externalizing test score	-0.000	1.000
Hyperactivity test score	0.000	1.000
Gross motor test score	0.000	1.000
Fine motor test score	-0.000	1.000
Coordination test score	-0.000	1.000

Note: Table 3.1 shows summary statistics of the main variables for the whole analytical sample.

Table 3.2 shows the descriptive statistics of the main variables across occupation groups as well as those not in the labor market at the age of 26. Across groups, the weekly wages (in log) of individuals are fairly comparable across occupation groups. However, the highest average of wages is from the intensive social tasks occupations, followed by intensive cognitive tasks occupations, and intensive manual tasks occupations. In terms of test scores at age 10, the average test scores in the intensive cognitive tasks occupations are the highest in almost all the test scores, followed by the average test scores in the intensive social tasks occupations, and not working. The average of test scores for those in the category of intensive manual occupations is the lowest in all the tests.

Table 3.2: Summary statistics - By occupation group

	Not working		Intensive social tasks		Intensive cognitive tasks		Intensive manual tasks	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Variables at age 26								
Weekly wages (in log)	-	-	5.967	0.291	5.936	0.309	5.856	0.349
Married	0.487	0.501	0.311	0.463	0.285	0.452	0.292	0.455
Children	0.513	0.501	0.135	0.342	0.081	0.272	0.205	0.404
Variables at age 10								
Male	0.130	0.337	0.501	0.500	0.363	0.481	0.647	0.478
Mom with a degree	0.021	0.142	0.042	0.200	0.044	0.205	0.018	0.134
Dad with a degree	0.107	0.309	0.167	0.373	0.193	0.394	0.072	0.259
Reading test score	-0.134	0.968	0.272	0.982	0.340	1.015	-0.116	0.916
Math test score	-0.031	1.019	0.096	0.980	0.199	0.934	-0.084	1.010
Pattern test score	-0.124	1.014	0.285	0.909	0.292	0.923	-0.071	0.949
Internalizing test score	-0.050	1.032	0.051	0.965	0.054	0.990	0.023	0.957
Externalizing test score	0.001	1.001	0.115	0.934	0.236	0.856	-0.046	0.994
Hyperactivity test score	-0.032	0.970	0.111	0.959	0.221	0.894	-0.092	1.027
Gross motor test score	0.078	1.023	0.053	0.942	0.102	0.973	-0.084	0.990
Fine motor test score	0.004	0.995	0.072	0.965	0.110	0.953	-0.063	0.994
Coordination test score	0.051	0.974	0.069	0.964	0.089	0.987	-0.095	1.022

Note: Table 3.2 shows summary statistics of the main variables by occupation group.

3.4.2 Sorting patterns

Table 3.3 sheds light on how cognitive, social, and manual abilities influence an individual's occupation sorting process at age 26. It delves into this by using a multinomial probit model, where each column represents a specific occupation group: intensive social tasks, intensive cognitive tasks, and intensive manual tasks. The "Not Working" category serves as the reference group. Specifically, the results are estimated from the following equation:

$$Occupation_i^k = \alpha + \beta^C Cognitive_i + \beta^S Social_i + \beta^M Manual_i + \mathbf{X}_i' \gamma + \varepsilon_i \tag{3.10}$$

where $Occupation_i^k$ is the indicator equal to 1 if individual i works in occupation k at age 26. $Cognitive$, $Social$, and $Manual$ are the cognitive, social, and manual abilities, respectively. $\mathbf{X}$ is the observable covariate, including gender, regions of residence, marital status, and having children. ε_i is the error term. The coefficients of interests are β^C, β^S, and β^M.

Table 3.3: Occupation sorting

Dependent Variable *Occupation groups*	Not working (1) MNP	Occupation group 1 Intensive social tasks (2) MNP	Occupation group 2 Intensive cognitive tasks (3) MNP	Occupation group 3 Intensive manual tasks (4) MNP
Cognitive ability	-	0.300***	0.379***	-0.025
		(0.040)	(0.032)	(0.046)
Social ability	-	0.092***	0.180***	0.048**
		(0.015)	(0.019)	(0.021)
Manual ability	-	0.064***	0.006	0.017*
		(0.014)	(0.004)	(0.010)
Observations	6,529	6,529	6,529	6,529

Note: Table 3.3 shows the sorting into occupation groups at age 26 from the MNP. Dependent Variable: tasked-based occupation groups. The sample includes respondents at age 26. In all regressions, additional controls are added. Additional controls include gender, region of residence, marital status and having children. All test scores are normalized to zero-mean, and unit standard errors. Cognitive, social, and manual abilities are constructed from the factor analysis of the normalized test scores. Standard errors are in parenthesis. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

The results reveal some interesting patterns. For both intensive social and cognitive tasks occupations, individuals with higher levels of cognitive, social, and manual abilities are more likely to end up in these jobs compared to remaining "Not Working." This suggests that a well-rounded skillset across all three dimensions is generally beneficial for securing these knowledge-based occupations.

The pattern gets more nuanced when looking at intensive manual tasks. Here, cognitive abilities appear to play no significant role in determining whether someone ends up in this occupation group. Interestingly, social abilities actually increase the likelihood of being in a manual labor occupation, while manual abilities themselves also exhibit a positive likelihood. This could be because some manual labor jobs require strong interpersonal abilities for teamwork or customer interaction, even if they don't necessarily emphasize cognitive abilities. Overall, from this table, it is evident that self-selection occurs across task-based occupations. Further, all cognitive, social, and manual abilities are significant variables in this process.

3.4.3 Bias in the returns

To understand if self-selections affect the returns to abilities at this age, Table 3.4 shows the returns to abilities at age 26. The results are estimated from the following equation:

$$lnWages_i = \alpha + \beta^C Cognitive_i + \beta^S Social_i + \beta^M Manual_i + \mathbf{X}_i' \gamma + \varepsilon_i \quad (3.11)$$

where $lnWages_i$ is the log weekly wages of individual i at age 26. $Cognitive$, $Social$, and $Manual$ are the cognitive, social, and manual abilities, respectively. **X** is the observable covariate, including gender, regions of residence, marital status, and having children. ε_i is the error term. In some specifications, **X** includes occupation dummies, and the interactions of occupation dummies and abilities to account for occupations self-selection. The coefficients of interests are β^C, β^S, and β^M.

In Column (1), no selection into occupation is accounted for. In this regression, the coefficients on the returns to cognitive and manual abilities are positive and statistically significant. In Column (2), dummies for occupation groups are added. The occupation dummies are statistically significant, with intensive manual tasks occupations showing lower returns. On its own, this result shows evidence of occupation premiums. In terms of the returns, while the magnitude of the returns to cognitive abilities decreases from 6.6% to 5.6%, the returns to social and manual abilities do not change. In Column (3), to account for the selection on abilities, the specification includes the interactions between abilities and occupation dummies. In this column, once the interactions are added, the signs and magnitudes of the returns change. Specifically, the coefficient on the returns to cognitive abilities continues decreasing from 5.6% to 4.1%. Whereas, the coefficient on the returns to social abilities increases from a null effect to 2.0% and becomes statistically significant. Finally, the coefficient on the returns to manual abilities increases from 2.9% to 3.6%. Across the three columns, the results show that unaccounted selection into occupations leads to an upward bias in the returns to cognitive abilities and a downward bias in the returns to social, and manual abilities. This implies that failing to account for occupation sorting may inflate the values of cognitive abilities, and downplay the values of other abilities.

In addition to selection bias, measurement errors in abilities test scores are another potential bias. The bias can come from random noise or influence from family backgrounds. Further, the direction of the bias is unclear. Column (4) investigates whether test score bias affects the returns. Instead of allowing test scores to enter the regression directly as in Columns (1) to (3), in Column (4), test scores are first residualized on family characteristics at the age of 10 before being aggregated into the three abilities dimensions. Using residualized test scores reduces the returns to all three abilities. This suggests that family background affects test scores that are recorded in the data. It is important to note that, although residualizing the test scores helps correct for some influences from the family backgrounds, it does not address the concerns that test scores may be affected by noise.

Overall, the results from this section show evidence that the returns to abilities can be affected by two main sources of biases, selection into task-based occupations and measurement errors in the recorded test scores. Both types of biases highlight the importance of employing an empirical model that can account for these biases instead of allowing for test scores to enter the regressions directly.

Table 3.4: Returns to abilities

Dependent Variable *Wages at age 26*	(1) OLS	(2) OLS	(3) OLS	(4) OLS
Cognitive ability	0.066***	0.056**	0.041***	0.037***
	(0.005)	(0.009)	(0.001)	(0.002)
Social ability	0.003	-0.001	0.020***	0.018**
	(0.007)	(0.008)	(0.001)	(0.002)
Manual ability	0.030**	0.029**	0.036**	0.030***
	(0.007)	(0.006)	(0.008)	(0.002)
Intensive cognitive tasks occupations		-0.007	-0.014	-0.012
		(0.008)	(0.009)	(0.008)
Intensive manual tasks occupations		-0.103**	-0.105***	-0.115***
		(0.011)	(0.007)	(0.006)
Intensive cognitive tasks occupations × Cognitive ability			0.027**	0.023**
			(0.003)	(0.004)
Intensive manual tasks occupations × Cognitive ability			0.008***	0.003***
			(0.001)	(0.001)
Intensive cognitive tasks occupations × Social ability			-0.018***	-0.022***
			(0.002)	(0.002)
Intensive manual tasks occupations × Social ability			-0.035***	-0.038***
			(0.003)	(0.003)
Intensive cognitive tasks occupations × Manual ability			-0.009*	-0.003
			(0.003)	(0.002)
Intensive manual tasks occupations × Manual ability			-0.006	0.021**
			(0.004)	(0.004)
Observations	2,990	2,990	2,990	2,990
R-squared	0.182	0.201	0.204	0.189

Note: Table 3.4 shows the returns to abilities at age 26 from the OLS. Dependent Variable: Log weekly wages in dollar value in 2013. The sample includes respondents at age 26. In all regressions, additional controls are added. Additional controls include gender, region of residence, marital status and having children. All test scores are normalized to zero-mean, and unit standard errors. In Columns (1) to (3), cognitive, social, and manual abilities are constructed from the factor analysis of the normalized test scores. In Column (4), cognitive, social, and manual abilities are first residualized, then constructed from the factor analysis. Standard errors are in parenthesis. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

3.5 Empirical Model

This section presents an empirical model to estimate the conceptual framework. In the following setting, each individual is endowed with three abilities, cognitive, social, and manual abilities. All three sets of abilities are used to produce tasks in an occupation. These abilities are assumed to be known to the individual, but unobserved by the econometrician. Further, these abilities are assumed to be fixed and predetermined prior to the individual's entrance to the labor market.

3.5.1 The decision process

An individual chooses his first occupation based on the latent utility gained from different occupations. Imposing linearity in parameters, the net benefit of an individual i in an occupation k is:

$$I_i^k = X_i^{k,I}\beta^{k,I} + \eta_i^{k,I}, \quad \text{for } k = 1, 2, 3 \tag{3.12}$$

where X_i includes the individual i's observable attributes that affect his initial occupation choices, for instance, gender, marital status, and regions of residence. $\eta_i^{k,I}$, on the other hand, captures the unobserved factors that influence the individual's initial decision. The structure of $\eta_i^{k,I}$ is explained in the last section.

Let D_i indicate the individual i's initial occupation choice. Then, D_i takes the following form of multinomial choices:

$$D_i = \text{argmax}_{k\in K}\{I_i^k\} \tag{3.13}$$

3.5.2 The wage equations

The present earning of the initial period are linear in observables and unobservables as follows:

$$Y_i^k = X_i^{k,Y}\beta^{k,Y} + \eta_i^{k,Y}, \quad (3.14)$$

$$\text{for } k = 1, 2, 3$$

where X_i includes the individual i's observables. $\eta_i^{k,Y}$ is the individual's unobservables that affect earnings in occupation k. The full list of variables included in X is in the table below.

Table 3.5: Variables included in the empirical model

	Multinomial Choice Model Age 26	Linear Wage Equations Age 26	Test scores Age 10
Male	✓	✓	✓
SES, Age 10	✓	✓	✓
Marital Status	✓	✓	
Children	✓	✓	
Region of Residence	✓	✓	✓
Cognitive Latent Factor	✓	✓	✓
Social Latent Factor	✓	✓	✓
Manual Latent Factor	✓	✓	✓

Note: Table A.4 shows the variables being included in the emprical model.

3.5.3 Structure of unobservables

Denote the latent cognitive variable θ_i^C, the latent social variable θ_i^S, and the latent manual variable θ_i^M. All latent factors enter the unobserved components of the latent utility in occupation choices and present earnings in a linear structure.

$$\eta_i^{k,I} = \theta_i^C \lambda_C^{k,I} + \theta_i^S \lambda_S^{k,I} + \theta_i^M \lambda_M^{k,I} + \varepsilon_i^{k,I}, \tag{3.15}$$

$$\text{for } k = 1, 2, 3$$

$$\eta_i^{k,Y} = \theta_i^C \lambda_C^{k,Y} + \theta_i^S \lambda_S^{k,Y} + \theta_i^M \lambda_M^{k,Y} + \varepsilon_i^{k,Y}, \tag{3.16}$$

$$\text{for } k = 1, 2, 3$$

where $\{\lambda_C^{k,I}, \lambda_S^{k,I}, \lambda_M^{k,I}, \lambda_C^{k,Y}, \lambda_S^{k,Y}, \lambda_M^{k,Y}\}$ are the factor loadings of each abilities dimension in the corresponding equation. In equation (3.16), $\{\lambda_C^{k,I}, \lambda_S^{k,I}, \lambda_M^{k,I}\}$ are the influences of the latent abilities on the individual's occupation choices. Whereas, in equations (3.17), $\{\lambda_C^{k,Y}, \lambda_S^{k,Y}, \lambda_M^{k,Y}\}$ indicate the returns of the latent abilities.

$\{\varepsilon_i^{k,I}, \varepsilon_i^{k,Y}\}$ are the error terms that are orthogonal to X_i as well as θ_i^C, θ_i^S, and θ_i^M. Further, $\varepsilon_i^{k,I}$, and $\varepsilon_i^{k,Y}$ are independent from one another, and they are both mutually independent across occupations. Finally, the error terms are normally distributed with mean zero, $\varepsilon_i^{k,I} \sim N(0, \sigma_{\varepsilon_{k,I}})$, and $\varepsilon_i^{k,Y} \sim N(0, \sigma_{\varepsilon_{k,Y}})$.

3.5.4 Measurement System

The measurement system relies on three sets of test scores for cognitive, social, and manual abilities. The test scores for cognitive abilities include three measures: mathematics, reading, and pattern recognition. The test scores for social abilities include three measures: hyperactivity, internalizing behaviors, and externalizing behaviors. The test scores for manual abilities include: gross motor skills, fine motor skills, and coordination skills. As shown in Table 3.6, correlations within the cognitive test scores range from 0.321 to 0.649, indicating strong associations. Similarly, correlations within the social test scores are robust, ranging from 0.374 to 0.583. The manual abilities dimension also demonstrates strong correlations, ranging from 0.114 to 0.574. Across dimensions, while social abilities demonstrate stronger correlations with cognitive and manual abilities, manual abilities show a weak correlation with cognitive abilities.

Based on these correlations and following previous work (Prada and Urzúa 2017), the measurement system is constructed as follows:

$$C_{j,i} = X_i^{j,C}\beta^{j,C} + \theta_i^S\lambda^{j,S} + \theta_i^C\lambda^{j,C} + \varepsilon_i^{j,C}, \tag{3.17}$$

for $j = 1, ..., J$

$$S_{l,i} = X_i^{l,S}\beta^{l,S} + \theta_i^S\lambda^{l,S} + \varepsilon_i^{l,S}, \tag{3.18}$$

for $l = 1, ..., L$

$$M_{m,i} = X_i^{m,M}\beta^{m,M} + \theta_i^S\lambda^{m,S} + \theta_i^M\lambda^{m,M} + \varepsilon_i^{m,M}, \tag{3.19}$$

for $m = 1, ..., M$

where X_i includes the individual i's observables at the time taking the test, at age 10. $C_{j,s}$ is the individual i's cognitive test score j; $S_{l,i}$ is the individual i's social test score l; and $M_{m,i}$ is the individual i's manual test score m. $\{\varepsilon_i^{j,C}$, $\varepsilon_i^{l,S}$, $\varepsilon_i^{m,M}$ $\}$ are idiosyncratic shocks that are independent across test scores. Normality is not imposed on $\{\varepsilon_i^{j,C}$, $\varepsilon_i^{l,S}$, $\varepsilon_i^{m,M}$ $\}$, rather, $\{\varepsilon_i^{j,C}$, $\varepsilon_i^{l,S}$, $\varepsilon_i^{m,M}$ $\}$ are assumed to follow a mixed normal distribution with two mixtures.

Table 3.6: Test score correlations

	Cognitive			Social			Manual		
	Math	Reading	Pattern	Internalizing	Externalizing	Hyperactivity	Gross Motor	Fine Motor	Coordination
Cognitive									
Math	1.000								
Reading	0.325	1.000							
Pattern	0.321	0.649	1.000						
Social									
Internalizing	0.096	0.161	0.152	1.000					
Externalizing	0.070	0.103	0.089	0.476	1.000				
Hyperactivity	0.152	0.200	0.168	0.583	0.374	1.000			
Manual									
Gross Motor	0.116	0.080	0.087	0.076	0.044	0.080	1.000		
Fine Motor	0.030	0.034	0.038	0.205	0.181	0.215	0.114	1.000	
Coordination	0.031	0.048	0.055	0.221	0.188	0.243	0.115	0.574	1.000

Note: Table 3.6 shows the correlation of test scores at the age of 10.

3.5.5 Occupation Premiums

To obtain the premium for each occupation, consider the classical potential outcome framework in the context of multivalued treatment effects, where each treatment effect is an occupation choice. This framework is composed of the observed log wages from the observed occupation choice Y_i and the K log wages from the potential occupation choices $Y_i(k)$ for each occupation choice $k = 1, ..., K$. In this framework, the observed log wages are given by:

$$Y_i = D_i(1)Y_i(1) + D_i(2)Y_i(2) + ... + \left(1 - \sum_{k=1}^{K-1} D(k)\right)Y_i(K) \tag{3.20}$$

Fix one of the occupation choices, $\bar{k}$, as the normalized option, the occupation premium of a given occupation k relative to occupation $\bar{k}$ is defined by the ATE as follows:

$$ATE = \mathbf{E}[Y_i(k) - Y_i(\bar{k})] \tag{3.21}$$

for $k \neq \bar{k}$

where $\mathbf{E}[.]$ is the expectation operator with respect to $\{X_i, \theta_i^C, \theta_i^S, \theta_i^M, \varepsilon_i^{k,Y}\}$. Based on the previous assumptions on selection on observables, and selection on the latent unobserved abilities, $Y_i(k) \perp\!\!\!\perp D_i(k)|(X_i, \theta_i^C, \theta_i^S, \theta_i^M)$, the ATE recovers the unbiased effect of the occupation choice in the initial period.

3.5.6 Identification

The identification and estimation follows previous works incorporating latent abilities in the Roy setting (Carneiro, Hansen, and J. J. Heckman 2003b; J. J. Heckman, Stixrud, and Urzua 2006; Prada and Urzúa 2017; Rodríguez, Saltiel, and Urzúa 2022).

To evaluate the returns to abilities as well as the occupation premiums, the joint distribution of counterfactual wages at each occupation choice needs to be recovered, that is $F(Y(k), Y(\bar{k})|X)$ needs to be recovered. However, the identification of $F(Y(k), Y(\bar{k})|X)$ is subjected to two problems. The first problem is analogous to a missing data problem: for each individual, only one realization of the wage is observed, depending on the individual's chosen occupation. Following Carneiro, Hansen, and J. J. Heckman 2003b, the empirical model overcomes this problem by exploiting the variations in the measurement system as well as the occupation choices. The model leverages the fact that although both the measures and the occupation choices are driven by the latent abilities factors, the observed measures do not suffer from the selection problem, whereas the observed wages do. Therefore, the variations, specifically the cross-covariance in the test scores, can first be used to identify the distributions of the latent factors.

Second, instead of the joint distribution of wages, only the marginal distributions of the potential wages $F(Y(k)|X)$ are observed in the data. Following J. J. Heckman and Honore 1990, the joint distributions can be identified from marginal distributions by leveraging variation in choices, observables, and observed wages when there is no selection on unobservables. Following previous literature (Carneiro, Hansen, and J. J. Heckman 2003b; J. J. Heckman, Stixrud, and Urzua 2006; Rodríguez, Saltiel, and Urzúa 2022), the empirical model extends on J. J. Heckman and Honore 1990 by incorporating the latent factors in identifying the joint distribution of counterfactual wages from the marginal distributions, condition on the observable characteristics X as well as the latent factor θ.

In the context of the empirical model, the parameters on the latent factors are first defined through the cross covariance of test scores. Once, the factor distributions are pinned down, the parameters $\beta's$ in the choice equation and the outcome equations, wages, are identified, leveraging variation in the observed choice, wages, and observed characteristics. The identification of $\beta's$ is possible due to the separability between the observables, the factors, and the error terms. Moreover, to secure the identification, the error terms in the model are assumed to be not only mutually independent from one another, but also independent from the observables and the latent factors. Specifically, the assumptions of the model are listed below:

- (A-1): $\{\varepsilon^{k,I}, \varepsilon^{k,Y}, \varepsilon^{j,C}, \varepsilon^{l,S}, \varepsilon^{m,M}\}$ are mutually independent

- (A-2): $\{\varepsilon^{k,I}, \varepsilon^{k,Y}, \varepsilon^{j,C}, \varepsilon^{l,S}, \varepsilon^{m,M}\}$ are independent from the observables and latent factors.

- (A-3): Independence of the latent factors with respect to the observables

$$\boldsymbol{\theta} \perp X^{k,I}, X^{k,Y} \qquad \forall k$$

- (A-4): Distributions of the error terms

$$\varepsilon_i^{k,I} \sim N(0, \sigma_{\varepsilon_{k,I}})$$

$$\varepsilon_i^{k,Y} \sim N(0, \sigma_{\varepsilon_{k,H}})$$

$$\varepsilon^{j,C} \sim p_1^{j,C} N(\mu_1^{j,C}, \sigma_1^{j,C}) + p_2^{j,C} N(\mu_2^{j,C}, \sigma_2^{j,C}) \qquad p_1 + p_2 = 1$$

$$\varepsilon^{l,S} \sim p_1^{l,S} N(\mu_1^{l,S}, \sigma_1^{l,S}) + p_2^{l,S} N(\mu_2^{l,S}, \sigma_2^{l,S}) \qquad p_1 + p_2 = 1$$

$$\varepsilon^{m,M} \sim p_1^{m,M} N(\mu_1^{m,M}, \sigma_1^{m,M}) + p_2^{m,M} N(\mu_2^{m,M}, \sigma_2^{m,M}) \qquad p_1 + p_2 = 1$$

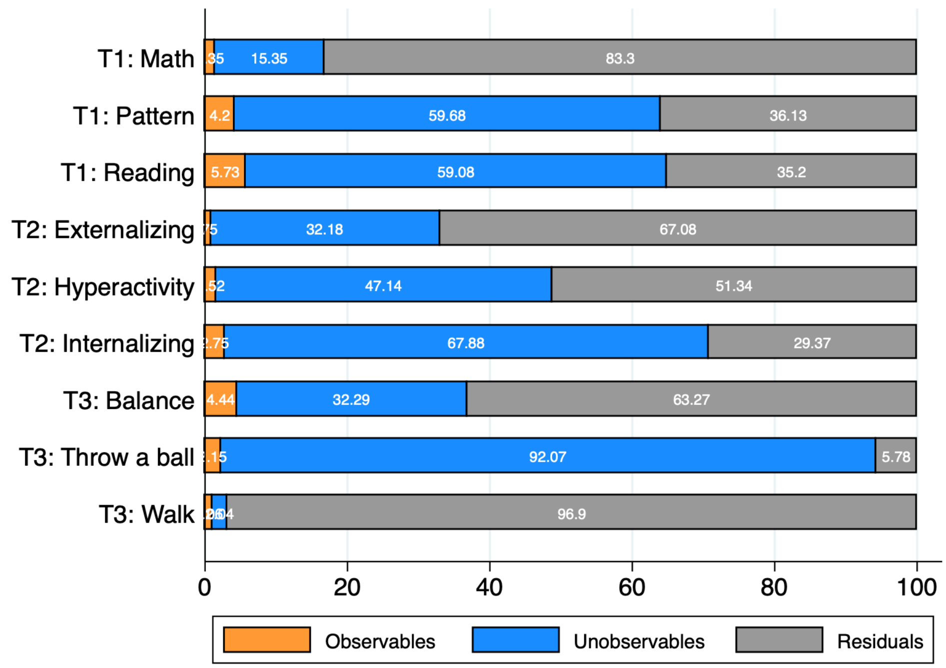
It is important to note that without exclusion restriction, the model is identified by the distributions of unobserved abilities and the assumption on the normality distribution. Exclusion restriction, if included, helps relaxing the assumptions on the functional form. To relax the normality assumption with some form of non-parametric specification, the model would require the inclusion of exclusion restriction (Aakvik, J. Heckman, and Vytlacil 1999; Carneiro, Hansen, and J. J. Heckman 2003a). In other contexts, the inclusion of an exclusion restriction, provided it is valid, serves to enhance the conceptual understanding of choice behaviors and contributes to the technical improvement of the model's fit.

3.6 Results

3.6.1 Variance decomposition

To investigate the importance of the latent factors in explaining the variation in test scores, Figure 3.5 shows the variance decomposition of the nine test scores, using ANOVA method. The figure confirms the importance of latent factors with their contribution to the observed test scores varying between 2.04% to 97.07%. Moreover, the figure also highlights the fact that observed test scores are measured with a high degree of noise - the percentage of residuals varies between 5.78% and 96.90%. Together, these results emphasize the importance of incorporating test scores into the measurement system instead of directly using test scores.

Figure 3.5: Variance Decomposition

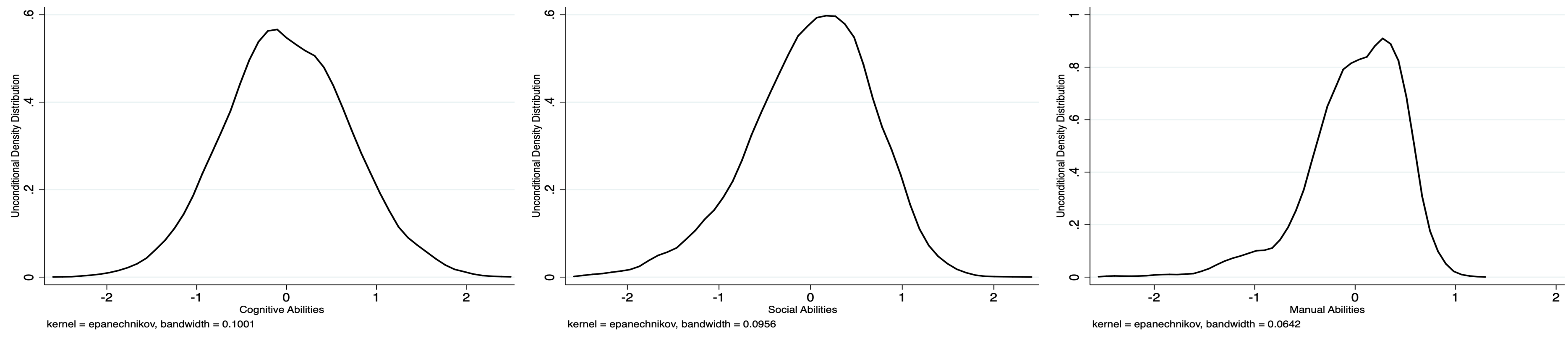


Note: Figure 3.5 shows the variance decomposition

3.6.2 Abilities distributions

Figure 3.6 and Figure 3.7 illustrate the distributions of the three dimensions of abilities, derived from the estimated parameters of the model. Figure 3.6 shows the abilities distributions without considering occupation sorting, while Figure 3.7 presents the distributions conditional on occupation sorting. Evidence of occupation sorting along the three dimensions of abilities is observed in Figure 3.7, wherein cognitive and social abilities demonstrate stronger sorting patterns compared to manual abilities. Specifically, individuals with high cognitive and social abilities tend to concentrate in occupations characterized by cognitive or social intensity.

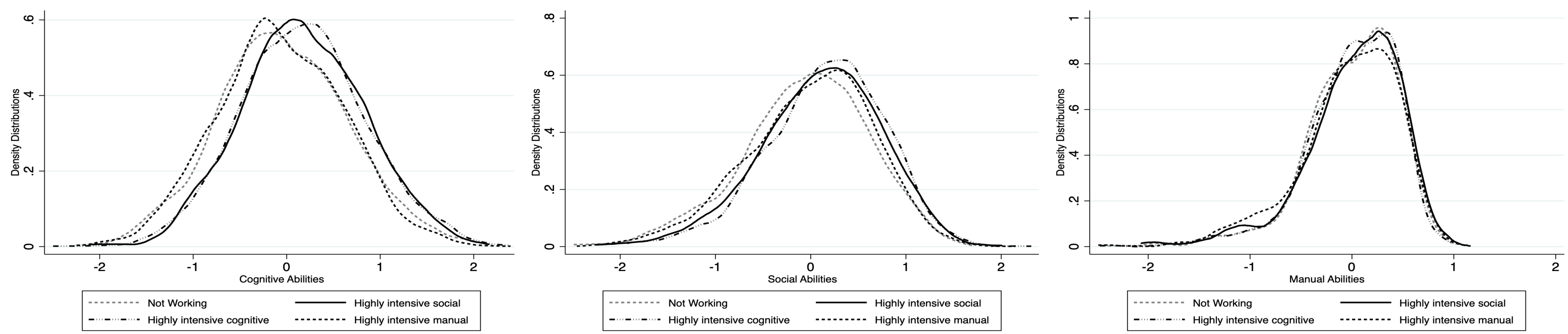
Figure 3.6: Abilities Distributions



(a) Cognitive abilities (b) Social abilities (c) Manual abilities

Note: Figure 3.6 shows the distributions of the unconditional distributions of the three abilities dimensions.

Figure 3.7: Ability Distributions by Occupation Groups



(a) Cognitive abilities (b) Social abilities (c) Manual abilities

Note: Figure 3.7 shows the abilities distributions by task-based occupations groups.

3.6.3 Effects of abilities on occupation sorting

Building on the insights from Figure 3.7, Table 3.7 delves deeper into how these abilities influence occupation sorting compared to not working. The results highlight the distinct roles of cognitive and social abilities. Cognitive abilities appear to be a strong driver of sorting into specific occupations. A one standard deviation increase makes individuals more likely to end up in occupations that are intensive in cognitive tasks or social tasks. Conversely, it decreases the chance of sorting into manual occupations. This suggests that cognitive abilities are an important determinant of sorting into non-manual occupations at an early career stage.

Table 3.7: Effects of abilities on occupation sorting

	Not Working (1) MNP	Occupation group 1 Intensive social tasks (2) MNP	Occupation group 2 Intensive cognitive tasks (3) MNP	Occupation group 3 Intensive manual tasks (4) MNP
Cognitive	-	0.333***	0.321***	-0.104*
		(0.064)	(0.056)	(0.056)
Social	-	0.236***	0.314***	0.023
		(0.067)	(0.062)	(0.057)
Manual	-	0.130*	0.080	0.033
		(0.076)	(0.070)	(0.068)
Observations	6,529	6,529	6,529	6,529

Note: Table 3.7 shows the effects of abilities and education on sorting. Dependent Variable: tasked-based occupation groups. The sample includes respondents at age 26. In all regressions, additional controls are added. Additional controls include gender, region of residence, marital status and having children. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Social abilities appear as equally important as cognitive abilities. A one standard deviation increase increases the likelihood of sorting into social- or cognitive-task intensive occupations, but has no significant impact on sorting into manual labor jobs. This indicates that social abilities are determinant of sorting into knowledge-based occupations, but may not be as crucial for manual occupations. Lastly, the table reveals that manual abilities do not significantly influence occupation sorting besides a minimal effect on increasing the probability of sorting into intensive social tasks occupations.

3.6.4 Returns to abilities

Table 3.8 presents empirical evidence on the impact of different abilities on individual earnings across various occupational categories. These findings, derived from the model's estimated linear wage equations, offer insights into the nuanced dynamics of abilities returns in early careers. A key takeaway is the heterogeneity in the returns to different abilities across occupational groups, highlighting the task-specific nature of abilities valuation within specific occupations contexts.

Table 3.8: The returns to abilities by occupation group

Dependent Variable *Wages at age 26*	Occupation group 1 Intensive social tasks (1) Linear	Occupation group 2 Intensive cognitive tasks (2) Linear	Occupation group 3 Intensive manual tasks (3) Linear
Cognitive ability	0.034*	0.079***	0.057***
	(0.020)	(0.013)	(0.016)
Social ability	0.049***	0.025*	0.006
	(0.022)	(0.015)	(0.016)
Manual ability	0.047*	0.041***	0.053***
	(0.025)	(0.016)	(0.020)
Observations	2,990	2,990	2,990

Note: Table 3.8 shows the returns of abilities and education. Dependent Variable: Log weekly wages in dollar value in 2013. The sample includes respondents at age 26. In all regressions, additional controls are added. Additional controls include gender, region of residence, marital status and having children. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

In occupations focused on intensive cognitive tasks, cognitive abilities yield the highest returns. A one standard deviation increase in cognitive abilities corresponds to a 7.9% increase in wages within this category. However, this effect diminishes to 5.7% in intensive manual tasks occupations and 3.4% in intensive social tasks occupations.

Similarly, social abilities demonstrate the highest returns within their most natural alignment – intensive social tasks occupations. A one standard deviation increase leads to a 4.9% wage increase. While these abilities also offer benefits in intensive cognitive tasks occupations, 2.5% increase, their impact is less pronounced in intensive manual tasks occupations.

The value of manual abilities is most apparent in intensive manual tasks occupations, where a one standard deviation increase results in a 5.3% wage increase. Although these abilities still contribute positively in intensive social tasks, 4.7% increase, and intensive cognitive tasks, 4.1% increase, their rewards are relatively lower.

These findings underscore the importance of aligning individual abilities with job requirements to maximize earnings potential. Mismatches between abilities and occupational demands may lead to suboptimal outcomes, such as wage penalties for individuals with strengths that are undervalued in their chosen occupations. For instance, individuals with strong cognitive abilities may experience reduced earnings if placed in occupations that prioritize social tasks where cognitive abilities are less valued.

3.6.5 Occupation premiums

Table 3.9 provides insights into the wage differentials associated with various task intensities within early career occupations. The reported coefficients are calculated based on the ATE as in equation (3.21). In column (1), the focus is on the wage differential between knowledge-based occupations, namely those with intensive social tasks or intensive cognitive tasks. Surprisingly, the wage disparity between occupations with intensive social tasks and those with intensive cognitive tasks is not statistically significant during the early career phase. This finding raises intriguing questions about the factors driving wage differentials at this career stage. One possible explanation stems from the role of experience. In early career stages, individuals may lack extensive work experience or specialized credentials, making both social and cognitive abilities valuable assets within knowledge-based tasks. Consequently, similar wage outcomes may emerge for occupations requiring either social or cognitive tasks.

Table 3.9: The average difference across occupation groups

Dependent Variable *Wages at age 26*	Intensive social tasks relative to intensive cognitive tasks (1) ATE	Intensive social tasks relative to intensive manual tasks (2) ATE	Intensive cognitive tasks relative to intensive manual tasks (3) ATE
Occupation premium	0.018 (0.014)	0.126*** (0.016)	0.107*** (0.013)
Observations	3,251	3,251	3,251

Note: Table 3.9 shows the ATE. Dependent Variable: Log weekly wages in dollar value in 2013. The sample includes respondents at age 26. In all regressions, additional controls are added. Additional controls include gender, region of residence, marital status and having children. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Moving to column (2), a comparison between social-task intensive occupations and manual-task intensive occupations reveals a striking wage premium associated with social task intensity. Workers in occupations demanding strong social tasks earn a substantial 12.6% more than their counterparts in manual labor occupations. This significant disparity underscores the potential for higher earning potential in jobs emphasizing social tasks.

Lastly, column (3) examines the wage differential between intensive cognitive tasks and intensive manual tasks. The results indicate a premium of 10.7% for workers in cognitive-task intensive occupations, suggesting a significant wage advantage over manual labor occupations.

Overall, these findings underscore the importance of knowledge-based tasks, whether social or cognitive, in shaping early career wage outcomes. While no statistically significant difference is observed between intensive social tasks and intensive cognitive tasks, both categories command considerable wage premiums compared to intensive manual tasks. This emphasizes the economic significance of abilities associated with knowledge-based tasks in early career trajectories.

3.6.6 Heterogeneity in occupation premiums

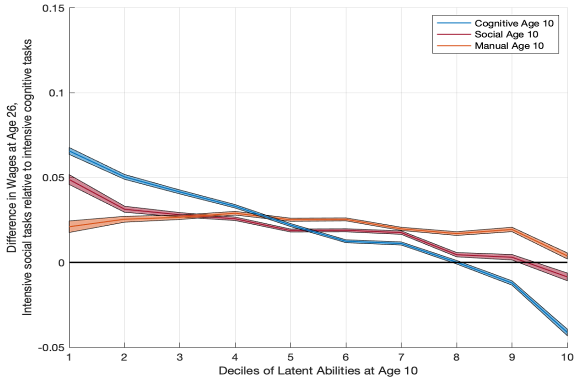
Figure 3.8 sheds light on how occupational premiums vary based on an individual's abilities level. Each panel explores the contribution of cognitive, social, and manual abilities to wage premiums across different abilities deciles. This provides an understanding of the benefits of whether certain abilities are concentrated at specific points in the abilities distribution.

Figure 3.8a highlights the wage premium associated with intensive social tasks occupations compared to intensive cognitive tasks occupations. The figure reveals the pronounced premium observed at the lower deciles of the abilities distributions. This suggests that individuals with lower levels of cognitive, social, and manual abilities tend to experience a more substantial wage premium when employed in occupations characterized by intensive social tasks as opposed to intensive cognitive tasks.

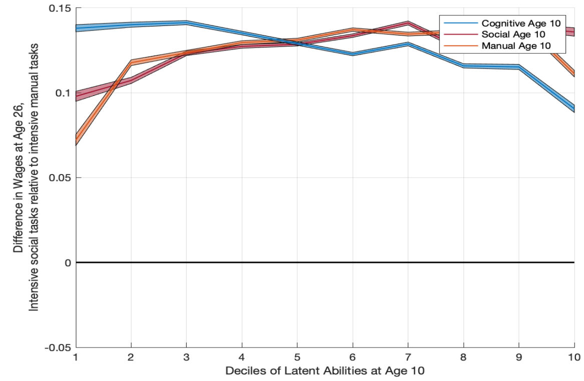
Figure 3.8b presents the comparison between social-task intensive occupations and manual-task intensive occupations. Unlike the previous comparison, the wage premium associated with social abilities remains relatively consistent across all deciles of the abilities distributions. This indicates that the advantage in wages linked to social abilities, as opposed to manual abilities, persists regardless of an individual's level of cognitive, social, or manual abilities. In simpler terms, individuals employed in occupations characterized by intensive social tasks consistently earn higher wages compared to those in manual labor occupations, irrespective of their levels of cognitive, social, or manual abilities. This suggests that the value placed on social tasks in the labor market remains consistent across a wide range of abilities profiles.

Finally, Figure 3.8c investigates the wage premium associated with intensive cognitive tasks in comparison to intensive manual tasks. The figure indicates that the highest premiums are concentrated among individuals in the top deciles of the abilities distributions. This result implies that while cognitive tasks generally command higher wages compared to manual tasks, the extent of this premium is particularly notable for individuals with superior cognitive, social, and manual abilities.

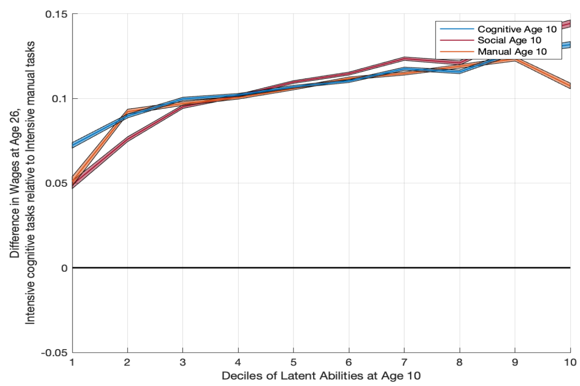
Figure 3.8: Heterogeneous Returns



(a) Intensive Social Tasks
Relative to Intensive Cognitive Tasks



(b) Intensive Social Tasks
Relative to Intensive Manual Tasks



(c) Intensive Cognitive Tasks
Relative to Intensive Manual Tasks

Note: Figure 3.8 shows the heterogeneous returns for cognitive, social, and manual abilities along with the 95% confidence interval. Each sub-figure represents the heterogeneous returns for a task-based occupations group.

Overall, it is important to note that the three dimensions of abilities align in the same direction across the three comparisons. Such alignment across dimensions of abilities implies that individuals with higher levels of cognitive, social, and manual abilities tend to experience similar patterns of wage premiums across different types of occupations. In other words, the relative advantage or disadvantage associated with these abilities remains consistent across groups. This suggests that a well-rounded skillset, encompassing cognitive, social, and even manual abilities to some extent, is generally rewarded in the early career labor market.

3.6.7 Goodness of fit

To assess whether the model represents well the underlying sorting pattern in the data, Table 3.10 presents the goodness of fit of the model. Column (1) displays the means of wages observed in the actual data set. These represent the benchmark against which the model's performance will be evaluated. Column (2) presents the means of wages predicted by the model based on its estimated parameters. Ideally, these simulated wage means should closely resemble the observed wage means in Column (1). Column (3) shows the statistical significance of the difference between the observed and simulated wage means. A statistically insignificant p-value indicates that the discrepancies between the two columns are likely due to random chance. Conversely, a significant p-value suggests a systematic difference between the model's predictions and the actual data.

Table 3.10: Goodness of fit

Log wages at age 26	Data Mean (1)	Simulated Mean (2)	H0: Data = Simulated (p-value) (3)
Unconditional	5.912	5.912	0.508
Conditional on occupation groups			
Intensive social tasks occupations	5.967	5.967	0.480
Intensive cognitive tasks occupations	5.935	5.935	0.525
Intensive manual tasks occupations	5.857	5.857	0.500

Note: Table 3.10 shows the goodness of fit. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

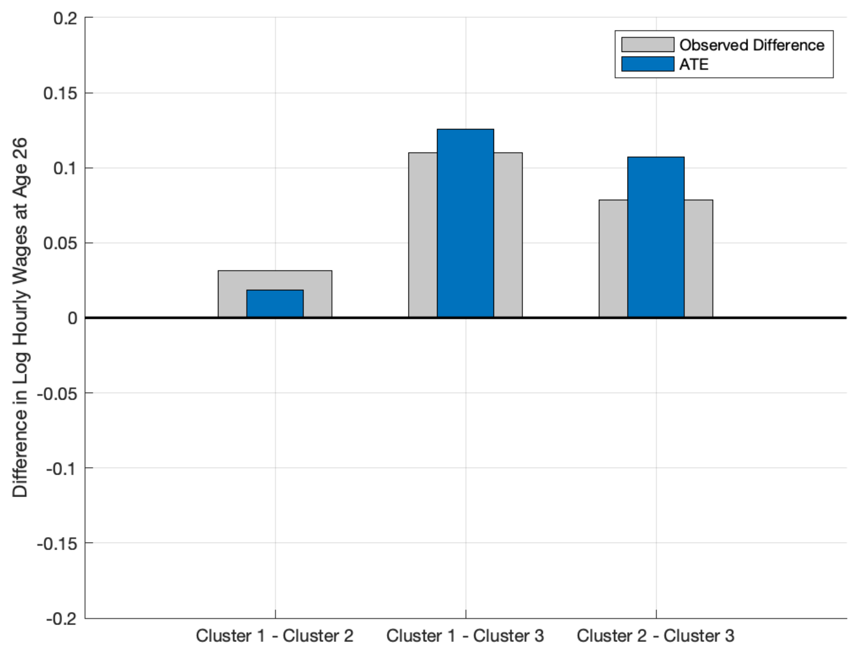
In this analysis, in both the unconditional and conditional data scenarios, in which occupation sorting is controlled for, the p-values are statistically insignificant. This implies that the model represents well the observed wage patterns in the observed data. In other words, the simulated wage data generated by the model closely mirrors the actual wage distribution, suggesting a good fit between the model and the underlying sorting process.

3.7 Decomposition of occupation premiums

This section highlights a key strength of the empirical model – its ability to address selection bias. In this context, it's important to understand if selection is a concern and, if so, what type is most prevalent.

To assess this, the analysis compares occupational premiums derived from the empirical model, ATE, with those from the raw data, and observed data. Figure 3.9 showcases these comparisons. The figure reveals that the observed data underestimates the wage premiums associated with both intensive social tasks and intensive cognitive tasks occupations, relative to intensive manual tasks occupations. This suggests that selection bias is likely at play.

Figure 3.9: Biased in occupation premiums



Note: Figure 3.9 compares the occupation premiums between the observed data and the ATE. Occupation premium refers to the difference in the average wage between two occupations groups. The observed data is the raw difference from the data. The ATE is calculated based on equation (3.21).

Building on this initial observation, Table 3.11 delves deeper to decompose the sources of these biases. The results highlight the presence of sorting on gains in the comparison between intensive cognitive tasks and intensive manual tasks, as well as selection bias across all comparisons.

Table 3.11: Occupation premiums bias decomposition

	Occupation premiums bias decomposition				
	Observed difference (1)	ATE (2)	Sorting on gains (3)	Selection bias observables (4)	Selection bias unobservables (5)
Intensive social tasks - Intensive cognitive tasks	0.031**	0.018	-0.005	-0.017***	-0.002***
	(0.015)	(0.014)	(0.004)	(0.003)	(0.001)
Intensive social tasks - Intensive manual tasks	0.110***	0.126***	-0.003	-0.033***	0.021***
	(0.016)	(0.016)	(0.004)	(0.004)	(0.005)
Intensive cognitive tasks - Intensive manual tasks	0.078***	0.107***	0.021***	-0.068***	0.018***
	(0.014)	(0.013)	(0.005)	(0.007)	(0.005)

Note: Table 3.11 shows the bias decomposition of the occupation premiums. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

3.8 Conclusion

The initial phases of one's career serve as a pivotal period for professional development and laying the foundation for future professional endeavors. This paper begins by highlighting the role of abilities in shaping career trajectories. The findings illustrate that cognitive, social, and manual abilities significantly influence individuals' occupational choices during the early stages of their careers. This suggests that young professionals strategically select career paths based on a careful assessment of their strengths and weaknesses, rather than through random assignment. In light of these findings, educational and career guidance programs should be tailored to provide young individuals with the necessary tools for self-assessment of their core abilities. Insights into their cognitive, social, and manual abilities allow individuals to make well-informed decisions regarding career paths that align with their abilities, thus maximizing their potential for success.

Secondly, the paper reveals that a diversified set of abilities is highly valued in the labor market during the early career stage. All three dimensions of abilities yield positive returns, emphasizing the importance of nurturing a broad range of abilities. Consequently, policymakers should prioritize educational initiatives that extend beyond a narrow focus solely on cognitive abilities. These programs should aim to cultivate a comprehensive set of abilities, encompassing social competencies such as communication, teamwork, and interpersonal abilities, while also considering potential manual dexterity tailored to meet the diverse requirements of the workforce.

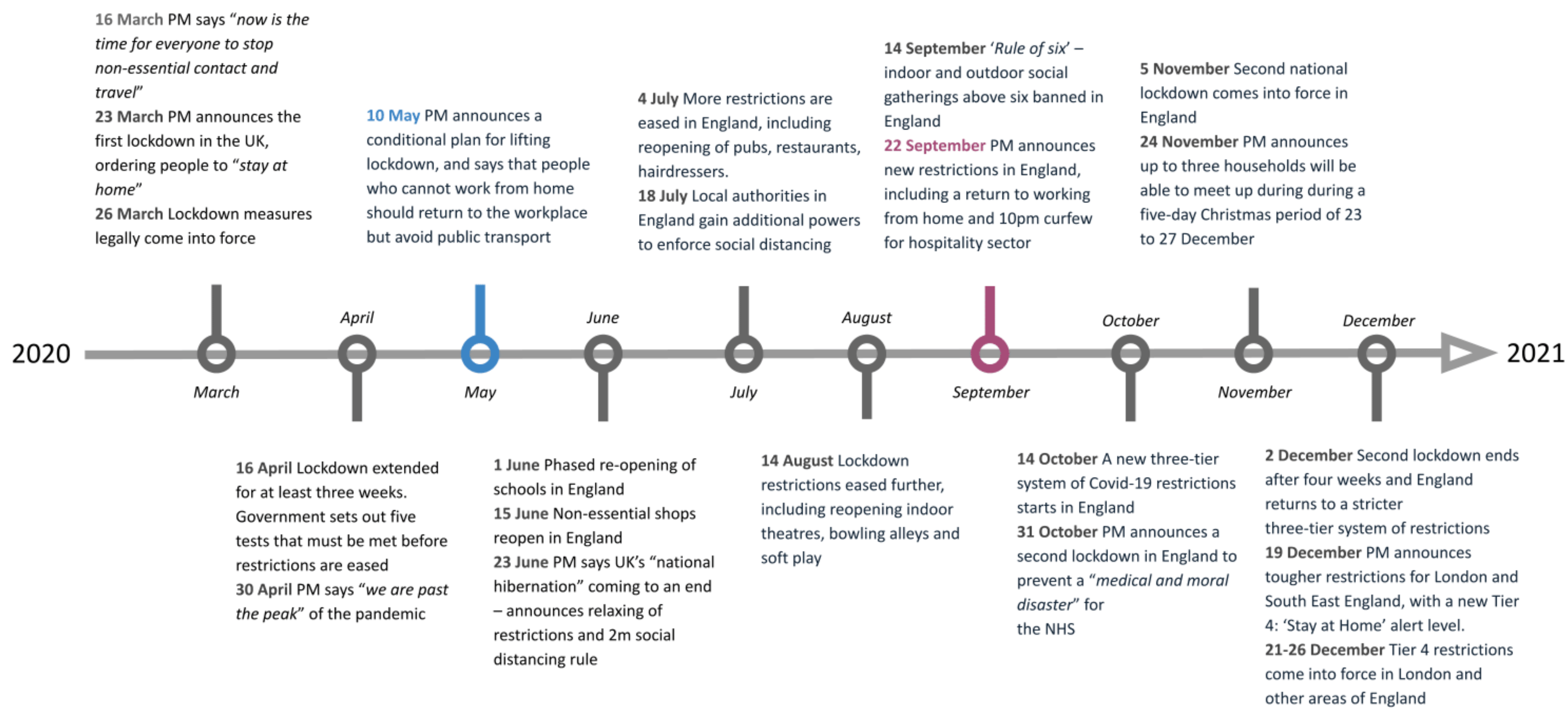
Most notably, the paper underscores the significance of aligning abilities with specific tasks for maximizing returns. The results highlight that the highest rewards for abilities are task-specific, implying that possessing strong cognitive, social, or manual abilities alone may not suffice. To optimize early career rewards, individuals must strategically match their abilities with the specific task demands of their chosen occupations. In this regard, career guidance services play a crucial role in promoting ability-task alignment. By providing young professionals with insights into the labor market and the specific abilities valued within different occupations, these services empower individuals to make informed career choices that enhance both their financial rewards and career satisfaction.

Overall, this paper sheds light on the intricate relationship between early career choices and the returns to abilities. By recognizing the distinct value attributed to different abilities across various task-based occupation groups, it advocates for the creation of a more efficient and rewarding early career landscape.

Appendix A: Complementary Material to Chapter 1

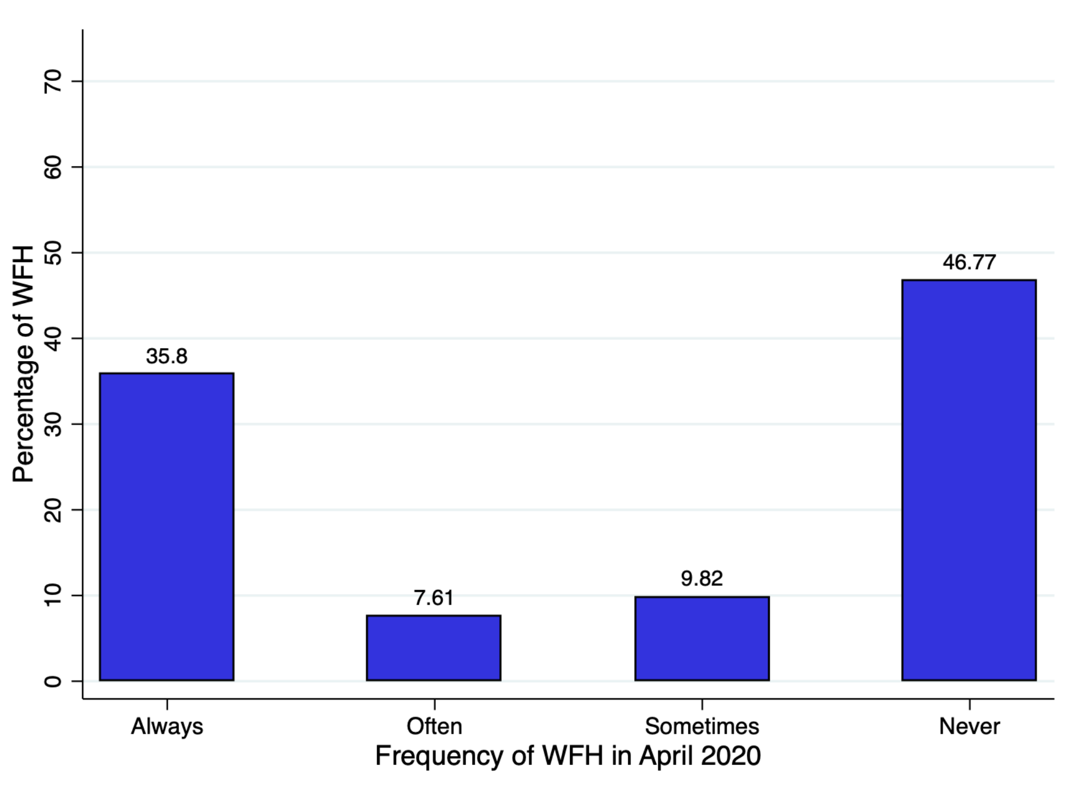
A.1 Additional Figures

Figure A.1: COVID Lockdown Policies in the UK



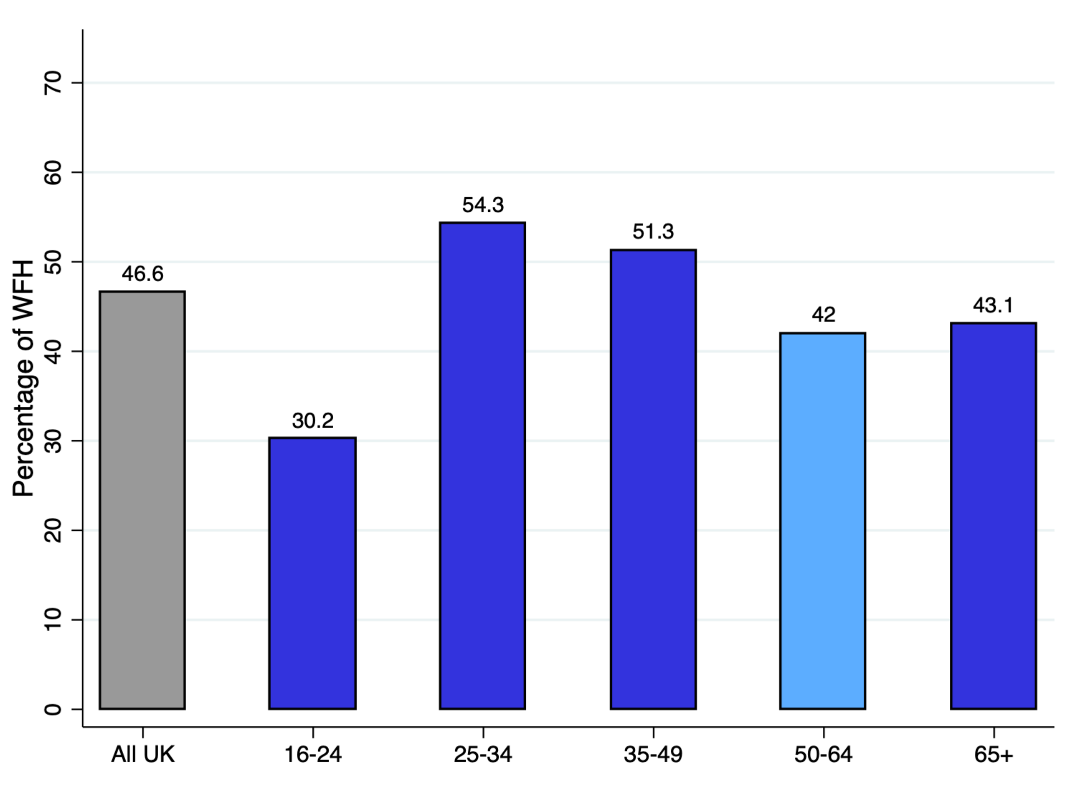
1cm2cm *Note*: Figure A.1 summarizes changes in COVID lockdown policies between March and December 2020.

Figure A.2: Frequency of WFH in April 2020



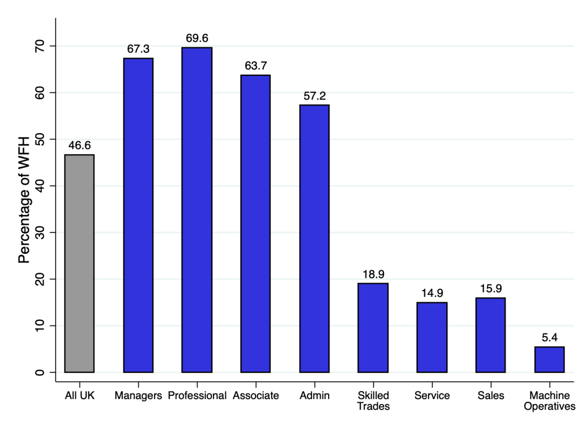
Note: Figure A.2 shows the percentage of homeworkers in April 2020 by the frequency of working from home, conditional on working. Source: Office for National Statistics

Figure A.3: WFH in April 2020, by Age Group

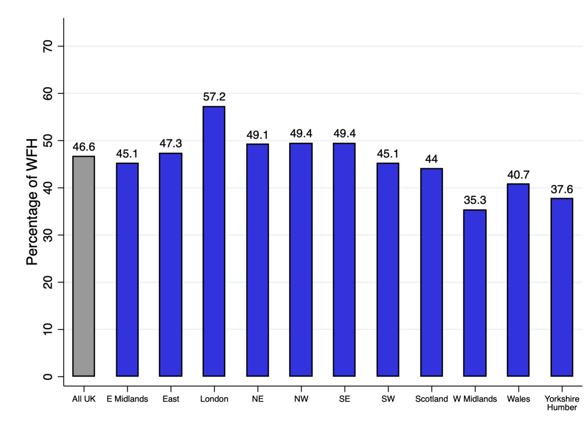


Note: Figure A.3 shows the percentage of homeworkers in April 2020 by age group, conditional on working. Source: Office for National Statistics

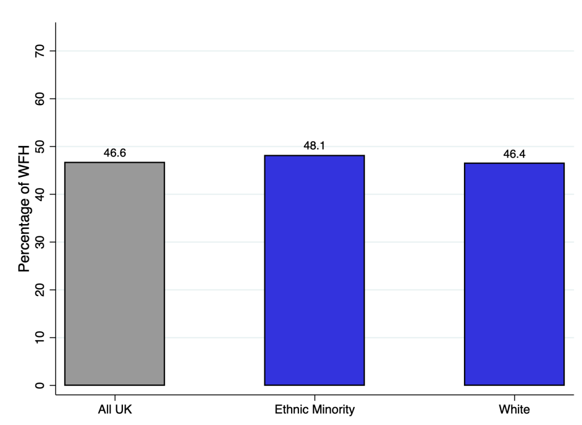
Figure A.4: % WFH in the UK in April 2020,
by Different Aggregated Level



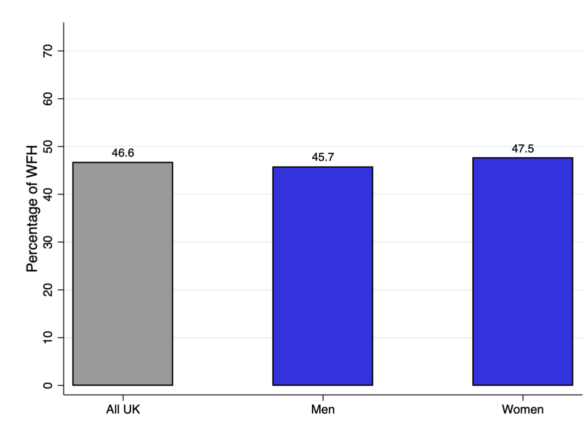
(a) % WFH in April 2020, by Occupations



(b) % WFH in April 2020, by Regions



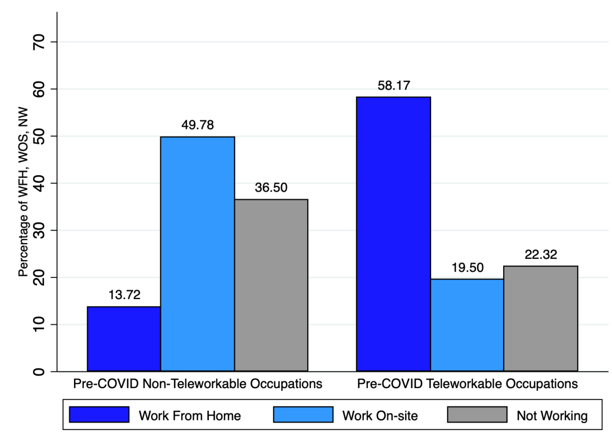
(c) % WFH in April 2020, by Race



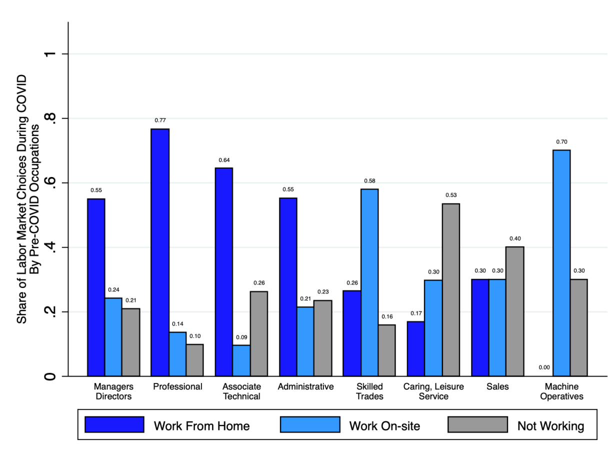
(d) % WFH in April 2020, by Gender

Note: Figure A.4 shows the percentage of homeworkers in the UK in April 2020 by occupations, regions, race and gender. Figure A.4a shows the percentage of homeworkers in April 2020 by one-digit SOC group, conditional on working. Figure A.4b shows the percentage of homeworkers in April 2020 by region, conditional on working. Figure A.4c shows the percentage of homeworkers by race. Figure A.4d shows the percentage of homeworkers by gender. Source: Office for National Statistics

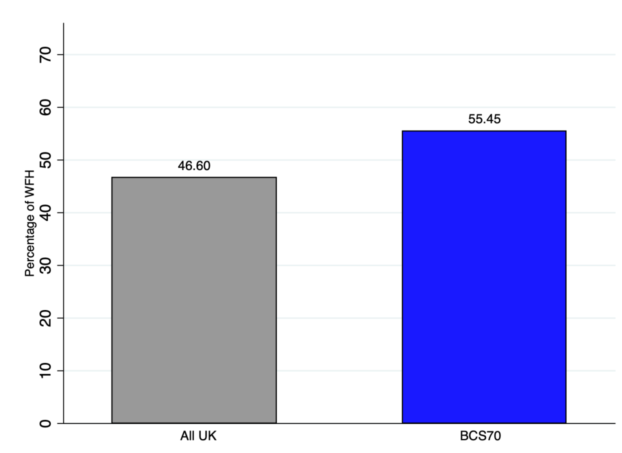
Figure A.5: WFH in the BCS



(a) % of WFH by Teleworkability



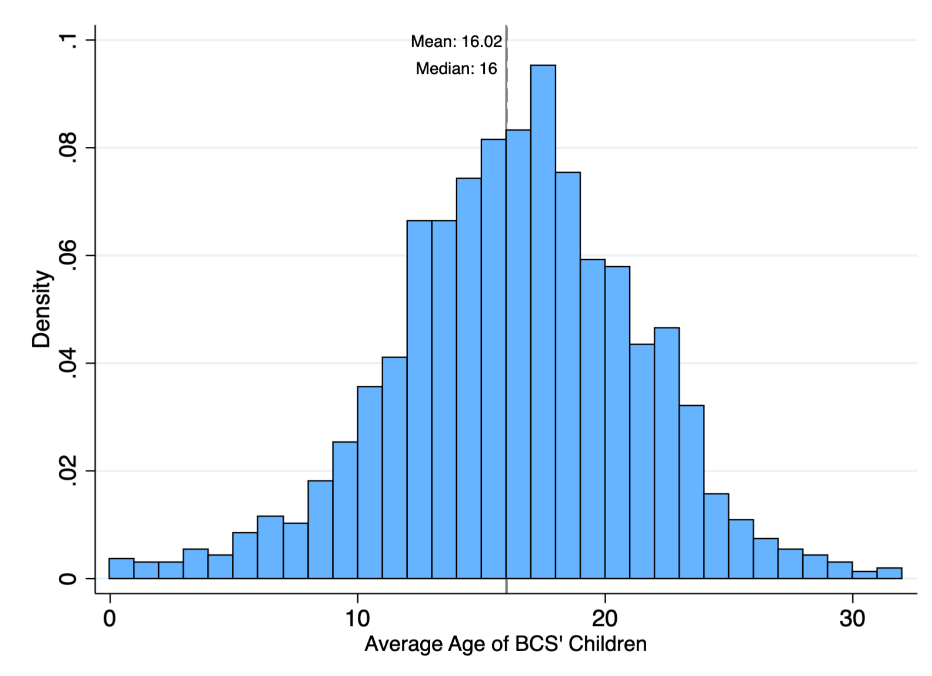
(b) % WFH by Teleworkable Occupation



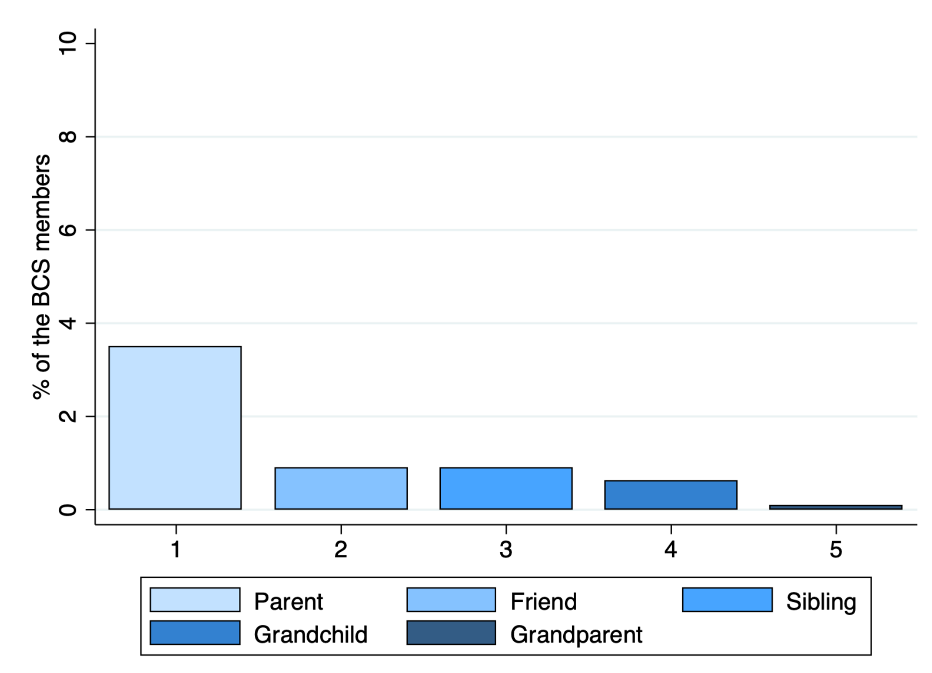
(c) % WFH in the BCS compared with the UK

Note: Figure A.5 shows the percentage of WFH in the BCS sample. Figure A.5a compares the percentage across the teleworkable category, defined by Dingel and Neiman (2020). Figure A.5b shows the percentage across one-digit SOC occupation. Figure A.5c compares the percentage of WFH in the analytical sample versus the overall UK. The overall WFH in the UK is from the Office for National Statistics.

Figure A.6: Additional Information about the BCS' Family



(a) Age Distribution of BCS' Children

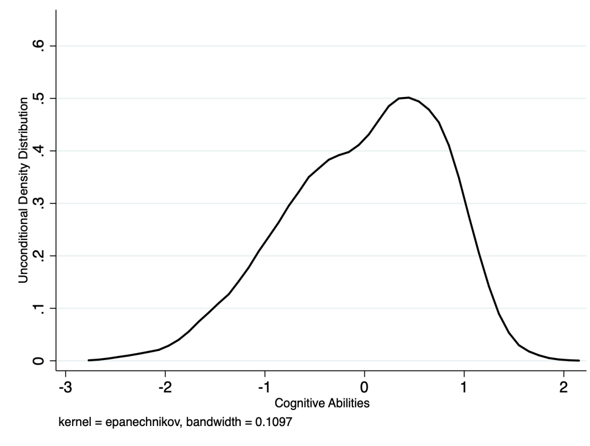


(b) Additional Members living with the BCS

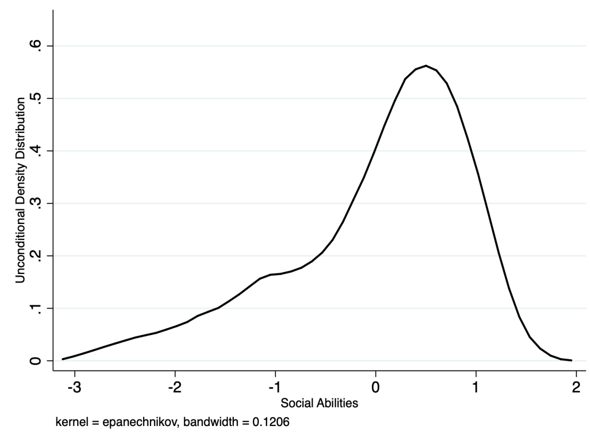
Note: Figure A.6a shows the age distribution of children of the BCS members. Figure A.6b shows the fraction of the BCS living with additional household members that are not their partner or children.

Figure A.7: Distributions of Unobserved Cognitive and Social Abilities

A. Unconditional Distributions

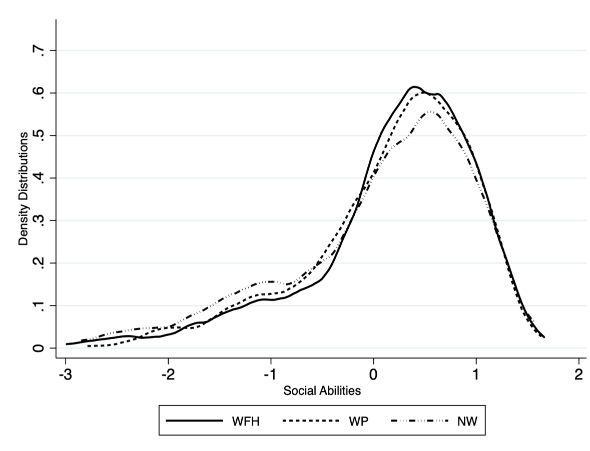


(a) Cognitive

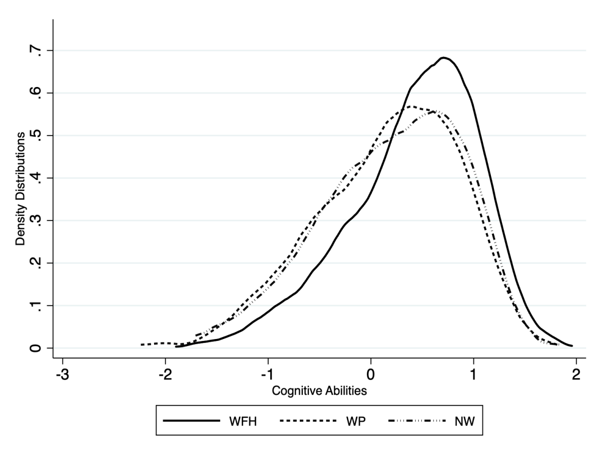


(b) Social

B. Conditional Distributions: By Work Arrangement Option



(c) Cognitive



(d) Social

Note: Figure A.7 shows the unconditional and conditional distributions of the two latent abilities (factors)

A.2 Additional Tables

Table A.1: COVID-19 Survey Target Population and Responses within the Target Population for the BCS

Wave 1		Wave 2	
Issued Sample (n)	Response within the Issued Sample	Issued Sample (n)	Response within the Issued Sample
10,458	4,223 (40.4%)	12,133	5,320 (43.9%)

Note: Table A.1 shows the responding rate of the BCS cohort. Response was defined as completion of the first block of the questionnaire. Target population includes participants that are alive and still residing in the UK. *Source*: CLS COVID Wave 1, 2, and 3 Document.

Table A.2: O*NET Items Used in the Classification

Work Context	**Generalized Work Activities**
Use email less than once per month	Performing physical activities
Deal with violent people at least once a week	Handling and moving objects
Work outdoors every day	Controlling machines, or processes
Exposed to diseases or infection at least once a week	Operating vehicles, mechanized devices, or equip.
Exposed to minor burns, cuts, bites, or stings at least once a week	Performing for or working directly with the public
Spent majority of time walking, running	Repairing, maintaining mechanical equip.
Spent majority of time wearing common specialized protective, safety equip.	Repairing, maintaining electronic equip.
	Inspecting equip., structures, materials

Note: Table A.2 shows the 15 items in O*NET being used in the classification of teleworkable occupations, following Dingel and Neiman (2020).

Table A.3: Mental Health Questions

Measure	**Question**	**Respondent Options**
Loneliness (UCLA Loneliness scale)	How often do you feel that you lack companionship?	3 Frequency: Hardly ever, Sometimes, Often
	How often do you feel left out?	3 Frequency: Hardly ever, Sometimes, Often
	How often do you feel isolated from others?	3 Frequency: Hardly ever, Sometimes, Often
	How often do you feel lonely?	3 Frequency: Hardly ever, Sometimes, Often
Life Satisfaction	Overall, how satisfied are you with your life nowadays?	Scale: 0 (Not At all) - 10 (Completely)
Malaise Inventory	Do you feel tired most of the time?	Binary Choice: Yes, No
	Do you often feel miserable or depressed?	Binary Choice: Yes, No
	Do you often get worried about things?	Binary Choice: Yes, No
	Do you often get in a violent rage?	Binary Choice: Yes, No
	Do you often suddenly become scared for no good reason?	Binary Choice: Yes, No
	Are you easily upset or irritated?	Binary Choice: Yes, No
	Are you constantly keyed up and jittery?	Binary Choice: Yes, No
	Does every little thing get on your nerves and wear you out?	Binary Choice: Yes, No
	Does your heart often race like mad?	Binary Choice: Yes, No

Note: Table A.3 shows the questions being used for constructing the mental health measures.

Table A.4: Control and Instrument Variables in Corresponding Equations

	Measurement Equations	Sorting Equations	Outcome Equations
Age 10 Variables			
Male	x	x	x
SES	x		
Regions of Residence	x		
Nb days reading to the child	x		
Autonomous parenting style	x		
COVID Variables (Age 50)			
Having a Partner		x	x
Having Children		x	x
Financial Status		x	x
Pre-covid Occupation		x	x
Regions of Residence		x	x
Pre-covid Mental Health Self-Assessment			x
Cost Shifters			
Distance to Work		x	
Past Unemployment Spells		x	
Unobserved Factors			
Cognitive Factor	x	x	x
Social Factor	x	x	x

Note: Table A.4 displays the list of variables entering the associating equations. *Region-occupation Wages* enters the NW sorting equation; *Region-occupation WFH Share* enters the WFH sorting equation. *Cognitive Factor* enters the cognitive measurement equations; *Social Factor* enters the social as well as cognitive measurement equations; both factors enter all the choice equations and outcome equations.

Table A.5: Correlations Between Test Scores

	Reading	Math	Pattern Recognition	Externalizing	Internalizing	Hyperactivity
Reading	1.000					
Math	0.739	1.000				
Pattern Recognition	0.587	0.580	1.000			
Externalizing	0.208	0.191	0.150	1.000		
Internalizing	0.094	0.117	0.083	0.408	1.000	
Hyerpactivity	0.250	0.252	0.164	0.560	0.379	1.000

Note: Table A.5 shows the correlation between the test scores taken at early age. Cognitive test scores include: Reading, Math, Pattern Recognition; Social test scores include: Externalizing, Internalizing, Hyperactivity behaviors.

Table A.6: Effects Size from Previous Studies

Paper	Geo	Population	Effect
Adams-Prassl et al, 2022 (Economic Policy)	US	12,010 respondents Cross-State	Lowered mental health by 0.083 SD
Brodeur et al, 2021 (Journal of Public Economics)	US, Europe	Google Trends Data	Boredom: - 2 SD in Europe - 1 SD in the US Loneliness worry and sadness: - 1.5 SD in Europe - Lower in the US
Altindag et al, 2022 (AEJ: Applied Economics)	Turkey	Senior adults, survey (1,907 participants)	Increased mental distress by 0.2 SD
Wang et al, 2022 (Journal of Social Policy)	UK	UK Household Longitudinal Panel Study	Increased mental distress by 1.32 SD
García-Prado et al, 2022 (Economics & Human Biology)	Europe	Survey of Health, Ageing and Retirement in Europe (SHARE) Oxford COVID-19 Government Response Tracker	Anxiety: 0.072 SD Depression: 0.051 SD

Note: Table A.6 summarizes the effects size from previous studies.

Table A.7: Fraction of Individuals Changing Their Workplace Arrangements

	Worplace Arrangement 2021			
	WFH	WP	NW	Total
Worplace Arrangement 2020				
WFH	1,353	48	91	1,492
	(90.68)	(3.22)	(6.10)	(100.00)
WP	240	668	123	1,031
	(23.28)	(64.79)	(11.93)	(100.00)
NW	62	52	192	306
	(20.26)	(16.99)	(62.75)	(100.00)
Total	1,655	768	406	2,829
	(58.50)	(27.15)	(14.35)	(100.00)

Note: Table A.7 shows the number of individuals changing the workplace arrangement between 2020 and 2021. The row percentage is reported in the parenthesis.

A.3 Identification of Unobserved Abilities Distributions

This section describes the identification of the unobserved cognitive and social abilities distributions, based on the measurement system in Section 4.4. First, I follow Prada and Urzua (2017) and assume the dependence between cognitive and social abilities are linear in the following structure:

$$\theta^C = \gamma\theta^S + \theta_{\text{aux}} \tag{AA.1}$$

Where θ_{aux} is an auxiliary factor that is independent from the social factor. γ is the correlation between cognitive and social abilities.

The distribution of social ability can be characterized by assuming that social ability is the only factor that links the correlation across the three observed social test scores: externalizing, internalizing and inconsequential behaviors. The covariance of any two social test scores can be written as:

$$\text{Cov}(S^i, S^j) = \beta^{S,S^i}\beta^{S,S^j}\sigma^2_{\theta^S} \tag{AA.2}$$

Where β^{S,S^i} is the loading of social ability to the social test score i, or the contribution of social ability factor to test score i. $\sigma^2_{\theta^S}$ is the variance of the social ability distribution. From three observed social test scores, there are three equations derived from the test scores covariance similar to equation (AA.2), and four unknown $\{\beta^{S,S^{\text{Inter}}}, \beta^{S,S^{\text{Exter}}}, \beta^{S,S^{\text{Ins}}}, \sigma^2_{\theta^S}\}$. Thus, one normalization is required. In the estimation, I normalize the loading of inconsequential behaviors test score to be one, $\beta^{S,S^{\text{Ins}}} = 1$. With this normalization, there are three equations for three unknowns. Thus, the social ability distribution can be identified up to a constant from the three observed social test scores.

Since cognitive ability correlates with social ability, to identify the distribution of cognitive ability, I rely on the covariances across cognitive test scores as well as the covariances between cognitive and social abilities. From equation (AA.2), the covariances of any cross cognitive test scores or between cognitive and social test scores can be written as:

$$\begin{aligned} \text{Cov}(C^k, S^j) &= (\gamma\beta^{C,C^k} + \beta^{S,C^k})\beta^{S,S^j}\sigma^2_{\theta^S} \\ &= \pi^{C^k}\beta^{S,S^j}\sigma^2_{\theta^S} \qquad \text{(AA.3)} \\ \text{Cov}(C^k, C^l) &= (\gamma\beta^{C,C^k} + \beta^{S,C^k})(\gamma\beta^{C,C^l} + \beta^{S,C^l})\sigma^2_{\theta^S} + \beta^{C,C^k}\beta^{C,C^l}\sigma^2_{\theta^{\text{aux}}} \\ &= \pi^{C^k}\pi^{C^l} + \beta^{C,C^k}\beta^{C,C^l}\sigma^2_{\theta^{\text{aux}}} \qquad \text{(AA.4)} \end{aligned}$$

Where β^{C,C^k} is the loading of cognitive ability to cognitive test score k. β^{S,C^k} is the loading of social ability to cognitive test score l. And, β^{S,S^j} is the loading of social ability to social test score j. Since β^{S,S^j} and $\sigma^2_{\theta^S}$ are identified through the social test scores system, the covariances across cognitive and social test scores identify the composite contribution of cognitive and social ability to cognitive test score, π^{C^k}. Once π^{C^k} are identified, the cross covariances across cognitive test scores, as in equation (AA.4) identifies β^{C,C^l}. Similar to before, there are three cross cognitive test scores covariances equations and four unknowns $\{\beta^{C,C^{\text{Reading}}}, \beta^{C,C^{\text{Math}}}, \beta^{C,C^{\text{Pattern}}}, \sigma^2_{\theta^{\text{aux}}}\}$. Thus, one normalization is required. I normalize the loading of $\beta^{C,C^{\text{Reading}}}$ to be one.

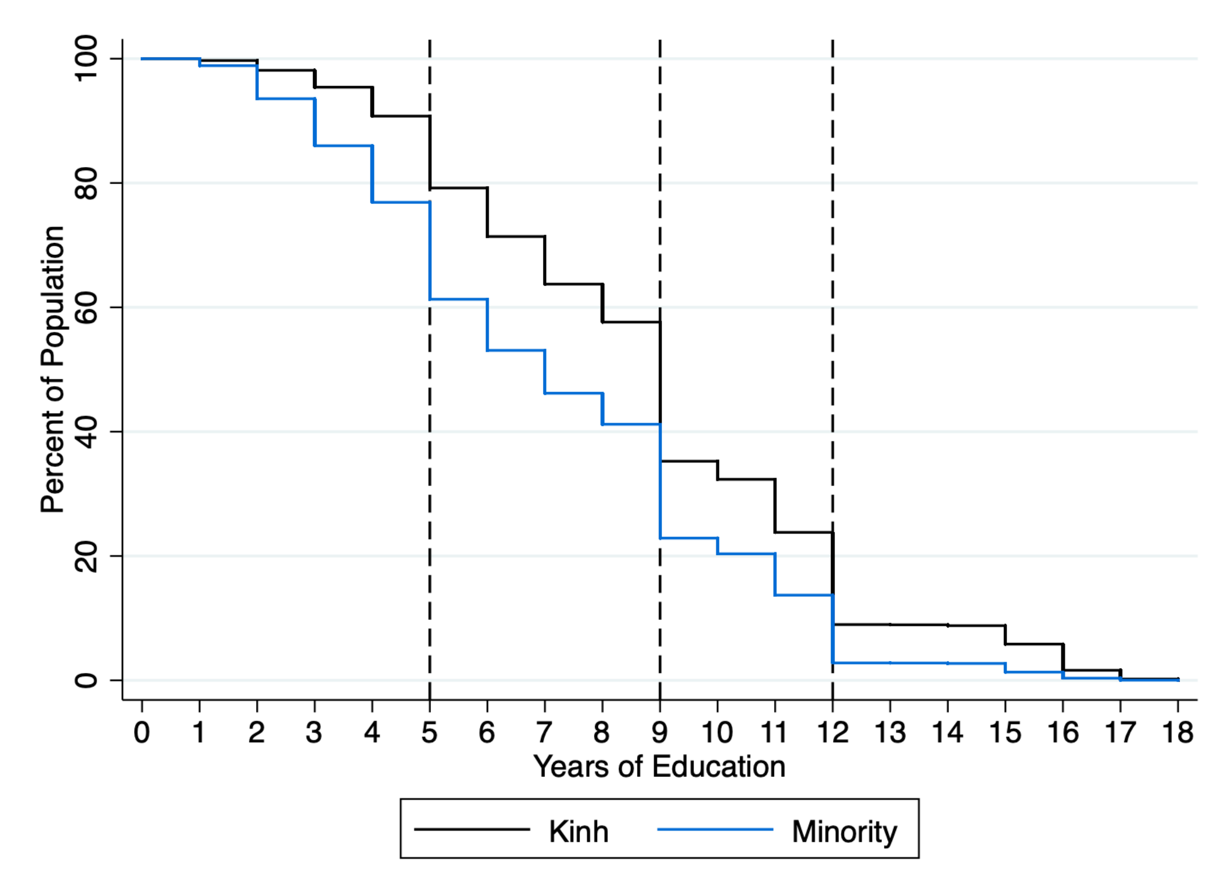
Finally, the identification of β^{S,C^k} and γ can be secured through the identity equation π^{C^k} with one last normalization. Following Prada and Urzua (2017), one cognitive test score is chosen as the dedicated measure. That is, for that cognitive test score the loading of social ability is normalized to zero. In the estimate, the contribution of social ability to math is normalized to zero. The normalizations of the measurement system can be summarized as below.

$$M = \begin{bmatrix} \beta^{C,C^{\text{Math}}} & 0 \\ 1 & \beta^{S,C^{\text{Reading}}} \\ \beta^{C,C^{\text{Pattern}}} & \beta^{S,C^{\text{Pattern}}} \\ 0 & \beta^{S,S^{\text{Exter}}} \\ 0 & 1 \\ 0 & \beta^{S,S^{\text{Inter}}} \end{bmatrix} \tag{AA.5}$$

Appendix B: Complementary Material to Chapter 2

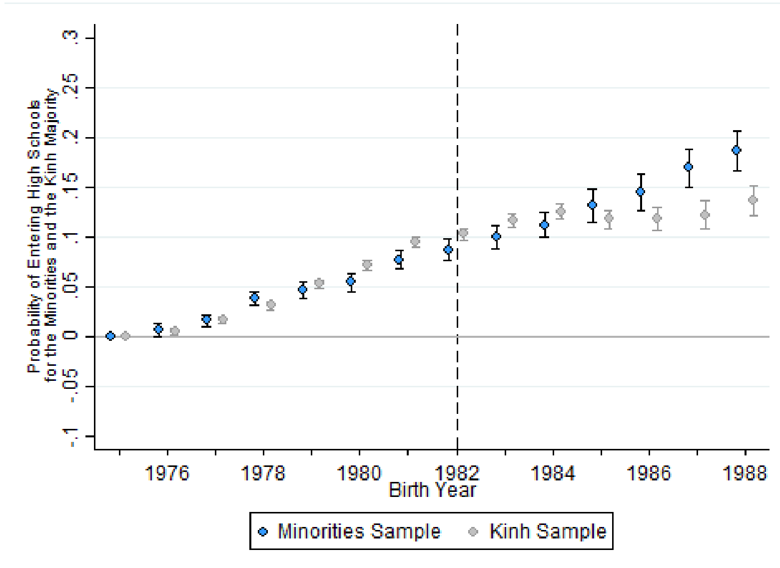
B.1 Additional Figures

Figure B.1: Distribution of Years of Schooling
Kinh and Minority Students

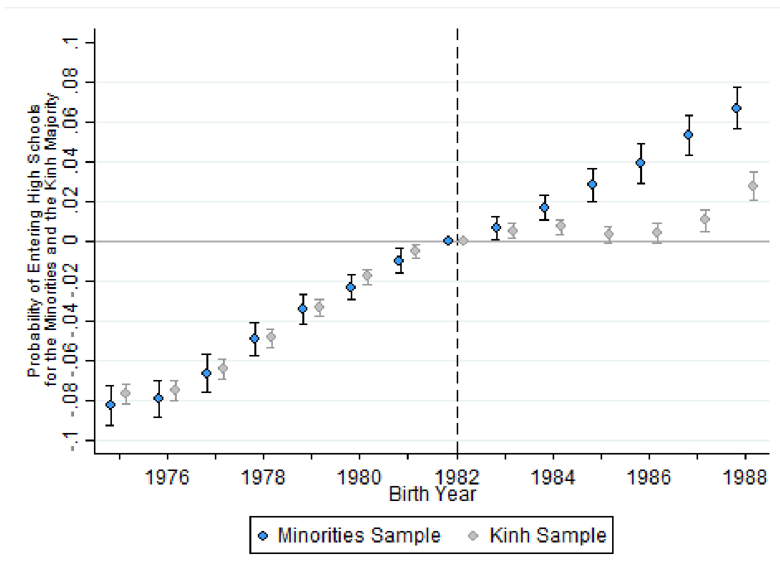


Note: Figure B.1 shows the cumulative percentage of ethnic minority and Kinh majority students by the number of schooling years. Survey weights are applied.

Figure B.2: Trends of the Average Probability of Entering High School for Ethnic Minorities and the Kinh Majorities



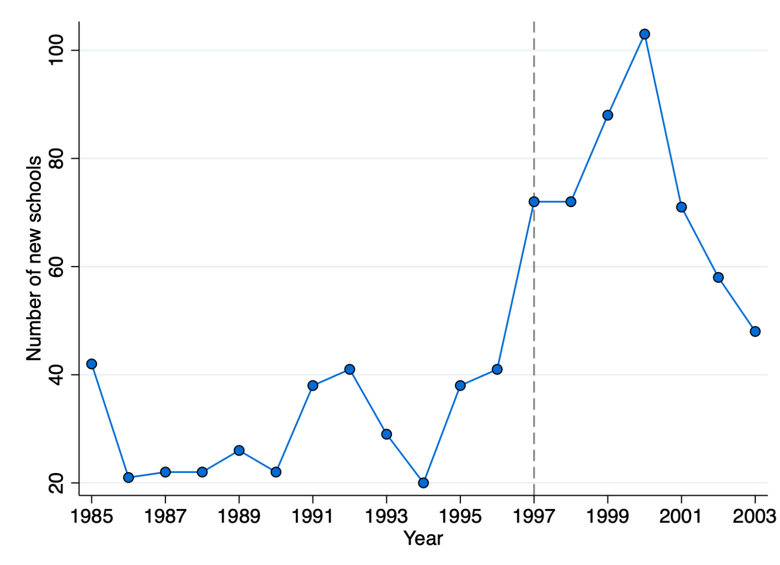
(a) Raw Trends



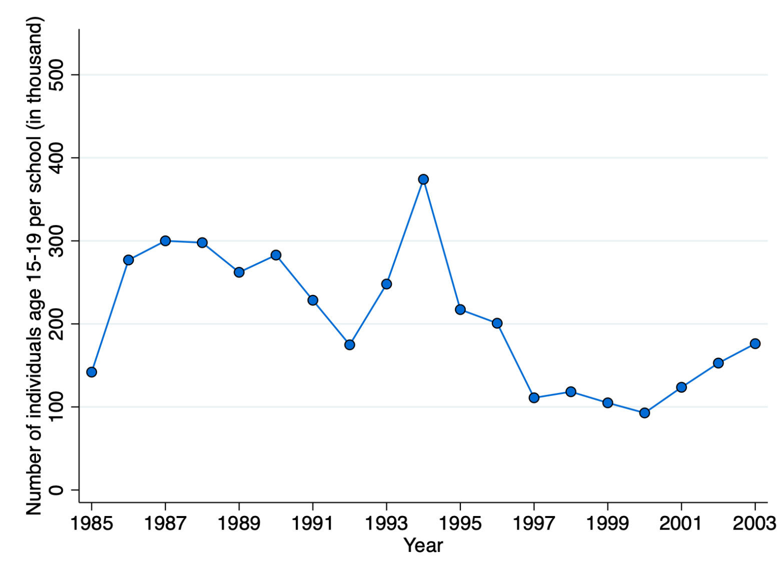
(b) Residualized Trends

Note: Figure B.2 shows the trends for the average probability of entering high school for ethnic minorities an the Kinh majority students. Figure B.2a shows the raw trends, with the birth year 1975 being normalized. Figure B.2b shows the residualized trends, controlling for the individual and household characteristics. Birth year 1982 is normalized. Survey weights are applied in both subfigures.

Figure B.3: Number of New High Schools being Constructed and Number of High School Aged Individuals per Schools



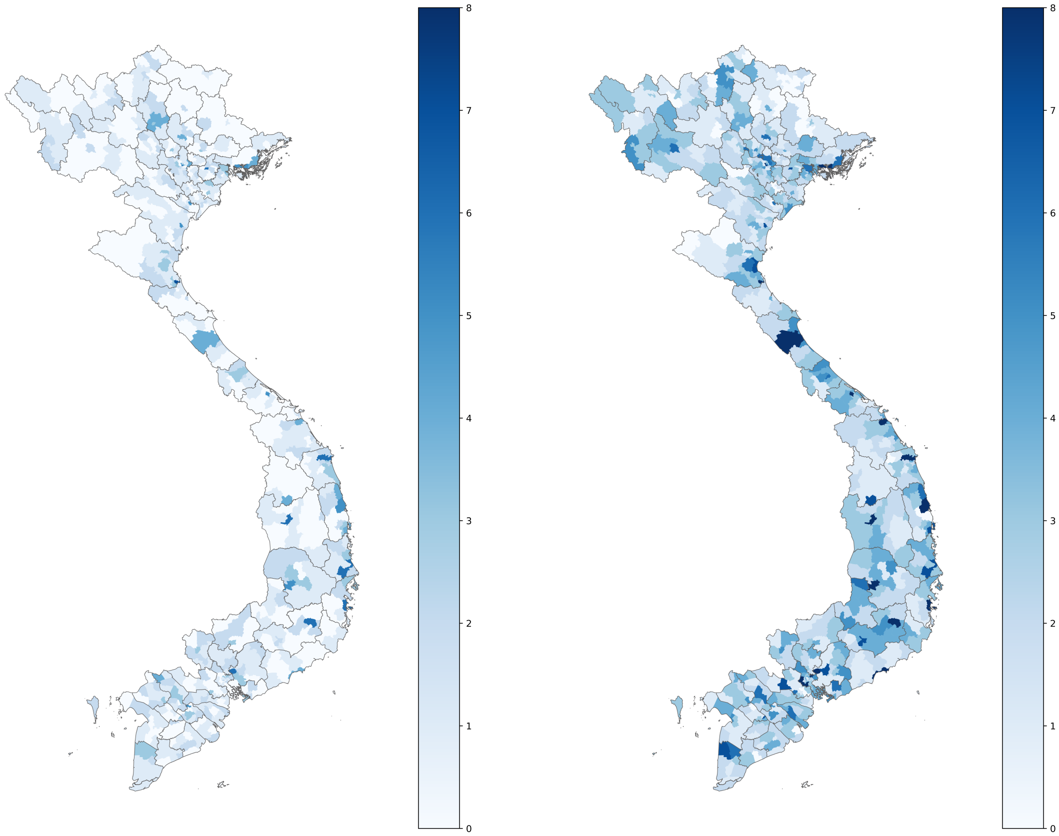
(a) New High School Constructed Nationwide



(b) Number of High School Aged Individuals per Schools

Note: Figure B.3a shows the aggregated number of new high schools being constructed at the national level. Figure B.3b shows the number of high school aged individuals per high school in the same period. The data for the number of new high schools is from the scraped data described in the text, and the data for the number of high school aged individuals is from the World Bank national accounts data.

Figure B.4: Number of New High Schools being Constructed Before and After 1998

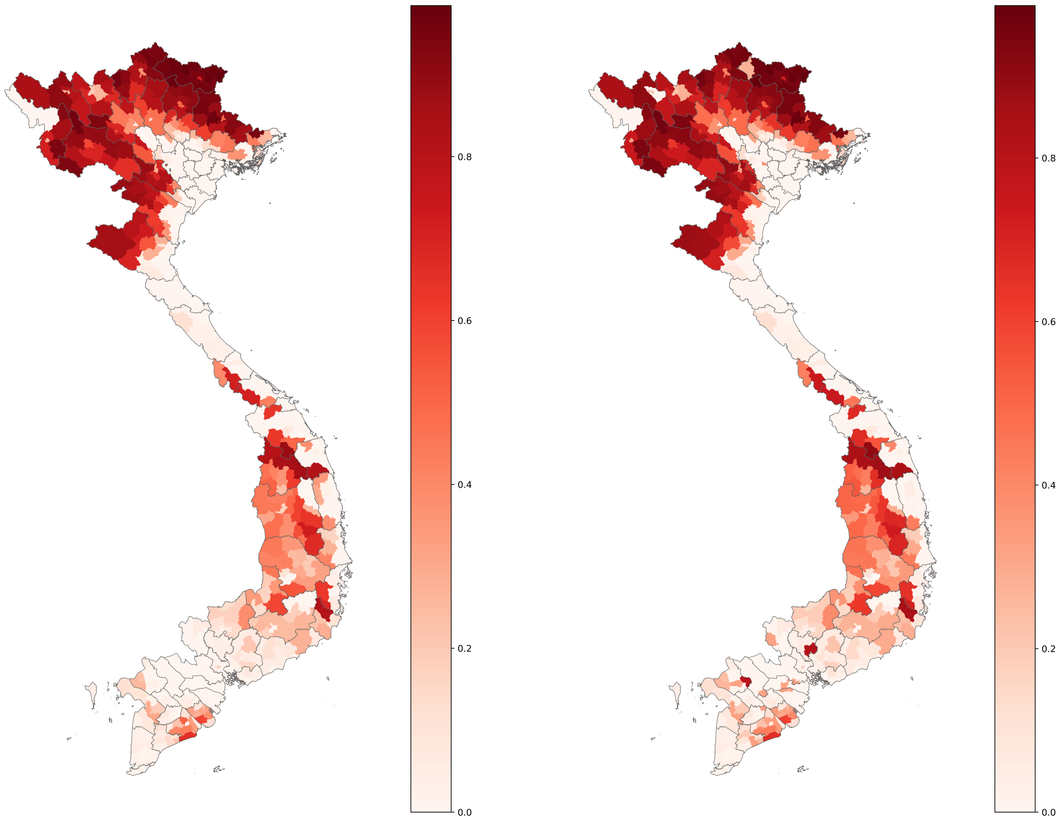


(a) New High School Constructed Before 1998

(b) New High School Constructed On or After 1998

Note: Figure B.4a shows the aggregated number of new high schools being constructed across years before 1998. Similarly, Figure B.4b shows the aggregated number of new high schools being constructed across years after 1998. A darker color indicates a higher level of new schools. The calculation is based on the scraped schools data described in the text.

Figure B.5: Fraction of Ethnic Minorities Before and After 1998

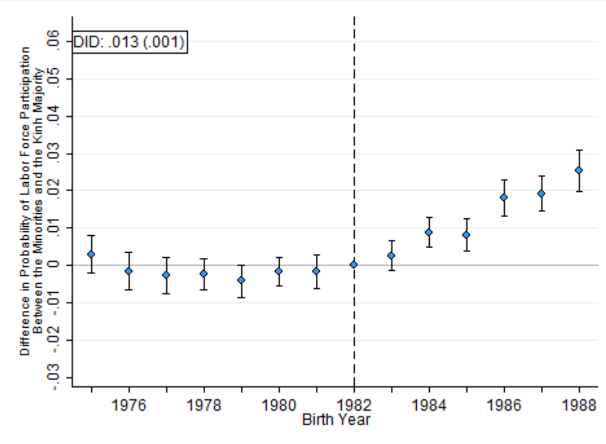


(a) Fraction of Ethnic Minorities Before 1998

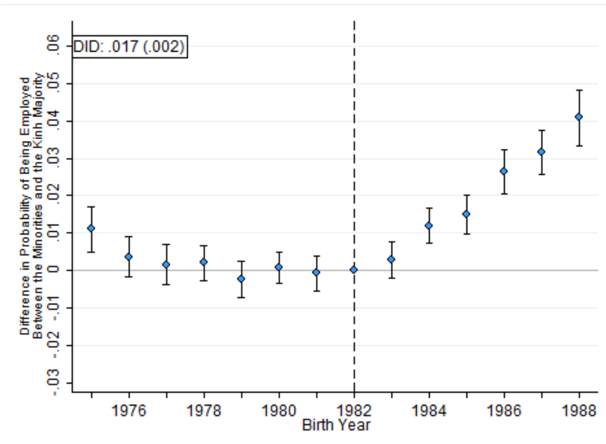
(b) Fraction of Ethnic Minorities On or After 1998

Note: Figure B.5a shows the aggregated fraction of ethnic minorities across years before 1998 at the district level. Similarly, Figure B.5b shows the aggregated fraction of ethnic minorities across years after 1998 at the district level. A darker color indicates a higher fraction of ethnic minorities. The calculcation is based on the census data.

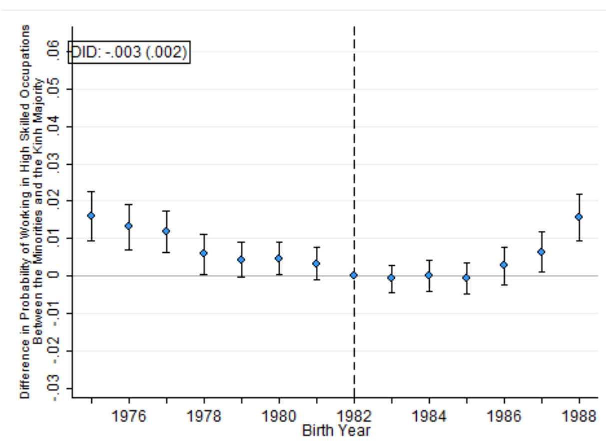
Figure B.6: Difference in the Labor Market Outcomes Between Ethnic Minority and Kinh Majority Students



(a) Prob. Participating in the Labor Force



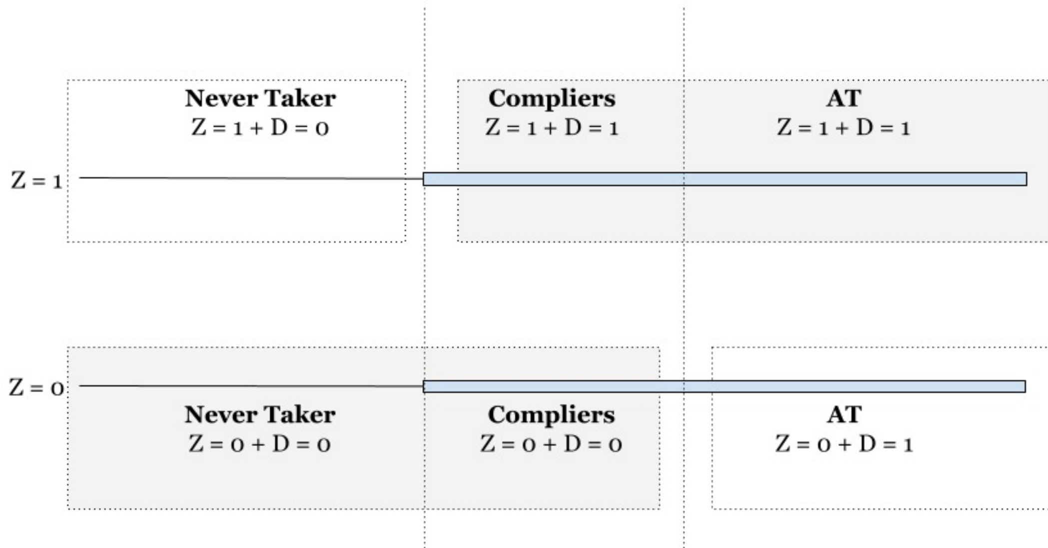
(b) Prob. Being Employed



(c) Prob. Working in High Skilled Occupations

Note: Figure B.6 shows the difference in long-term labor market outcomes between Kinh and ethnic minority students. Figure B.6a, B.6b, B.6c show the difference in the probability of labor force participation, being employed, and working in high-skilled occupations, respectively. Each point shows the estimated coefficient β_{1j} from equation (2.6) and its associated 95% confidence interval. Survey weights are applied. The normalized birth year is 1982.

Figure B.7: Compliers Groups



Note: Figure B.7 shows the overlap of different complier groups.

B.2 Additional Tables

Table B.1: Effects on Probability of Entering and Completing High School Without Survey Weights

Dependent Variable	Prob. Entering High School				
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS
Minority × Post	0.017*** (0.005)	0.020*** (0.004)	0.021*** (0.004)	0.017*** (0.003)	0.018*** (0.003)
Observations	2,660,938	2,660,938	2,660,938	2,660,938	2,660,938
Nb. Clusters	674	674	674	674	674
Dependent Mean	0.249	0.249	0.249	0.249	0.249
R-squared	0.089	0.169	0.169	0.169	0.169
Birth Year FE	✓	✓	✓	✓	✓
District FE	✓	✓	✓	✓	✓
Indv and HH Controls		✓	✓	✓	✓
Fraction of Ethnic Minorities			✓	✓	✓
Region × Linear, Quadratic Trend				✓	✓
Number of High Schools					✓

Note: Table B.1 shows the effects of the policy on the probability of entering and completing high school. The estimated coefficient is β_1 in equation (2.5). No survey weights are applied. Standard errors are clustered at the district level. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table B.2: Long Term Effects on Labor Market and Non-Labor OutcomesWithout Survey Weights

Dependent:	LFP (1) IV	Employed (2) IV	Salaried Worker (3) IV
Entering High School	0.241*** (0.021)	0.160*** (0.013)	0.694*** (0.041)
Observations	2,643,894	2,453,842	2,403,914
Nb. Clusters	674	674	674
Dependent Mean	0.921	0.900	0.392
F-Statistics	116.506	123.453	125.168
Birth Year FE	✓	✓	✓
District FE	✓	✓	✓
Indv and HH Controls	✓	✓	✓
Fraction of Ethnic Minorities	✓	✓	✓
Region $\times$ Linear, Quadratic Trend	✓	✓	✓
Number of High Schools	✓	✓	✓
Experience	✓	✓	✓

Note: Table B.2 shows the effects of the policy on labor and non-labor long-term outcomes. The estimated coefficient is π_1 in equation (2.8). Column (2) is conditional on participating in the labor force, Column (3) is conditional on being employed. No survey weights are applied. Standard errors are clustered at the district level. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table B.3: Descriptive Statistics - Cambodia Sample

	Full Sample		Kinh Ethnic		Other Ethnic Groups	
	Mean	SD	Mean	SD	Mean	SD
Kinh Ethnicity	0.004	0.062	-	-	-	-
Outcomes						
Entering High School	0.162	0.369	0.093	0.290	0.163	0.369
LFP	0.880	0.325	0.871	0.335	0.880	0.325
Employed	0.864	0.343	0.823	0.382	0.864	0.343
Salaried Workers	0.161	0.367	0.187	0.391	0.161	0.367
Individual Characteristics						
Female	0.487	0.500	0.462	0.499	0.487	0.500
Religion						
Buddhist	0.978	0.147	0.744	0.437	0.979	0.144
Muslim	0.016	0.127	0.014	0.119	0.016	0.127
Christian	0.003	0.054	0.142	0.349	0.002	0.048
Other	0.003	0.054	0.100	0.300	0.002	0.050
Marital Status						
Single	0.355	0.478	0.429	0.495	0.355	0.478
Married	0.624	0.484	0.552	0.498	0.624	0.484
Separated	0.001	0.032	0.000	0.000	0.001	0.032
Divorced	0.015	0.121	0.014	0.119	0.015	0.121
HH Characteristics						
HH Size	5.192	2.313	5.365	2.378	5.191	2.313
Nb. Females in HH	1.131	0.579	1.076	0.555	1.131	0.579
Home Ownership	0.934	0.248	0.878	0.328	0.934	0.248
Nb. Appliances	1.178	0.868	1.140	0.755	1.178	0.868
Electricity	0.309	0.462	0.470	0.499	0.308	0.462
Piped Water	0.164	0.370	0.204	0.403	0.164	0.370
Urban Status	0.792	0.406	0.628	0.484	0.793	0.405

Note: Table B.3 shows the mean and standard deviation of the overall sample and by ethnic groups for the Cambodia sample. Similar sample restrictions are applied to obtain the final analytical sample. The analytical sample includes 206,716 individuals. Survey weights are applied.

B.3 Scraped Data for School Construction

The collection of data concerning the count of high school institutions per administrative district along with their respective founding years has been accomplished through the consolidation of information derived from diverse sources. The administrative delineation of Vietnam consists of 58 provinces and 5 municipalities, designated for major urban centers such as Hanoi and Ho Chi Minh City. Each of the 58 provinces is subsequently demarcated into three distinct categories of districts: provincial cities, towns, and rural municipalities. Given that the oversight of educational administration is vested at the provincial level, the number and official name of each school within each district have been procured from the official sources of individual provinces. The cumulative tally of secondary educational institutions, specifically high schools, amounts to approximately 3000 schools.

With the sole exception of a few larger municipalities, provinces refrain from sharing a publicly accessible archive detailing the founding year of individual schools under their administration. To obtain this data, the year of establishment for each high school institution has been collected by combining a variety of administrative outlets, governmental bulletins, Wikipedia entries, self-reported dates by the schools on their official websites, and residual online reports and interviews. Where a structure collection of establishment years was available, web scraping has been implemented to organize this data at scale. On the other hand, where no alternative source was available, information from sectoral publications and local newspapers was manually retrieved.

In its entirety, this data collection process facilitated the construction of a comprehensive dataset of high schools and their respective years of establishment at district level, which is the most granular administrative level of the Vietnamese public administration. The data includes the founding year of 2700 high school institutions, representing over 97% of the total number of high schools in operation across Vietnam. The founding dates of these institutions span from the earliest establishment in 1854 to the most recent foundations in 2022. For the purpose of this work, only high schools instituted between the years of 1978 and 2019 have been retained.

Appendix C: Complementary Material to Chapter 3

C.1 Estimation

The empirical model implies the following sample likelihood:

$$\mathbf{L}(\Theta|.) = \prod_{n=1}^{N} \left\{ \int_{\boldsymbol{\theta}} \prod_{j \in J} f_C(C_{i,k}|X_i^{j,C}, \boldsymbol{\theta}) \prod_{l \in L} f_S(S_{l,i}|X_i^{l,S}, \boldsymbol{\theta}) \prod_{m \in M} f_M(M_{i,k}|X_i^{m,M}, \boldsymbol{\theta}) \varphi(Y_i|X_i^Y, X_i^I, \boldsymbol{\theta}) dF(\boldsymbol{\theta}) \right\} \tag{AC.1}$$

where Θ is the set of parameters to be estimated; $\boldsymbol{\theta}$ contains all the latent factors, $\boldsymbol{\theta} \equiv \{\theta^C, \theta^S, \theta^M\}$; $F(\boldsymbol{\theta})$ is the cumulative density functions of the latent factors; $f_C(.)$, $f_S(.)$, and $f_M(.)$ are the density of the cognitive, social, and manual test scores, respectively; $\varphi(.)$ is the estimation functions of the earnings and occupation choice.

$$\varphi(Y_i|X_i^Y, X_i^I, \boldsymbol{\theta}) = \prod_{k \in K} \left\{ f(Y_i(k)|X_i^Y, \boldsymbol{\theta}) Pr(I_i^I \geq 0|X_i^I, \boldsymbol{\theta}) \right\}^{\mathbf{1}\{q=k\}} \tag{AC.2}$$

I use Markov Chain Monte Carlo to estimate the likelihood function (AC.1). The estimated parameters are derived from the average of 1,000 draws from the posterior distributions. The variables entering the equations in the model are listed in Table A.4.

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