Re-skilling, Up-skilling, and the Role of Education in the Adjustment to Economic Shocks

Karl Schulze *

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Abstract

One way workers adapt to adverse shocks experienced after joining the labor market is by returning to school later in life, which may increase income but also involves opportunity costs in terms of foregone earnings and work experience. This paper uses administrative panel data on earnings and enrollment histories to estimate a dynamic model that captures the tradeoffs workers face in pursuing education later in life. I focus on one shock that was accompanied by large increases in adult community college enrollment, the Great Recession. I first show patterns of selection into schooling and fields of study based on prior industry and worker demographics. I then use a research design based on the exposure of workers to the employment losses of the Great Recession to show that this heterogeneity plays a crucial role in determining how workers use education to respond to adverse shocks. The dynamic model unpacks what these patterns mean for policies intended to increase worker earnings, such as a targeted tuition subsidy. A key contribution of the framework is to flexibly quantify worker skills using a data-driven approach. Estimates indicate substantial heterogeneity in the returns from returning to school, but that these effects are limited or negative for those at the margin of enrollment. This suggests that education can be effective in raising earnings for those who face large frictions in returning to work, but also stresses that later-life schooling can be risky if it does not lead to a relevant job.

*Department of Economics, Princeton University: kschulze@princeton.edu

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1 Introduction

Many workers experience adverse shocks after having made their initial career and educational choices. For example, between 2000 and 2019, employment in manufacturing shrank by 25 percent, with over half of this decline occurring over the course of the Great Recession.[1] These adverse shocks can have effects that persist throughout a worker's career. Studies of displaced workers (Jacobson et al. [1993]), recessions (Yagan [2019]), and exposure to import competition (Autor et al. [2014]) all find that short-term hardship has long-run consequences. Workers face frictions in finding new jobs, and old skills do not always transfer to new kinds of work, meaning the specificity of human capital is a key determinant of the incidence of such shocks (Neal [1995], Gathmann and Schoenberg [2010], Traiberman [2019], Huckfeldt [2022], Deming and Noray [2022]).

Returning to school later in life is a common adjustment strategy that workers use, whether in response to job loss, business cycles, or trade exposure. In 2018, 3.1 percent of U.S. adults between the ages of 30 and 55 were enrolled in some kind of public higher education.[2] Policymakers often suggest investments in training programs - much of which takes place at community colleges - as a means by which workers may adapt to economic change. However, while this policy may increase earnings, it also involves substantial opportunity costs in terms of foregone earnings and lost accumulated work experience. Because adult workers have already made substantial investments in their prior career, new human capital investment may also require foregoing valuable existing skills. As this trade-off is heterogeneous, varying by both industry of employment and field of study, the value of these investments likely depends on who chooses to take up these programs and the nature of their future work transitions.

This paper studies the tradeoffs that low-skill workers face when pursuing later-life human capital investment. I focus on workers in Texas, for whom I have comprehensive administrative data on earnings and enrollment histories, and on one particular shock that was accompanied by substantial increases in community college enrollment, the Great Recession. I ask - which workers take up and benefit from training through the public post-secondary education system? To what degree do these patterns vary among different groups of workers? From a policy perspective, what impact would lowering community college tuition have on the earnings of those induced to enroll and how can we target this policy to maximize earnings gains?

To quantify the heterogeneous earnings benefits of later-life education and identify which workers are most sensitive to counterfactual tuition policies, this paper develops and estimates a dynamic discrete choice model of a worker's decision to return to school and switch industries in response to various kinds of shocks. I begin the paper by documenting patterns in the pathways taken between school and the labor

[1] See `https://fred.stlouisfed.org/series/MANEMP`

[2] This number comes from my calculations in the American Community Survey. While this enrollment rate declines with age, even among the 40 to 55-aged population the enrollment rate stands at 2.0 percent. When restricting the sample to Texas, the 30 to 55 enrollment rate increases to 3.5 percent when restricting the ACS to Texas.

market for adult workers and examine how these relationships translate into which workers return to school in response to granular, industry-level shocks from the Great Recession. Building off these results, the empirical model takes into account the imperfect transferability of prior work experience as a key determinant of enrollment choices. I develop a novel, data-driven approach to estimating the transferability of worker skills, which allows me to incorporate types of training and comparative advantage into the empirical model. By incorporating dynamics, the framework endogenizes the full pathway of work and schooling options taken by workers, capturing key complementarities between past work experience, fields of study while in school, and post-schooling work transitions. The model is quite rich, being tailored to match patterns of selection into schooling that have been documented as important in the training literature (Heckman et al. [1999], McCall et al. [2016]). I use the model to assess the distributional impact on earnings from reducing the price of community college and examine margins on which these subsidies could be better targeted to increase earnings.

The main finding is that workers are responsive to changes in tuition but that training is not effective in raising earnings for the average worker induced to enroll by a tuition subsidy. However, these average effects mask substantial underlying heterogeneity. Specifically, I find that lowering the price of community college results in an increase in enrollment of 2.9 percentage points but average earnings losses of 3.8 percent for those induced to enroll, with only 22.9 percent seeing earnings gains in the counterfactual. The model indicates that those who gain would have experienced counterfactually longer unemployment spells in the absence of the subsidy. By contrast, those who experience earnings losses tend to be characterized by failed re-skilling - these workers are induced by the subsidy to move out of their baseline sectors but fail to see earnings gains from training. This is driven by a combination of foregoing old specific skills, losing out on work experience during enrollment, and a failure to find work in a relevant job after training. The results also indicate an important role for fields of study, where subsidizing technically-oriented fields, which have more general returns across sectors, fares relatively better than subsidizing health care, which sees potentially high returns that are very specific. This specific nature of human capital investment - that some training is only relevant in certain industries - magnifies the negative effects from failing to secure a job in a target industry. Taken together, these results indicate that *training is no substitute for on-the-job work experience* for adult workers and emphasizes the important interaction between education and work transitions. However, while re-skilling can be risky, education can be effective for those who face large frictions in returning to work after a job loss.[3]

[3] A natural question is why forward-looking individuals return to school if they experience negative returns. From the perspective of the model, this will be driven by workers' preferences, which will adjust to rationalize why workers return to school at high observed rates in the face of low returns. The model conducts a positive analysis of the distributional earnings effects of training and does not take a stand on a specific market inefficiency justifying government involvement in post-secondary education. In particular, I do not take a stand on whether the tuition subsidy is "good" from a welfare perspective (lowering the cost of college can only make people "better off" in this framework) and focus on effects on earnings. For example, it could be the case that people are misinformed about the earnings value of college and would not go if they had better information (Jensen [2010], Hastings et al. [2015]). At the same time, it could also be the case that schooling has a return not captured by earnings, such as an amenity value of studying. Both of these mechanisms are picked up in the estimated preference for schooling and I cannot distinguish between them.

I begin by outlining evidence that students select into particular education pathways based on their prior work experience and demographic types. For example, workers from health care make up only 3.4 percent of enrollment in vocational technical degrees (e.g. welding) while making up 44.6 percent in health care related fields. Women are also much more likely to pursue later-life schooling, enrolling at nearly twice the rate of men. I examine how this heterogeneity drives worker responses to shocks using an event study design that compares changes in enrollment between observably similar industries that experience different levels of employment losses from the Great Recession. This analysis shows that workers in more negatively shocked industries respond by pursuing further education - a one standard deviation increase in my measure of an industry's exposure to the Great Recession increases the probability of enrollment by 0.37 percentage points, a 7.1 percent increase relative to the 2007 baseline. However, these effects are heterogeneous by field of study and a worker's baseline industry. For example, I find that about 40 percent of the overall enrollment effect is driven by enrollment in health-related fields and that workers from professional industries (e.g. finance and real estate) are most responsive to the shock. These facts indicate that a worker's decision to enroll in school varies based on their prior labor market experience as well as their chosen field of study.

To understand how these selection patterns matter for earnings and identify the workers most sensitive to counterfactual policies, I develop and estimate a rich empirical framework that quantifies key mechanisms affecting the tradeoffs a worker faces in deciding to return to school. The framework is composed of a dynamic model of enrollment and work decisions combined with a rich statistical decomposition of life cycle earnings, building off work in the dynamic discrete choice literature (Keane et al. [2011]). In each period, workers make the joint choice of sector of employment and field of study, with the goal of maximizing the present discounted value of lifetime utility. Flow utility consists of both earnings and non-pecuniary factors, capturing the preferences of different worker types across sectors and fields of study. A key feature of the framework is that I model earnings as a weighted sum of latent skills in the spirit of Lazear [2009], where an individual's time-varying skills receive industry-specific weights and accumulate with work and schooling choices. This feature captures that workers may have comparative advantage across sectors based observed work histories. For example, a worker with experience in construction may have higher potential earnings in manufacturing than in health care. It also enables a tractable incorporation of fields of study, as certain types of training will be more or less relevant across sectors. The framework allows individuals to respond to various kinds of adverse shocks, including job loss, persistent shocks to earnings on the job, aggregate changes in labor market frictions, and aggregate changes in industry conditions. These create rich persistence in the unexplained portion of earnings, substantially weakening identification assumptions, as well as enables the model to match transition and enrollment patterns in the presence of possibly persistent adverse shocks.

Estimation of the earnings parameters leverages the panel structure of the data to identify how a chosen sequence of industries and school enrollment decisions maps into earnings, measuring heterogeneous returns to work experience and fields of study. The crucial identifying assumption is that individuals cannot select on within-period changes in the error term in the earnings equation. However, due to the flexibility with which I model skills and the persistent process on the errors, individuals can select on their entire work and schooling history and a prior period's earnings. This amounts to a timing assumption. The intuition is similar to research designs based on movers (Card et al. [2013], Bonhomme et al. [2019]) or matching estimators using lagged earnings and work histories (Heckman et al. [1998a], Leung and Pei [2020]).[4] Specifically, given individuals with identical work and schooling histories up to a point, the model imputes average earnings changes upon an industry switch (or into enrollment) as the counterfactual earnings for stayers (non-enrollees). In practice, the estimation routine makes many such comparisons — occurring across different histories, types of transitions, and over multiple future periods — to inform parameters governing how skills are augmented by different paths of choices. The role of the Great Recession in identification is to generate exogenous variation in such transitions, disciplining model parameters through the increased mobility across industries and into education.[5]

A concern with this approach is that individuals who make certain kinds of transitions are selected on earnings in a way that is not accounted for in the framework. I address this concern in several ways. First, the model directly incorporates mechanisms that can generate Ashenfelter [1978]-dip dynamics, such job loss and persistent shocks to earnings, the inclusion of which also substantially weakens identification requirements. Second, I directly check implications of the identification assumptions, such as that future choices should not affect current earnings differences conditional on a state and a choice. This exercise indicates that the potential for residual bias to drive the results to be limited.[6] Third, I assess the fit of the model around job separation and enrollment events, which poses a difficult test for the model to match. I show that the model replicates earnings trajectories around these events, underscoring the credibility of the estimates. Finally, I directly implement matching estimators to estimate enrollment effects based on a richer set of covariates than the model can tractably incorporate. While this exercise misses the relevant population for policy counterfactuals and does not characterize mechanisms, I measure average earnings effects that are close to zero and often negative, indicating that results from the model are plausible when focusing on the policy-relevant population.

[4] My model allows for match effects based on observed work histories as well as prior earnings to affect selection into education and mobility across employers. In this spirit, my framework is most related to the dynamic model considered in Bonhomme et al. [2019] that relaxes assumptions in Abowd et al. [1999] (AKM)-style analysis. My framework differs in that it allows the entire past history of choices to affect earnings, incorporates education choices, and treats industry as the relevant level of firm classification.

The richness of the model also makes the identification of returns similar to arguments invoked in studies that use non-experimental methods to evaluate training programs. These non-experimental estimators have been shown to reasonably replicate experimental results when using rich lagged earnings histories (Heckman et al. [1998a], Dehejia and Wahba [1999], Card et al. [2018]). My framework is most similar to the strategy in Ashenfelter and Card [1985] in this literature, in that I estimate persistence parameters on the idiosyncratic component of earnings that give forecasts of how quickly shocks to earnings die away. The model differs in that I jointly estimate these persistence parameters at the same time as parameters governing heterogeneous returns, while the dynamic choice model microfounds the selection rule in the Ashenfelter and Card [1985] context.

[5] I provide proofs of the semi-parametric identification of the skill process in a simple case.

[6] Future versions of this paper can enrich the framework and level of heterogeneity considered, which would further mitigate these concerns. For example, a simple extension would be to include time-invariant unobserved types as in Traiberman [2019]. However, given the limited earnings gains I estimate using matching estimators, I see it as unlikely this additional heterogeneity will substantially change the results.

The estimates hold several important lessons about the interaction between labor market trajectories and later-life education. First, all else equal, returns from studying health have the potential to be high but are only relevant in the health care sector. In contrast, technically-oriented fields have returns that are lower but rewarded more consistently across sectors. Other fields of study consistently show limited returns relative to working. Second, there are large returns from continuous employment, indicating a substantial cost of job loss and an important role for job-ladder dynamics. Third, preferences are heterogeneous by gender and baseline education across fields and sectors. Men tend to have relatively high preferences for working in construction and manufacturing and lower preferences for working in health care. Fourth, I estimate large costs of switching sectors that are in line with the literature, where I additionally find that schooling plays a role in reducing these switching frictions. This echoes work which argues that part of what education does is to facilitate access to jobs that differ in on-the-job learning (Deming [2023]). Finally, workers are quite sensitive to tuition even at the low levels of tuition seen in the data.

The model is used to evaluate the take up and distributional effects on earnings of tuition subsidies. By modeling heterogeneity in choices and outcomes, the model sheds light on who could be targeted to maximize earnings gains. I focus on a hypothetical surprise $1,000 reduction in the cost of schooling that coincides with the onset of the Great Recession, representing more than 50 percent reduction in price. By comparing simulation results under the baseline and counterfactual data, the model identifies those who comply with the policy and counterfactual changes in earnings for this group. I find that 2.9 percent of all workers are induced to enroll between 2009 and 2015 but that only 22.9 percent of this group see earnings increases. Those who benefit from the policy face difficulty in returning to their old industry after a layoff, being characterized in the baseline scenario by long non-employment spells during the Recession followed by transitions into the low-paying service sector. For these workers, community college provides a pathway back onto the job ladder while also building new skills at a time when they lack on-the-job work experience. In contrast, those who see earnings losses are associated with failed re-skilling - the subsidy induces them to switch out of their baseline industry but does not translate into higher earnings in the target sector. Finally, examining fields of study shows that some of this risky re-skilling is amplified by the specificity of human capital investment. Despite having the potential to have the highest earnings growth, health care fares the worst in terms of earnings gains due to the irrelevance of the degree for those who do not find employment in that sector.

The results of this paper provide valuable takeaways for policymakers, showing that training programs can be most effective when they combine skills learned in the classroom with straightforward pathways back into the labor market. First and foremost, the findings indicate that later life education is no substitute for work experience once relatively low-skill workers have entered the labor market. Not only do workers face a substantial opportunity cost from foregone earnings, but they also incur lost on-the-job experience. At the same time, this means that the population most likely to benefit from training are those who face substantial difficulty returning to work to gain such work experience. Re-skilling is also risky, as it may be detrimental if it does not translate into a relevant job at the end of education. This is especially true if the human capital investment from schooling is highly specific to narrowly defined sectors. The importance of post-schooling work transitions can rationalize some disparate results from the training literature even when experimental evidence is available, both reinforcing findings from evaluations of sectoral training programs (Katz et al. [2022]), which combine training with assistance transitioning into a targeted industry, and explaining disappointing results from other randomized evaluations (Fortson et al. [2021]).

Related Literature: This paper contributes to our understanding of the ways in which workers may respond to economic shocks. Studies have shown long-lasting negative effects of job loss (Jacobson et al. [1993], Couch and Placzek [2010]) that worsen during recessions (Davis and von Wachter [2011]). Echoing these results, trade shocks (Autor et al. [2013], Autor et al. [2014]) and recessions (Yagan [2019]) show scarring effects on worker and labor market outcomes. A natural question is why these effects are so persistent - one might expect workers to simply transition towards industries, occupations, and labor markets that are less affected by sudden declines in labor demand. However, it has long been a source of concern that low-skill workers typically do not move across labor markets in response to demand shocks (Bound and Holzer [2000], Yagan [2019]). Moreover, workers face substantial earnings penalties when transitioning to types of work that are less related to their prior work experience (Neal [1995], Parent [2000], Gathmann and Schoenberg [2010]).[7]

Given the evident difficulty that low-skill workers face in adjusting to shocks along the margins discussed above, education holds potential as an alternate means to help workers adapt to sudden economic change. Prior work has found that the propensity to return to schooling is associated with adverse economic conditions (Betts and McFarland [1995], Barrow and Davis [2012]). Most related to the focus of this paper, Foote and Grosz [2019] and Minaya et al. [2023] identify causal increases in enrollment in response to mass layoff events, Barr and Turner [2015] show that more generous unemployment benefits increase enrollment in two-year colleges, and Boustan et al. [2022] find increases in enrollment in response to industry-specific exposure to technological change.[8] A related literature focuses on the impact of the business cycle on field of study choices for first-time students as well as how different college majors fare over the business cycle.[9] What this literature does not tell us is whether returning to school is the best

[7]The trade literature, for example, has argued that slow adjustment to trade shocks is driven by difficulty in adjusting skills and switching industries or occupations (Artuc et al. [2010], Dix-Carneiro [2014], Traiberman [2019]). Finally, job loss often entails the permanent destruction of valuable worker-employer matches (Lachowska et al. [2020]), which may entail occupational downgrading (Huckfeldt [2022]) or loss of job stability (Jarosch [2023]) due to frictions in finding jobs that substitute for prior employment.

[8]Conversely, Charles et al. [2018] and Schazenbach et al. [2023] find that enrollment declines in response to positive shocks to outside options, which is especially salient for community colleges.

[9]The use of education as an adjustment mechanism extends beyond the extensive margin of enrollment. Blom et al. [2021] finds that exposure to high unemployment causes individuals to select into different fields of study at the time of their first enrollment. Liu et al. [2019] and Esroy [2020] use cohort and state-based variation respectively to show that first-time students substitute towards majors less affected by the Great Recession. Acton [2021] shows that students enrolling in community college substitute towards less-affected majors with similar skill requirements in response to local mass layoff events. Altonji et al. [2016b] finds that the penalty for graduating in a Recession differs by college major. Deming and Noray [2022] show that changes in demand for skills taught in initial college major affect later life-cycle wage growth.

course of action for adult workers in response to the particular shocks they face. My empirical framework advances our understanding of these issues by linking the decision to enroll in response to adverse shocks with mechanisms that drive earnings outcomes.

This paper relates to the substantial literature on the return to education for adults, both in terms of training programs and community colleges. The literature on active labor market and training programs (Heckman et al. [1999], McCall et al. [2016]) tends to find mixed evidence on average returns with substantial differences by type of training and worker demographics.[10] The literature that uses panel data methods to estimate the returns to community college tends to find more significantly positive effects when exploiting variation in the number of credits or using non-completers as a comparison group.[11] These papers also tend to find that effects vary by field of study and are higher for women, findings that are also common in the training literature. A subset of these papers seek to estimate returns to community college for workers who have recently experienced an adverse shock, either focusing on displaced (Jacobson et al. [2005]) or unemployed (Leung and Pei [2020]) workers. These papers tend to find positive effects that are especially driven by health and technical degrees but with some types of training having zero effect. In particular, Leung and Pei [2020] point out that positive returns tend to be related to post-enrollment industry switching, which is an endogenous outcome of treatment in this literature. I build on this literature by providing a framework to understand mechanisms driving effects and worker selection into endogenous pathways. For example, my findings suggest that, by focusing on recently laid off workers, this literature may be restricting to a population with heterogeneously positive treatment effects, even if they have internally valid research designs. Policymakers should be careful when extrapolating the results from this literature to those directly affected by policies.

Finally, this paper contributes to an extensive literature that models selection into education and life-cycle skill accumulation. Work on selection into schools for K-12 students (Walters [2018], Abdulkadiroglu et al. [2020]) and college majors (Arcidiacono [2005]) finds that the type of person enrolling is an important driver of observed returns. Some of this literature has considered whether returns to college major are general or specific (Kinsler and Pavan [2015], Eckardt [2022]),[12] finding that high-return education choices are sometimes specific to certain types of work. This paper extends this literature to consider these issues in later-life retraining decisions. This paper also relates to an extensive literature focusing on life-cycle human capital formation (see Keane and Wolpin [1997], Lee and Wolpin [2006], Roys and Taber [2019], among others). Applications of these models have shown that specific human capital determines who is

[10] See Card et al. [2018] for a meta-analysis of the literature. Recently, Andersson et al. [2013] evaluate the Workforce Investment Act (WIA) training programs, finding modest positive to negative impacts depending on the specific stream of services. Hyman [2018] finds positive effects for those participating in Trade Adjustment Assistance (TAA) based on quasi-random assignment to case workers. Humlum et al. [2023] find large positive effects for those retraining after suffering physical injuries. In terms of experimental evidence, Fortson et al. [2021] find no impact of WIA training programs on earnings and employment. In sharp contrast, experimental evaluations of sectoral training programs, which target in-demand sectors and provide assistance with job development and placement, show large positive effects (Katz et al. [2022]).

[11] See Kane and Rouse [1995], Jepsen et al. [2014], Belfield and Bailey [2017], and Stevens et al. [2019], among others

[12] See also Lemieux [2014] or Leighton and Speer [2020] for additional empirical evidence.

affected the most by shocks, especially in the context of trade exposure (Dix-Carneiro [2014], Traiberman [2019]) or business cycles (Adda et al. [2013], Huckfeldt [2022], Grigsby [2022]).[13] I contribute to these literatures by combining a life-cycle model of worker mobility with a dynamic model of educational investment, tailoring the framework to match patterns of selection that are important in the training literature as well as my specific application.[14]

Organization: The structure of the paper is as follows. Section 2 outlines data and motivating facts concerning enrollment in my sample and over the Great Recession; Section 3 examines how the Great Recession shock impacts enrollment and field choices for adult workers; Section 4 outlines the model of work and schooling choices; Section 5 and 6 discuss identification and estimation, respectively; Section 7 presents parameters estimates and initial results from the model; Section 8 presents counterfactuals and decomposition exercises; and Section 9 concludes.

2 Data and Motivating Facts

2.1 Texas Schools Project Data

I use individual-level high school and college enrollment records linked with longitudinal earnings data from the state unemployment insurance (UI) system. These data are provided by the Texas Schools Project at the University of Texas at Dallas Education Research Center (ERC). High-school and college enrollment records come from the Texas Education Agency (TEA) and the Texas Higher Education Coordinating Board (THECB), respectively. The TEA records comprise the universe of Texas public high school students. The THECB enrollment data comprise all Texas public colleges (from 1992 onward) and private non-profit colleges (from 2003 onward). I use data on financial aid records for those receiving aid at any college in Texas (from 2001 onward), which includes all sources of federal, state, and categorical aid disbursed during the relevant academic year. When defining enrollment, I include all sectors of college, although my focus on relatively lower-skill workers means that more than 80 percent of enrollment in my baseline sample occurs at public 2-year institutions with almost the entire remainder at other public colleges. For each enrollment spell, I identify fields of study by combining information on the primary Classification of Instructional Programs (CIP) codes of study across semesters and CIP codes for degrees received. Details are provided in Appendix Section B.2.

These data are linked with quarterly earnings records from the Texas Workforce Commission (TWC), capturing the universe of Texas workers subject to the UI system.[15] Earnings are deflated to 2019 dollars

[13] This paper is also related to the literature on dynamic treatment effects in sequential discrete choice models (Heckman and Navarro [2007], Heckman et al. [2016], Heckman et al. [2018]). Closely related to this paper, Rodriguez et al. [2022] adapt the empirical framework of Heckman et al. [2018] to understand the dynamic effects of multi-period job training programs. Relative to this literature, my paper fully specifies the earnings and choice process of forward-looking agents over many periods.

[14] A related literature considers the process by which workers learn about skills and match effects. See Miller [1985], Neal [1999], Papageorgiou [2014], Sanders [2014], Guvenen et al. [2020], and Arcidiacono et al. [2023], among others. I abstract from these considerations as the focus of the paper is how experienced workers, who likely have an idea of their skills, may use education to adjust these skills in response to changes in their labor market prospects. While potentially important, incorporation of this mechanism would greatly complicate my framework and make the current richness infeasible.

[15] Missing earnings in UI data could indicate out-migration, working in jobs not covered by UI, or that the individual is out of the

and winsorized at the 99.9th percentile. The data contain granular measures of industry of employment, which I aggregate into 5-digit North American Industry Classification System (NAICS) codes after some harmonization across years. Additional details on data cleaning are provided in Appendix Section B.2.

2.2 Basic Enrollment Patterns

Figure 1 gives a first indication of the importance that the business cycle, worker heterogeneity, and fields of study play in driving enrollment decisions. This figure plots age 25-plus enrollment counts in the community college sector as observed in the raw THECB data, broken out by gender and field of study. Appendix Table A1 reports the complete counts over various subgroups.[16]

Role of the Great Recession: *Figure 1a shows that the business cycle is a key driver of enrollment decisions, with a 34.7 percent increase in adult enrollment during the Great Recession.*[17] In the 2007-2008 academic year, total enrollment across both genders was 317,958 for age 25-plus students, spiking to 428,394 in the 2010-2011 academic year. This rapid increase followed a period of minimal changes in enrollment prior to the Recession, where aggregate enrollment actually declined by 1.9 percent between 2005-2006 and 2007-2008. In 2017-2018, enrollment remains 8.1 percent above the pre-Recession level.[18]

Differences by Gender: *Figure 1a also shows that women are much more likely to enroll in community college, representing about two-thirds of overall enrollment*. In the 2007-2008 academic year, women make up 64 percent of overall enrollment (204,076 women versus 113,882 men). Both men and women increase enrollment during the Great Recession, with women increasing enrollment at a slightly faster rate than men during the downturn. Female enrollment increases by 32 percent (to 269,558), accounting for 59 percent of the overall increase in enrollment. This is striking as industries dominated by men were most affected in the Great Recession.

Differences by Fields of Study: *Figure 1b examines differences by fields of study, underscoring that special-*

labor force. Fortunately, Texas is a state with the lowest out-migration of any state (Aisch et al. [2014]). Moreover, my focus on relatively low-skill workers means that out-migration is less of a concern, as these workers tend not to migrate in response to shocks (Bound and Holzer [2000]). Moreover, mobility responses across locations to the Great Recession are limited (Yagan [2019]). Additionally, I later make several sample restrictions to mitigate concern over these issues within sample, such as allowing longer periods of non-employment than other studies using state UI data (e.g. Lachowska et al. [2020]). Nevertheless, my result should be interpreted as conditional on the sample of workers with some minimal attachment to the Texas labor force over the period of analysis. I compare the representatives of my baseline sample to the same cohorts born in Texas in the American Community Survey in Appendix Figure B1.

[16] The focus of this paper is on older workers who already have some work experience. These age 25-plus enrollees account account for 34 percent of the total in 2007-2008 (317,958 out of a total of 935,455). However, younger enrollees also see increased enrollment during the Great Recession, increasing 20 percent (from 617,497 in 2007-2008 to 740,485 in 2010-2011). This indicates that the age-25 plus enrollees account for about half of the overall enrollment increase, which - given the other adjustment mechanisms available to older workers - merits a focused study. It is likely that the increase in enrollment for younger enrollees reflects the same shocks to outside options and policy changes that driver older enrollment. See Barr and Turner [2013] for an excellent summary of the impacts of the Great Recession on American higher education more generally.

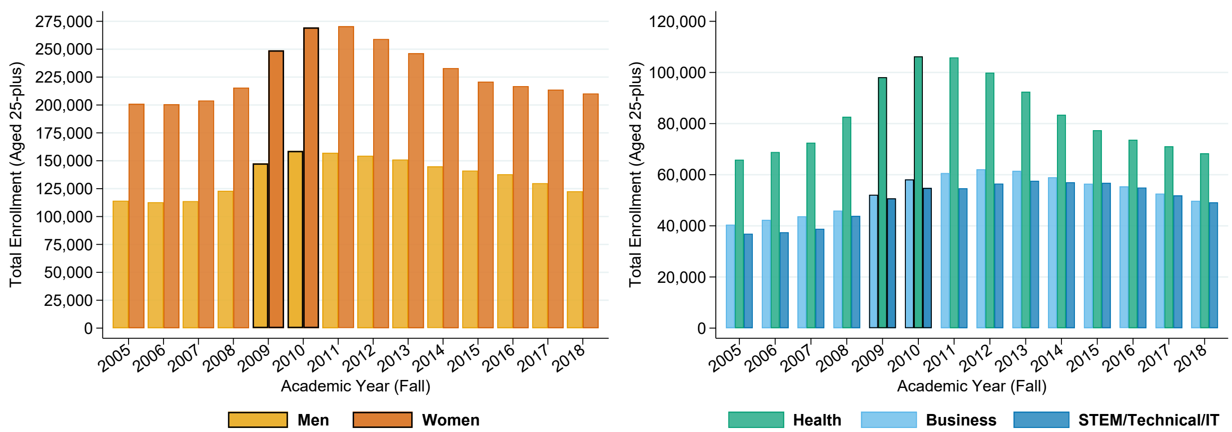
[17] The official dates of the Great Recession are between December 2007 and June 2009. However, this dating does not map cleanly into the slack experienced in the labor market. First, there was a significant delay for the financial crisis to hit the labor market. Unemployment only rose above 5 percent in April 2008 and did not peak at 10 percent until October 2009. Second, it took quite a while for the unemployment rate to return to normal levels — it only returned to below 9 percent in October 2011 and did not return to below 6 percent until September 2014. For this reason, I would not expect the labor market downturn to have its full impact on enrollment until the 2009-2010 academic year and for any transitory effects to have recovered by 2014-2015.

[18] Since these are aggregate numbers, one might expect enrollment to increase over time due to in-migration into Texas. However, I show below that being exposed to employment losses of the Great Recession has a permanent effect on one's propensity to enroll.

ization through different fields matters for these adult enrollees as well as how they respond to the business cycle. This figure displays enrollment counts for the three largest areas of study (excluding liberal arts and general studies),[19] which make up about half of total enrollment in 2007-2008. Health degrees account for a large share of total enrollment - 22.8 percent of the total in 2007-2008 (72,548) - and are highly cyclical, increasing 46.5 percent to 106,289 in 2010-2011 before declining to a slightly lower enrollment level in 2017-2018 (71,112). Business and STEM fields also see large enrollment increases coinciding with the onset of the Great Recession, increasing by 32.9 percent for business (from 43,751 to 58,152) and 41 percent for STEM (38,876 to 54,819) between 2007-2008 and 2010-2011, respectively. In contrast to health, the increases in enrollment for these fields persist after the Great Recession, remaining 20.3 percent for business (at 52,642) and 33.5 percent for STEM (at 51,885) above pre-Recession enrollment levels in 2017-2018.[20]

Figure 1: Aggregate Adult Enrollment in the Public Two-Year Sector

(a) By Gender (b) By Field of Study



Notes: Raw annual age 25-plus enrollment counts in the community college sector from THECB data prior to any sample selection based on work histories, including both full and part-time enrollment counts. Classification of enrollments into fields of study is outlined in Appendix Section B.2. Aggregation of CIP codes to broad areas of study is exhibited in Appendix Section B.4. The outlined bars mark school years that occur when the unemployment rate was over 9 percent during the Great Recession: April 2009 until September 2011. The 2009-2010 and 2010-2011 school years fall in this range. See Appendix Table A1 for complete results.

2.2.1 Sample Definitions

I now investigate how these factors relate to an individual's prior work experience and future transitions, which requires some sample selection to incorporate information on labor market dynamics for a consistent panel of workers. I focus my analysis on two panels of adult workers' employment and education histories. The first sample is the *full sample* of workers in the UI data with some attachment to the Texas labor market. The second panel is the *baseline sample*, a subset of the full sample on which I present most of my main analysis and conduct the structural estimation. This second sample is restricted to the 1994 to 1998 cohorts of Texas high school graduates who do not attain advanced education degrees. These

[19] Field shares are broken out into more detail on my analysis sample in Figure 2.

[20] The fields excluded from this figure also see large but less pronounced increases - increasing from 162,783 in 2007-2008 to 209,134 in 2010-2011 for a 28.5 percent growth. These other enrollments are not persistent, remaining 3.3 percent above pre-Recession-levels in 2017-2018 (at 168,143).

individuals are aged 29 to 33 in 2009 and 39 to 43 at the end of the observed panel period in 2019. The advantage of the baseline sample is the ability to observe demographic information for non-enrollees as well as the full history of work and education choices.[21] Additional details on data cleaning, sample definitions, and aggregation of industries and fields of study are discussed in Appendix B. Summary statistics for this sample are shown in Table B1 and comparisons with the American Community Survey are shown in Figure B1.

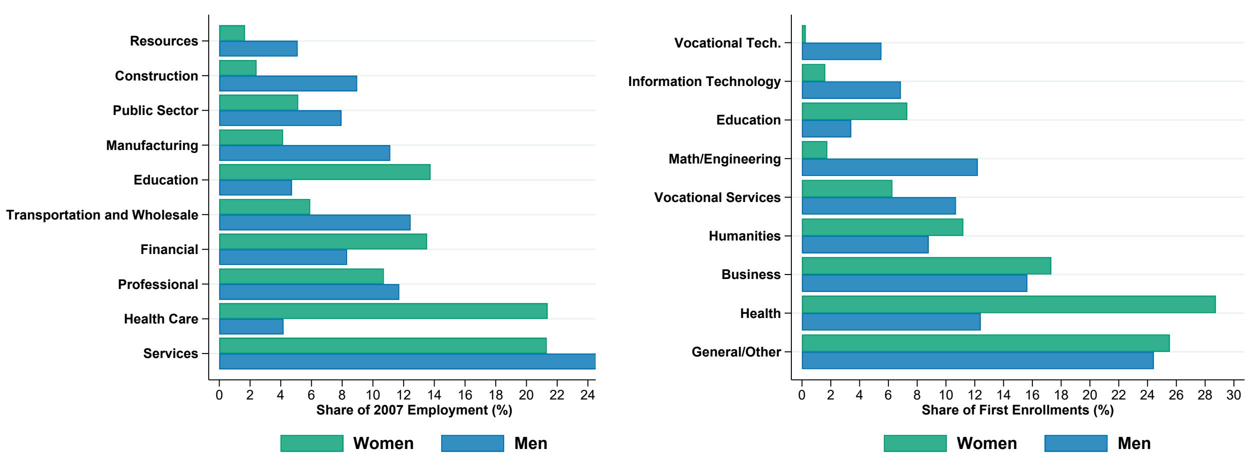
2.3 Descriptive Patterns of Selection by Industry and Field of Study

In Figure 2, I summarize the distributions of fields of study and industries of employment in the baseline sample, broken out by gender. A person's field of study is the field associated with their first enrollment spell after age 25. Industry is based on 2007 employment.

Differences in Selection by Gender: *Figure 2 shows that women tend to work in different industries than men and, when they go to school, they make different enrollment choices.* The largest industry category across both genders is services with 23.4 percent of employment in 2007. Other industries show larger differences in employment, with women more than 5.1 times more likely to work in health care and men more than 3.7 times more likely to work in construction. Turning to fields of study, health, business, and general/other make up a majority of study in the sample - totaling 63.7 percent of enrollments in the sample. Again, there are large gender differences, with women being more than 2.3 times likely to study health care than men and men are 6.9 times more likely to study math/engineering.

Figure 2: Field of study and industry shares of enrollment

(a) Previous Industry (b) Fields of Study



Notes: Both figures are computed on the baseline sample of $N = 247,973$. See Appendix Table B1 for additional variables. Panel (a) shows industry of employment in 2007 for the industry with highest earnings. Panel (b) shows fields of study associated with first enrollment spell after age 25, preceded by three years of no enrollment. See Appendix Section B.4 for details on how fields of study and industry codes were aggregated. Appendix Figure A1 shows this figure for the full sample, but not separated by gender.

Selection into Field of Study by Prior Industry: *Table 1 shows that pathways from work to school depend*

[21] The nature of the data is that I do not observe demographic information for individuals who neither enroll in the college or K-12 system.

on prior industry, suggesting comparative advantage across courses of study based on prior work experience. This table shows the share of enrollment in a field coming from the largest industry of enrollment, excluding services.[22] While health care workers comprise 44.6 percent of enrollment in health fields, only 3.4 percent of enrollment in vocational technical fields and 5 percent in math/engineering comes from health care workers. In the latter two fields, workers from manufacturing make up 19.3 and 17.6 percent of enrollment, respectively. These numbers rise to 48.4 and 41.8 percent when combining manufacturing, construction, wholesale trade, and resource extraction industries.

At the same time that the patterns in Table 1 suggest predictable pathways between work and education, the relationships are not deterministic, indicating both re-skilling and up-skilling motivations in driving enrollment decisions. The majority studying health did not previously work in the health care sector, indicating many workers may be transitioning into health care. Individuals coming from service industries are a large share of enrollment and are represented fairly equally across all fields of study, indicating that these workers may be up-skilling without regard to comparative advantage.

Table 1: Shares of Field Enrollment and Five-Year Switching Rates by Last Industry

	Primary Source Industry		*Future Outcomes*		
	Industry	Share (%)	Switch (%)	Work in Primary (%)	Graduate (%)
A. By Field of Study					
General/Other	Health Care	17.4	36.6	18.6	6.5
Business	Financial	19.1	37.2	18.5	27.1
Humanities	Financial	12.6	43.2	9.6	41.4
Math/Engineering	Manufacturing	17.0	46.9	22.9	31.2
Health	Health Care	41.3	41.4	54.6	36.2
Vocational Tech.	Manufacturing	18.2	52.0	19.0	37.8
Vocational Services	Public Sector	31.8	41.2	37.9	32.4
Education	Education	40.5	33.8	50.6	13.8
Information Technology	Professional	17.8	42.6	19.4	25.9
B. By Overall Enrollment					
Non-Enrollee			30.5		
Enrollee			39.8		25.4

Notes: Sample is workers with 4 quarters of consecutive employment in their baseline industry. Baseline industry is most common 5-digit industry of employment in quarters 5 to 12 prior to enrollment. Fields for enrollees comes from enrollments spells where the individual was not enrolled in the previous three years. Switching industries is defined as switching 1-digit industries defined relative to the baseline industry. Appendix Table A2 shows these results for the full sample.

Future Transitions of Enrollees: *The remaining columns of Table 1 show that enrollment is often, but not always, used as a means to switch industries, with differing use across fields of study.* Overall, enrollees tend to switch industries at a higher rate than non-enrollees. 39.8 percent of enrollees will switch 1-digit industries within five years while 30.5 percent of non-enrollees will do the same. These switches are at the 1-digit industry code level, indicating substantial changes in a person's career.[23] Some fields tend to

[22] As enrollment from the service sector is uniformly large across fields, focusing on the largest non-service sector is more informative for these relationships.

[23] Comparing differences in these switching rates indicates that most of this switching is due to these large 1-digit industry changes. The comparable numbers for 5-digit switching is 60 percent for enrollees and 48.5 for non-enrollees, indicating that 80 percent of the gap in switching between enrollees and non-enrollees is largely due to these large 1-digit industry changes.

be associated with industry switching more than others. For example, for those studying business, 37.2 percent switch 1-digit industries in five years and 59.1 percent will switch 5-digit industries. In contrast, for those studying vocational technical degrees, 52 percent will switch 1-digit industries while nearly 70 percent will switch 5-digit industries.[24]

Decomposition of Field-Industry Pathways by Gender: *Appendix Table A3 evaluates whether gender differences in enrollment choices are driven by differences in the baseline industry selected by men and women, consistently showing that most of the patterns are driven by differing choices by gender within an industry.* This table decomposes gender differences in enrollment into within- and across- industry differences for each field of study.[25] The results consistently show that about two-thirds of differences in field shares between men and women are due to differences in gender-specific enrollment within industries, whereas one-third is due to industry-specific enrollment rates across gender.[26] This within-industry variation in enrollment by gender will later be captured in gender-specific preferences in the model.

2.4 Sources of Selection and Heterogeneity in Enrollee Earnings Trajectories

I now briefly characterize how these patterns relate to earnings, underscoring important mechanisms driving enrollment decisions of adult workers - dynamics and fields of study. Both the decision of *when* to return to schooling and *what* to study are related to an individual's experience in the labor market. I capture these relationships in the model outlined in Section 4, where the analysis incorporates dynamic selection, dynamic treatment effects, and multiple unordered intensive margin treatments in a single empirical framework.

Earnings and Employment Dynamics around Enrollment: *Figure 3 plots employment rates and average earnings around enrollment events, showing key patterns suggestive of complex dynamics that drive the decision to return to school.* . The typical pattern is a steep drop in earnings and employment during enrollment followed by robust post-enrollment earnings growth, amounting to about a 25 percent increase in earnings over the 10 years considered. First, the decline in earnings while enrolled (i.e., the "lock-in" effect) is preceded by a decline in employment rates prior to enrollment, which is worse for those enrolling in the Recession. The pre-enrollment drop in earnings is a well-known phenomenon in the training literature, reflecting selection based on transitory changes in labor market prospects (Ashenfelter [1978], Heckman and Smith [1999]). Second, we see that pre-enrollment earnings differ based on the timing of enrollment - those enrolling during the Recession have higher pre-enrollment earnings at the same time that they

[24]Additionally, I investigate the how the relationship of industry switching and fields of study varies over the business cycle. These results are displayed in Appendix Figure A2 for both samples. Enrollees have a higher rate of industry switching rates across all years but there is actually little change in the probability of switching conditional on enrollment over the business cycle. The notable exception is health degrees, which exhibit about a 5pp increase in the rate of switching 1-digit industries conditional on enrollment across both samples.

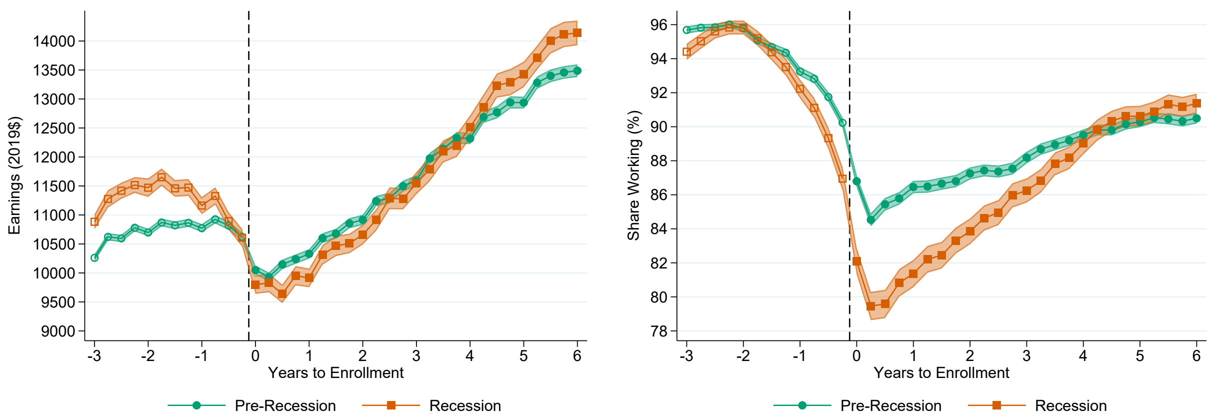
[25]Table A4 shows the results for the full sample.

[26]For example, conditional on enrollment, women are 16pp more likely to enroll in health care than men. After equalizing the industry employment shares by gender, women still are 10.4pp more likely to enroll in health care. In other words, men tend to enroll less than women in health fields, even if they are working in health care. This indicates that most of the difference is not accounted for by the industries in which men and women work.

have a sharper drop in pre-enrollment earnings. This shows that accounting for differences in the level of pre-enrollment earnings is important as individuals may be differentially selected on the permanent components of their earnings. Finally, the robust post-enrollment earnings growth is faster for those enrolling in the Recession than other years. This may partially reflect the fact that Recession-era enrollees return to work in a thawing labor market, but may also reflect that these enrollees may differ in their potential for faster earnings growth, which may be related to higher initial earnings. These selection patterns will be incorporated into the modeling framework.

Figure 3: Employment and Earnings Trajectories around Enrollment Event

(a) Total Quarterly Earnings (b) Share Working



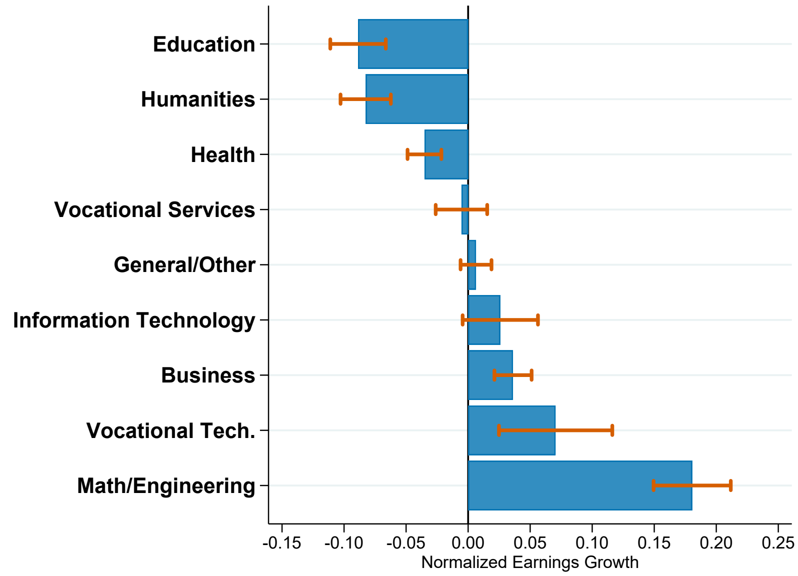
Notes: Earnings trajectories around target enrollment events (see Appendix B.2 for more information) for the baseline sample. Sample is balanced around the enrollment event. See Figure A3 for the full sample results.

Heterogeneity in Fields of Study: *Figure 4 shows that different types of training are associated with different rates of post-enrollment earnings growth.* I sidestep selection bias stemming from extensive margin enrollment decisions in this analysis by focusing on intensive margin differences in earnings growth, demeaned relative to average earnings growth in the sample. More sophisticated analyses are exhibited in Appendix A.2, including results from matching estimators using previous histories. There is a clear ordering to estimated returns, with math/engineering having the highest relative returns, resulting in earnings growth 15 to 20 percent higher than the average field. Education and humanities yield earnings growth that is significantly lower than the average course of study. Appendix Figure A6 shows these patterns survive adjusting for demographics and pre-enrollment employment dynamics. These results show that majors play an important role in my context, as has been shown in other education settings (e.g. Altonji et al. [2016a]).

Comparison with Non-enrollees: *Figure 5 constructs counterfactual non-enrollment paths for enrollees using matched controls, showing that there appear to be limited earnings gains from enrollment for enrollees on average.* Matches are constructed in the baseline sample by finding individuals of the same age, gender, pre-enrollment industry, and have similar earnings and employment dynamics prior to enrollment.[27] Em-

[27]Details are discussed in the notes to Figure 5. Results from placebo matches are shown in Appendix Figure A7, which indicates

Figure 4: Relative Post-Enrollment Earnings Growth by Field of Study



Notes: Earnings growth for 41,857 target enrollments (see Section B.2) that occur between 2002 and 2013 in the baseline sample. Additionally, I restrict to enrollments where there is at least one period of work in periods 4 to 6 after enrollment. I use average non-zero earnings in quarters 9 to 12 prior to enrollment as baseline earnings. Using observations 12 quarters after enrollment, I run a regression of percent earnings relative to baseline on dummies for fields of study (excluding a constant) and control for a quadratic in earnings growth centered at 20 quarters post-enrollment and report clustered standard errors at the individual-level.

ployment and earnings prior to enrollment shows that the matching is done well.

However, the results show only an insignificant $14 (53.1) increase in earnings, not accounting for the lock-in effect. We see that part of this is driven is by lower rates of employment in Figure 5b, where enrollees are 2 percentage points less likely to be employed. The implication is that enrollees earn more than matched comparisons when working, but have lower employment rates overall. This is consistent with other research that finds a key role for the extensive margin.[28] An advantage of the structural model is to separate these extensive versus intensive margin effects and aid in identifying the policy-relevant population by modeling choice.

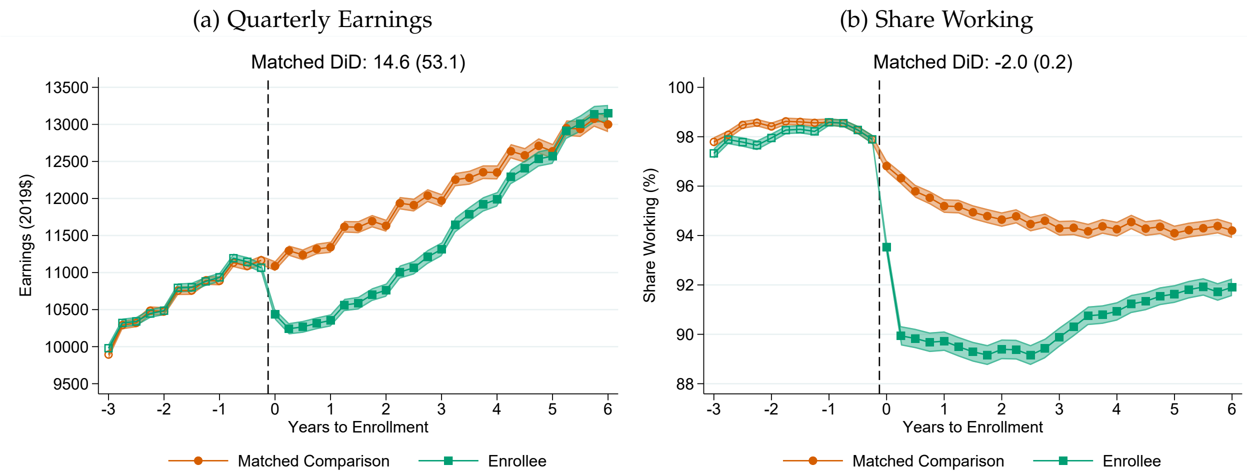
3 The Impact of Exposure to the Great Recession on the Schooling Choices of Adult Workers

In this section, I show that exposure to the Great Recession across industries has a causal impact on a worker's decision to return to school. Using an exposure design in the spirit of Autor et al. [2014] and Yagan [2019], I show that *a 1 standard deviation increase in exposure to the Great Recession causes a 7.1 percent (0.37pp) increase in the probability of enrollment for adult workers.* This research contributes to the extant literature on economic shocks and schooling decisions (e.g., Betts and McFarland [1995], Barrow and

that results are not driven by a mechanical relationship driven by the matching procedure.

[28]For example, Leung and Pei [2020] find that most of their *positive* effects are driven by increases in employment for unemployed enrollees.

Figure 5: Matching Estimates of Enrollment



Notes: For an individual enrolling in quarter t_0, I construct matches by first blocking on (i) gender, (ii) graduation cohort (iii) 3-digit NAICS of employment in $t_0 - 8$, (iv) indicators for positive earnings in $t_0 - 1$ to $t_0 - 4$, (v) earnings in each of the three years prior to be within \$5000. Then, I do nearest-neighbor Mahalanobis matching using quarterly earnings in each quarter $t_0 - 1$ through $t_0 - 12$. I use Mahalanobis matching rather than propensity score matching to account for different choices of time of enrollment and fields of study, which could be thought of as different treatments. Results are reported for the 22,594 enrollees and their matched comparisons for whom a control could be found. I check the quality of this matching procedure using placebo matches in Appendix Figure A7. Figure (a) plots total average earnings and Figure (b) plots any employment.

Davis [2012], Foote and Grosz [2019], Boustan et al. [2022], Minaya et al. [2023]), where my contribution is to leverage the administrative data to dig into heterogeneity by industries, fields of study, and other outcomes. In addition to providing direct evidence that workers use education as a means to adapt to shocks, this variation will be directly incorporated into the later modeling framework.

3.1 Defining Great Recession Exposure

I begin by defining my measure of exposure to the Great Recession and describing its relationship to enrollment decisions. I measure exposure to the Great Recession as the negative of the percent change in quarterly employment between 2007 and 2009 in a 5-digit industry. To get baseline exposure, I link individuals to their 5-digit industry of employment in 2007:Q4.[29]

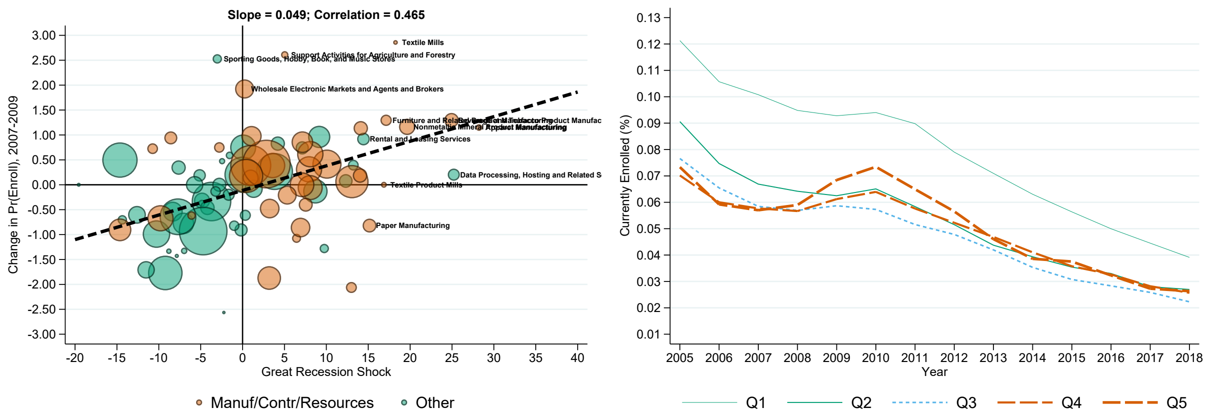
Figure 6 shows that industries having a greater measured exposure to the Great Recession see increases in the rate of enrollment. This figure plots the raw variation of the exposure measure, aggregating up to the 3-digit NAICS-level. In particular, a 10 percentage point increase in exposure to the Great Recession is associated with about a 0.49 percentage point increase in the probability of enrollment. Notably, sectors associated with manufacturing, construction, and resource extraction are especially hard-hit, shown in orange.

One concern with drawing causal inferences from this variation is that industries that are more exposed to the Great Recession have higher pre-Recession enrollment rates and may be on different enrollment trends. For example, health-oriented sectors tend to have higher baseline enrollment and are among the least exposed to the Great Recession. This is confirmed in Panel (b) of Figure 6, which plots enrollment

[29] To ensure attachment to this industry and a sufficient earnings history to define control variables, I restrict to the sample of workers who have at least one year of tenure in the baseline industry and are employed at least one quarter in 2006 and 2005. The panel is balanced through 2019, as per the sample restrictions discussed in Appendix B.2.

Figure 6: Variation from Industry-Level Employment Shocks from the Great Recession: Baseline Sample

(a) Change in Enrollment by Shock Measure (b) Enrollment Rate over Time by Quintile of Shock



Notes: Panel (a) shows a scatter-plot of the change in the probability of enrollment against the raw Great Recession exposure measure. Probability of enrollment and the Great Recession exposure measure are aggregated to the 3-digit NAICS level using baseline employment weights. Manufacturing, construction, and resource extraction industries are plotted in orange. Panel (b) shows the probability of being enrolled by year, separately for quintiles of the Great Recession exposure measure. Q4 and Q5 measure the industries most exposed to the Great Recession.

rates by quintiles of the shock measure, where we see that the least shocked industries do have higher baseline enrollment and see faster declines. Nevertheless, severely shocked industries also have marked increases in enrollment that represent a stark break in trend. For example, the most severely shocked quintile (Q5) increases its enrollment probability by 1.5pp between 2007 and 2010, from a baseline rate of 5.2 percent, around a 30 percent increase. To account for the potential effect of this aspect of the data, I control for baseline industry fixed effects and include pre-determined individual and industry-level controls interacted with time effects in my regression analysis. This ensures comparisons between individuals most likely to be on similar trends in the absence of the Recession. I also conduct several additional analyses in the appendix, showing my findings are robust and that parallel trends likely hold.[30]

3.2 Baseline Event Analysis

Let j_0 be the individual's baseline 5-digit industry in 2007:Q4. I model individual i's outcome in quarter t as:

$$Y_{it} = \alpha_{j_0(i)} + \alpha_t + \sum_{y(t)\neq 2007} \delta_y Z(SHOCK)_{j_0(i)} + \beta_t X_i^{2007} + \gamma_t W_{j_0(i)}^{2007} + \epsilon_{it} \tag{3.1}$$

where X_i^{2007} and $W_{j_0(i)}^{2007}$ are individual- and industry-level covariates defined prior to the Great Recession.[31] These coefficients are allowed to vary flexibly with time, weakening the parallel trends assumption to need only hold conditional on these controls. I also control for industry fixed effects $\alpha_{j_0(i)}$ and time fixed effects

[30]These results are shown in Table A6. Specifically, I investigate the performance of the controls and robustness to a sample defined relative to 1997 baseline industry, showing that parallel trends across industries are likely to hold conditional on the controls. I also use an exposure measure using data on sectoral employment outside Texas from the Statistics of U.S. Businesses. I also use the main sample to assess impacts on three-year industry transition probabilities, displayed in Appendix Figure A4, where the transition probability is redefined relative to an industry in every year.

[31]The individual-level covariates are worker earnings in 2007, worker earnings growth between 2005 and 2007, total experience in the labor market as measured in the TWC data, tenure in baseline industry, as well as age, gender, race, and observed education prior to 2007 for the baseline sample. The industry-level controls are 2007 average industry earnings, industry enrollment rates, and average industry earnings growth.

α_t. I cluster at the j_0-level to reflect that the exposure measure varies at the baseline industry level.[32]

Under this specification, δ_y measures the association between the degree to which a baseline industry is shocked and changes in Y_{it} relative to 2007, after removing common trends in the time-invariant controls. Interpreting δ_y as a causal effect of exposure on affected industries requires assuming that individuals with similar X_i^{2007} working in industries with similar $W_{j_0(i)}^{2007}$ would be on similar trends in Y_{it} in the absence of the Recession shock. This assumption is invalidated if workers with similar observables in low-shock industries are on a different paths of the outcome than observably similar workers in high-shock industries. This assumption can be checked by looking at pre-trends prior to 2009, where we should not see a change in the association with the shock measure for pre-Recession years.

Enrollment Effects: *Figure 7a shows that individuals working in shocked industries look similar in terms of enrollment rates before the Great Recession and then increase enrollment after the start of the downturn.* A 1 standard deviation increase in exposure causes a 0.37pp increase in the probability of enrollment in 2009, representing an 7.1 percent increase off these shocked industries' baseline enrollment rates (measured at a 1 standard deviation).[33] Interestingly, these enrollment effects persist on those impacted after the Recession has ended. In 2018, individuals shocked by the Recession are still 0.26pp more likely to be enrolled, although this effect is only marginally significant. Point estimates are shown in Appendix Table A5.[34]

New Enrollment Effects: *Figure 7b shows strong effects on new enrollment in exposed industries, indicating that that almost all of the baseline enrollment effect is driven by workers enrolling for the first time.* New enrollment is defined as a current enrollment without any enrollment in the previous three years. These new enrollment effects are much larger relative to the baseline, representing a 0.33pp increase or a 20 percent increase. Comparing to the overall enrollment effect, these results indicate that 90 percent of the increase in overall enrollment is made by new enrollees (0.33/0.37) rather than extending enrollment. Interestingly, these effects persist after the Recession ends as well.

Other Results: Looking at other outcomes reported in Appendix Table A5, I find significant effects on graduation but only in 2010, indicating that some enrolling individuals complete degrees but not in large numbers. These patterns are consistent in the full sample, where I estimate enrollment impacts of 0.17 percentage point (5.9 percent increase) on any enrollment and 0.11 percentage point on new enrollment (12.2 percent increase). I also conduct an exhaustive set of robustness exercises which lead to similar results, including a placebo analysis using 1997 as the baseline industry to assess the scope for mean reversion in driving the results. I also compare the results against alternate controls and when using

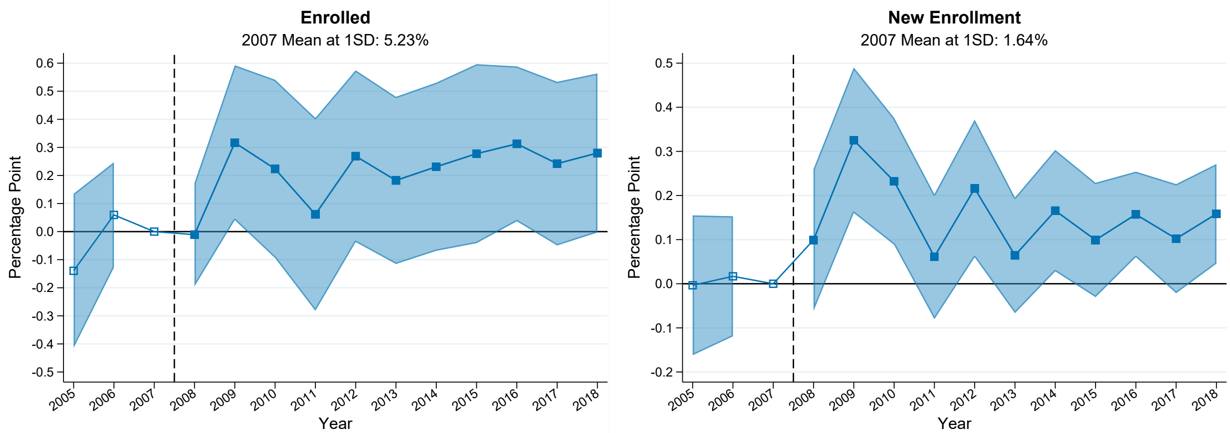
[32] Since I run this regression on a balanced panel and the exposure varies at the 5-Digit baseline industry level, the inclusion of individual-level fixed effects will not affect the results.

[33] To get baseline averages for these industries, I regress the 2007 outcome on the Z-score of the exposure measure and compute the predicted value at 1 SD. The average 5-digit industries experiences a 1.7 percent decline in employment with a standard deviation of 15.2 percent.

[34] Appendix Table A5 shows that the exposure measure captures deteriorating labor market prospects for workers from shocked industries more broadly, despite being constructed using only employment declines. A 1 standard deviation increase in the shock from the Great Recession leads to a persistent decline in earnings, beginning with a negative $2,654 effect in 2009 (a 4.2 percent decline) and persisting to a negative $1,796 in 2018 (a 2.8 percent decline). While there is a slight pre-trend in earnings, it is small relative to the magnitude of the post-Recession effect.

Figure 7: Industry-Level Exposure Shock Event Study Results

(a) (b)



Notes: Plots coefficient estimates of δ_y in Equation 3.1, which measures changes in the association between the outcome and the exposure measure of the Great Recession relative to 2007 after accounting for trends based on pre-determined controls. The exposure measure in this regression is set to be mean zero and standard deviation of one; the average 5-digit industries experiences a 1.7 percent decline in employment with a standard deviation of 15.2 percent. Panel (a) shows results for the outcome as a dummy for being currently enrolled. Panel (b) shows the results for a new enrollment, defined as being currently enrolled but not enrolled in the previous three years. Standard errors clustered based on an individual's pre-Recession 5-digit industry code. "2007 Mean at 1SD" is based on predicted values from a linear probability model of 2007 enrollment on the exposure measure, evaluated at 1 SD of the exposure measure. See Appendix Table A5 for point estimates and additional results.

an exposure measure defined using employment losses outside of Texas. These results are shown in Appendix Table A6.

3.3 Heterogeneity by Industry and Field of Study

Table 2 shows heterogeneity in responsiveness to shocks from the Great Recession by outcome and within broad industry groups. To gain precision, I focus on the full sample and combine 2009 and 2010 coefficients from the event study. Results for the baseline sample, shown in Table A7, exhibit similar magnitudes although are often imprecise.

Heterogeneity by Industry: *Panel (a) of Table 2 shows that different types of industries differ in the responsiveness of enrollment to the shocks of the Great Recession, with professionally-oriented being the most responsive.* This panel reports results that subset the sample to compare industries in the same category. This means that each regression in Panel (a) is implicitly comparing changes in the association between enrollment and the Great Recession shock within groups. Professional sectors (which includes financial services and real estate) increases enrollment rates by 0.42 percentage points (or 10.5 percent off of the baseline for this group). Manufacturing and production-oriented sectors (which include construction, resource extraction, and wholesale trade), see increases in enrollment that are significant but less striking. Other industries see noisily estimated or limited increases in enrollment.

Heterogeneity by Field of Study: *Panel (b) of Table 2 examines heterogeneity by field of study, showing that by far the biggest enrollment increase comes from enrollment in health-related fields.* In this panel, enrolling in a field of study changes the outcome considered. Enrollment in health increases by 0.09pp in response to the shock, representing a 73.1 percent increase off the baseline. This large percent change is due to low enrollment rates in health prior to the Recession for those working in high-shock industries such as manufacturing and construction. Looking to the overall enrollment effect of 0.25pp (which combines 2009 and 2010) indicates that enrollment in health studies accounts for 38 percent of the total enrollment effect. While imprecise, the comparable number for the baseline sample is a 0.14pp increase in health (a 48 percent effect) that accounts for 40 percent of the total enrollment effect. When looking at other fields of study, we see that all fields somewhat increase enrollment in response to the shock.

Heterogeneity by Field-Industry Pairs: *Looking at the interaction between field and industry shows that many workers use this as an opportunity to up-skill while others use this as an opportunity to re-skill, with the re-skilling effect driven by moves into health care.* Appendix Table A8 reports a full breakdown of industry and field of study combinations for the full sample.[35] The results indicate field-by-industry patterns in enrollment responses to the shock. The response of production-oriented industries to studying health is large, representing 22 percent of the overall effect for these workers. This indicates that many manufacturing workers change tracks in response to the shock. At the same time, the remainder of the response is dominated by enrollment in more technically-oriented fields, where vocational technical degrees and other engineering degrees account for 75 percent of the effect for these workers. We see a similar set of patterns when looking at what drives the effects for professional workers: 22 percent of the effect is driven by health and 32 percent is driven by business enrollment.

Table 2: Heterogeneity by Field and Industry: Full Sample

A. By Industry:					
	Production/Manufacturing	Services	Professional/Finance	Other	
Enroll (pp)	0.159**	0.053	0.420***	0.129	
SE	(0.073)	(0.058)	(0.127)	(0.120)	
Effect (%)	[6.4%]	[1.6%]	[10.5%]	[5.3%]	
N (Industries)	142	130	79	210	
N (Individuals)	411,385	685,468	594,704	1,748,053	
B. By Fields of Study:					
	Study Health	Study Business	Study Information Technology	Study Vocational Services	Study Education
Enroll (pp)	0.094***	0.031*	0.014***	0.029***	0.018***
SE	(0.025)	(0.016)	(0.005)	(0.010)	(0.006)
Effect (%)	[73.1%]	[3.9%]	[8.2%]	[22.7%]	[5.8%]
N (Industries)	561	561	561	561	561
N (Individuals)	3,439,610	3,439,610	3,439,610	3,439,610	3,439,610

Notes: Coefficients pool the event study parameters δ_y for 2009 and 2010 from the event study specification in Equation 3.1. Standard errors, shown in parentheses, are clustered based on an individual's pre-Recession 5-digit industry code. Standard errors clustered based on an individual's pre-Recession 5-digit industry code. Percent effects, shown in brackets, are based on predicted values from a linear probability model of 2007 enrollment on the exposure measure, evaluated at 1 SD of the exposure measure. Results for the baseline sample are shown in Appendix Table A7 and a full breakdown of outcomes by industry groups are reported in Appendix Table A8. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4 An Empirical Model of Adult Labor Supply and Schooling Choices

The results thus far show systematic patterns of selection by past work experience and fields of study that determine how workers respond to the shocks of the Great Recession. While valuable pieces of evidence, these results do not speak to whether returning to school was the best course of action for these workers or how policy could be better designed to aid transitions and increase worker earnings. In order to shed light on these issues, I now outline a structural model of a worker's choice of industry

[35]These crosstabs are almost always statistically insignificant for the baseline sample but typically report similar magnitudes.

of employment, field of study, and resulting earnings. At a high level, the empirical framework has two components: a dynamic model of work and schooling choices and a rich statistical model of life-cycle earnings. By incorporating dynamics, the model endogenizes the full pathway taken by workers, accounting for selection into education based on past work experience as well as the indirect effect of schooling on future work transitions.

Preliminaries: Time is discrete. In each year t, individual i makes a choice $k \in \{1, ..., K\}$ in order to maximize their present discounted value of lifetime utility,[36] which includes both earnings and non-pecuniary factors. Each action the individual takes corresponds to a joint choice of working in industry j and studying field of study f: $k = (j, f)$ where $j \in \{0, 1, ..., J\}$ and $f \in \{0, 1, ..., F\}$. Individuals can both work in industry j and study in field f, which I call *part-time study* (i.e., $j(k)$>0 and $f(k)$>0) or be entirely non-employed (in which case j=0 and f=0).[37] Let $j(k)$ and $f(k)$ to denote the corresponding sector and field of study resulting from action k.[38] As $J = 7$ and $F = 5$, there are $K = 1 + J + F + F \cdot J = 48$ actions.[39]

Time-invariant worker heterogeneity comes through $q \in \{1, 2, 3, 4\}$ discrete worker types.[40] These are observable demographic groups - defined as gender and observed college attendance before age 25. Each type q differs in terms of their preferences and comparative advantage over work and schooling options.[41] Let $\mathscr{H}_i^{-t}$ denote the *history* of individual i's work and schooling choices prior to period t.

Timing: The timing is summarized in Figure 8 below. A worker begins period t in their previous industry $j_{i,t-1}$, previous idiosyncratic productivity $\eta_{i,j_{i,t-1},t-1}$ in that industry, prior schooling state $s_{i,t-1}$ ($s_{i,t-1} = 1$ if in school), and other continuous states Ω_{it} to be discussed in detail below. At the start of the period, individuals experience exogenous separations with probabilities depending on the their starting industry, $j_{i,t-1}$. Upon a separation, workers lose some job-specific skills and get shifted into non-employment. Workers then observe the idiosyncratic component of flow utility, ϵ_{it}^k, and make a choice k, taking into account expectations over realized idiosyncratic productivity η_{ijt} given current values of $\eta_{i,j_{i,t-1},t-1}$. After making a choice, workers realize the shock determining η_{ijt} and consume flow utility u_{qt}^k, which depends on their worker type q, time t, action k, as well as current states. At the end of the period, the state evolves, which includes skill accumulation as outlined in the following section.

[36]Workers enter the labor market at age 25 and retire at 55.

[37]Workers may be fully employed in sector j (in which case $j > 0$ and $f = 0$), study full-time in field f (in which case $j = 0$ and $f > 0$), or be voluntarily non-employed (in which case $f = 0$ and $j = 0$). The $J = 7$ industries are: A General Sector, Construction, Manufacturing, Health Care, Services, Financial Services, and a Public Sector (including Education). The $F = 5$ fields of study are: General Studies, Technical Fields, Health Care, Humanities, and Business.

[38]There are no restrictions on the choice set an agent has, however, agents will face switching costs to capture labor market frictions.

[39]I do not directly model intensive margin of labor supply. In my setting, *part-time* simply indicates whether the person is engaging simultaneous work and study. These intensive margin labor supply decisions are partly captured in the persistent η shocks, discussed below.

[40]Future work will seek enrich the degree of time-invariant worker heterogeneity by identifying latent worker types in a first-step clustering procedure using the EM algorithm. See Traiberman [2019] and Arcidiacono et al. [2023] for recent applications. These procedures pool information across periods to identify latent types, using persistent patterns in earnings and choices to identify the covariance between comparative advantage and preferences in an analogous manner to a fixed effects argument.

[41]Agents are also differentiated by their graduation cohort. I leave this as implicit, but in practice each of the five cohorts is a different age in each year t. This necessitates solving the model and evaluating choice probabilities separately for each cohort. For tractability, I only estimate the choice model for the 1994 and 1998 cohorts, but use all cohorts in earnings estimation and counterfactuals.

4.1 Earnings and Human Capital Dynamics

Earnings: If individual i in period t makes the choice k to work in industry j (i.e, $j = j(k_{it}) > 0$), their log-earnings are decomposed into the following components:

$$y^k_{ijt} = \underbrace{r_{jt}}_{\textbf{Skill Prices}} - \underbrace{\alpha^{PartTime} D\left[f(k) > 0\right]}_{\textbf{Part-Time Penalty}} + \underbrace{\sum_{s=1}^{S} \pi_j^{(s)} \omega_{it}^{(s)}}_{\textbf{Transferable Skills}} + \underbrace{\alpha_j^\tau \tau_{ijt}}_{\textbf{Job-Specific Skill}} + \underbrace{\eta_{ijt}}_{\textbf{Idiosyncratic Productivity}} \tag{4.1}$$

Skill prices r_{jt} are industry-time fixed effects in log-earnings that measure the return to human capital in industry j at time t, capturing time-varying industry conditions that affect wages.[42] These are equilibrium objects that may change due to aggregate or industry-wide productivity shocks or changes in the availability of inputs. I do not directly model changes in the non-stationary wage-setting equilibrium.[43] I discuss the information agents have on aggregate states below. Agents who both work and study face a part-time penalty $\alpha^{PartTime}$, capturing that workers may be less able to supply human capital to the labor market while enrolled.

Transferable Skills: My approach to modeling human capital is quite general: worker skills are neither completely general nor completely specific, with the degree of transferability informed by the data through observed transitions. I adopt a skill weights approach to human capital in the spirit of Lazear [2009]. This framework nests multiple models of human capital.[44] Relative to prior work that adopts related approaches,[45] I do not use measures of skill directly. Using a fully data-driven approach that is based on observed transitions allows me to capture components of human capital not measured in such data. Since skill measures are typically only available for occupations, this approach also enables me to overcome limitations of industry-level data as well as incorporate fields of study.[46]

I model earnings as an industry-specific weighting of S individual-specific latent skills.[47]. Individual i

[42] Restricting skill weights to be positive treats human capital as a Cobb-Douglas production function across model objects. Exponentiating yields:

$$Y^k_{ijt} = R_{jt}\left(\exp\left\{\alpha^{PartTime} D\left[f(k) > 0\right]\right\} \prod_{s=1}^{S} \left(\exp\left\{\omega_{it}^{(s)}\right\}\right)^{\pi_j^{(s)}} \left(\exp\left\{\tau_{ijt}\right\}\right)^{\alpha_j^\tau} \exp\left\{\eta_{ijt}\right\}\right) = R_{jt} H^k_{ijt}$$

where R_{jt} is the skill price such that $r_{jt} = \log\left(R_{jt}\right)$ and H^k_{ijt} is human capital supplied to industry j.

[43] Skill prices and separation rates, objects that vary at the industry-time level, should be interpreted as reduced-form for the non-stationary equilibrium that a general equilibrium model would micro-found.

[44] For example, if $S = J$ and $\Pi = I$, then skills are perfectly non-transferable. In contrast, if $\Pi = \iota_J$ and $S = 1$, then there is only general human capital. My approach quantifies the intermediate cases, under the restriction that $S = 3$. This number is motivated by the fact that the prior work that uses skill measures typically considers two or three dimensions of skills. For example. Deming [2017] considers the returns to cognitive, non-cognitive, and social skills. The choice of $S = 3$ is quite flexible, but is still a substantive restriction.

[45] Some examples are Yamaguchi [2012], Roys and Taber [2019], and Lise and Postel-Vinay [2020].

[46] A restriction of this model is that skill weights are time-invariant. This means that the process by which past experience gets translated into human capital in each industry is constant, with time-varying changes in how this experience is rewarded being captured in the skill price. A literature has documented that skill demands may have increased after the Great Recession (e.g. Hershbein and Kahn [2018], Blair and Deming [2020], Modestino et al. [2020]). These patterns will be captured in systematic changes in the skill prices r_{jt}. This abstraction can be made more realistic in future work by increasing the number of industries workers can choose from.

[47] I use the term latent in that the econometrician does not observe skills prior to estimation. In particular, given a guess of parameters,

begins a period with latent skill $\omega_{it}^{(s)}$ which gets weight $\pi_j^{(s)}$ in industry j. I choose $S = 3$. Skill weights are restricted to be positive, $\pi_j^{(s)} > 0$, and time-invariant.[48] Based on their current vector of skills $\vec{\omega}_{it}$, a worker has comparative advantage over sectors as skills are portable across industries. All else equal, workers prefer working in the sector that gives the highest weight to their skills.

In addition to these industry-specific returns, each skill is also differentiated in its accumulation process. Current choice k impacts the future values of skills, which change with schooling and work experience and depreciate with non-employment. Each skill has a worker type-specific technology of accumulation, $\Gamma_q^{(s)}()$. Each worker type q and latent skill s follows its own recursive law of motion:

$$\omega_{i,t+1}^{(s)} = \Gamma_q^{(s)}(k|\omega_{it}^{(s)})\omega_{it}^{(s)}$$

where $\Gamma_q^{(s)}$ captures the percent growth in skills and is flexibly parameterized as:

$$\log \Gamma_q^{(s)}(k|\omega_{it}^{(s)}) = \begin{cases} \log\left(\underbrace{1-\gamma_{Depr}^{(s)}}_{\textbf{Depreciation}}\right) & \text{if } j(k)=0 \text{ and } f(k)=0 \text{ (non-employment)} \\ \underbrace{\exp\left\{-\gamma_{Dim:School}^{(s)}(\omega_{it}^{(s)}-1)\right\}\left(\gamma_{School:q}^{(s)}+\gamma_{School:f(k)}^{(s)}\right)}_{\textbf{Education Investments}} & \text{if } j(k)=0 \text{ and } f(k)>0 \text{ (full-time study)} \\ \underbrace{\exp\left\{-\gamma_{Dim:Work}^{(s)}(\omega_{it}^{(s)}-1)\right\}\left(\gamma_{Work:q}^{(s)}+\gamma_{Work:j(k)}^{(s)}\right)}_{\textbf{Learning-by-doing}} & \text{if } j(k)>0 \text{ and } f(k)=0 \text{ (full-time work)} \\ \underbrace{\gamma^{PartTime}\exp\left\{-\gamma_{Dim:School}^{(s)}(\omega_{it}^{(s)}-1)\right\}\left(\gamma_{School:q}^{(s)}+\gamma_{School:f(k)}^{(s)}\right)}_{\textbf{Part-Time Education Investments}} & \text{if } j(k)>0 \text{ and } f(k)>0 \text{ (part-time study)} \\ +\underbrace{\left[1-\gamma^{PartTime}\right]\exp\left\{-\gamma_{Dim:Work}^{(s)}(\omega_{it}^{(s)}-1)\right\}\left(\gamma_{Work:q}^{(s)}+\gamma_{Work:j(k)}^{(s)}\right)}_{\textbf{Part-Time Learning-by-doing}} & \end{cases} \tag{4.2}$$

This flexible skill accumulation function captures several sources of differentiated human capital investment. First, $\gamma_{Work:j(k)}^{(s)}$ and $\gamma_{School:f(k)}^{(s)}$ capture how work experience in sector j and studying field f modifies each latent skill. Some fields of study may be useful in some industries but not in others. For example, it may be the case that studying health increases one's earnings as a nurse, but these skills will not be very useful in construction. This would be captured in a high $\gamma_{School:f}^{(s)}$ for nursing and a high $\pi_j^{(s)}$ for health, but a low $\pi_{j'}^{(s)}$ for construction. Second, $\gamma_{School:q}^{(s)}$ and $\gamma_{Work:q}^{(s)}$ capture comparative advantage to investing in human capital through school or work experience by worker type q on each skill margin. For example, college-educated workers may have higher returns to experience and this pattern may be

skills in my context are a deterministic functions of past work histories. This approach is distinct from those that estimate factor models using skill data. For example, in Yamaguchi [2012], a stochastic process governs how skills change over time, so individual skills are not known even given a guess of parameters. In his context, the accumulation process must be disciplined using observed occupation-level measures of skill and an individual's time-varying skills are backed out using the Kalman filter.

[48] One limitation is that the model does not account for occupation or task information. These are partially accounted for through the $\pi_j^{(s)}$. One reason industries may have similar weights is that they have similar occupation distributions, making work experience more transferable between them.

more salient in finance than construction. Third, $\gamma^{PartTime} \in (0,1)$ captures how much skill accumulation is from work compared to school when studying part-time. If workers are only working or only studying, they receive the full benefits of learning through either work or study but otherwise receive a convex combination. Last, $\gamma^{(s)}_{Dim:School} > 0$ and $\gamma^{(s)}_{Dim:Work} > 0$ capture diminishing benefits to further investing in human capital as skills increase, which may differ by type of skill as well as by schooling or work.[49]

Specific Skill: Job-specific skill τ_{ijt} captures the return to remaining continuously employed. Importantly, this object is entirely lost upon a job separation, grows identically in each industry, and is not modified through schooling. Like transferable skills, this skill receives industry-specific weights and accumulates over time. Unlike transferable skills, the specific skill is memoryless in that the specific sequence of sectors does not matter for its level. This mechanism is meant to capture match effects with current employer, firm-specific human capital, and job-shopping dynamics in a reduced form relationship that is held fixed in the counterfactual (Bagger et al. [2014]).

To capture these job-shopping and job-ladder dynamics, the specific skill is allowed to grow both within and across periods, depending on if the worker makes a voluntary or involuntary transition. If an individual switches industries or experiences an involuntary separation, $sep_{it} = 1$, τ_{ijt} changes immediately from its value at the start of the period $\tau_{i,j_{i,t-1},t}$:[50]

$$\tau_{ijt} = \begin{cases} 0 & \text{if } sep_{it} = 1 & \text{(involuntary separation)} \\ \gamma^{(\tau)}_{Vol}\tau_{i,j_{i,t-1},t} & \text{if } sep_{it} = 0 \text{ and } j(k) \neq j_{i,t-1} & \text{(voluntary switch)} \\ \tau_{i,j_{i,t-1},t} & \text{if } sep_{it} = 0 \text{ and } j(k) = j_{i,t-1} & \text{(remain)} \end{cases} \tag{4.3}$$

After making choice k, growth in specific skills to the next period is:

$$\tau_{ij,t+1} = \Psi(k|\tau_{ijt})\tau_{ijt}$$

where:

$$\Psi(k|\tau_{ijt}) = \begin{cases} 0 & \text{if } j(k) = 0 & \text{(non-employment)} \\ 1 & \text{if } \tau_{ijt} = 0 \text{ and } j(k) > 0 & \text{(entry-level employment)} \\ \exp\{\gamma^{(\tau)}_{Accum}\exp\{-\gamma^{(\tau)}_{Dim}(\tau_{ijt} - 1)\}\} & \text{if } \tau_{ijt} > 0 \text{ and } j(k) > 0 & \text{(experienced employment)} \end{cases} \tag{4.4}$$

where the last line uses a functional form that mirrors the law of motion for transferable skills. Taken together, these equations mean that specific skill τ_{ijt} is a function of the duration of continuous employment

[49] Note that $\gamma^{(s)}_{School:f(k)}$, $\gamma^{(s)}_{Work:j(k)}$, $\gamma^{(s)}_{Work:q}$, and $\gamma^{(s)}_{School:q}$ are not sign-restricted, so individuals can lose skills from taking certain actions.

[50] This skill is industry and job-specific in that it changes when an individual switches industries voluntary and, once lost, it cannot be recovered even if returning to the same industry. The choice to allow the specific skill to potentially grow across industry transitions is meant to reflect that workers move to better job-matches over time.

and timing of voluntary transitions.[51]

Persistent Idiosyncratic Productivity: The structure on idiosyncratic productivity η_{ijt} allows for persistent heterogeneity in earnings, both weakening identification requirements and capturing patterns of selection documented as important in the training literature. Idiosyncratic productivity η_{ijt} follows the AR(1) process:

$$\eta_{ijt} = \rho^{j}_{j_{i,t-1}} \eta_{i,j_{i,t-1},t-1} + \varphi_{i,j,j_{i,t-1},t} \tag{4.5}$$

where $\varphi_{i,j,j_{i,t-1},t} \underset{\text{i.i.d.}}{\sim} N(0, \sigma^{j}_{j_{i,t-1}})$.[52] The persistence parameters, ρ, and variance of the innovations, σ, both depend on chosen in industry j as well as last activity $j_{i,t-1}$ through the type of work transition.[53] Specifically, parameters governing the variance in the innovations differ by the target industry j and whether a worker remains in their current industry (*Remain*), switches industry voluntarily (*EE*), or switches out of non-employment (*EN*): σ^{Remain}_{j}, σ^{EE}_{j}, σ^{EN}_{j}. For tractability, the persistence parameters ρ vary by only the type of transition: $\rho^{Remain}, \rho^{EE}, \rho^{EN}$.

The agent knows previous productivity $\eta_{i,j_{i,t-1},t-1}$ at the time of choosing k but $\varphi_{i,j,j_{i,t-1},t}$ is realized after the individual's choice is made. This timing assumption aids greatly in the tractability of the model while still allowing selection in response to shocks, which is needed in order to capture the potential dips earnings prior to enrollment (Ashenfelter [1978]). Specifically, individuals with negative η_{ijt} will respond by taking low-ρ actions while those with high η_{ijt} will take high-ρ actions, resulting in positive values to realized to η_{ijt} over time. Specifically, at estimated parameters, this will mean that individuals will be more likely to switch in response to negative draws of $\varphi_{i,j,j_{i,t-1},t}$.

Initial Conditions: Observables prior to age 25 are used to parameterize initial conditions. This captures that workers may be different in their pre-sample work experiences which may affect their payoff to working in certain industries. These are modeled as:

$$\log\left(\omega^{(s)}_{i1}\right) = z_i' \gamma^{(s)}_{Z:1} + \gamma^{(s)}_{q:1}$$

where z_i is a vector of these initial observables with $\gamma^{(s)}_{Z:1}$ a vector of coefficients for each skill s and dummies for worker type $\gamma^{(s)}_{q:1}$. I observe full work history prior to age 25 for high school graduates. Elements of z_i are indicator variables for most recent industry of employment in age 23 or 24 (including none). I impose the normalization that $\mathbb{E}\left[\omega^{(s)}_{i1}\right] = 1$ in the population, which helps fix the location and scale of $\omega^{(s)}_{it}$. Normalizations are discussed more in Section 5.

For other initial conditions, $j_{i,t-1}$ in $t = 1$ is set to the the same recent industry of employment that

[51] A key identifying assumption will be that I can distinguish involuntary and voluntary employment-to-employment transitions across industries (in a way that matters for earnings), which is accomplished by using quarterly data. The normalization of $\tau_{ij,t+1} = 1$ if $\tau_{ijt} = 0$ will separate the level of τ_{ijt} from the levels of α^{τ}_{j}, the industry-specific return to τ_{ijt}.

[52] In practice, all that is needed for estimation of the earnings parameters is the mean-independence of $\varphi_{i,j,j_{i,t-1},t}$. Full independence and the normal distributional assumption will be used in choice estimation and counterfactual simulations.

[53] These work transitions are determined by both target j and previous activity $j_{i,t-1}$, necessitating the need for cumbersome notation.

determines z_i. Initial specific skill $\tau_{i,j_{i,t-1},t}$ in this industry is determined by Equation 4.4 based on observed tenure. The initial persistent shock is drawn independently with zero mean and a variance parameter specific to the first period: $\eta_{ij1} \underset{\text{i.i.d.}}{\sim} N(0, \sigma_j^0)$.

4.2 Utility, Choices, and Beliefs

I now describe the behavioral model underlying the earnings dynamics outlined above. This allows us to predict counterfactual worker choices and relate them to changes in earnings.

A worker's choice is determined by the state in which they start the period. In addition to previous activities $j_{i,t-1}$ and $s_{i,t-1}$, these include continuous states Ω_{it}. These continuous states include current transferable skills $\omega_{it}^{(s)}$ $\forall s$, specific skill $\tau_{i,j_{i,t-1},t}$ in the industry at the start of the period, previous period's income $Y_{i,t-1}$, and age Age_{it}: $\Omega_{it} = \{\omega_{it}^{(1)}, \omega_{it}^{(2)}, \omega_{it}^{(3)}, \tau_{i,j_{i,t-1},t}, Y_{i,t-1}, Age_{it}\}$.

Flow Utility: An agent of type q receives the following flow utility from taking action k in year t:

$$u_{qt}^k(j_{i,t-1}, s_{i,t-1}, \Omega_{it}; \vec{\epsilon}_t, \eta_{ijt}) = \underbrace{\mu_q^k(Age_{it})}_{\textbf{Preferences for Actions}} + \underbrace{\beta_Y y_t^k(\Omega_{it}, j_{i,t-1}; \eta_{ijt})}_{\textbf{Preference for Log-Income}} \tag{4.6}$$

$$- \underbrace{\beta_P Price_t^k(Y_{i,t-1})}_{\textbf{Sensitivity to Tuition Costs}} - \underbrace{C_{qt}^k\left(j_{i,t-1}, s_{i,t-1}\right)}_{\textbf{Switching Cost}} + \underbrace{\epsilon_t^k}_{\textbf{EV1}} \tag{4.7}$$

$$= \bar{u}_{qt}^k(j_{i,t-1}, s_{i,t-1}, \Omega_{it}; \eta_{ijt}) + \epsilon_t^k \tag{4.8}$$

which depends upon type-specific non-pecuniary benefits from taking action k, $\mu_q^k()$;[54] preference for labor market earnings, y_t^k; disutility from net tuition costs that vary by full- or part-time study; switching costs $C_{qt}^k()$; and the vector of extreme-value shocks, $\vec{\epsilon}_t$.[55]

Tuition and Financial Aid Functions: I take sticker prices for attending college from the Integrated Post-Secondary Education Data System (IPEDS), accounting for differences in full and part-time tuition.[56] I incorporate administrative financial aid data from THECB in order to get realistic measures of price sensitivity needed for the main counterfactuals, modeling grant aid as a flexible function of the prior year's income $Y_{i,t-1}$.[57] I treat negative values of tuition net of aid as zeros, meaning that individuals with more aid than tuition will not be sensitive to price although still face a cost of switching into school.

[54] In practice, the function $\mu_k^q(Age_{it})$ consists of indicators for each industry, indicators field of study, an indicator for part-time study, and quadratic slopes in age for being employed full-time. All coefficients are specific to worker type q

[55] I normalize the variance of ϵ to 1 to fix scale. To fix the location of utility, choosing non-employment has utility of 0. As agents prefer log-income, they will prefer to have predictable streams of income over time.

[56] I total reported full-time full-year tuition, fees, and books/supply costs for each two-year college in Texas and average these using full-time equivalent enrollment for that academic year. To create part-time prices, I convert these into a per-credit cost by dividing this average cost by 30 credits, which is equivalent to attending full-year and full-time enrollment. Then, I assume that students enrolled part-time enroll in 18 credits which is close to the observed average for those who work and enroll at the same time. I do this rather than using cost measures from the financial aid data as the prices from IPEDS lined up with reported per-credit tuition costs reported on community college websites.

[57] I model aid as splines with kinks at \$10,000 and \$30,000 and allow estimated aid schedules to vary across groups of years associated with significant policy changes: 2001-2008, 2009-2012, 2013-2019. Agents prior to the Recession expect the 2001-2008 functions to last indefinitely and are surprised by changes in aid in 2009-2012. For tractability, agents know the 2013-2019 aid schedules and expect it to continue indefinitely. I treat these schedules as a calibration and do not adjust standard errors for them. The estimated aid functions are shown in Figure D3.

Switching Costs: Frictions in transitioning across industries and out of non-employment are captured in switching costs. Switching into non-employment or remaining in the same industry is costless. Let $E(j_{i,t-1}) = D[j_{i,t-1} > 0]$ denote whether a worker starts in an employed state and $U(j_{i,t-1})$ whether they start in a non-employed state, such that $E(j_{i,t-1}) = 1 - U(j_{i,t-1})$. If a worker makes choice k to switch industry (i.e., $j(k) \neq j_{i,t-1}$), they incur the following disutility:

$$C^k_{qt}\left(j_{i,t-1}, s_{i,t-1}\right) = \exp\{\underbrace{\kappa^U U(j_{i,t-1}) + \kappa^E E(j_{i,t-1})}_{\textbf{Employment Status}} + \underbrace{\kappa_q}_{\textbf{Worker Type}} + \underbrace{\kappa_{j(k)}}_{\textbf{Target Industry}} + \underbrace{\kappa_{FromSchool} D\left[s_{i,t-1} = 1\right]}_{\textbf{From School}}$$
$$+ \underbrace{\kappa^U_{GR} U(j_{i,t-1}) D\left[t \geq 2009, t \leq 2011\right] + \kappa^E_{GR} E(j_{i,t-1}) D\left[t \geq 2009, t \leq 2011\right]}_{\textbf{Business Cycle}}\} \quad (4.9)$$

The parameters $\kappa^{U(j_{-1})}$ and $\kappa^{E(j_{-1})}$ allow switching costs vary by employment status at the start of the period, capturing that search frictions may vary in unemployment. These are further allowed to vary over the business cycle through $\kappa^{E(j_{-1})}_{GR(t)}$ and $\kappa^{U(j_{-1})}_{GR(t)}$, increasing temporarily and unexpectedly between 2009 to 2011. The parameters κ_j allows this friction to vary by target industry, measured in differences relative to the general sector. I also allow worker types to differ in their switching rate κ_q, relative to non-college men. Finally, I allow starting in a schooling state to potentially decrease these switching costs through $\kappa_{FromSchool}$, permitting returning to school to act as a form of job search as has been suggested to be important in the training literature (Heckman and Smith [1999]).

If workers do not start in school and switch into schooling, they incur disutility:

$$C^k_{qt}\left(j_{i,t-1}, s_{i,t-1}\right) = \exp\{\kappa_{IntoSchool}\} \qquad \text{if} \qquad s(k) \neq s_{i,t-1} \text{ and } s_{i,t-1} = 0$$

This feature captures difficulties individuals may face in returning to schooling that are not captured by direct tuition costs. For example, registering for courses may be especially costly when one first enrolls.

Exogenous Separations: Individuals starting in an employed state ($j_{i,t-1} > 0$) may be exogenously separated with a probability that varies by industry and year: δ_{jt}. Two important things happen upon separation. First, while they retain their vector of transferable skills ω_{it}, they lose job-specific skills $\tau_{i,j_{i,t-1},t} = 0$. Second, they face the switching costs of non-employed workers. Both exogenous separations δ_{jt} and negative shocks to productivity η_{ijt} will capture dynamics generating the pre-program/Ashenfelter dip in earnings (Ashenfelter [1978]). Combined with unexpected changes in skill prices r_{jt}, these forces will drive training and transition decisions in response to both individual-level and aggregate shocks.

Beliefs on Aggregate States and Policy Regimes: I treat the Great Recession as a one-time, unanticipated shock. Agents are not myopic and use a forecasting rule for the aggregate states prior to the Recession. Practically, I linearly interpolate skill prices and separation rates for the years 2009 through

2015, assuming agents use these interpolated states to make their decisions prior to 2009.[58] By doing so, I treat agents as having biased beliefs about aggregate skill prices and separation rates in the sense that they are completely surprised by these changes. This is shown below for select industries in Figure 11. Similarly, policy changes to financial aid rules as well as increases in switching costs are modeled as unanticipated in the pre-period. It should be emphasized that, due to my two-step approach to estimation, any assumptions about beliefs do not affect estimates of earnings parameters.

Dynamic Problem: Agents make choices taking into account both current and future payoffs. Given current beliefs about aggregate states, this involves taking expectations over future separations δ_{jt}, preference shocks $\vec{\epsilon}_{it}$, and persistent shocks to idiosyncratic productivity η_{ijt}.

At the time of making a decision, workers have experienced exogenous separations based on $\delta_{j_{i,t-1},t}$ and know the value of the preference shocks $\vec{\epsilon}_t$, but do not know the realization of idiosyncratic productivity η_{ijt} in the period. Let $\hat{\eta}$ denote a potential realization drawn from the distribution $F^k(\hat{\eta}|\eta_{i,j_{i,t-1},t-1}, j_{i,t-1})$, depending on k through Equation 4.5. Similarly, let $\hat{\Omega}^k_q(\Omega_{it})$ be the future continuous states resulting from taking action k for worker type q.[59] Net of logit shocks $\vec{\epsilon}_t$,[60] the value from taking action k at t for a worker of type q with $\hat{\eta}$ is:

$$\begin{aligned} v^k_{qt}(j_{i,t-1}, s_{i,t-1}, \Omega_{it}; \hat{\eta}) = {} & \bar{u}^k_{qt}(j_{i,t-1}, s_{i,t-1}, \Omega_{it}; \hat{\eta}) \\ & + \underbrace{\delta_{j(k),t}\beta V_{q,t+1}\left(0, s(k), \hat{\eta}, \hat{\Omega}^k_q(\Omega_{it})\right) + \left(1-\delta_{j(k),t}\right)\beta V_{q,t+1}\left(j(k), s(k), \hat{\eta}, \hat{\Omega}^k_q(\Omega_{it})\right)}_{\textbf{Expected Continuation Value}} \end{aligned} \tag{4.10}$$

where $\beta = 0.96$ is the discount factor and $V_{q,t+1}()$ denotes the expected value of starting the next period in a state. The ex-ante value of action k involves integrating over potential innovations in earnings productivity $\hat{\eta}$:[61]

$$\bar{v}^k_{qt}(j_{i,t-1}, s_{i,t-1}, \eta_{i,j_{i,t-1},t-1}, \Omega_{it}) = \int_{\hat{\eta}} v^k_{qt}(j_{i,t-1}, s_{i,t-1}, \Omega_{it}; \hat{\eta}) dF^k(\hat{\eta}|\eta_{i,j_{i,t-1},t-1}, j_{i,t-1}) \tag{4.11}$$

Integrating over the preference shocks $\vec{\epsilon}$ gives the expected value of being in a state at time t:

$$V_{qt}(j, s, \eta, \Omega) = \gamma_{Euler} + \log\left(\sum_k \exp\{\bar{v}^k_{qt}(j, s, \eta, \Omega)\}\right) \tag{4.12}$$

The full timing of the model is illustrated in Figure 8.

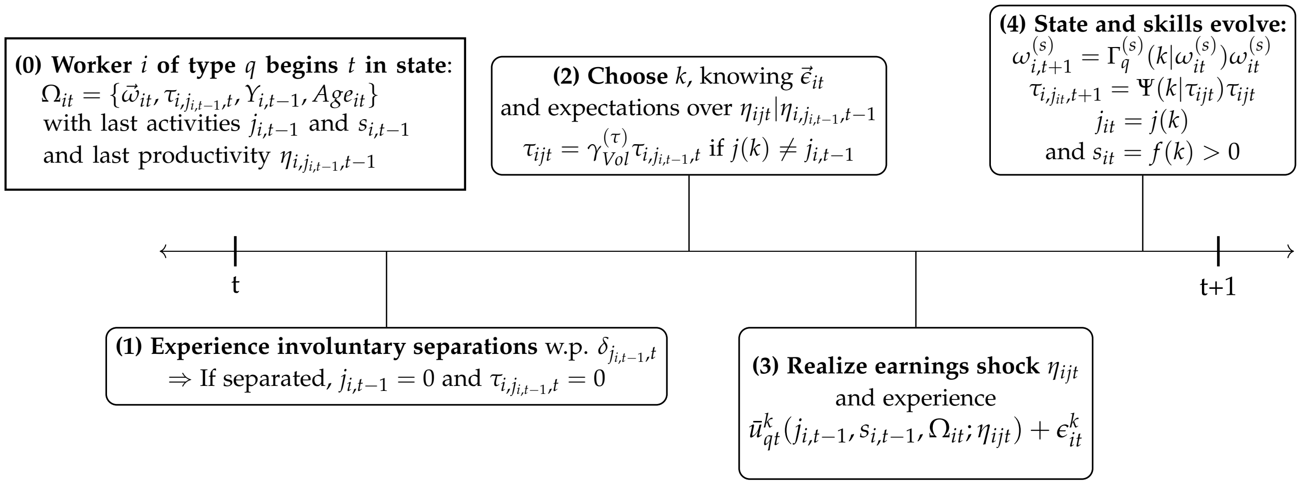
[58] An alternative would be to estimate an autoregressive process on skill prices in each industry and use this as a rational expectations forecasting rule (e.g. Lee and Wolpin [2006]). I do not pursue this approach as the number of sectors is large and the deviations from the trend would enter the state space separately. In addition, the length of the panel is short meaning that there are few observations to inform the process. I consider my approach as the best choice available.

[59] This is worker-type q specific as the skill accumulation process $\Gamma_q()$ is q-specific.

[60] The logit shocks are removed from $\bar{v}^k_{qt}$ as they are unaffected by realizations of $\hat{\eta}$. They re-enter when computing the expected value of starting in a state in Equation 4.12.

[61] I use Gaussian-Quadrature with 5 nodes to evaluate this expectation.

Figure 8: Timing of one period of the model



Approximate Solution: Solving this model is computationally difficult. The practical implication resulting from treating the Great Recession an unanticipated shock is that I need to solve the model under two belief regimes: the pre-Recession decision rules (through the whole life-cycle) and the post-Recession decision rules (from 2009 on-wards, when agents are surprised). In addition, I need to solve the model for each worker type q and graduation cohort. Moreover, the state space is large and has many continuous states. Due to the history dependence in skills, there is no renewal action or finite dependence argument that allows for estimation without solving the model (e.g. Arcidiacono and Miller [2011], Arcidiacono and Miller [2020]).

To make this problem computationally feasible, I solve the model through backwards recursion on a subset of possible states and approximate the value functions using regression interpolation.[62] Expected value functions $V_{q,t+1}(j, s, \eta, \Omega)$ are approximated using the regression:

$$\tilde{V}_{q,t+1}(j, s, \eta, \Omega) = x(\Omega, \eta, s)'\hat{\pi}^j_{t+1}$$

Thus, a solution to the agent's problem consists of all $\hat{\pi}^j_t$ governing decisions. For the design matrix $x(\Omega, \eta, s)$, I use all linear effects, pairwise interactions, and own-quadratic effects for all continuous states in Ω, excluding Age_{it}.[63] I include an additional fixed effect and linear interactions if the individual was in school in the previous period, $s_{i,t-1} = 1$. Letting $\hat{\pi}^j_{t+1}$ depend on j also implicitly interacts all of these covariates with the discrete employment state j at the start of the period. This creates 2,160 linear regressions that must be run to solve the model.

In choosing the number of states on which to evaluate the value function, I leverage the fact that the empirical distribution of states is observed after separately estimating the skill accumulation functions in a

[62]Similar interpolation methods to quickly compute value functions through regression interpolation have been used in Keane and Wolpin [1997], Lee and Wolpin [2006], Sweeting [2013], and Dix-Carneiro [2014].
[63]Since I interpolate each cohort and time period separately, age is implicitly interacted with all coefficients as well.

first-step.[64] I randomly sample 500 states, sampling from each continuous state's marginal distribution.[65] This approximation performs very well in practice, as shown in in Appendix Figure D1, where I vary the number of evaluation states on which to interpolate.

5 Identification

The key endogeneity problem the structure of the model helps address is the dynamic relationship between past industry, current enrollment choices, and future transitions in determining earnings. Identification relies on having rich panel data on earnings and sufficient variation in work and school transitions. The main assumption is the mutual independence of time-varying unobservables, which breaks estimation into two steps. These assumptions are common in the dynamic discrete choice literature dating back to Rust [1987]. The persistent process on η_{ijt} substantially weakens the implications of these assumptions by allowing persistence in η_{ijt} that is correlated with skills while preserving tractability.

5.1 Key Assumptions

Assumption 5.1. *(Information Sets) The agent's information at the time of choosing k consists of their current state, $\{\Omega_{it}, j_{i,t-1}, s_{i,t-1}, \eta_{i,j_{i,t-1},t-1}\}$, including whether the previously employed state $j_{i,t-1}$ measures realized separations; the currently expected paths of policy regimes, switching costs, separation rates δ_{jt}, and skill prices, r_{jt}; and the unobserved preference shock, $\vec{\epsilon}_t$. In particular, the shock to productivity η_{ijt} is not known at the time of making a choice and agents take this into account by taking expectations over potential realizations, conditioning on previous $\eta_{i,j_{i,t-1},t-1}$.*

Assumption 5.2. *(Unobserved Shock to Utility) Conditional on the state, the preference shocks $\vec{\epsilon}_t$ are identically distributed extreme value type 1 and independent over both individuals and time periods.*

These assumptions create separability of the earnings and choice models, which buys tractability while also permitting the model a richness that would otherwise be difficult. In particular, the earnings equation is semi-parametrically identified, meaning that estimated earnings parameters are not sensitive to the structure of the choice model. Since choices are made without knowing independently drawn innovations in productivity η_{ijt}, the full distribution of η_{ijt} is revealed *ex post* in the microdata.[66]

[64] I divide each continuous state into quintiles and add additional states that are higher than the maximum observed value. I draw states at which to evaluate the value function by first sampling from these bins and then sampling uniformly within bin. I repeat this for the marginal distribution of each state.

[65] To account for states outside of this observed distribution (which agents may take into account when making choices), I make sure to sample slightly outside the observed range.

[66] It is worth comparing these assumptions to alternative setups of the model. First, one could allow idiosyncratic productivity to be drawn in each industry in every time period and be known to the agent at the time they made decisions. In this case, one could in principle allow η and ϵ to be correlated by drawing them from a jointly multivariate normal distribution. This is the approach taken in papers such as Lee and Wolpin [2006] and Dix-Carneiro [2014]. I do not pursue this route for two reasons. First, my inclusion of part-time study blows up the choice space, making the dimensionality of ϵ too large for this procedure to be practical. Second, it would also mean estimation would need to occur in a single step, making computation more difficult.

A different potential setup would be to estimate a model of search, matching, and bargaining (e.g. Postel-Vinay and Robin [2002], Taber and Vejlin [2020], Huckfeldt [2022]). Bargaining with current employers in response to unobserved outside wage offers would also generate correlation between unobserved utility shocks (e.g.,through realized offer probabilities) and unobserved productivity (e.g., through bargaining outcomes). I do not pursue this setup as bargaining is not the main focus of the paper and would necessitate a loss of richness in other dimensions to remain traceable.

Another issue is whether transitions are voluntary or involuntary. To account for this in a tractable way, I add the following assumption:

Assumption 5.3. *(Observed Involuntary Employment-to-Employment Transitions) An involuntary separation is observed, $sep_{it}^{Obs} = 1$, if the employed individual experiences one or two quarters of non-employment before switching back to an employed state. If the worker immediately re-enters an employed state, involuntary separations only affect earnings through the specific skills τ, as the worker does not experience skill depreciation.*

While the model is estimated at the annual level, Assumption 5.3 leverages the quarterly data to enrich unemployment dynamics. An involuntary switch into non-employment where the individual does not return to work affects earnings in the same way as a voluntary switch into non-employment, as τ_{ijt} is always lost whenever individuals enter non-employment. This assumption abstracts from the earnings impact of short unemployment spells of less than a quarter. One may think of any permanent effects on earnings resulting from short unemployment spells to be captured by the process governing idiosyncratic productivity η_{ijt}.[67]

5.2 Margins of Selection and Implied Restrictions on Worker Mobility

There are several well-known identification challenges to estimating the returns to education that are captured in the framework. The two most pressing concerns in estimating returns to education are (1) ability bias, that individuals may be positively selected on earnings in the absence of enrollment, and (2) the pre-program/Ashenfelter dip in earnings, the degree to which individuals are selected on a possibly persistent negative shock. The second source of bias makes comparisons using lagged earnings challenging, as the degree of persistence in the adverse shock affects the appropriate comparison group.[68]

From the perspective of the model, levels of skills ω_{it} and τ_{ijt} and idiosyncratic productivity η_{ijt} proxy for worker ability. Selection on the transitory component of earnings is captured by shocks to productivity η_{ijt}, changes in aggregate skill prices r_{jt}, and realized separations δ_{jt}. Each of these objects create forces that may drive an individual to enroll in response to these shocks when enrollment may not have been the optimal choice in prior periods. By estimating the parameters of this autoregressive process, I am quantifying the degree of persistence of these shocks directly from the data.[69]

[67] In Figure 13, I show below that the model reasonably matches the earnings patterns of workers separated during the Great Recession.

[68] For example, if shocks are perfectly persistent, the appropriate comparison group are individuals who have the same pre-enrollment dips in earnings as the treatment group. Failure to make this correct comparison will result in negative estimated returns. If shocks are entirely transient, the appropriate comparison group are individuals with similar earnings prior to the observed dip for enrollees. Failure to make this correct comparison will result in a positive bias, as individuals will be erroneously compared to those with low permanent earnings. See Table 2 in Ashenfelter and Card [1985] for an excellent illustration of how differing base periods affect estimates of training. See also Ashenfelter [1978], Heckman and Robb [1985], Heckman and Smith [1999].

[69] Ashenfelter and Card [1985] estimate the training effect by modeling the autocorrelation structure of comparison worker earnings and using this to form predictions about counterfactual trainee earnings. The key insight is that trainees are different on this transitory shock but the researcher can use the covariance structure of earnings and a selection rule in terms of pre-training earnings to forward predict the contribution of this transient shock to post-training earnings. We can think of identification in my model as related in that I am jointly estimating the effect of schooling on skills at the same time as the autocorrelation parameter. The autocorrelation parameters ρ in my model gives expected earnings in subsequent periods in terms of this transient component. Moreover, the selection rule in my context is micro-founded by the dynamic discrete choice model.

As a result of the structure on the unobservable terms, the crucial identifying assumption becomes a timing assumption: individuals cannot select on within-period changes in the error term in the earnings equation. However, due to the rich structure of the earnings model, individuals can select on their entire work and schooling history and a prior period's earnings. This means that identification comes from movers (or enrollees), with past earnings and work histories proxying for selection in a relatively flexible way that allows for match effects and persistent shocks to earnings.

Intuitively, given individuals with identical work and schooling histories up to a point, the model imputes average earnings changes upon an industry switch (or into enrollment) as the counterfactual earnings for stayers (non-enrollees). The estimation routine outlined in Section 6 makes many such comparisons in practice, finding persistent patterns in earnings changes associated with different transitions occurring at different levels of work experience. I prove in a simple case in Appendix Section C.1 how to identify latent skills from work transitions.

The key moment condition justifying my approach to estimation of the earnings and skill parameters is the mean independence of innovations in the error conditional on other attributes of the model:

$$\mathbb{E}[\varphi_{ij,j_{i,t-1},t}|k_{it}, X_{it}, t] = 0 \tag{5.1}$$

where X_{it} is conditioning set consisting of the entire sequence of past employment histories $\mathscr{H}_i^{-t}$, prior period earnings $Y_{i,t-1}$, determinants of initial conditions z_i, and the worker types q_i are allowed to drive selection. This is implied by Assumptions 5.1 and 5.2 as well as the following restriction on worker mobility patterns: $P_t(k_{it} = k|\varphi_{ij,j_{i,t-1},t}, X_{it}) = P_t(k_{it} = k|X_{it})$. Importantly, φ is allowed to drive selection, but with a lag. This is key to incorporating Ashenfelter [1978] dynamics.

Formally, the assumptions of the structural model imply that $\mathbb{E}[Y_{it}^k|k, X_{it}] = \mathbb{E}[Y_{it}^k|X_{it}]$. Similar assumptions is also invoked in the voluminous literature that uses fixed effects and matching approaches to estimate returns to education in similar panel data contexts.[70] It is also related to the literature on worker and firm decompositions of earnings (Abowd et al. [1999], Card et al. [2013]), specifically those that allow for match effects and persistent heterogeneity (e.g. Bonhomme et al. [2019]). Once we condition on X_{it}, individuals are in the same state and have the same expected earnings from making choice k. Conditional on X_{it}, differences in choices are only driven by the preference shocks, $\vec{\epsilon}_t$, which are independent from all other objects in the model by Assumption 5.2.[71]

[70]See Jepsen et al. [2014], Stevens et al. [2019], and Altonji and Zhong [2021] for recent examples. The training literature has extensively evaluated this assumption in the context of matching estimators that used lagged earnings histories, finding that these non-experimental approaches replicate experimental estimates (Heckman et al. [1998a], Dehejia and Wahba [1999], Card et al. [2018]) as noting that adding additional variables to the conditioning set matters little beyond lagged earnings histories (Andersson et al. [2013], Caliendo et al. [2017]).

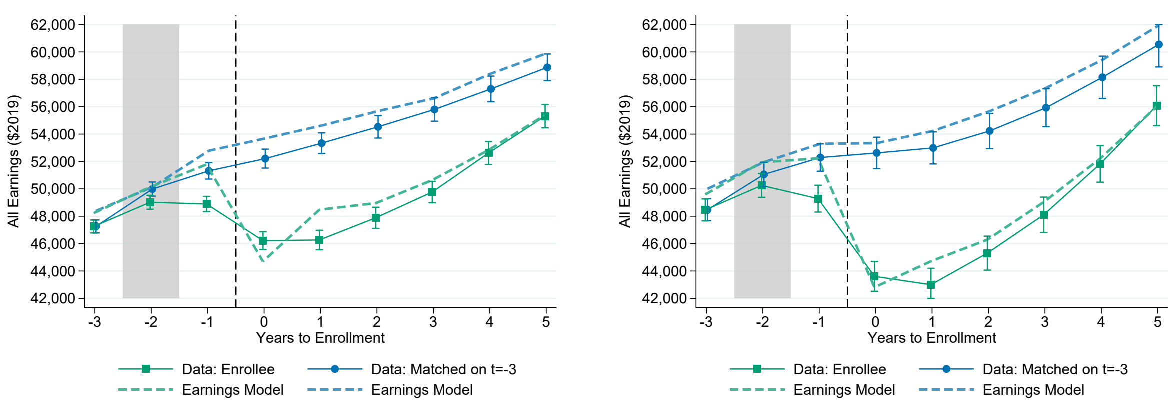
What the structure of the model adds relative to these research designs is a framework for characterizing mechanisms and predicting how workers change their industry and schooling choices in counterfactual environments.

[71]An extension to allow for time-invariant unobserved heterogeneity as in an Arcidiacono and Miller [2011] procedure would these latent worker types to X_{it}. This implicitly adds *future* choices to the conditioning set under the assumption of a finite number of types. I plan to extend my estimation procedure to incorporate this in future work.

An implication of the timing assumption is directly assessed in the data in Figure 9, which supports the notion that the estimated parameters will likely purged of the most important sources of selection bias. Observables from outside the conditioning set X_{it} should not add information about the potential outcome Y_{it}^{k}. For example, this would be the case if enrollees were an unobserved type that is not accounted for in X_{it}, in which case future choices would reveal information about the current type. I compare two individuals who should have identical earnings from the perspective of the model based on X_{it} prior to $t = -2$ and make the same choice in $t = -2$, but differ in their future enrollment choices at $t = 0$. For each new enrollee, I construct a matched comparison based on this exercise.[72] Specifically, the model predicts that enrollees and matched comparisons should have identical earnings in the gray-shaded area of Figure 9. There is a small difference in earnings in this period on the order of $964 in non-Recession years and $802 in Recession years. This difference is statistically significant in non-Recession years. This indicates that there may be a small amount of bias in estimated parameters resulting from negative selection of enrollees into schooling, but overall supports that the structure of the model is supported by the data.[73][74]

Figure 9: Check of Selection Assumptions

(a) Non-Recession (b) Enroll in 2009-2010



Notes: This figure uses observed earnings histories to check the implication of the independence of changes in time-varying unobservables, as implied by Assumptions 5.1 and 5.2. I match individuals based on information used in the model prior to $t = -2$ and stratify earnings histories based on enrollment choices made in $t = 0$. An implication of the timing assumptions is that future enrollment decisions should not affect current earnings, as individuals are in identical states based on past histories. For each enrolling individual, I match them to a non-enrollee that has identical work and schooling histories up until $t = -3$ (at the coarseness of the model), makes the same labor supply decision in $t = -2$, and is restricted to the closest comparison with earnings within $1,000 bandwidth of earnings in $t = -3$. Conditional on these observables, individuals have the same earnings in $t = 2$ from the perspective of the model. Dashed lines show predicted earnings from the model at estimated parameter values, predicting earnings using $\eta_{i,j_{i,t-1},t-1}$ and current observed choice $j(k_{it})$, ignoring the contribution of current innovations.

I also implement matching estimators based on a much richer set of covariates than what is able to be taken account of in the model. While these results abstract from the policy-relevant population by not modeling choices, they indicate whether the results of negative returns for marginal enrollee are plausible. Mirroring the results from the model, I estimate average treatment effects on the treated that are close to

[72] To account for the role of auto-correlated productivity, I find the individual who has the closest earnings within a common history, restricting to comparisons within a $1000 difference of the enrollee earnings in $t = -3$

[73] This figure also shows the fit of the earnings model on this sample, holding choices fixed and forecasting future earnings based on $\eta_{i,j_{i,t-1},t-1}$.

[74] As these are forecasts based on lagged states, the apparent lack of model fit in $t = -1$ is not surprising as this gap reflects that individuals have negative realizations of the innovation in productivity prior to enrollment $\varphi_{i,j,j_{i,t-1},t}$.

zero and exhibit substantial heterogeneity. These results are shown in in Appendix Section A.2.

5.3 Identification of Key Parameters

I now turn to a more focused discussion concerning identification of specific parameters. These arguments are summarized in Table 3. As is well known, dynamic discrete choice models cannot generically distinguish between flow utility and continuation values (Magnac and Thesmar [2002]). I fix the discount factor to $\beta = 0.96$, normalize flow utility to zero for non-employment at age 30, and fix the variance of idiosyncratic preference shocks to 1.

Latent Skills: Skills are unobserved quantities prior to estimation. Just like utility, we need to fix their location and scale to recover them from the data. Observably high earnings may be rationalized by high skill prices r_{jt}, by high skills $\omega_{it}^{(s)}$, or by high returns to skills $\pi_j^{(s)}$. I discuss the identification arguments behind these components at a high-level here and provide semi-parametric identification proofs for a simple version of the model in Appendix Section C.1. The bottom line of these proofs is that Γ and Ψ are in principle directly recoverable from the data given the mean-independence assumptions on φ, additive separability, and a sufficient number of informative moves.

Scale is fixed by assuming that there are fewer skills than industries, that skills evolve deterministically, and that skills weights are invariant over time. This allows cross-industry but within-work history comparisons of average earnings to identify the skill accumulation process. For example, comparing earnings differences across industries for individuals with the same initial z_i identifies skill weights, since workers with the same z_i have the same first-period skills by assumption. Then, location is fixed by normalizing each initial skill to be one in the population, $\mathbb{E}[\omega_{i1}^{(s)}] = 1$ for each s, separating the level of skills from the level of skill prices.[75] The match component τ has similar scale and location issues, which are fixed through its growth process as exhibited in Equation 4.4. Specifically, τ goes to zero upon non-employment, which fixes location, and one period of tenure in an industry sets it to unity, which fixes scale.

Implicit in these arguments and those formally outlined in Appendix Section C.1 is the assumption that there are enough transitions to identify the parameters. At the extreme, we cannot identify the transferability of work experience if individuals never move.

Separation Rates, Switching Costs, and Flow Payoffs: The assumptions that guarantee separability of the model means that transition probabilities can be non-parametrically identified after identifying the earnings parameters, since states are known given the earnings parameters. If separation rates were known, this would permit identification of conditional choice probabilities (CCPs). By inverting the CCPs and fixing the discount factor, we can recover differences in value of taking an action at each state relative to some reference value through standard arguments (Hotz and Miller [1993], Magnac and Thesmar

[75] I choose this normalization with the goal of creating concave age-skill profiles. Alternate normalizations one could have considered are normalizing one skill weight for each skill (e.g. forcing the weight for skill 2 to be 1 in construction) or normalizing one of the growth rate parameters. At a minimum, we need at least S normalizations since $\pi^{(s)} \cdot \omega^{(s)}$ could equivalently be rationalized by $\tilde{\pi}^{(s)} \cdot \tilde{\omega}^{(s)}$, where $\tilde{\pi}^{(s)} = \alpha \pi^{(s)}$ and $\tilde{\omega}^{(s)} = \frac{\omega^{(s)}}{\alpha}$. I plan to assess the sensitivity of my estimates to these alternate normalizations in future work.

Table 3: Identification

Structural Parameters	Variation in Data
Earnings Parameters	
Skill Transferability: $\pi_j^{(s)}$	Cross-industry, within-history differences in earnings
Skill Accumulation: $\Gamma_q^{(s)}$	Within-industry, cross-history differences in earnings
Return to Specific Skill: α_j^{τ}	Within-industry differences in earnings loss after switches into non-employment
Specific Skill Accumulation: Ψ	Earnings growth for industry stayers versus switchers
Specific Skill Voluntary Switch: γ^{Vol}	Earnings growth across voluntary industry transitions
Initial Skills: $\omega_1^{(s)}$	Cross-industry differences in earnings conditional on z_i
Skill Prices: r_{jt}	Average industry-year earnings
Part-Time Penalty: $\alpha^{PartTime}$	Within-history earnings loss for part-time school
Idiosyncratic Shocks Persistence: ρ_j	Within-industry, within-history covariance across lagged earnings
Idiosyncratic Shocks Variance: σ_j	Within-industry, within-history in earnings changes
Preference Parameters:	
Preferences: μ_k^q	Common directions of transitions not explained by earnings gains
Income Coefficient: β_Y	r_{jt} and ω are excluded from utility directly. Unexpected shifts in r_{jt} and how different skill levels respond traces out responsiveness to income maximization.
Tuition Coefficient: β_P	Sensitivity to education take-up over predicted financial aid schedule
Friction Parameters:	
Separation Rates: δ_{jt}	Calibration from the ACS
Switching Cost - Non-employed: κ^U	Duration of non-employment spells
Switching Cost - Employed: κ^E	Frequency of industry switching in data
Switching Cost - From School: $\kappa_{S_{-1}}$	Frequency of sectoral switching out of enrollment
Switching Cost - Into School: $\kappa_{S(k)}$	Frequency of transitions into school not explained by price/aid

[2002]). Changing relative values of work versus non-employment is captured through a work-type specific quadratic relationship with age relative to age 30. I calibrate separation rates using annual transition rates from employment to unemployment by industry in the American Community Survey.[76]

Once separation rates and the relative payoffs of actions in different states are identified, an additional issue is separating the time-invariant preferences for actions from switching costs. Here, the probability of remaining in the same state pins down the mean utility while the probability of switching identifies mean utilities plus the switching costs.[77]

Persistence and Shock Parameters: Shock parameters σ are identified by within-history, across-person variation in earnings. The persistence parameters ρ are identified off of the degree to which this variation dies away within individuals. More practically, the assumption that the initial distribution of the productivity shock is independent reveals its full distribution. Then, the timing assumptions on the innovations

[76]These are displayed in Figure 11(b). Specifically, I compute the unemployment rate for aged 25 to 55 adults in Texas who were employed at least 26 weeks in the prior year. I aggregate the variable INDNAICS to match my industry definitions. For individuals who are currently unemployed, this variable defines the last industry of employment. I ignore sampling error resulting from these rates which I believe is reasonable due to the size of the ACS/Census. Similar to skill prices, the values for 2009 to 2015 are interpolated in the beliefs prior to the Recession.

[77]Consider an illustrative example with only two industries $\{j_1, j_2\}$ and non-employment. We wish to separate mean utilities μ_{j_1} and μ_{j_2} and switching costs $C(j_1|j_2)$ and $C(j_2|j_1)$. By the previous arguments, once we identify separation rates, we can invert choice probabilities to recover:

$$\begin{aligned} u(j_1|j_1) &= \mu_{j_1} & \qquad u(j_1|j_2) &= \mu_{j_1} \\ u(j_2|j_1) &= \mu_{j_2} - C(j_2|j_1) & \qquad u(j_1|j_2) &= \mu_{j_1} - C(j_1|j_2) \\ u(0|j_1) &= 0 & \qquad u(0|j_2) &= 0 \end{aligned}$$

which has 4 equations in 4 unknowns. Generalizing to J industries, we get $J \times J$ equations and $J + J \cdot (J-1) = J \times J$ unknowns. This argument can be repeated for every possible state and worker type.

in individual productivity η allows the econometrician to observe how this object is related across periods, given a guess of parameters. In particular, the full distribution of η is identified in each period under the semi-parametric assumptions on the innovation. This identification argument is implicit in the estimation procedure outlined below.

Income Coefficient: The income coefficient β_Y is a key parameter that captures the degree to which individuals maximize income versus non-pecuniary factors, which affects the incentive to invest in human capital. This parameter is identified from exclusion restrictions that provide independent variation in the earnings equation. Specifically, skill prices and skills levels are excluded from utility directly, only affecting an individual's decision through their valuation of income. Since the Great Recession is a surprise, workers cannot be selecting on industry conditions during the downturn prior to the Recession. The degree to which they respond to changes in industry conditions helps identify β_Y.[78]

Tuition Coefficient: The sensitivity of individual choices to net tuition prices β_P also affects human capital investments. This is identified from estimated financial aid schedules as well as assumptions on beliefs. Financial aid schedules shift the cost of schooling, so the elasticity of schooling as individuals receive additional aid through higher lagged income identifies this parameter. Moreover, changes in this schedule are modeled as unexpected prior to 2009 - how individuals of different potential financial aid shift their decisions before and after the onset of the Great Recession aids in identification of this parameter.

6 Estimation

Estimation is through a maximum likelihood procedure that is broken into two steps for tractability.[79] In the first step, parameters of earnings and the skill process are estimated. In the second step, parameters governing transitions are estimated by maximizing the likelihood of observed choices, conditioning on earnings parameters. The separability of these two steps depends on Assumptions 5.2, 5.1, and 5.3 as discussed in the previous section.

6.1 Estimation Strategy

I first clarify the structure of the estimation problem. Let θ_Y denote all parameters affecting the earnings process and θ_C denote the parameters governing transition probabilities. θ_C includes both utility and switching cost parameters. The parameters θ_Y contain several sub-components. First, there are the non-

[78] For example, in the context of the original Roy [1951] model, where individuals choose between hunting and fishing, changes in skill prices in my model are analogous to changes in the market price of rabbits or fishes. This shifts the monetary return to hunting or fishing holding all else equal. As both comparative advantage and preferences are held fixed, changes in prices help reveal maximization on pecuniary versus non-pecuniary factors. See French and Taber [2011] for a thorough discussion on the non-parametric identification of the generalized Roy model.

[79] This multi-step approach has three key advantages. First, estimation of the earnings equation is separated from assumptions entering the choice equation, meaning that identification does not depend on beliefs or exact distributional assumptions, only on semi-parametric assumptions on the errors. The procedure is therefore more robust to misspecification than joint estimation. Second, breaking estimation into multiple steps aids in tractability by simplifying the estimation problem in each step. Finally, this approach deals with restrictions that often stem from using administrative data, as the more computationally expensive second step can be implemented outside the secure computing environment.

linear parameters α_Y which affect earnings through the skill accumulation functions in Equation 4.2 and Equation 4.4. Second, there are auxiliary parameters λ_Y, which can be read off the data given a guess of α_Y. These auxiliary parameters λ_Y include skill prices r_{jt}, which affect earnings only linearly conditional on α_Y, and parameters governing the variance of the earnings shock process σ_j. As individuals can select on idiosyncratic productivity η, meaning $\rho \in \alpha_Y$ as these are non-linearly estimated.

The observed data in each period are log-earnings conditional on employment, y_{it}; observed work and schooling choices, k_{it}; and observed separations at the beginning of period t, sep_{it}^{Obs}.[80] The econometrician also observes the time-invariant worker type q_i and covariates determining initial skills z_i. Recall that $\mathscr{H}_i^{-t}$ denote the observed history for individual i up to the time of making a choice in period t.

We seek to find values of $\theta = \{\theta_Y, \theta_C\}$ that maximize the likelihood of the observed histories:

$$L(\theta) = \prod_{i=1}^{N}\prod_{t=1}^{T_i} f\left(y_{it}|k_{it}, sep_{it}^{Obs}, \Omega(\mathscr{H}_i^{-t};\alpha_Y), q_i;\theta_Y\right) P\left(k_{it}, sep_{it}^{Obs}|\Omega(\mathscr{H}_i^{-t};\alpha_Y), q_i;\theta_Y,\theta_C\right) \tag{6.1}$$

Equation 6.1 shows key features of the estimation problem. The two pieces of the likelihood are dependent only through worker type q_i and θ_Y - parameters θ_C do not affect the likelihood of y_{it} once we condition on k_{it}, sep_{it}^{Obs}, $\mathscr{H}_i^{-t}$, and type q_i. In addition, the current state Ω is affected by the worker's prior history $\mathscr{H}_i^{-t}$ and non-linear parameters governing earnings α_Y. This is due to the fact that skills are history dependent and different α_Y will result in different levels of skill in period t given the same $\mathscr{H}_i^{-t}$.

Taking logs shows the separability of the estimation procedure when maximizing the likelihood:

$$l(\theta) = \underbrace{\sum_{i=1}^{N}\sum_{t=1}^{T_i} \log f\left(y_{it}|k_{it}, sep_{it}^{Obs}, \Omega(\mathscr{H}_i^{-t};\alpha_Y), q_i;\theta_Y\right)}_{\textbf{Step 1: Earnings and Human Capital Parameters}} + \underbrace{\sum_{i=1}^{N}\sum_{t=1}^{T_i} \log P\left(k_{it}, sep_{it}^{Obs}|\Omega(\mathscr{H}_i^{-t};\alpha_Y), q_i;\theta_Y,\theta_C\right)}_{\textbf{Step 2: Transition Parameters}} \tag{6.2}$$

I exploit the fact that one can estimate this likelihood in two steps in estimation, which is made possible by Assumptions 5.1 and 5.2.[81]

6.2 Estimation Procedure - Step 1: Earnings and Human Capital Parameters

The left part of the likelihood in Equation 6.2 can be maximized using a non-linear least squares (NLLS) procedure. This estimation routine has the same first-order condition with respect to parameters in α_Y as the left side of the Equation 6.2 but only invokes the mean independence assumption on innovations in idiosyncratic productivity φ. Full independence and normality are explicitly invoked to recover σ_j and in the second-step of estimation of the choice model.

Given a guess of non-linear earnings parameters α_Y, skill prices r_{jt} are simply recovered as averages

[80] This follows from Assumption 5.3.

[81] The separability of estimation also easily permits an extension to the model based on clustering workers into latent types in a manner consistent with the model. This is because the two likelihoods are linked only through worker types. See Traiberman [2019] and Bonhomme et al. [2019] for examples of such applications.

of earnings residuals within each industry-year cell. This involves iterating through a worker's entire sequence of choices to keep track of history-dependent states $\Omega(\mathscr{H}_i^{-t};\alpha_Y)$, including the contribution of idiosyncratic productivity in the previous period, $\eta_{ij_{i,t-1},t-1}$. After minimizing this NLLS problem, parameters governing the variance of the shock process are computed using the full distribution of residuals.

For the purposes of clarifying the estimation procedure (and abusing notation slightly to ignore the direct dependence of j on k), Equations 4.1 and 4.5 can be rewritten as:

$$y_{it} = r_{jt} + h\left(k_{it}|\Omega(\mathscr{H}_i^{-t};\alpha_Y);\alpha_Y,\lambda_Y(\alpha_Y)\right) + \rho_j^{j-1}\eta_{i,j_{-1},t-1} + \varphi_{ij,j_{i,t-1},t} = y(k_{it}|\mathscr{H}_i^{-t},q_i;\alpha_Y) + \varphi_{ij,j_{i,t-1},t} \quad (6.3)$$

where r_{jt} is the skill price resulting from choice k_{it}, $h\left(k_{it}|\Omega(\mathscr{H}_i^{-t};\alpha_Y);\alpha_Y,\lambda_Y(\alpha_Y)\right)$ is the contribution of supplied human capital, $\rho_j^{j-1}\eta_{i,j_{i,t-1},t-1}$ is the contribution from the persistence in idiosyncratic productivity, and $\varphi_{ij,j_{i,t-1},t}$ is the contribution from shocks to idiosyncratic productivity.

The NLLS objective is defined as:[82]

$$Q^{NLLS}(\alpha_Y) = \frac{1}{2N}\sum_{i=1}^{N}\frac{1}{T_i}\sum_t\left(y_{it} - y(k_{it}|\mathscr{H}_i^{-t},q_i;\alpha_Y)\right)^2 = \frac{1}{2N}\sum_{i=1}^{N}\frac{1}{T_i}\sum_t\varphi^2_{ij,j_{i,t-1},t} \quad (6.4)$$

where $\varphi_{ij,j_{i,t-1},t}$ is the error defined above. The key moment condition justifying this NLLS procedure is given in Equation 5.1 above.

Given a guess of α_Y and prior values of $\eta_{i,j_{i,t-1},t-1}$, skill prices are estimated internally as the average of industry-year residuals:

$$\hat{r}_{jt} = \frac{1}{N_{jt}}\sum_{i \text{ s.t.} j(k_{it})=j}\left(y_{it} - h\left(k_{it}|\Omega(\mathscr{H}_i^{-t};\alpha_Y);\alpha_Y,\lambda_Y(\alpha_Y)\right) + \rho_j^{j-1}\eta_{i,j_{-1},t-1}\right) \quad (6.5)$$

Including an individual's productivity in the previous period in Equation 6.4 and 6.5 presents a computational challenge. Agents select on $\eta_{i,j_{i,t-1},t-1}$ but this quantity also depends on prior period skill prices $r_{j,t-1}$. To overcome this issue, I sequentially update current skill prices r_{jt} given lagged productivity $\eta_{i,j_{i,t-1},t-1}$, followed by updating current productivity η_{ijt} given current skill prices r_{jt} and residuals $\varphi_{ij,j_{i,t-1},t}$. The exact algorithm is outlined in Appendix Section D.1:

6.3 Estimation Procedure - Step 2: Transition Parameters

I now turn to estimation of θ_C. Given values of α_Y, we can compute the ex-ante unobservable state $\Omega(\mathscr{H}_i^{-t};\alpha_Y)$ for latent skills in terms of work histories. Thus, the only thing the econometrician does not

[82] I minimize this objective using Gauss-Newton approximations of the Hessian based on the outer-product of each observation's gradient. To deal with sensitivity to starting points, I first explore the parameter space using stochastic gradient descent algorithms with multiple starting points and multiple restarts. Specifically, I use mini-batch samples of 1000 individuals to evaluate the gradient from randomly chosen starting points, restarting the algorithm and moving the current set of points randomly towards the current best point in the full-sample. In simulated data, this procedure reliably gets parameters in the region of the global minimum even when starting from remote starting points. Finally, to assess whether the final parameters are stuck in a local minimum, I do a one direction line search for each parameter.

observe at this point is if a transition into non-employment (or full-time study) is due to an involuntary separation or voluntary transition into non-employment. I calibrate the separation rates from the ACS, both simplifying the estimation problem and enriching the model in terms of industry-time variation.

This second-step is estimated outside of the ERC's secure data environment using a second maximum likelihood procedure that maximizes the likelihood of observed transitions over states:

$$Q^{CCP}(\theta_C|\hat{\theta}_Y) = \sum_{s=1}^{S} w_s \sum_{k=1}^{K} \hat{P}_{k|s}(\hat{\theta}_Y) \log P(k|\Omega_s, \hat{\theta}_Y, \theta_C) \tag{6.6}$$

where $\hat{P}_{k|s}$ is the reduced-form probability of an individual in the baseline sample choosing action k at state s, discussed below. Weights w_s are computed based on the share of person-year observations in a cell that defines s. Equation 6.6 is thus an approximation of the likelihood governing choices in Equation 6.2.

Evaluating Equation 6.6 requires solving the dynamic problem on each evaluation. This is because the history-dependence of skills and non-stationarity of problem makes finite-differencing and other forward simulation techniques difficult to implement (Arcidiacono and Miller [2011], Arcidiacono and Miller [2020], Hotz and Miller [1993]). The reduced-form conditional choice probabilities $\hat{P}_{k|s}$ are predicted from K linear probability models that pool across years of the same and condition on θ_Y.[83] There is then the issue of choosing states at which to evaluate the objective function 6.6. I leverage the fact that I observe the states once α_Y is estimated, picking states based on the observed distribution in the data.[84]

6.4 Standard Errors

I compute the asymptotic variance-covariance matrix of the parameters using the non-parametric bootstrap over 100 bootstrap samples. These standard errors account for clustering at the individual level by drawing each individual's panel with replacement when estimating θ_Y and $P_{k|s}$. The second-step of the estimation procedure simply maximizes the likelihood of $\hat{P}_{k|s}$, which does not use any individual-level data directly. To compute standard errors on estimates of θ_C, I repeat the second-stage estimation conditioning on each bootstrap draw of $\hat{\theta}_Y^b$ and $\hat{P}_{k|s}^b$. This accounts for covariance between $\hat{P}_{k|s}$ resulting from the panel data.[85]

[83]For covariates for this linear probability model, I use (a) a constant, (b) splines in year with a break at 2009: $\{year, year - 2009, D(year \geq 2009\}$, (c) indicators for each industry of prior employment and additional indicators for full-time or part-time study in the previous period, (d) continuous states affecting choices that include age, skills, periods of tenure in prior activity, lagged incomes, predicted financial aid, and previous idiosyncratic productivity, (e) worker types q, and (f) all pairwise and quadratic interactions for the previous. At each state, I bound the predicted probabilities and between 1e-100 and 1-1e-100 to avoid negative or unusually large probabilities.

[84]Specifically, I divide the continuous states that define Ω into quartiles based on the observed distribution of states implied by $\hat{\theta}_Y$. Further, I also only evaluate the objective at the years 2003, 2006, 2009, 2012, 2017 and for the 1994 and 1998 cohorts for simplicity. These years, cohorts, quartiles of continuous states, discrete schooling state $s_{i,t-1}$, and discrete employment state $j_{i,t-1}$ define the state cell s. I compute the share of individuals in s choosing k, using the median values of continuous states to define Ω_s on which I evaluate the model. Finally, I only disclose cells with at least 5 observations resulting in a total of $S = 51,430$ cells representing $1,379,330$ person-year observations. I use the linear probability models to predict $\hat{P}_{k|s}$ at each state.

[85]I need to bootstrap since the same individual may contribute to CCPs estimated across multiple states. Note that standard errors do not account for (a) choice of states on which to evaluate the model or (b) calibration of industry separation rates or financial aid parameters.

7 Estimation Results

This section focuses on a selected overview of parameter estimates, fit and validation of the model, and some key implications. Complete estimates are reported in Appendix Section D.3.

7.1 Parameter Estimates

Skill Weights and Skill Process: Estimates of skill weights are shown in panel A of Table D1. These results indicate that skill 1 tends to be general skill while and skills 2 and 3 are relatively more specific. The weights on skill 1 range from about 0.56 (0.07) for construction to about 0.67 (0.08) for services. In other words, a 1 unit increase in skill 1 increases earnings by 55 percent to 67 percent across these sectors, respectively. A one unit increase in skill 2 increases earnings from about 7 percent for services to 21 percent for manufacturing. Skill 3 has returns ranging from about 23 percent for health care and the public sector to about 49 percent for financial services and the general sector.

Each skill differs substantially in its accumulation process as defined by Equation 4.2, as shown in panels B and D of Table D1. These numbers indicate that different work and studying choices show substantial variation on each skill margin, including the fact that some skills may depreciate upon taking an action. These parameters are normalized to the men with no prior college attendance and 1 unit of the target skill. Moreover, these represent earnings gains from the prior period on each skill margin holding all else equal, rather than relative to an alternate choice.

Non-college men have a 0.1 increase in the log-rate of accumulation of skill 1 for each period they work in health care whereas those studying health care have a 0.3 increase in this growth. Combining this information with the skill weights above, this indicates that working in health care boosts earnings through skill 1 by 6.6 percent ($100 \times (\exp\{0.100\} - 1) \times 0.627$) while studying health care boosts earnings by 22.2 percent ($100 \times (\exp\{0.303\} - 1) \times 0.627$) in the same sector. In contrast, the comparable numbers for skill 2 are -0.8 percent ($100 \times (\exp\{-0.040\} - 1) \times 0.203$) for working in health care and 2.8 percent ($100 \times (\exp\{0.127\} - 1) \times 0.203$) for studying health. For skill 3 these are -6.5 percent ($100 \times (\exp\{-0.143\} - 1) \times 0.489$) for working in health care and -30.2 percent ($100 \times (\exp\{-0.963\} - 1) \times 0.489$) for studying health.

The previous discussion shows that the process by which estimated parameters map into earnings is complex and reported only for non-college men normalized to a skill level of 1. To ease interpretation in translating what parameter estimates mean for earnings growth from taking certain actions, Tables 4 and 5 show implied one-year earnings growth due to skills using the ex-post distribution of skills in simulated data. To make comparisons relative to an action, I compute these numbers relative to working full time in the prior industry. It is important to note that this exercise ignores earnings impacts from skill prices, specific skills, and selection on idiosyncratic productivity over time. Looking at fields of study in Table 4, we see three key patterns. First, only technical and health studies have any scope to boost average earnings - the other fields have uniformly negative earnings impacts across sectors. Second, while health has the highest earnings impacts on the health care and public sectors, it has negative earnings impacts in all other sectors. This underscores the importance of the specificity of human capital - some fields are only valuable if individual obtain a job in the target sector. Finally, there is substantial heterogeneity in effects. For example, the average increase in earnings from technical studies is half of the standard deviation in returns.

Table 4: Fields of Study and One-Year Sector-Specific Earnings Growth from Latent Skills

	General	Construction	Manufacturing	Health Care	Service	Financial	Public
General	-14.7	-11.9	-14.6	-10.6	-9.6	-14.2	-9.8
SD	[5.0]	[3.6]	[5.2]	[4.8]	[2.8]	[4.7]	[4.4]
Technical	5.7	3.3	6.2	5.8	0.6	5.2	5.3
SD	[11.4]	[7.6]	[11.9]	[10.9]	[4.2]	[10.5]	[9.9]
Health	-3.0	-9.6	-0.7	10.9	-17.1	-5.1	9.5
SD	[22.2]	[14.9]	[23.3]	[21.1]	[8.8]	[20.5]	[19.2]
Humanities	-4.2	-5.1	-3.7	-0.2	-6.5	-4.6	-0.3
SD	[8.5]	[5.7]	[8.9]	[8.2]	[3.5]	[7.8]	[7.5]
Business	-5.5	-4.2	-5.6	-4.4	-2.9	-5.2	-4.0
SD	[5.4]	[3.8]	[5.6]	[5.3]	[3.0]	[5.0]	[4.8]

Notes: Constructed on baseline simulated dataset of 1,000,000 at estimated parameter values. Each (f, j') cell reports average growth in log-earnings from studying field f (rows) and switching to industry j' (columns), computed as $100 \times \sum_{s=1}^{S} \pi_{j'}^{(s)} \left(\Gamma_{q_i}^{(s)}(f|\omega_{it}^{(s)}) - \Gamma_{q_i}^{(s)}(j_{-1}|\omega_{it}^{(s)}) \right)$ and averaged over the realized distribution of ω_{it}. These growth rates do not account for changes in earnings due to other objects impacting earnings. Standard deviations of these individual-level growth rates are reported below.

Similar patterns for the transferability of sector-specific work experience across potential future sectors are shown in Table 5. The general sector, manufacturing, and financial services all have the highest growth in earnings from skill. Working in the service sector tends to result in skill depreciation with the least amount of depreciation occurring in the service sector itself. Working in health care or the public sector tend to result in a small increase in skills in those sectors but result in skill depreciation in other sectors. Last, the overall standard deviation in implied returns to sector-specific experience is much lower than for field of study in Table 4.

The heterogeneous returns to work experience in Panel C of Table D1 show that women tend to accumulate skills 1 and 2 slower than men but have some comparative advantage in accumulating skill 3. For example, women working in health care increase earnings in the general sector through skill 1 by 6.4 percent if non-college ($100 \times (\exp\{0.111 - 0.014\} - 1) \times 0.627$) and 6.5 percent if college ($100 \times (\exp\{0.111 - 0.012\} - 1) \times 0.627$), whereas the same numbers are 7.3 percent and 9 percent for men, respectively. In contrast, men with prior college appear to more easily accumulate all skills through work. The schooling returns in panel E show that men with no college have an easier time accumulating skills via school overall, with the notable exception being that men with prior college have a much easier time accumulating skill 2.

Panel F of Table D1 shows that the earnings gain from human capital investments declines as workers

Table 5: Learning-by-Doing and One-Year Sector-Specific Earnings Growth from Latent Skills

	General	Construction	Manufacturing	Health Care	Service	Financial	Public
General	3.7	3.0	3.7	3.1	2.7	3.6	2.9
SD	[3.4]	[2.6]	[3.4]	[3.1]	[2.5]	[3.2]	[2.9]
Construction	2.1	2.0	2.0	1.5	2.2	2.1	1.4
SD	[3.4]	[2.6]	[3.4]	[3.1]	[2.5]	[3.2]	[2.8]
Manufacturing	3.6	3.1	3.6	2.6	2.8	3.6	2.4
SD	[3.3]	[2.6]	[3.4]	[3.1]	[2.4]	[3.2]	[2.8]
Health Care	-1.4	-2.0	-1.2	0.6	-2.5	-1.6	0.5
SD	[3.3]	[2.6]	[3.4]	[3.1]	[2.4]	[3.2]	[2.8]
Service	-4.4	-2.7	-4.6	-4.7	-1.0	-4.0	-4.3
SD	[3.5]	[2.7]	[3.5]	[3.1]	[2.5]	[3.3]	[2.8]
Financial	4.3	3.5	4.3	3.0	2.7	4.1	2.8
SD	[3.4]	[2.7]	[3.4]	[3.1]	[2.4]	[3.2]	[2.8]
Public	-0.9	-1.5	-0.6	1.0	-2.1	-1.1	0.9
SD	[3.3]	[2.6]	[3.4]	[3.1]	[2.4]	[3.2]	[2.8]

Notes: Constructed on baseline simulated dataset of 1,000,000 at estimated parameter values. Each (j, j') cell reports average growth in log-earnings from working in industry j (rows) and working in industry j' (columns), computed as $100 \times \sum_{s=1}^{S} \pi_{j'}^{(s)} \left(\Gamma_{q_i}^{(s)}(j|\omega_{it}^{(s)}) - \Gamma_{q_i}^{(s)}(j_{-1}|\omega_{it}^{(s)}) \right)$ and averaged over the realized distribution of ω_{it}. These growth rates do not account for changes in earnings due to other objects impacting earnings. Standard deviations of these individual-level growth rates are reported below.

accumulate skills, captured in the diminishing investment parameters $\gamma_{Dim:Work}^{(s)}$ and $\gamma_{Dim:School}^{(s)}$. For skill 1, investments from work are 70 percent $(100 \times (\exp\{-1.189\} - 1))$ less productive for individuals with 2 units of skill 1 than at 1 unit. Turning to skill 2, we see that work investments do not diminish as quickly but that investments from schooling diminish as rapidly as skill 1. In contrast, these parameters are close to zero for skill 3. Since skill 3 tends to diminish over time, this means that the rates at which the skill depreciates is relatively constant over the life-cycle. Panel F also shows parameters governing the effects of part-time study and non-employment on skills. We see that about 57 percent of part-time human capital investments come through work whereas 43 percent comes through schooling. Skills depreciate slightly in non-employment - individuals lose 3.2 percent of their stock of skill 1 while non-employed, little of skill 2, and about 0.7 percent of skill 3. Returning to Panel A shows that workers face about a 12 percent cut in earnings while enrolled relative to full-time (non-enrolled) work.

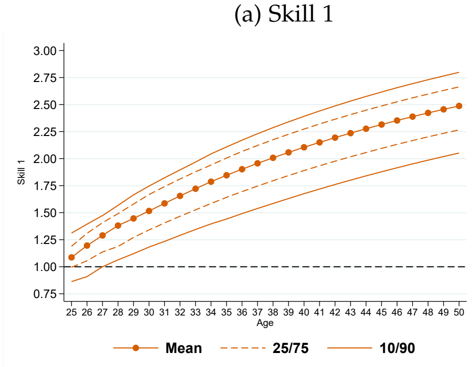
Finally, Panel G of Table D1 shows how initial conditions are determined, where covariates are defined prior to age 25. We see that skill 1 tends to be uniformly higher for those working, with non-college men having the lowest levels of skill. Skill 2 is more differentiated in terms of sectors - with construction and financial services having higher values. In terms of gender, women with prior college having lower values. In contrast, Skill 3 is highest for non-college men and for those working in manufacturing and the public sector, while being lower for those working in services.

Table D1 shows similar parameters for the specific skill. Panel A shows that this component is weighted relatively equally across sectors, with each sector returning about 30 percent higher earnings for each subsequent unit of skill 1. The specific skill grows by about 6.9 percent at one unit of skill for each period worked ($100 \times (\exp\{0.067\} - 1)$) translating into about 2.25 percent higher earnings in the general sector. The efficacy investments in specific skill is quickly diminishing - one period worked in the general sector raises earnings by 0.32 percent at 2 units of the specific skill, as shown in Panel F. Finally, specific skill tends to *grow* across voluntary employment transitions by about 2.1 percent. This growth likely captures the fact that individuals switch industries with an outside job offer in hand.[86]

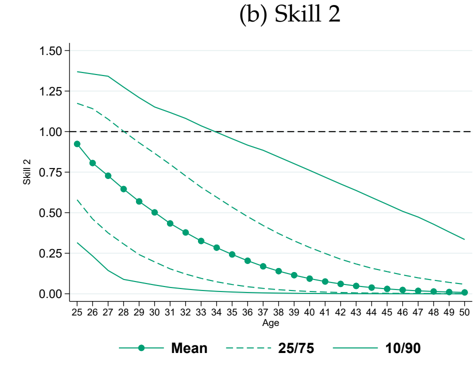
Figure 10 and Appendix Figure A5 show the ex-post distribution of skill in simulated data. Figure 10 shows how the marginal distributions of skill change with age. First, we see that all skills start on average close to 1, reflecting the normalization of the initial condition. Latent skill 1 grows deterministically over the life cycle with relatively low variation at each age. The specific skill, shown in panel (d), also increases over the life cycle. However, there is a large tail to the distribution, reflecting that individuals can fall off a job ladder in a way that permanently affects their earnings. In contrast, latent skill 2 and latent skill 3 diminish over the life cycle but have a large amount of variation.[87]

Figure 10: Marginal Distributions of Latent Skills by Age

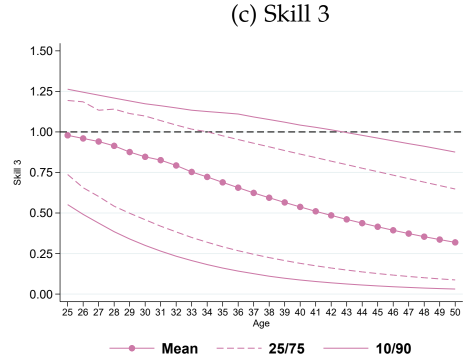
(a) Skill 1



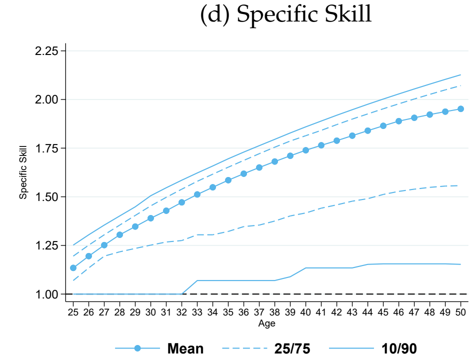
(b) Skill 2



(c) Skill 3



(d) Specific Skill



Notes: Plots the marginal distribution of each skill at each age in a simulated dataset of N =1,000,000 . At each age, the average, 10th, 25th, 75th, and 90th percentile of each skill is computed across all workers, without regard to labor force status.

Table 6 shows an ensemble decomposition of earnings with respect to each component on the realized skill distribution in the administrative data, broken out into groups of ages. First, the earnings model

[86] Workers anticipate that if they pay the cost to voluntarily switch they will accumulate this. This stands in contrast to a random search model, where workers passively receive offers and then decide to move.

[87] Appendix Figure A5 does a compatible exercise to examine ex-post sorting behavior by plotting average skill components in each industry over time. Here, we visually see the importance of skill 1 and the specific skill. We also see cross-sector sorting on skill 2 and skill 3. For example, individuals working the health care sector have no skill 3 while those working in the service sector have no skill 2 on average.

does quite a good job at explaining the variation in the data - the implied R^2 at ages 30 to 34 of the NLLS procedure is 0.744 when including lagged errors and 0.268 when only looking at skill and price components. The persistent component captures about half of the variance in earnings, 47.6 percent. Each skill also explains a non-trivial share of total earnings variance with important changes over time. The importance of skill 1 rises sharply as individuals age and that of skill 2 declines over age. The importance of the specific skill τ is fairly constant at around 9 percent of the total variance in earnings, reflecting that remaining continuously employed is quite important for earnings.

Table 6: Ensemble Variance Decomposition of Earnings into Skill Components

	Log-Earnings		Contribution of:					
	Variance	Share Explained	r_{jt}	$\pi_j^{(1)}\omega_{it}^{(1)}$	$\pi_j^{(2)}\omega_{it}^{(2)}$	$\pi_j^{(3)}\omega_{it}^{(3)}$	$\alpha_j^{\tau}\tau_{it}$	$\rho_j^{j-1}\eta_{i,t-1}$
Age 25-29	0.33	60.0%	3.3%	1.9%	4.6%	4.8%	8.9%	36.5%
Age 30-34	0.39	74.4%	2.9%	5.1%	3.8%	6.0%	9.0%	47.6%
Age 35-39	0.44	77.9%	3.1%	7.0%	3.0%	6.8%	9.0%	49.1%

Notes: Conducts an ensemble decomposition of the variance in log-earnings in the baseline sample of N =247,973. For each employed individual, I report $100 \times Cov(y_{it}, w_{it})/Var(w_{it})$ where w_{it} is one of the listed model components. The unexplained portion of earnings is φ.

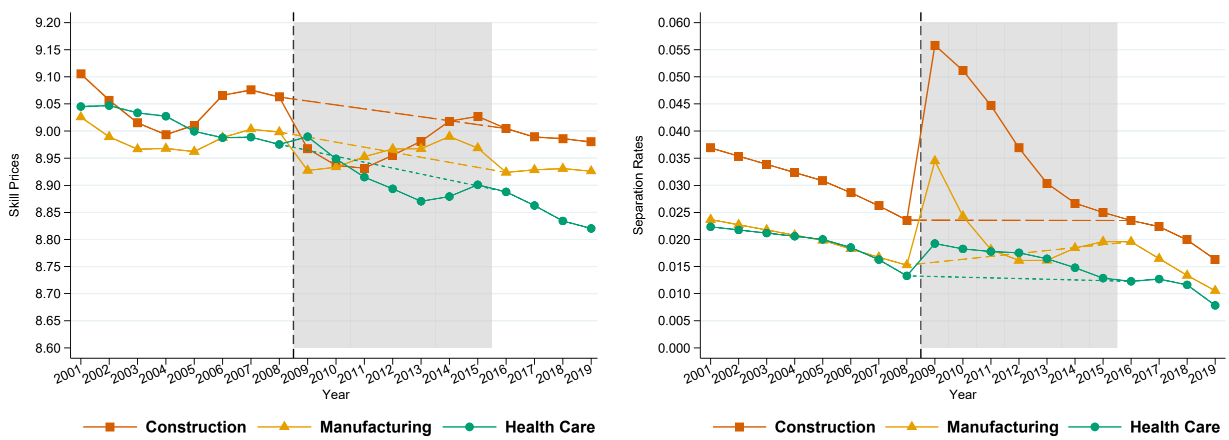
Examining these key patterns allows for a brief characterization of the estimated skills: skill 1 tends to capture a general skill that cannot be modified later in life. Skill 2 tends to capture more specific investments where health and technical studies have returns, which college educated men tend to be better at accumulating and are less rewarded in services or construction sectors. Skill 3 tends to capture skills that are specifically not rewarded in the health and public sectors. In particular, high-levels of this skill generates an opportunity cost of switching into health and the public sector for those with high levels.

Persistence and Shock Process Parameters: The parameters of the shock process are shown in Table D2. Shocks to productivity are quite persistent for those remaining in their current industry with an autocorrelation parameter of 0.888 (0.001). This is lower for those voluntarily switching industries at 0.719 (0.002) and higher for those switching out of non-employment at 0.350 (0.003). The variance parameters indicate that remaining in your current industry is lower-variance, but switching is more uncertain, especially coming out of non-employment. The public sector is routinely the lowest variance in productivity draws and construction is among the highest.

Aggregate Parameters: Separation rates and skill prices generate industry-by-time variation and affect which workers are most affected by the business cycle. These are shown for key industries in Figure 11 and for all industries in Appendix Figure D2. Panel (a) shows skill prices recovered as auxiliary parameters in the estimation procedure. Industries differ in their levels of skill prices as well as their sensitivity to the business cycle. For example, construction has the highest return to skill and is the most affected by declines over the business cycle. In contrast, health care is less sensitive to the business cycle but has lower skill prices. Separation rates, shown in Panel (B), also show differentiation in baseline levels, with construction having the highest baseline rate of layoffs. Industries are differentially affected by the business cycle. Corroborating Figure B1, construction and manufacturing have large increases in separation rates in 2009.[88]

Figure 11: Skill Prices and Separation Rates - Selected Industries

(a) Skill Prices (Estimated) (b) Separation Rates (Calibrated)



Notes: Plots skill estimated skill prices r_{jt} (see Equation 4.1) and calibrated separation rates δ_{jt} (see Equation 4.10) for selected industries. Dashed lines indicate the biased beliefs agents act on prior to the impact of the Great Recession, which linearly interpolates the years 2009 and 2015. See Appendix Figure D2 for all industries.

Figure 11 also includes a graphical depiction of how beliefs about the Great Recession are modeled, previously discussed in section 4.2. The lightly shaded area in Figure 11 indicates the region over which individuals project the future aggregate state prior to the Recession, during which they have biased beliefs. These biased beliefs are shown in the dashed line. There is a clear dip in skill prices and increases in separation rates during this period, indicating that the approach to beliefs approximate the region over which the economy is pushed off its long-running trend by the Recession well.

Income Coefficient: Table D3 shows the estimated preference and transition parameters. I estimate a preference for log-income of 0.738 (0.024). This is a key parameter as it governs the degree of income maximization in the model, determining the degree to which individuals make forward-looking investments in human capital .[89]

Switching Costs: Panel C of Table D3 shows time-varying switching costs that vary by employment status, target industry, and type of worker. Since utility is linear in log-income, we can translate these into dollar terms. Since switching costs are paid once, they should be compared to a present value increase in an income earnings, which can be solved by multiplying switching costs by $1-\beta$. This implies switching costs for employed non-college men of 20.7 percent of income. Since the average observed earnings in the sample is \$60,635, this implies moving costs on the order of \$12,127.[90] For comparison, Traiberman

[88] For example, construction sees 5.5 percent of the workforce get laid off, whereas health care sees only a small increase to about 2 percent.

[89] For a comparable estimate, Ransom [2022] estimates 0.916 on expected log-earnings in a model of geographic mobility.

[90] The average observed earnings in the sample is \$60,635 or about 11.01 log-points. The equivalent present value percent increase is then: $100 \times \exp\left(\left(1-\beta\right)\frac{\exp\{\kappa^E\}}{0.738}\right) - 1\% = 20.7$ percent

[2019] estimates occupational switching costs of 17 percent of income, Ransom [2022] estimates geographic switching costs of 30-40 percent of income, and Kennan and Walker [2011] estimate geographic switching costs that are equivalent to a $17,897 flow increase.[91]

The non-employed face switching costs that are 17 percent higher ($100 \times \left(\frac{\exp\{1.401\}}{\exp\{1.244\}} - 1\right)$. Sectors also differ in the utility cost of switching into them, reflecting structural industry differences in the job-finding rate. Most substantially, the service sector has switching costs that are 30 percent lower ($100 \times \left(\frac{\exp\{1.244-0.359\}}{\exp\{1.244\}} - 1\right)$ than the general sector, reflecting that these are easier jobs to find. The switching costs increase in the Recession and especially so for the employed workers. This indicates increasing frictions from making voluntary switches but only a slight increase in switching out of non-employment, all else equal.

The estimates indicate an important role for schooling in terms of increasing the rate of job finding. The parameters indicate that, all else equal, being currently in school lowers the switching cost by 26%. This provides an indirect role for schooling in increasing human capital - it can serve a job search function, providing an indirect mechanism for schooling to increase earnings.

Tuition Sensitivity and Switching Costs into School: The estimates indicate that workers face substantial frictions in paying for and returning to school. The parameter governing sensitivity to tuition β_P is estimated to be 0.467 (0.016). Using the same conversion as for switching costs above, this implies that individuals would need a present value increase in income of 2.6 percent in order to offset the current dis-utility of tuition payments. For the average worker, this translates into an increase in income of $1,552.

Preference Heterogeneity: Finally, Table D3 indicates heterogeneous preferences by gender and prior education. The first column gives the common preferences, normalized to men with no prior college, while the remaining columns report these preferences for other worker types. We see that women tend to have higher preferences for working in health care and the financial sector, while relatively disliking construction and manufacturing. Preferences for working full-time tend to be convex over the life cycle.

7.2 Model Fit and Validation

To assess the fit of the model, I simulate a dataset of 1,000,000 individuals at estimated parameters values. I simulate initial conditions for these individuals by grouping the raw observed initial conditions into finely grained cells and drawing from the resulting distribution.[92] I compare the earnings and choice of various cuts of the real data to this simulated dataset. While all moments of the data are implicitly targeted in estimation, the procedure does not force each moment to match mechanically.

Figure 12 shows that the model fits basic patterns of the data quite well. In Panel (a), the model fits

[91] Due to my inclusion of γ^{Vol}, which I estimate to slightly increase specific skills across voluntary transitions and gives an incentive to switch to increase earnings, I expect my estimates of sectoral switching to be slightly higher than the literature.

[92] Specifically, to simulate initial conditions, I group the raw data into cells based on a dummy for education before age 25, gender, previous industry before age 25 (including non-employment), and years of tenure in this activity and draw from the resulting frequency distribution. To get the initial lag of income, I compute the mean and standard deviation of income within each cell and draw from the resulting normal distribution.

the life-cycle log-earnings profile of observed worker types, with the possible exception of early in their careers. Panel (b) and (c) shows that the model fits the work and schooling choices of each of these demographic types. Importantly, the model is able to reproduce differences by gender and education in sectoral and enrollment choices. Finally, panel (d) shows the probability of enrollment over time. The model is able to fit the level in enrollment by age but misses some of the steepness of the descent over the life cycle. In addition, the model does not precisely fit the increase in enrollment during the Recession for this sample.[93]

Figure 12: Model Fit: Basic Patterns

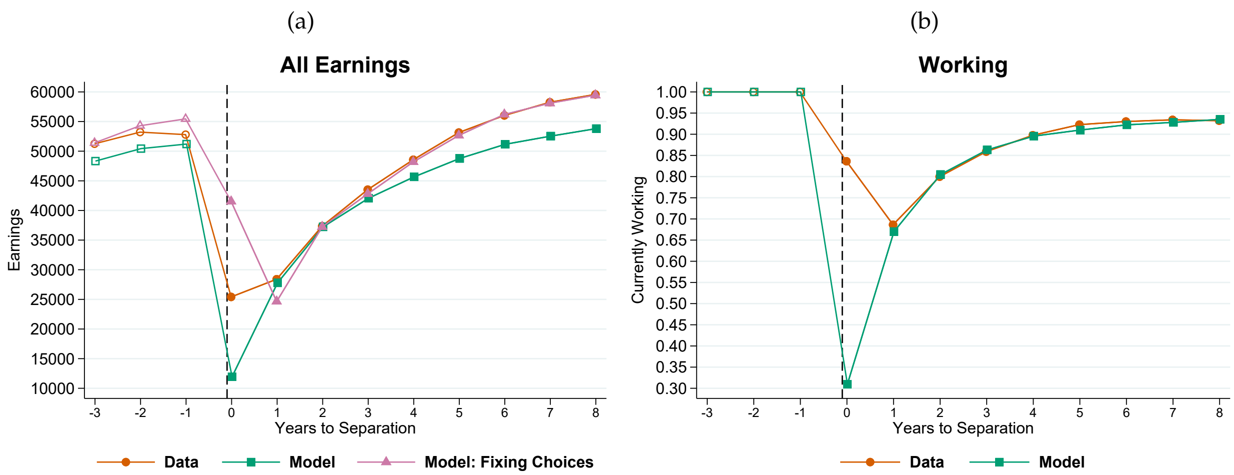
Notes: Compares fit in baseline sample with simulated data of size N=1,000,000 . Panel (a) plots the model predictions of log-earnings in marked-lines with data in dashed lines. Panels (b) and (c) shows sector of employment and field of study for each of these groups, outlining the data in dark lines. Panel (d) shows the probability of enrollment in each year, with data shown in orange and the model in green.

Next, I turn to examining how the model predictions stack-up when compared to quasi-experimental events studies. In Figure 13, I show that the model roughly matches employment probabilities and average total earnings for workers with a tenure of three years in one of the $J = 7$ industries and who enter non-employment in 2009. Through the lens of the model, this includes both short non-employment spells (observed exogenous separations) and complete switches into non-employment (endogenous or exogenous). Panel (a) shows that the model does a good job of matching earnings trajectories around a job

[93] This pattern regarding enrollment over the Recession is hard to see since young workers enroll at a higher rate. Since I focus on five cohorts, the sample mechanically ages over time and life-cycle trends swamp out business cycle trends. Each year the enrollment probability declines except for in 2009 and 2010, which ends around to a 1pp in extra enrollment after age adjusting.

separation. Importantly, the model roughly matches the earnings levels prior to displacement, indicating that it captures which kinds of workers get separated at the start of the Recession. The pink (triangle) line shows predicted earnings holding transitions fixed to those in the raw data, which indicates that most differences are due to the choice model not matching transitions precisely rather than poor fit of the earnings model. The model does not match expected earnings at the exact time of separation, which is mostly due to a lack of fit of the earnings parameters. Panel (b) shows why - many separated workers have some employment in the year of impact in the data and the earnings model expects these individuals to have some earnings based on their observed employment status. This is clearly due to workers who have some employment with extremely low earnings in the year of separation, likely measuring part-time work (e.g. only a few weeks the quarter after separation) that the model is not set up to capture (or is not measured in the quarterly data). The model otherwise replicates the share working almost exactly otherwise, which is very encouraging.

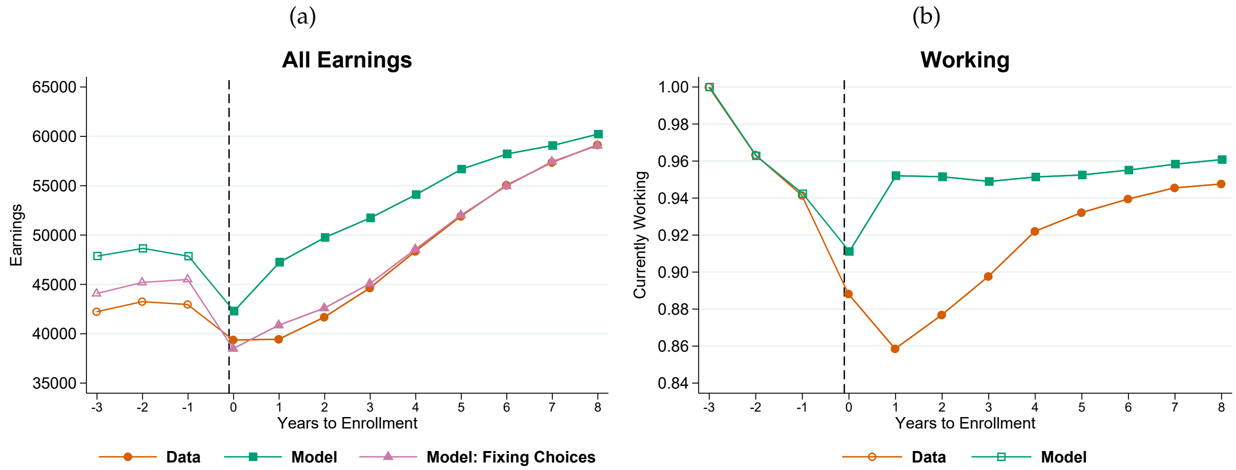
Figure 13: Model Fit: Employment and Earnings of Workers Separated in 2009



Notes: Share employed and total earnings, including zeros, for $N = 13,487$ workers in the baseline sample who are employed for three years prior to an entry into non-employment in 2009. Orange line (circles) shows the fit of the raw data, green lines (squares) show the fit of data simulated from the full model, pink (triangle) line shows the fit of the earnings model holding choices fixed to the path observed in the data. Share employed for the pink line fits the orange line mechanically. For earnings, the pink line plots expected earnings from the model, accounting for idiosyncratic productivity by adding the observed $\rho\eta_{-1}$ as well as adding $\sigma_{\varphi}^2/2$ to account for the expected impact of the idiosyncratic innovation on log-earnings converted into levels. Since choices are fixed, the pink line fits share employed mechanically.

Figure 14 shows these patterns for new enrollees around an enrollment event that begins in 2009 or 2010. This is defined for individuals who shift into enrollment after not being enrolled in the previous three years and who have some work in year three prior to enrollment. The model roughly matches the earnings trajectories around enrollment, though admittedly worse than it does for worker separations. The most important differences are due to the model over-predicting the employed share of workers after enrollment. Comparing to the pink (triangle) line in Panel (a), which shows the fit of the earnings model, we see that almost all of the lack of fit on earnings comes from the choice model not fitting the sequence of transitions correctly. In the base period, the model exactly reproduces the employed share of workers and roughly matches pre-enrollment earnings, but over-predicts earnings by $5,159. Comparing overall earnings growth, growth in average earnings for enrollees is 40 percent in the data and 27 percent in the model due to this positive selection in the model. Most of these differences disappear when fixing the path of choices to those in the data, as shown in the pink line, where the pre-period gap in earning shrinks to $2,539 and the overall earnings growth is 34 percent. This gives some comfort that the differences in fit are not likely due to biased estimates of returns. Importantly, the fact that the model over-predicts how quickly people return to work likely results in an upward bias in the counterfactual results.

Figure 14: Model Fit: Earnings of Workers Enrolling in 2009 or 2010



Notes: Share employed and total earnings, including zeros, for $N = 14,950$ workers in the baseline sample who enroll in 2009 or 2010 after not being enrolled in the prior three years and with some employment in year three prior to enrollment. Orange line (circles) shows the fit of the raw data, green lines (squares) show the fit of data simulated from the full model, pink (triangle) line shows the fit of the earnings model holding choices fixed to the path observed in the data. For earnings, the pink line plots expected earnings from the model, accounting for idiosyncratic productivity by adding the observed $\rho\eta_{-1}$ as well as adding $\sigma_{\varphi}^2/2$ to account for the expected impact of the idiosyncratic innovation on log-earnings converted into levels. Since choices are fixed, the pink line fits share employed mechanically.

8 Decompositions and Counterfactual Exercises

I now use the estimated model to assess the effects of counterfactual policies and decompose mechanisms driving worker choices. I follow the same simulation procedure as in Section 7.2 to draw a large simulated dataset, but change primitives affecting workers' choices. To make individuals comparable across simulations, I fix realizations of random outcomes across simulations.[94]

8.1 Effects of Price Cuts and Field-of-Study Specific Subsidies

I assess the effect of price changes by making an unexpected and permanent change in sticker prices, occurring in 2009, which will thus not affect worker behavior prior to the Recession. This fixes initial human capital investments and lessens the influence of initial conditions.[95] I focus on the propensity to enroll between 2009 and 2015, before the oldest cohort in the sample turns forty, and on changes in total worker earnings in their forties.[96]

[94] These include the time-varying unobservables, including innovations in idiosyncratic productivity φ, time-varying preferences ϵ, and outcomes of separations δ. I also fix the draws of the initial conditions.

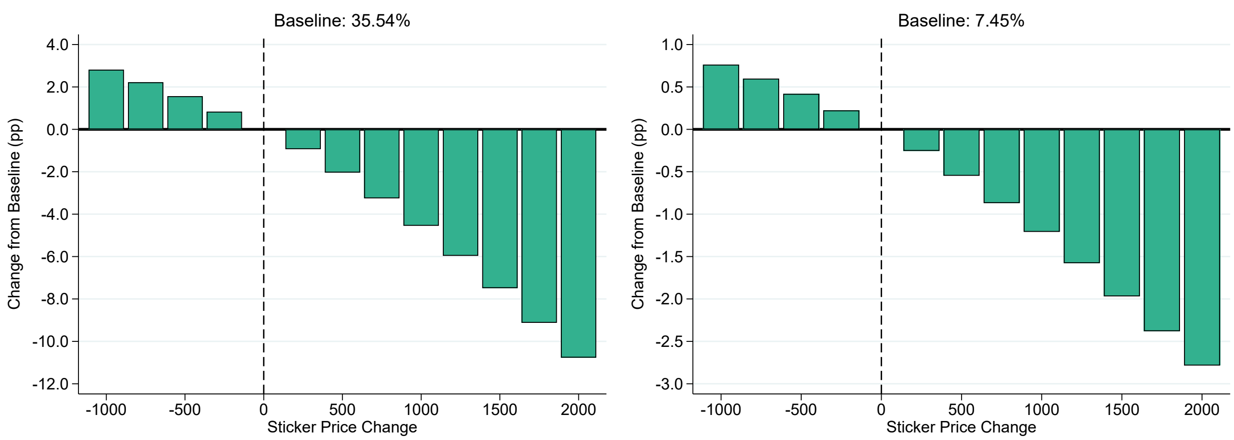
[95] For changes to the part-time prices, I compute a credit-equivalent price reduction and apply this to all enrolling workers.

[96] These numbers do not include the lock-in effect from enrolling, resulting from part-time penalties while enrolled or taking time away from work while studying. Excluding zeros or focusing on the discounted version of the realized earnings streams gives

Figure 15 shows the effect of these prices changes on enrollment. Mirroring the discussion in Section 7.1, workers are quite sensitive to tuition prices. Panel (a) examines the change in the probability a worker enrolls at any point between 2009 and 2015 and Panel (b) shows the change in the annual enrollment rate over the same period. The model indicates that that a $1,000 price decrease raises the propensity of workers to enroll in any period between 2009 and 2015 by about 2.9pp and the annual rate by 0.8pp. By comparison, a $1,000 price increase lowers enrollment in 2009 to 2015 by 4.1 percent and the annual rate by 1.3 percent. The seeming asymmetry between a price increase and price decrease is partially due to the fact that individuals with financial aid are less affected by price declines but will be affected by price increases. For reference, 35.5 percent of workers ever enroll and 7.5 percent enroll annually in the baseline simulation, indicating that these are substantial changes.

Figure 15: Take-up and Earnings Effects for Varying Tuition Subsidy Levels

(a) Ever Enroll in 2009 to 2015 (b) Annual Enrollment in 2009 to 2015



Notes: This figure shows the changes in the probability of enrollment in 2009 and 2015 from an unexpected and permanent decrease or decrease in the sticker in $2009. Each bar looks at differences of $250, comparing outcomes for in two simulated datasets of 1,000,000 individuals, holding random realizations fixed across datasets, only changing the price. For changes to the part-time prices, I compute a credit-equivalent price reduction by multiplying the subsidy by 18/30, where 30 credits is full-time and 18 credits is the average for part-time in the data.

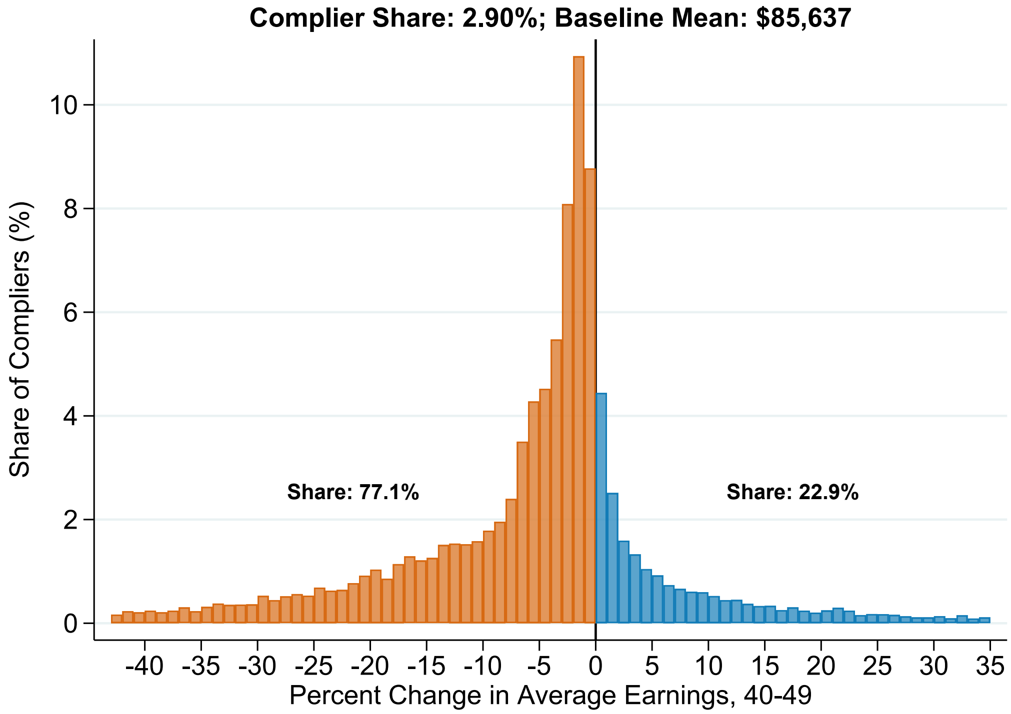
Figure 16 narrows the focus to those induced to shift behavior by the $1,000 price cut, focusing on earnings changes between the baseline and counterfactual scenario. Most individuals experience earnings losses from enrollment: only 22.9 percent of those enrolling due to the price cut see earnings increases. These changes in earnings are clustered near zero. However, the negative earnings losses have a long left-tail, resulting in an average earnings loss for compliers of -3.8 percent and a median loss of 2.9 percent. While negative, the wide variation in earnings changes also indicates the potential for better targeting.

Figure 17 investigates the drivers of this heterogeneity by summarizing the pathways taken for those who benefit in terms of earnings gains (defined as greater than 5 percent) and those who lose in terms of earnings (defined as more than a 5 percent earnings loss), comparing pathways under both the baseline and counterfactual for these groups.[97] The most striking pattern is in Panel (b) - those who benefit from

similar results.

[97]Since the policy is a surprise, these groups have the same path prior to 2009 by construction. Also by construction, Panel (a) shows

Figure 16: Earnings Effects for those shifted by Tuition Subsidy



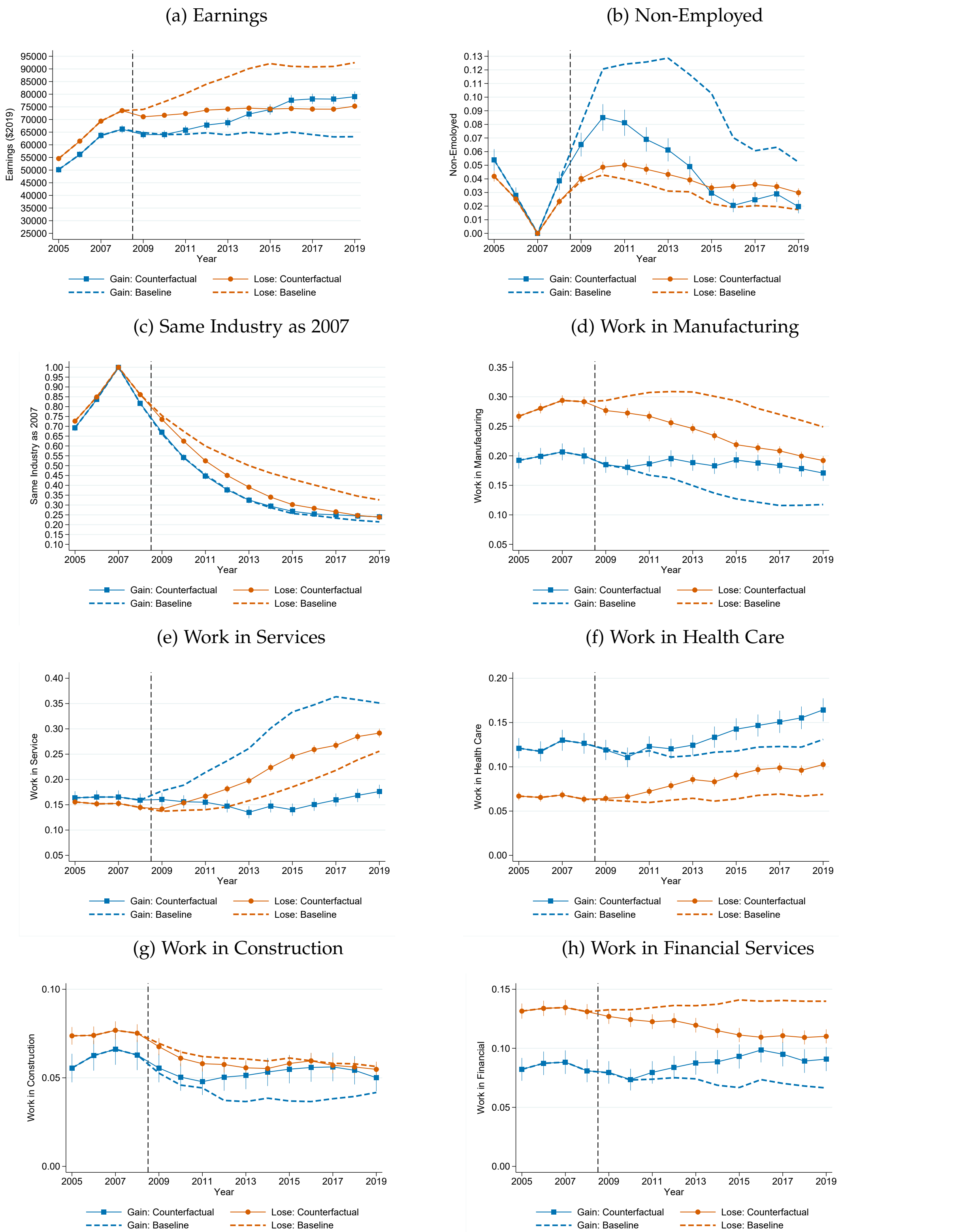
Notes: To construct this figure, I sum all earnings between the ages of 40 and 49 in the baseline and counterfactual scenario, for each simulated individual induced to change behavior as a result of the $1,000 price decrease. This holds fixed the sequence of idiosyncratic draws in both simulated datasets. This figure focuses on earnings between the ages of 40 to 49, but other outcomes give similar results.

the policy would have been much more likely to be non-employed between 2009 and 2015 under the baseline scenario. There is a marked reduction of non-employment in 2009 of about 4pp that persists through the rest of the panel for this group. In contrast, those who lose earnings see a slight increase in their rate of non-employment. Panel (c) shows that these individuals are much less likely to be employed in their baseline industry, while those who benefit see little change in this probability. The remaining panels show differences in the sectoral choices for these groups. Those who lose earnings tend to be more likely to be employed in manufacturing and financial services. There is a striking change in the decline in employment in the service sector in the post-2015 era for those who benefit, declining from around 35 percent to around 15 percent. The other sectoral probabilities show that those who gain tend to move out of manufacturing and financial services.

Figure 18 takes a closer look at how earnings changes between the benchmark and counterfactual scenarios relate to the probability of remaining in one's pre-Recession industry. Those who see earnings losses were induced to move out of their baseline industry by the subsidy, dropping from 40 percent to 20 percent. In contrast, those who benefit were going to have a lower baseline rate of remaining in their 2007 industry, but this is not affected by the counterfactual policy. If anything, those with very high earnings gains are more likely to remain in their baseline industry under the policy. These results give strong

that those who gain from the policy see large increases in earnings while those that lose see large declines.

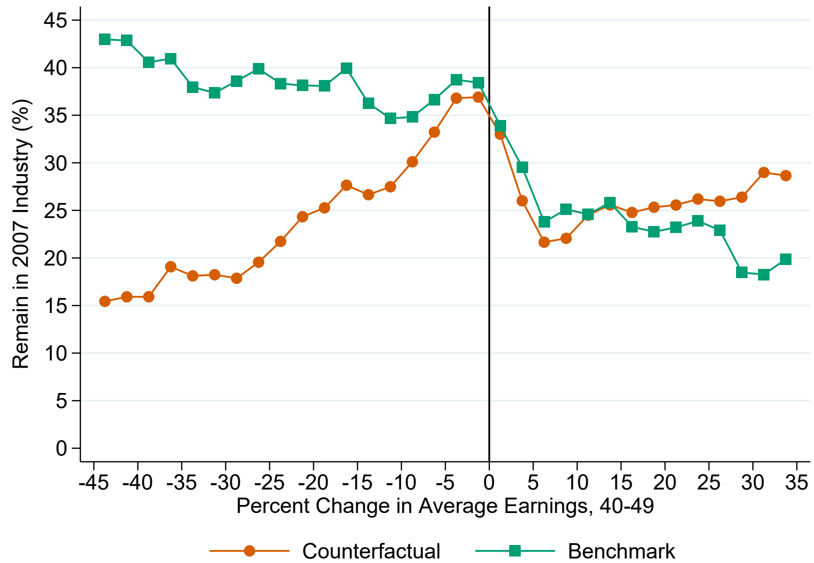
Figure 17: Sources of Earnings Gains and Losses for those Induced to Enroll



Notes: Plots history of variables for simulated individuals from Figure 16. Gain plots for those whose earnings increase by more than 5 percent; while losers are defined as earnings losses of more than 5 percent. Dashed lines plot these series under the baseline environment; solid lines plot for individuals in the counterfactual with price decreases. Error bars indicate simulation error resulting from sampling from simulated data.

indication that up-skilling may be more effective than re-skilling, at least in this context.

Figure 18: Probability of Remaining in Baseline Industry by Earnings Change



Notes: Plots the probability of remaining in 2007 industry in 2016, in the benchmark and counterfactual simulated data. Earnings changes are grouped into 2.5pp bins and smoothed over one neighbor in each direction.

Figure 19 decomposes changes in log-earnings into the components outlined in Equation 4.1.[98] A large share of the difference is driven by participation: those who benefit end up working more and those who lose earnings tend to work less. However, there are also key patterns on the intensive margin which become more important over time. First, all workers have counterfactually lower values of skill 3, which is the skill least rewarded in health care and the public sector. Second, those who benefit have much higher levels of skill prices and idiosyncratic productivity in later years, indicating that they are able to build these components over time through post-schooling work transitions. For these workers, education has put them on a path to working in higher earning industries and jobs. In contrast, those who lose earnings have lower values of these components, indicating they are knocked off the job ladder after failing to find a job. Importantly, skill 1 and skill 2, which are modified by schooling, increase but are a relatively small share of changes in earnings components. This indicates that much of what schooling does for those who benefit is to ease transitions back into the workforce, although it does increase earnings directly as well.

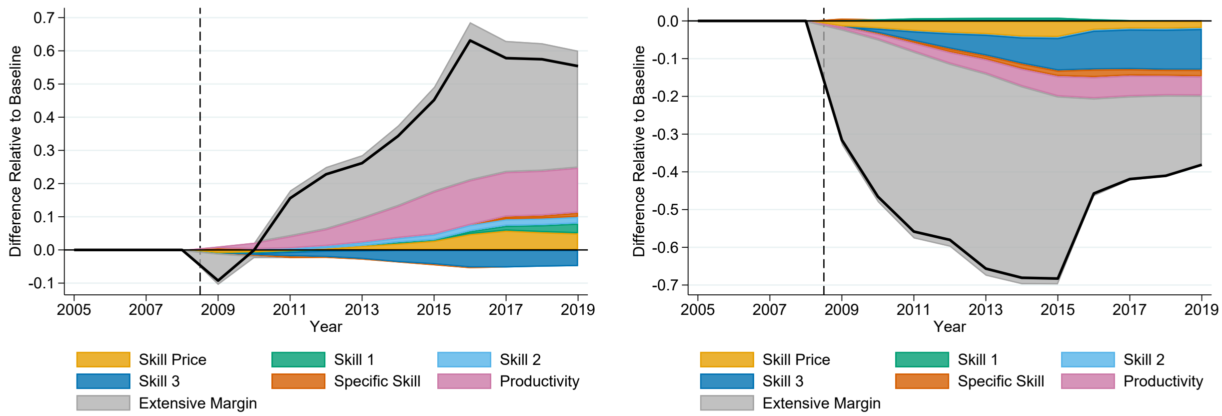
Figure 20 investigates the potential role for field-specific subsidies to increase earnings. Each row in the figure is a different counterfactual that only subsidies a specific field of study beginning in 2009.

[98] I focus on log-earnings to keep the decomposition linear. A key issue is dealing with the extensive margin differences in earnings, since Figure 17 shows differences in participation is important. The extensive margin component of these decompositions reflect differences in participation holding average log-earnings conditional on participation to the baseline scenario: $\mathbb{E}[y^0|D^0=1]\cdot\Big(P(D^1)-P(D^0)\Big)$, where y^0 and D^0 are earnings and participation under the baseline scenario. This follows from the decomposition:

$$\mathbb{E}[y^1]-\mathbb{E}[y^0]=\mathbb{E}[y^1|D^1=1]P(D^1)-\mathbb{E}[y^0|D^0=1]P(D^0)=\Big(\mathbb{E}[y^1|D^1=1]-\mathbb{E}[y^0|D^0=1]\Big)\,P(D^1)+\mathbb{E}[y^0|D^0=1]\,\Big(P(D^1)-P(D^0)\Big)$$

Figure 19: Decomposition of Sources of Earnings Gains and Losses

(a) Earnings Change: More than +5 percent (b) Earnings Change: Less than -5 percent

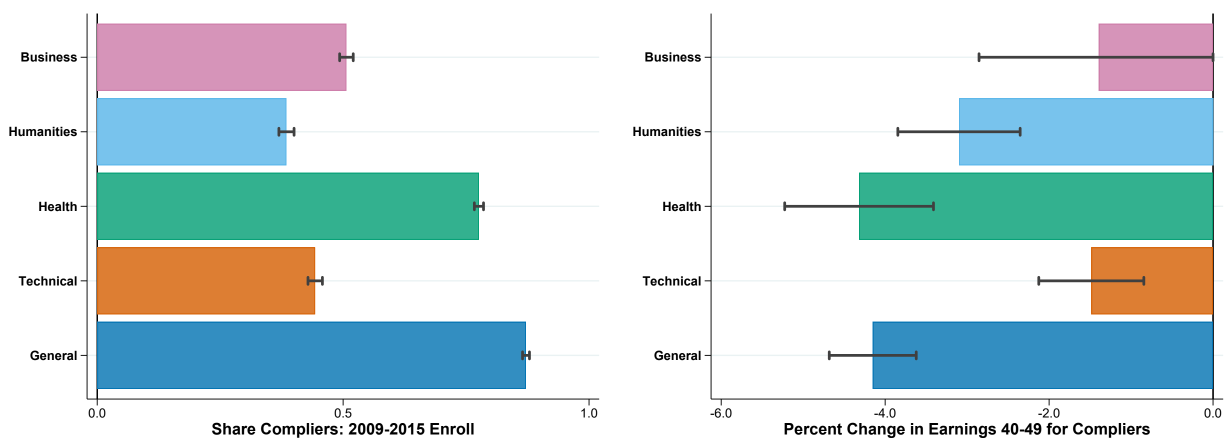


Notes: Decomposes difference in earnings between the baseline scenario and the counterfactual in terms of underlying model components.

Fields are substantially different in both the propensity for individuals to respond as well as in earnings effects. Panel (a) shows the share of the data that are compliers with each field-specific subsidy. Health and general studies both result in higher rates of take-up, mirroring the event study evidence. However, when looking at earnings effects in Panel (b), all fields have negative effects, with some key differences. In particular, health and general studies lead to larger earnings losses, but technical studies yields the least negative earnings losses. Business subsidies have effects on the order of technical studies but with a lot of variation.

Figure 20: Take-up and Earnings Effects for Field-of-Study Specific Subsidies

(a) Take-up (b) Earnings



Notes: Error bars are computed from simulated dataset of 1,000,000 , and thus represent simulation error. The large role for simulation error is due to the a large variance in earnings impacts and also the low rate take-up of the policy. In principle, this could be eliminated by taking more draws, but the number of draws already taken is cumbersome to manage.

Taken together, I interpret these results as indicating the substantial nuance surrounding education for adult workers. First and foremost, education is no substitute for direct work experience, with much of the positive effects of education being driven by its indirect effect on work transitions. On the one hand, this means that it can be effective for the long-term unemployed who face difficulty acquiring this experience, building a pathway back to previous types of work. On the other hand, re-skilling through education can be a risky investment for those who do not face such dire circumstances. Underscoring this risk, fields of study that deliver general returns, such as technical training, seem to be more effective than fields associated with high but specific returns. If individuals do not finish their education with a job lined up, pursuing later-life education may be quite detrimental.

8.2 Gender Differences in Enrollment and Earnings Trajectories

The descriptive analysis shows that men and women make quite different labor supply and education choices, with women enrolling at twice the rate of men. The model estimates of preferences and comparative advantage that vary by gender and prior education can be used to provide some insight into drivers of these differences. However, care should be taken in interpreting these numbers as gender-specific preferences capture any mechanism that drives differences in transitions net of earnings gains between men and women, not just gender-specific amenities.[99] At the same time, differences in earnings parameters only capture the degree to which groups are more or less able to convert their work and schooling history into earnings, which can be due to many factors.[100] Nevertheless, these numbers are useful in understanding the degree to which earnings gaps are due to pathways taken versus earnings differences within the same pathway.

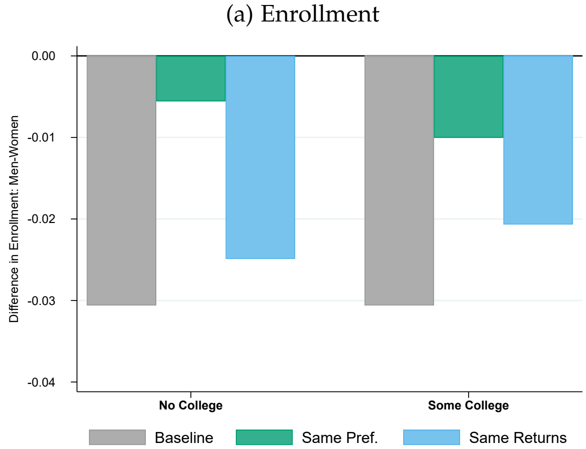
Panel (a) of Figure 21 investigates whether comparative advantage or preferences drives differences in enrollment. I sequentially shut down gender differences in preferences and earnings parameters, by assigning women to the same parameter values as men with the same initial education. Most of the difference in enrollment is due to gender-specific preferences rather than gender-specific returns. The gray bar shows the gap in the baseline simulated data, indicating that men enroll 3.1pp less than women of the same education level. When equalizing preferences between men and women, the enrollment gap shrinks to 0.5pp for non-college and 1.0pp for college. This remaining portion is due to differences in gender-specific returns, accounting for 18 percent and 33 percent of the enrollment gap.

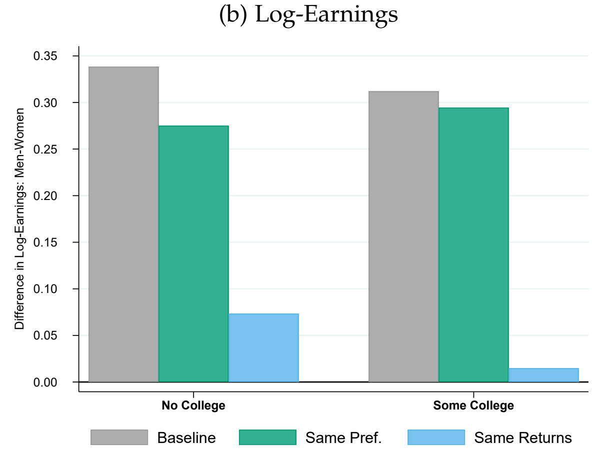
Panel (b) of Figure 21 conducts a similar exercise to analyze the gender earnings gap. Men earn 0.3 log-points more than women on average at baseline. Equalizing preferences within education groups shrinks this earnings gaps slightly, indicating that women have slight preferences for working in industries for which they have lower earnings growth. However, the majority of the gap is driven by differences in earnings potential between men and women given the same preference parameters, accounting for 78 percent of the earnings gap among the non-college group and 95 percent of the earnings gap among the college group.

[99] For example, if men lack information about jobs in health care, this will picked up as a man-specific disutility of working in health care. Similarly, if women are discriminated in hiring into construction, this will show up as a woman-specific disutility of construction.

[100] For example, if women receive within-industry discrimination in promotions, this will be captured in a lower return to experience.

Figure 21: Decomposition of Gender Differences in Enrollment and Earnings





Notes: These figures shows differences in enrollment and log-earnings (if working) between men and women of the same education level under the baseline scenario (gray), the scenario setting women's transition parameters to men's within the same pre-determined education level (green), and the scenario setting women's earnings parameters to men's within the same pre-determined education-level (blue). These figures do not adjust for differences in the covariance between gender and initial conditions. Based on 1,000,000 simulated individuals.

9 Conclusion

In this paper, I study the trade-offs that workers face when pursuing later-life human capital investment. The analysis combines rich administrative on earnings and enrollment records, a large shock that drives adult enrollment in the form of the Great Recession, and a structural model of worker choices to adjust to shocks by switching industries or returning to school. The modeling framework takes seriously that a worker's benefits from returning to school are heterogeneous, depending on their preferences and past work experience, while addressing selection issues documented in the prior literature.

We learn that there is substantial nuance that determines the effectiveness of training and not all workers should use education to adjust to shocks. I find both that workers are responsive to price reductions but that the average worker who responds to the counterfactual sees earnings declines. Re-skilling can be risky if it does not translate into a job in the target sector and returning to work quickly, often in the origin sector, is more effective for those who are able to do so. However, this means that the population that benefits the most from schooling are workers who would have had long periods out of work in the absence of returning to school. For these workers, education both helps build valuable skills and serves as a path back onto the job ladder. This may explain why studies that condition on displaced or unemployed workers find positive effects (e.g., Jacobson et al. [2005]). The structural model is necessary to uncover this fact as future industry switching is an endogenous outcome that can be affected by education directly.

Some extensions should be kept in mind for future research but are outside the scope of this paper. First, the framework does not deal with equilibrium considerations, analyzing choices for five cohorts of high-school graduates while holding the path of wage-setting equilibria fixed. Accounting for such equilibrium adjustment would require an overlapping generations model of the labor market. To my knowledge, the only paper that deals with this issue in the context of higher education is Heckman et al. [1998b] and there is scope to consider these issues in the context of multi-dimensional human capital. Second, the framework does not incorporate spatial considerations: in reality, workers may adjust to shocks by moving to less-shocked local labor markets. However, low-skill workers do not seem to use this margin to respond to shocks (Bound and Holzer [2000]), a fact that is especially true in the Great Recession (Yagan [2019]). Finally, information frictions may drive some of the results as preferences in my model do not distinguish between information frictions and true amenity values from studying. The effectiveness of training policies could be enhanced by providing workers information about types of training, economic conditions in the target industry, or worker fit for a specific field-industry pathway, topics that should be explored in future work.

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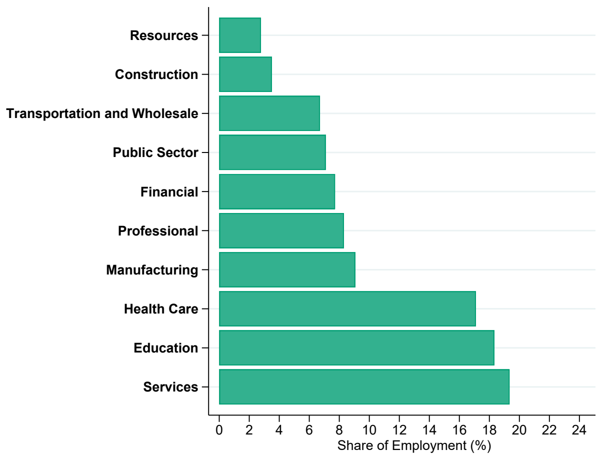
A Additional Figures and Tables

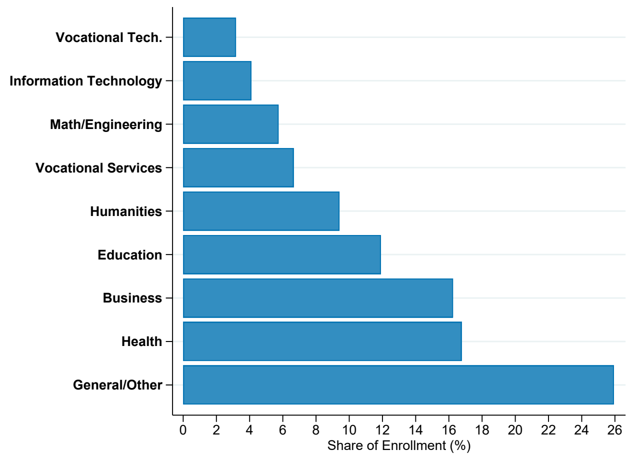
A.1 Additional Results

Figure A1: Field of study and industry shares of enrollment: Full Sample

(a) Last Industry



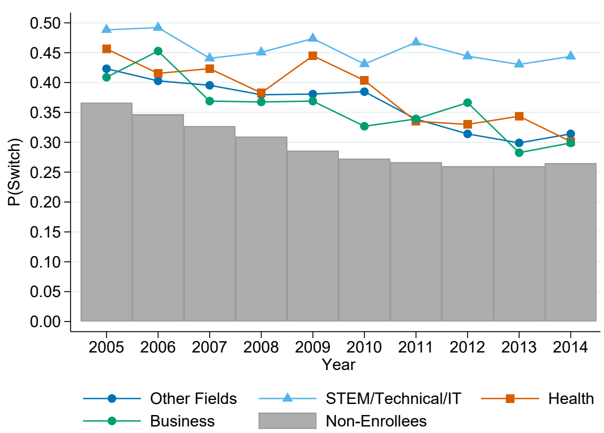
(b) Fields of Study



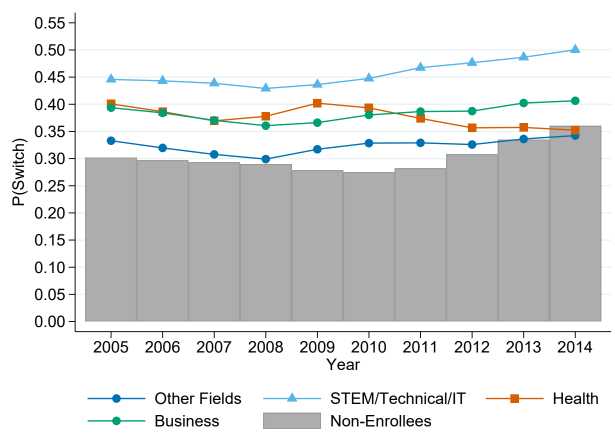
Notes: See notes to Figure 2.

Figure A2: Industry Switching and Field of Study over Time

(a) Baseline Sample



(b) Full Sample

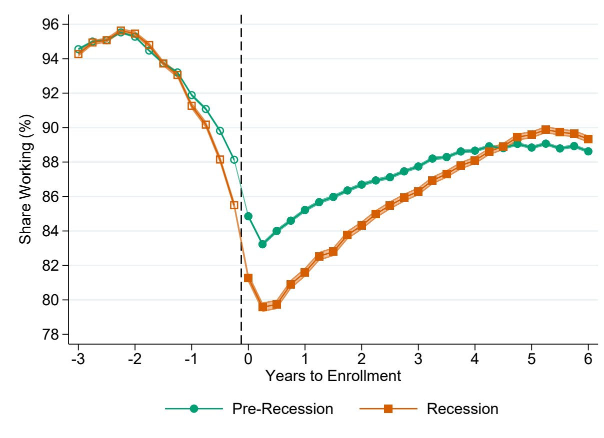


Notes: See notes to Table 1.

Figure A3: Employment and Earnings Trajectories around Enrollment Event: Full Sample

(a) Total Quarterly Earnings

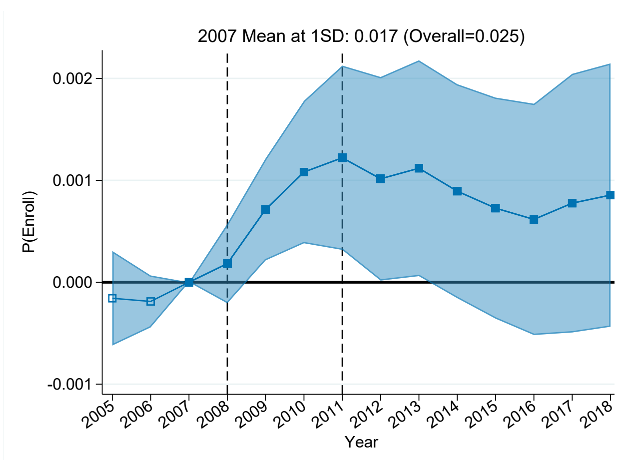
(b) Share Working



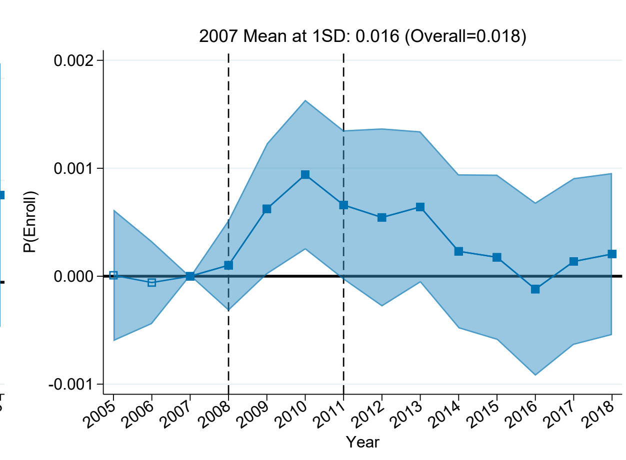
Notes: See notes to Figure 3.

Figure A4: Event Study Results using Industry-Level Panel of 3-Year Transition Probabilities

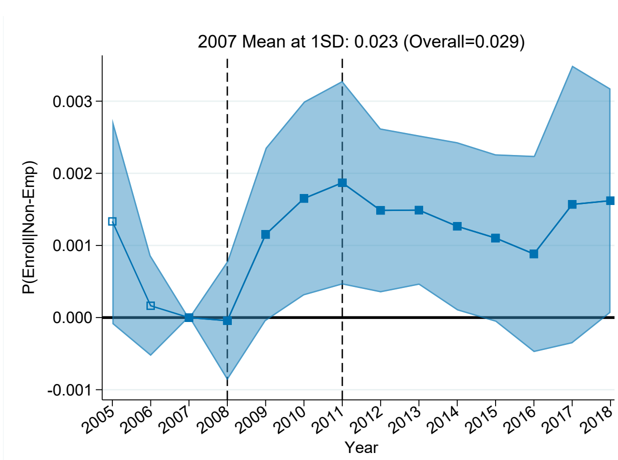
(a) Enrollment



(b) Enrollment - Unweighted



(c) Enroll after Non-employment



(d) Switch 1-Digit Industry after Enrollment

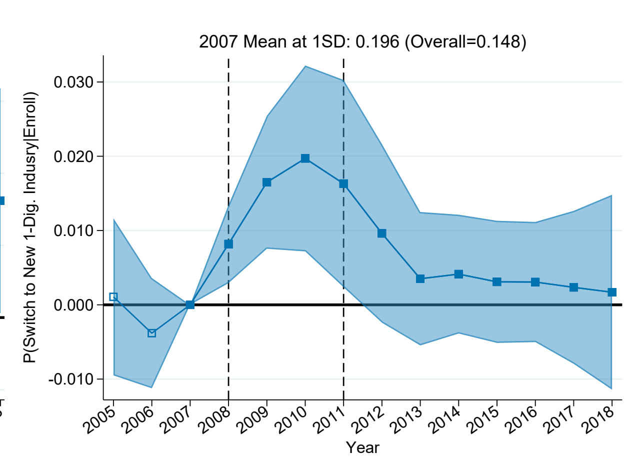


Figure A5: Decomposition of Skills in Each Industry and Time

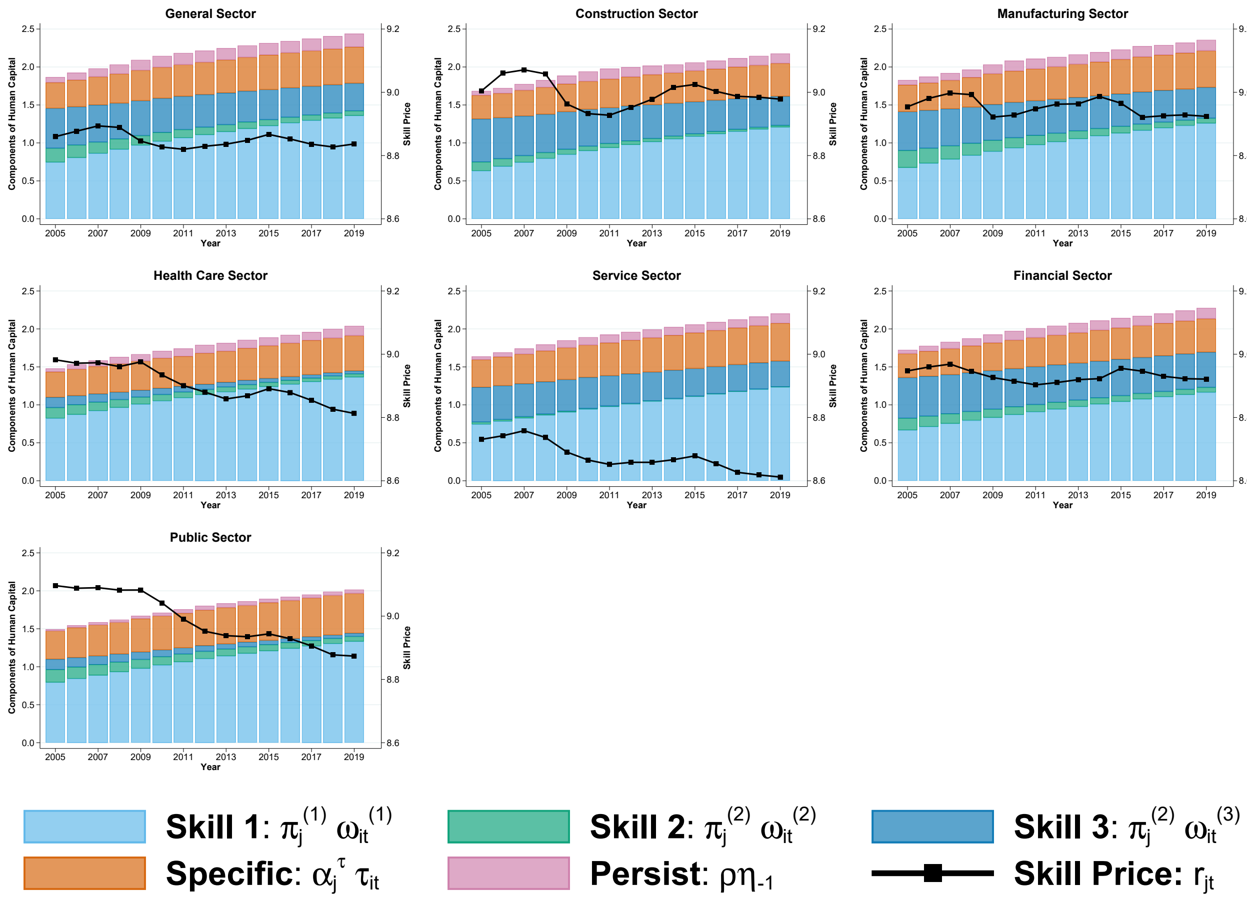


Table A1: Aggregate Enrollment in THECB Data

	Enrollment Count			*Increase from 2007-2008 (%)*		*Group Shares (%)*	
	2007-08	2010-11	2017-18	2007-08 to 2010-11	2007-08 to 2017-18	In 2007-08	Of 2007-08 to 2010-11 Change
A. By Gender							
Male	113,882	158,836	129,972	39.5	14.1	35.8	40.7
Female	204,076	269,558	213,810	32.1	4.8	64.2	59.3
B. By Prior Education							
No Prior College	121,433	155,450	105,091	28.0	-13.5	38.2	30.8
Prior College Attendance	170,057	235,239	196,192	38.3	15.4	53.5	59.0
Prior College Graduation	26,468	37,705	42,499	42.5	60.6	8.3	10.2
C. By Field of Study							
General/Other	104,242	131,289	112,400	25.9	7.8	32.8	24.5
Business	43,751	58,152	52,642	32.9	20.3	13.8	13.0
Humanities	26,048	28,085	20,996	7.8	-19.4	8.2	1.8
Math/Engineering	16,172	22,626	20,924	39.9	29.4	5.1	5.8
Health	72,548	106,289	71,112	46.5	-2.0	22.8	30.6
Vocational Tech.	8,123	12,627	11,325	55.4	39.4	2.6	4.1
Vocational Services	21,577	30,479	21,147	41.3	-2.0	6.8	8.1
Education	10,916	19,281	13,600	76.6	24.6	3.4	7.6
Information Technology	14,581	19,566	19,636	34.2	34.7	4.6	4.5
D. By Education Sector							
Community	317,958	428,394	343,782	34.7	8.1	61.6	76.1
Public 4-Year	190,200	219,439	222,889	15.4	17.2	36.9	20.1
Private	7,974	13,441	6,900	68.6	-13.5	1.5	3.8
E. By Age							
< 25	617,497	740,485	778,267	19.9	26.0	66.0	52.7
25+	317,958	428,394	343,782	34.7	8.1	34.0	47.3

Notes: Enrollment counts and changes in the THECB post-secondary education data prior to any sample selection using the TWC employment data. Panels A to C shows total enrollment in the community college sector for those aged 25-plus. Panel D shows enrollment counts across sectors for those aged 25-plus. Panel E shows enrollment counts in the community college sector for all age groups.

Table A2: Shares of Field Enrollment and Five-Year Switching Rates by Last Industry: Full Sample

	Primary Source Industry		*Future Outcomes*		
	Industry	Share (%)	Switch (%)	Work in Primary (%)	Graduate (%)
A. By Field of Study					
General/Other	Health Care	15.7	35.3	16.3	5.2
Business	Financial	14.5	39.0	14.9	31.1
Humanities	Education	21.5	39.7	29.8	39.6
Math/Engineering	Manufacturing	24.3	44.0	25.3	28.4
Health	Health Care	43.0	39.5	54.0	34.9
Vocational Tech.	Manufacturing	26.4	45.7	23.0	27.3
Vocational Services	Public Sector	29.6	39.8	34.3	33.9
Education	Education	73.6	18.0	78.8	48.2
Information Technology	Manufacturing	16.4	42.5	12.9	20.1
B. By Overall Enrollment					
Non-Enrollee			31.0		
Enrollee			36.4		27.1

Notes: See notes to Table 1.

Table A3: Decomposition of Gender Differences in Field of Enrollment by Last Industry: Baseline Sample

	Raw Female-Male Difference	*Within-Industry Female-Male Difference*		*Across-Industry Female-Male Difference*	
	Difference (p.p.)	Difference (p.p.)	Share (%)	Difference (p.p.)	Share (%)
General/Other	1.0	0.9	85.3	0.2	14.7
Business	2.0	2.8	138.1	-0.8	38.1
Humanities	2.1	2.3	107.8	-0.2	7.8
Math/Engineering	-10.0	-7.1	71.2	-2.9	28.8
Health	16.0	10.4	64.7	5.7	35.3
Vocational Tech.	-4.9	-3.5	72.1	-1.4	27.9
Vocational Services	-5.1	-3.2	62.1	-1.9	37.9
Education	4.1	2.7	65.5	1.4	34.5
Information Technology	-5.4	-5.3	98.2	-0.1	1.8

Notes: This figure decomposes differences in field of study shares by gender into within and across industry components using the law of total probability: $P(f|g) = \sum_j P(f|g,j)P(j|g)$ where j is industry, f is field, and $g \in \{M, W\}$ is gender. Using this identity, I perform the following decomposition:

$$P(f|F) - P(f|M) = \underbrace{\sum_j \left[P(f|W,j) - P(f|M,j)\right] P(j|W)}_{\textbf{Within Industry}} + \underbrace{\sum_j P(f|M,j) \left[P(j|W) - P(j|M)\right]}_{\textbf{Across Industry}}$$

The within industry share measures differences in field shares between men and women in the same industry, holding industry shares fixed to women. The across industry share measures differences in field shares driven by differences in where men and women work, holding the within-industry propensity to enroll in a field to men.

Table A4: Decomposition of Gender Differences in Field of Enrollment by Last Industry: Full Sample

	Raw Female-Male Difference	*Within-Industry Female-Male Difference*		*Across-Industry Female-Male Difference*	
	Difference (p.p.)	Difference (p.p.)	Share (%)	Difference (p.p.)	Share (%)
General/Other	0.5	1.1	205.1	-0.6	105.1
Business	0.1	1.8	2441.0	-1.7	2341.0
Humanities	2.4	2.0	83.7	0.4	16.3
Math/Engineering	-9.6	-6.4	66.5	-3.2	33.5
Health	12.3	8.2	66.4	4.1	33.6
Vocational Tech.	-7.0	-4.7	67.0	-2.3	33.0
Vocational Services	-2.6	-1.5	60.0	-1.0	40.0
Education	8.3	3.2	39.2	5.0	60.8
Information Technology	-4.5	-3.8	83.7	-0.7	16.3

Notes: This figure decomposes differences in field of study shares by gender into within and across industry components using the law of total probability: $P(f|g) = \sum_j P(f|g,j)P(j|g)$, where j is industry, f is field, and $g \in \{M, W\}$ is gender. Using this identity, I perform the following decomposition:

$$P(f|F) - P(f|M) = \underbrace{\sum_j \left[P(f|W,j) - P(f|M,j)\right] P(j|W)}_{\textbf{Within Industry}} + \underbrace{\sum_j P(f|M,j) \left[P(j|W) - P(j|M)\right]}_{\textbf{Across Industry}}$$

The within industry share measures differences in field shares between men and women in the same industry, holding industry shares fixed to women. The across industry share measures differences in field shares driven by differences in where men and women work, holding the within-industry propensity to enroll in a field to men.

Table A5: Preferred Industry Exposure Estimates

	Baseline Sample				Full Sample			
	Enrolled	New Enrollment	Earnings	Graduated	Enrolled	New Enrollment	Earnings	Graduated
Z(Shock)$_j$ $\times$ D(2005)	-0.10	-0.00	359.99**	-0.19***	-0.09*	0.00	566.15***	-0.12***
	(0.13)	(0.08)	(142.54)	(0.06)	(0.05)	(0.01)	(201.83)	(0.04)
Z(Shock)$_j$ $\times$ D(2006)	0.06	0.02	445.61***	-0.06	-0.04*	-0.03**	616.24***	-0.03***
	(0.09)	(0.07)	(113.38)	(0.04)	(0.02)	(0.01)	(174.29)	(0.01)
Z(Shock)$_j$ $\times$ D(2008)	0.01	0.10	-961.58***	0.01	0.05**	0.03*	-1215.50***	-0.00
	(0.09)	(0.08)	(223.59)	(0.04)	(0.03)	(0.02)	(348.70)	(0.01)
Z(Shock)$_j$ $\times$ D(2009)	0.37***	0.33***	-2653.57***	-0.01	0.17***	0.11***	-3396.18***	0.00
	(0.14)	(0.08)	(444.77)	(0.04)	(0.05)	(0.02)	(570.83)	(0.01)
Z(Shock)$_j$ $\times$ D(2010)	0.28*	0.23***	-2343.58***	0.08**	0.23***	0.09***	-3270.28***	0.03**
	(0.15)	(0.07)	(517.75)	(0.04)	(0.06)	(0.02)	(730.50)	(0.01)
Z(Shock)$_j$ $\times$ D(2011)	0.12	0.06	-1872.04***	0.01	0.21***	0.03	-2364.53***	0.03**
	(0.16)	(0.07)	(581.93)	(0.06)	(0.07)	(0.02)	(748.34)	(0.01)
Z(Shock)$_j$ $\times$ D(2012)	0.30**	0.22***	-1759.58***	0.06	0.21***	0.04**	-2301.22***	0.03*
	(0.15)	(0.08)	(648.53)	(0.06)	(0.08)	(0.02)	(847.10)	(0.01)
Z(Shock)$_j$ $\times$ D(2013)	0.19	0.06	-1381.96**	0.04	0.19**	0.02	-1721.28*	0.02
	(0.14)	(0.07)	(693.78)	(0.05)	(0.09)	(0.02)	(964.04)	(0.02)
Z(Shock)$_j$ $\times$ D(2014)	0.22	0.17**	-1366.22*	-0.04	0.22**	0.04*	-1663.69	0.02
	(0.14)	(0.07)	(770.17)	(0.04)	(0.09)	(0.02)	(1059.63)	(0.02)
Z(Shock)$_j$ $\times$ D(2015)	0.26*	0.10	-1892.98**	0.05	0.23**	0.05**	-1877.45*	0.02
	(0.15)	(0.07)	(801.11)	(0.04)	(0.09)	(0.02)	(984.34)	(0.02)
Z(Shock)$_j$ $\times$ D(2016)	0.29**	0.16***	-1845.12**	0.01	0.23**	0.04	-1441.62*	0.01
	(0.13)	(0.05)	(810.22)	(0.05)	(0.10)	(0.03)	(807.99)	(0.02)
Z(Shock)$_j$ $\times$ D(2017)	0.20	0.10	-1684.71**	0.00	0.23**	0.04*	-586.25	0.02
	(0.14)	(0.06)	(808.36)	(0.04)	(0.11)	(0.02)	(681.64)	(0.02)
Z(Shock)$_j$ $\times$ D(2018)	0.26*	0.16***	-1796.20**	-0.05	0.22**	0.04*	88.95	0.01
	(0.13)	(0.06)	(903.66)	(0.04)	(0.11)	(0.03)	(651.60)	(0.02)
Baseline Controls	X	X	X	X	X	X	X	X
Demographic Controls	X	X	X	X				
2007 Outcome Mean	7.3	2.2	56790	0.7	4.4	1.2	86349	0.5
at 1SD Z(Shock)	5.2	1.6	63456	0.5	2.9	0.9	92709	0.3
N (Individuals)	561	561	561	561	561	561	561	561
N (Industries)	189,073	189,073	189,073	189,073	3,439,610	3,439,610	3,439,610	3,439,610

Notes: Estimates of parameters δ_y based on the event study specification in Equation 3.1. Standard errors, shown in parentheses, are clustered based on an individual's pre-Recession 5-digit industry code. Outcome means in 2007 at 1SD of the shock measure are based on predicted values from a linear probability model of 2007 enrollment on the exposure measure, evaluated at 1 SD of the exposure measure. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Robustness of Industry Exposure Analysis

	External Shock		1997 Baseline		Alternate Controls I		Alternate Controls II	
	Enrolled	Earnings	Enrolled	Earnings	Enrolled	Earnings	Enrolled	Earnings
$Z(Shock)_j \times$ D(2005)	-0.220*	96.864	-0.182**	178.559	-0.140	341.717**	0.030	311.738**
	(0.114)	(144.022)	(0.072)	(187.853)	(0.140)	(144.161)	(0.135)	(151.280)
$Z(Shock)_j \times$ D(2006)	-0.100	334.632**	-0.034	95.139	0.060	465.500***	0.051	322.171***
	(0.094)	(142.855)	(0.032)	(142.962)	(0.095)	(112.433)	(0.091)	(111.925)
$Z(Shock)_j \times$ D(2008)	-0.021	-540.820***	-0.009	1016.685***	-0.011	-822.039***	0.044	-955.561***
	(0.079)	(177.219)	(0.032)	(287.155)	(0.094)	(234.085)	(0.097)	(245.230)
$Z(Shock)_j \times$ D(2009)	0.287***	-1096.239***	0.007	1537.426***	0.317**	-2507.155***	0.303**	-2567.577***
	(0.109)	(340.518)	(0.060)	(494.729)	(0.140)	(465.762)	(0.144)	(487.152)
$Z(Shock)_j \times$ D(2010)	0.216	-620.344*	0.015	2073.452***	0.223	-2118.237***	0.162	-2279.154***
	(0.137)	(371.348)	(0.069)	(649.541)	(0.162)	(546.004)	(0.163)	(583.000)
$Z(Shock)_j \times$ D(2011)	0.206	1.896	0.015	1166.552**	0.061	-1512.203**	0.004	-1963.609***
	(0.166)	(413.105)	(0.064)	(555.696)	(0.175)	(623.679)	(0.167)	(648.115)
$Z(Shock)_j \times$ D(2012)	0.157	486.977	0.041	-172.431	0.269*	-1277.925*	0.199	-2003.834***
	(0.165)	(431.583)	(0.068)	(508.232)	(0.156)	(714.853)	(0.155)	(693.484)
$Z(Shock)_j \times$ D(2013)	0.181	972.859**	0.098	-498.096	0.182	-793.205	0.048	-1817.688**
	(0.145)	(465.266)	(0.075)	(594.491)	(0.152)	(784.282)	(0.152)	(710.321)
$Z(Shock)_j \times$ D(2014)	0.168	1057.021**	0.085	-615.669	0.231	-685.414	0.054	-1805.448**
	(0.174)	(530.254)	(0.079)	(621.329)	(0.152)	(882.636)	(0.147)	(773.164)
$Z(Shock)_j \times$ D(2015)	0.189	1149.714**	0.088	-692.418	0.278*	-1179.636	0.086	-2427.194***
	(0.161)	(566.631)	(0.084)	(734.356)	(0.162)	(927.656)	(0.155)	(813.748)
$Z(Shock)_j \times$ D(2016)	0.114	1378.318**	0.114	-499.890	0.313**	-1165.222	0.160	-2358.616***
	(0.167)	(591.672)	(0.084)	(868.961)	(0.140)	(943.109)	(0.132)	(875.048)
$Z(Shock)_j \times$ D(2017)	0.126	1290.957**	0.114	-1052.173	0.242	-956.394	0.032	-2146.538**
	(0.164)	(629.570)	(0.088)	(938.671)	(0.148)	(957.642)	(0.134)	(851.302)
$Z(Shock)_j \times$ D(2018)	0.179	1568.184**	0.164*	-1946.960*	0.280*	-996.831	0.076	-2382.846**
	(0.176)	(707.415)	(0.088)	(1060.677)	(0.144)	(1075.996)	(0.131)	(929.174)
2007 Outcome Mean	7.2	57196			7.3	56790	7.3	56790
at 1 SD Z(Shock)	5.3	63665			5.2	63456	5.2	63456
Demographic Controls	X	X					X	X
Industry Controls	X	X	X	X	X	X		
1-Digit Controls							X	X
Sample	Baseline	Baseline	Full	Full	Baseline	Baseline	Baseline	Baseline
N (Individuals)	529	529	561	561	561	561	561	561
N (Industries)	174,855	174,855	1,924,805	1,924,805	189,073	189,073	189,073	189,073

Notes: Estimates of parameters δ_y based on the event study specification in Equation 3.1. Standard errors, shown in parentheses, are clustered based on an individual's pre-Recession 5-digit industry code. Outcome means in 2007 at 1SD of the shock measure are based on predicted values from a linear probability model of 2007 enrollment on the exposure measure, evaluated at 1 SD of the exposure measure. "External Shock" reports estimates using n exposure measure defined using industry-level employment losses defined outside of Texas using data from the Statistics of U.S. Businesses. "1997 Baseline" reports coefficients relative to 1997:Q4 as the base period rather than 2007:Q4. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Heterogeneity by Field and Industry: Baseline Sample

A. By Industry:					
	Production/Manufacturing	Services	Professional/Finance	Other	
Enroll (pp)	0.404	0.082	0.708**	-0.029	
SE	(0.348)	(0.262)	(0.323)	(0.325)	
Effect (%)	[7.6%]	[1.4%]	[10.4%]	[-0.9%]	
N (Industries)	142	130	79	210	
N (Individuals)	15,282	41,803	41,923	90,065	
B. By Fields of Study:					
	Study Health	Study Business	Study Information Technology	Study Vocational Services	Study Education
Enroll (pp)	0.136*	0.095*	0.020	0.045	0.018
SE	(0.078)	(0.049)	(0.020)	(0.028)	(0.018)
Effect (%)	[48.2%]	[6.8%]	[6.9%]	[14.1%]	[8.2%]
N (Industries)	561	561	561	561	561
N (Individuals)	189,073	189,073	189,073	189,073	189,073

Notes: Coefficients pool the event study parameters δ_y for 2009 and 2010 from the event study specification in Equation 3.1. Standard errors, shown in parentheses, are clustered based on an individual's pre-Recession 5-digit industry code. Standard errors clustered based on an individual's pre-Recession 5-digit industry code. Percent effects, shown in brackets, are based on predicted values from a linear probability model of 2007 enrollment on the exposure measure, evaluated at 1 SD of the exposure measure. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Heterogeneity by Field and Industry: Full Sample

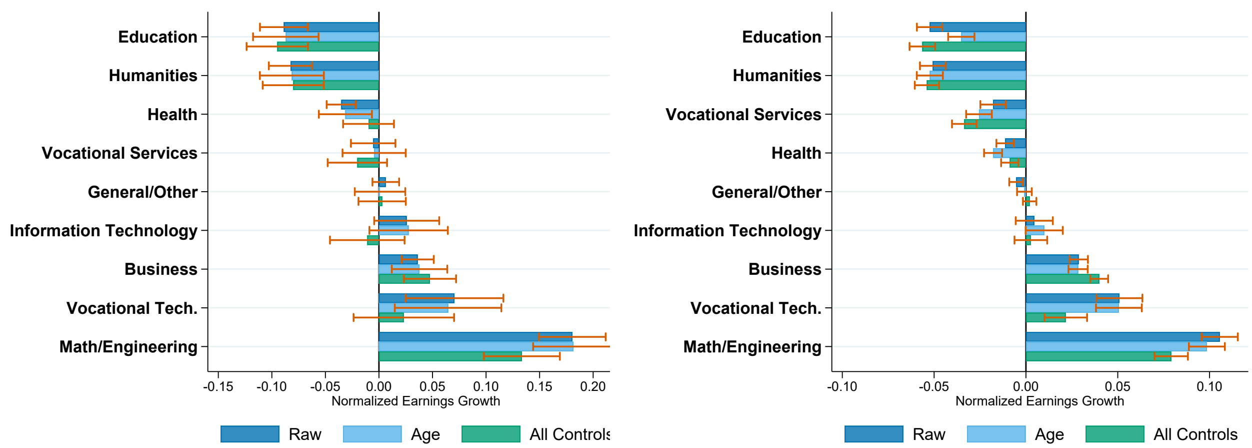
	All	Production/Manufacturing	Services	Professional/Finance	Other
A. Main Outcomes					
Earnings	-3727.360***	-1627.413***	-1705.510***	-2627.081***	-4617.686***
	(699.068)	(619.682)	(434.856)	(711.498)	(1656.782)
	[-4.0%]	[-1.7%]	[-2.2%]	[-2.7%]	[-4.9%]
Enrolled (pp)	0.245***	0.159**	0.053	0.420***	0.129
	(0.061)	(0.073)	(0.058)	(0.127)	(0.120)
	[8.3%]	[6.4%]	[1.6%]	[10.5%]	[5.3%]
New Enrollment (pp)	0.107***	0.050	0.084***	0.204***	0.064**
	(0.018)	(0.036)	(0.024)	(0.047)	(0.027)
	[12.5%]	[6.6%]	[8.7%]	[18.1%]	[9.3%]
B. Most Affected Fields					
Study Health (pp)	0.094***	0.036**	-0.000	0.092***	0.109**
	(0.025)	(0.017)	(0.035)	(0.023)	(0.047)
	[73.1%]	[17.1%]	[-0.0%]	[23.2%]	[-28.2%]
Study Business (pp)	0.031*	0.016	0.021	0.135**	0.001
	(0.016)	(0.020)	(0.016)	(0.053)	(0.024)
	[3.9%]	[2.3%]	[2.8%]	[10.9%]	[0.2%]
Study Information Technology (pp)	0.014***	0.016**	0.013	0.021	0.009
	(0.005)	(0.008)	(0.011)	(0.015)	(0.007)
	[8.2%]	[10.3%]	[7.3%]	[8.7%]	[7.2%]
Study Vocational Services (pp)	0.029***	0.011	-0.010	0.007	0.016
	(0.010)	(0.008)	(0.013)	(0.011)	(0.017)
	[22.7%]	[14.6%]	[-5.0%]	[4.4%]	[14.5%]
Study Education (pp)	0.018***	-0.000	0.026***	0.022**	-0.004
	(0.006)	(0.004)	(0.008)	(0.011)	(0.010)
	[5.8%]	[-0.6%]	[24.7%]	[15.4%]	[-0.6%]
C. Other Fields					
Study General/Other (pp)	0.02	-0.03**	0.00	0.06**	0.02
	(0.01)	(0.02)	(0.03)	(0.03)	(0.03)
	[3.2%]	[-7.5%]	[0.5%]	[7.3%]	[4.3%]
Study Humanities (pp)	0.02	-0.00	-0.01	0.02	-0.04
	(0.02)	(0.01)	(0.02)	(0.04)	(0.03)
	[3.8%]	[-0.7%]	[-1.2%]	[4.1%]	[-7.8%]
Study Vocational Technical (pp)	0.01	0.05***	-0.01	0.02**	0.01
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
	[9.5%]	[35.0%]	[-12.9%]	[42.3%]	[5.8%]
Study Math/Engineering (pp)	0.02	0.07***	0.02**	0.04	0.01
	(0.01)	(0.02)	(0.01)	(0.04)	(0.02)
	[4.6%]	[14.0%]	[7.2%]	[11.9%]	[2.9%]
N (Industries)	561	142	130	79	210
N (Individuals)	3,439,610	411,385	685,468	594,704	1,748,053

Notes: Coefficients pool the event study parameters δ_y for 2009 and 2010 from the event study specification in Equation 3.1. Standard errors, shown in parentheses, are clustered based on an individual's pre-Recession 5-digit industry code. Standard errors clustered based on an individual's pre-Recession 5-digit industry code. Percent effects, shown in brackets, are based on predicted values from a linear probability model of 2007 enrollment on the exposure measure, evaluated at 1 SD of the exposure measure. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.2 Additional Returns Estimates

Figure A6: Field of Study: By Sample and Controls

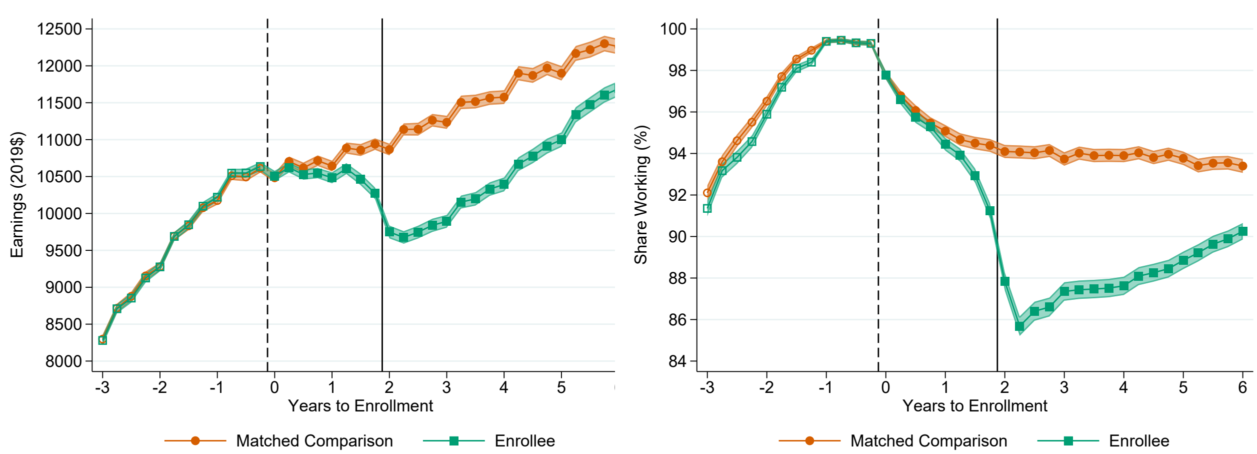
(a) Baseline Sample (b) Full Sample



Notes: This figure repeats the empirical exercise conducted in Figure 4. The second and third sets of bars ("Age" and "All Controls") add in studentized covariates that are also interacted with the quadratic in post-enrollment trends (centered at 20 quarters). Inclusion of these covariates and interactions with trends adjust for compositional differences in the covariates across field of study while still centering the reported estimates on the average, composition-adjusted earnings growth for that pathway. Controls for "Age" are age and age-squared. "All Controls" includes other demographics (indicators for gender, black, Hispanic, some prior college, and prior college graduation), total earnings in year 3 (quarters 9 to 12) prior to enrollment, total earnings in year 2 (quarters 5 to 8) prior to enrollment, annualized earnings growth between year 1 (quarters 1 to 4) and year 3 prior to enrollment, pairwise quadratic interactions between these, an indicator variable for any non-employment in pre-enrollment quarters 1 to 4, and an indicator variable for only being non-employed in quarters 1 to 4 prior to enrollment.

Figure A7: Matching Estimator: Placebo Check

(a) Quarterly Earnings (b) Share Working



Notes: This figure reproduces the matching procedure outlined in the notes to Figure 5, using a "fake" enrollment date two years prior to the actual enrollment quarter for each enrollee. This fake enrollment event is plotted in the dashed vertical line, and the real enrollment date is plotted in the solid vertical line. Figure (a) plots total average earnings and Figure (b) plots any employment.

B Data Appendix

B.1 Sample Definitions

My analysis focuses on two balanced panels of individuals' work and education decisions:

Full Sample: *This sample represents the universe of workers in the Texas UI data meeting the following sample definitions*:

(a) Have at least four consecutive quarters of full-time equivalent work,[101] during which they are not enrolled. I define the first quarter of the first such period as the quarter of labor market entry for this sample and measure variables such as experience and tenure relative to this base period.

(b) I define a worker as employed if they have quarterly earnings above $2,400 and restrict to individuals for whom the longest period of non-employment is 20 quarters (5 years) and they have some work experience in each of the years 2017, 2018, 2019. This restriction is meant to focus on workers with labor force attachment, while allowing for the inclusion of long-term unemployed, an important feature of the Great Recession (Yagan [2019]) as well as individuals leaving the labor force temporarily to pursue education.

While this data is great in its breadth, I am not able to link individuals with demographic information unless they enter either the Texas K-12 or higher education systems. For this reason, I focus on a second sample of high school graduates for whom I see complete labor market histories. It is on this sample that I estimate the structural model.

Baseline Sample: *This is sub-sample of the previous panel of workers for which I have demographics and complete work histories, on which I conduct most analysis and estimate the structural model.* These data have the following additional restrictions:

(c) Graduated from a high school in the TEA data in 1994 to 1998.

(d) Do not earn and advanced degree (defined as a masters degree or PhD).

(e) Does not have work or college enrollment before they are aged 14 and are not missing demographic data.

(f) Have initial work experience, defined as at least 4 consecutive quarters of non-enrolled work between ages 21 and 25. This is needed to define initial industry of employment. It also helps to ensure they do not begin their work history in a high education state (e.g. individuals pursuing masters/PhDs who are in education in this period are meant to be excluded).

(g) Have one calendar year of 4 quarters of non-enrolled work between the ages of 25 and 30. This ensures that individuals choose an industry in this period.

The ages in this sample will thus range from 29 to 33 at the onset of the Great Recession in 2009 and 39 to 43 at the end of the analysis period in 2019. In Figure B1, I compare the evolution of key variables

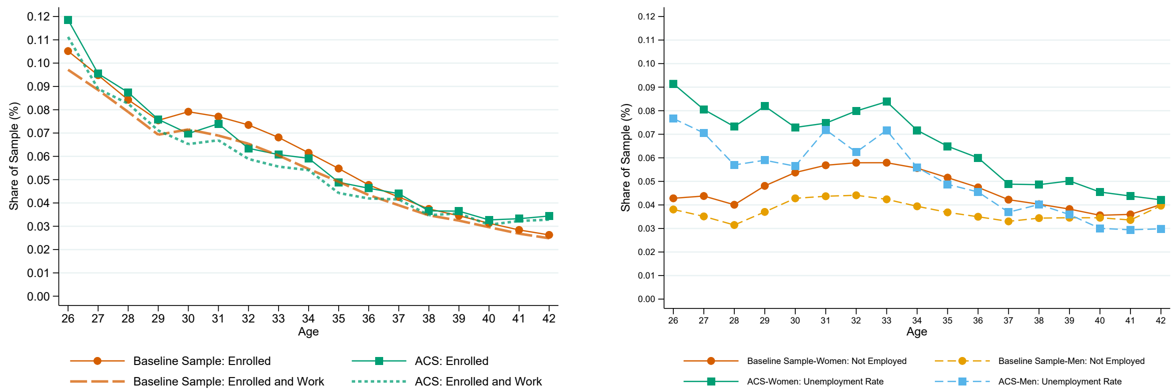
[101] Full-time equivalent work is defined as quarterly earnings above $4,800, or working 40 hours a week for 12 weeks at $10 an hour.

for the baseline sample panel to cohorts of the same age range in the American Community Surveys.

Figure B1: Comparison of Baseline Sample with Statistics in the ACS

(a) Enrollment

(b) Non-employment (ERC) v. Unemployment Rate (ACS)



Notes: These figures compare key variables from the 2006 to 2018 1-Year American Community Survey (ACS) waves, for the 1976 to 1980 birth cohorts in Texas who are marked as is in the labor force (LABFORCE=2). While not an exact comparison, I use the sample in the labor force from the ACS, since my ERC sample restriction limit the data to those attached to the labor force. Figure (a) compares my administrative marker for current enrollment to the ACS variable for currently attending college/graduate school (GRADEATT=6 or 7) and attending a public institution (SCHLTYPE=2). Figure (b) compares non-employment to the variables for unemployed (EMPSTAT=2 if EMPSTAT=1 or 2). OLF shares in the ACS are much higher than in my data (e.g. 25.2% in 2007).

B.2 Key Variable Definitions

Industry of Employment: I focus the analysis on the industry code related to the job with the highest earnings in a quarter but using earnings summed across all jobs. I use industry NAICS codes defined at the 5-digit level.[102]

Fields of Study: Information on programs of study pursued in college are reported as CIP codes from two sources: (i) the major field of study in each enrollment period or (ii) the CIP code associated with credentials received upon graduation. I focus on 2-digit CIP codes and further aggregate into broad areas of study, as exhibited in Table B2. I do some imputation to focus on the principal field of study associated with an enrollment spell.[103]

Enrollment Timing: I first map semesters into business quarters to be used with the UI data. Raw enrollment records are at the semester level and I convert these into quarterly data using the following schema: (a) Fall to Q3 and Q4, (b) Spring to Q1 and Q2, (c) Summer I to Q2, (d) Summer II to Q3. This maping roughly maps to that used in Jepsen et al. [2014]. For the fall and spring semesters, I divide

[102] This level of detail is quite low-level, differentiating between bars and restaurants. I do some harmonization to account for the fact that some industry codes may lose employment due to changes in how the underlying firm is classified. For example, I link industry codes where large numbers of individuals switch to the same new industry at the same time. I also combine industries with very small (< 100) employment. I never allow industries to be linked across 3-Digit codes. Further details are available upon request. This procedure results in 561 unique industries (from a total of 857). Additional details are available upon request.

[103] Many of the enrollment CIP codes are reported as general studies or as missings, likely not reflecting true courses taken. I focus on the "principal field of study" for an enrollment spell, which imputes the main CIP code pursued in a meriod of enrollment based on CIP code of degrees obtained, the number of periods a CIP code is reported as the main course of study, and the number of credit hours associated with each period of study towards a CIP code. do some imputation based on CIP codes pursued throughout an entire spell and from degrees obtained. Details are available upon request.

completed hours equally between quarters.

New and Target Enrollment: I define individuals as being *newly enrolled* if they were not enrolled in the prior three calendar years. For each individual, I define a *target enrollment*, as the first quarter when they transitioned from work to school as adults. This is the enrollment timing used in the returns analysis of Section 2.4. Specifically, I define this as the first new enrollment after labor market entry where the individual had some work experience in years 2 and 3 prior to enrollment.

B.3 Summary Statistics

Table B1: Summary Statistics for Baseline Sample

	Men	Women
A. Basic Variables		
Black	0.09	0.15
Hispanic	0.29	0.31
Some Prior College	0.21	0.17
B. 2007 Variables		
Work in 2007	0.97	0.95
Services	0.25	0.21
Health Care	0.04	0.21
Manufacturing	0.11	0.04
Earnings in 2007	57504.01	43255.02
Enrollment in 2007	0.06	0.10
C. 2010 Variables		
Work in 2010	0.95	0.94
Earnings in 2010	62302.13	46348.88
Enrollment in 2010	0.06	0.10
D. 2018 Variables		
Work in 2018	0.96	0.96
Earnings in 2018	85641.18	58876.98
Enrollment in 2018	0.02	0.04
E. Post-Work Education Outcomes		
Ever Enroll	0.18	0.27
Ever Graduate with Certificate	0.02	0.02
Ever Graduate with Associates	0.03	0.05
Ever Graduate with B.A.	0.02	0.03
F. At First Post-Work Enrollment		
Study in Business	0.16	0.17
Study in Math/Engineering	0.12	0.02
Study in Health	0.12	0.29
Study in Vocational Services	0.11	0.06
Study in Education	0.03	0.07
Number of Observations	126,431	121,542

Notes:

B.4 Aggregation of NAICS and CIP Codes

Table B2: Mapping between CIP Codes and Fields of Study

Broad Area of Study	Area of Study in Model	2-Digit CIP
General/Other	General	24. Liberal Arts and Sciences, General Studies and Humanities
		32. Basic Skills
		34. Health-Related Knowledge and Skills
		36. Leisure and Recreational Activities
		37. Personal Awareness and Self Improvement
		99. Not Classified
Business	Business	52. Business, Management, Marketing, and Related Support Services
Humanities	Humanities	5. Area, Ethnic, Cultural, and Gender Studies
		9. Communication, Journalism, and Related Programs
		16. Foreign Languages, Literatures, and Linguistics
		22. Legal Professions and Studies
		23. English Language and Literature/Letters
		30. Multi/Interdisciplinary Studies
		38. Philosophy and Religious Studies
		39. Theology and Religious Studies
		42. Psychology
		45. Social Sciences
		50. Visual and Performing Arts
		54. History
STEM	Technical	4. Architecture and Related Services
		10. Communication Technologies/Technicians and Support Services
		11. Computer Information Sciences and Support Services
		14. Engineering
		15. Engineering Technologies/Technicians
		27. Mathematics and Statistics
		40. Physical Sciences
		41. Science Technologies/Technicians
Health	Health	26. Biological and Biomedical Sciences
		51. Health Professions and Related Clinical Services
Vocational Technical	Technical	1. Agriculture, Agricultural Operations, and Related Sciences
		3. Natural Resources and Conservation
		21. Technology Education
		29. Military Technologies
		46. Construction Trades
		47. Mechanic and Repair Technologies/Technicians
		48. Precision Production
		49. Transpiration and Materials Moving
Vocational Services	General	12. Personal and Culinary Services
		19. Family and Consumer Sciences/Human Sciences
		31. Parks, Recreation, Leisure, and Fitness Studies
		43. Security and Protective Services
		44. Public Administration and Social Service Professions
Education	General	13. Education
		25. Library Science

C Mathematical Appendix

C.1 Identification of Earnings and Human Capital Accumulation Parameters

This section shows semi-parametric identification of key parameters in the earnings equation of the model, given linearity of the earnings equation, time-invariance of earnings coefficients π and α, and the mean independence assumptions on the stochastic process governing η.

For ease of exposition, this section makes several simplifications relative to the baseline model that are without loss of generality. First, only consider identification of the model where there is only one worker type, as the arguments can be repeated conditional on worker type. Parameters that exist across worker types, such as skill prices r_{jt} and skill weights π_j, will have additional cross-worker type restrictions in the more general model, which aids in identification. Second, consider a version of the model model where there is no schooling decision, as the arguments easily extend to that case but notation becomes complicated (e.g. one must consider part-time penalties, etc.). Thus, each period workers make the choice of which industry j to work in, denoted j_{it}. These consist of $J = 7$ industries plus non-employment, $j_{it} = 0$. To ensure that identifying equations are not redundant, we need these industries to be distinct in their parameters, π_j, α_j, and r_{jt}.

Finally, consider a version where the earnings shock η is drawn from a distribution that is mean independent of other components entering the earnings equation. Allowing for dependence across periods means the conditioning arguments used in the proofs will just need to include lagged earnings histories as well. What is necessary for identification regarding η is that the initial η is mean-independent of initial conditions and that innovations in η are mean independent of the state and choices in the state.

The equations in the model can be summarized as:

$$y_{ijt} = r_{jt} + \pi_j' \omega_{it} + \alpha_j \tau_{it} + \eta_{it}$$

$$\omega_{i,t+1}^{(s)} = \Gamma^{(s)}(j_{it} | \omega_{it}^{(s)}) \omega_{it}^{(s)}$$

$$\text{Covariates } z_i \text{ determine initial skill } \omega_{i1}^{(s)}(z_i) \text{ with } \mathbb{E}[\omega_{i1}^{(s)}] = 1, \forall s$$

$$\tau_{i,t+1} = \Psi(j_{it} | \tau_{it}, j_{i,t-1}) \tau_{it} \text{ with } \Psi(j_{it} | 0, j_{i,t-1}) = 1 \text{ and } \Psi(j_{it} = 0 \text{ or } sep_{it} = 1 | \tau_{it}, j_{i,t-1}) = 0$$

$$\mathbb{E}[\eta_{it} | j_{it}, \omega_{it}, \tau_{it}] = 0$$

Let F_z denote the distribution of z. For exposition, I consider z to be discrete taking on n_z possible values. The main text makes functional form restrictions on Γ and Ψ, which I do not impose here.

The econometrician observes y_{ijt}, j_{it}, sep_{it}^{Obs}, and their histories, $\mathscr{H}_{-t}$. The identification arguments rest on appeals to the fact that we have a sufficient richness in observed transitions. In particular, this can be thought of as an overlap assumption where at least some workers with work history $\mathscr{H}_{-t}$ that choose each action. This gives both enough distinct identifying equations to recover the parameters of the model.

Skill Weights and Initial Skills: Consider comparisons restricted to individuals who enter work from non-employment so that $\tau = 0$ can be ignored. The initial earnings of workers in the first period who have initial observables z can be written as:

$$y_{ij1}(z) = r_{j1} + \pi_j' \omega_{i1}(z) + \eta_{it}$$

We can use the assumptions on the earnings innovation η to take expectations so that the η drops out:

$$\bar{y}_{j1}(z) = r_{j1} + \pi_j' \omega_{i1}(z)$$

Fixing industry j, consider differences in earnings for workers with initial covariates z_A from a reference group with z:

$$\bar{y}_{j1}(z_A) - \bar{y}_{j1}(z) = \pi_j' \left(\omega_{i1}(z_A) - \omega_{i1}(z)\right)$$

This differences out skill prices. Now, integrate z over its population distribution:

$$\begin{aligned}
\int_z \bar{y}_{j1}(z_A) - \bar{y}_{j1}(\tilde{z}) dF_Z(\tilde{z}) &= \int_z \pi_j'(\omega_{i1}(z_A) - \omega_{i1}(z)) dF_Z(\tilde{z}) \\
\bar{y}_{j1}(z_A) - \int_z \bar{y}_{j1}(\tilde{z}) dF_Z(\tilde{z}) &= \pi_j' \omega_{i1}(z_A) - \pi_j' \int_z \omega_{i1}(\tilde{z}) dF_Z(\tilde{z}) \\
\bar{y}_{j1}(z_A) - \int_z \bar{y}_{j1}(\tilde{z}) dF_Z(\tilde{z}) &= \pi_j' \left(\omega_{i1}(z_A) - \iota_S\right)
\end{aligned}$$

where ι_S is an S-dimensional vector of ones. The second line follows as the distribution F_z must integrate to one and the last line follows from the normalization on initial skills. The left-hand side of this equation is observed, as $\int_z \bar{y}_{j1}(\tilde{z}) dF_Z(\tilde{z})$ are earnings in j for difference z, weighted by the population distribution of Z.

For every z_A, we need to recover S initial skills parameters $\omega_{i1}(z_A)$. Thus, there are $n_Z \cdot S$ parameters. For every industry j, we need to recover S skill weights $\pi_j^{(s)}$, so there are $J \cdot S$ of these parameters. This gives a total of $(n_Z + J) \cdot S$ unknowns. In contrast, we have $J \cdot (n_z - 1)$ comparisons given by the equation. This means that we a linear system with more equations than parameters as long as $(n_z + J)S \leq J(n_z - 1)$. For this application, $J = 7$ and $S = 3$, meaning that we have identified the skill weights and initial skills as long as $n_z \geq 4$, which is satisfied.

Skill Accumulation Parameters: I now discuss identification of $\Gamma^{(s)}$, assuming that π and $\omega_0(z)$ are known. These parameters are identified through within-industry but across-work history variation in average earnings.

Consider two individuals, A and B, who have the same initial Z and tenure and thus ω_{i1} and τ_1. Consider a comparison such that $j_{2A} = j_{2B} = l$ but $j_{1A} \neq j_{1B} \neq l$. Then, comparing earnings in period 2 gives:

$$\begin{aligned}\bar{y}_{2A} - \bar{y}_{2B} &= \left(r_{l2} + \pi_l' \Gamma(j_{1A}|\omega_1) \cdot \omega_1 + \alpha_l^\tau \tau_2\right) - \left(r_{l2} + \pi_l' \Gamma(j_{1B}|\omega_1) \cdot \omega_1 + \alpha_l^\tau \tau_2\right) \\ &= \pi_l' \left[\Gamma(j_{1A}|\omega_1) - \Gamma(j_{1B}|\omega_1)\right] \cdot \omega_1\end{aligned}$$

Since A and B-type histories work in the same final industry, skill prices are differenced out. Moreover, since they have the same initial τ and transition each period (but not to l!), they have the same final τ_2, which also gets differenced out.

We have J choices for l and $J-1$ choices for j_{1A} and j_{2B} where ordering doesn't matter, giving $J \cdot \frac{(J-1)(J-2)}{2}$ possible comparisons. We have $J \cdot S$ Γ parameters to identify. Thus, for this single comparison, we have identification of Γ as long as $\frac{(J-1)(J-2)}{2} > S$, which is satisfied for $J = 7$ and $S = 3$.

We can repeat these arguments conditional on work histories $\mathscr{H}_{-t}$ in each period t to recover Γ for every possible ω. In practice, the functional forms on Γ implied by Equation 4.2 determines this process in a tractable way.

Specific Skill Parameters: The process governing τ and its industry-specific weight α_j^τ are recovered by exploiting the assumptions regarding involuntary separations. Consider two types of individuals, C and D, who have the same prior work history and same skills at the start of period $t-2$ and work in the same industry in periods j_t, j_{t-1} and j_{t-2}. They will thus have the same ω_t.

Suppose D suffers and involuntary separation at the beginning of period $t-1$ and C suffers an involuntary separation at the beginning of period t. Then, $\tau_{Ct} = 0$ and $\tau_{Dt} = 1$. Comparing average differences in earnings between these two groups will pin down α_j^τ.

Then, Ψ can be recovered through average differences between stayers and switchers who end up in the same industry. Consider individuals E and F who have the same work history $\mathscr{H}_{-t}$. For simplicity, assume they have have $\tau_t = 1$ (so they are separated at the beginning of t or transition from non-employment). E continues to work at $j_{t-1} = l$ in t and $t+1$. F switches to $j_{Ft} \neq j_{t-1}$ before choosing $j_{t-1} = j_{t+1} = l$. Then, average differences in $t+1$ earnings between these two types of individuals is:

$$\begin{aligned}\bar{y}_{t+1,E} - \bar{y}_{t+1,F} &= \left(r_{l,t+1} + \pi_l' \Gamma(j_{tE}|\omega_t) \cdot \omega_t + \alpha_l^\tau \Psi(j_{Et}|\tau_t, l)\tau_t\right) - \left(r_{l,t+1} + \pi_l' \Gamma(j_{tF}|\omega_t) \cdot \omega_t + \alpha_l^\tau \Psi(j_{Ft}|\tau_t, l)\tau_t\right) \\ &= \pi_l' \left[\Gamma(j_{tE}|\omega_t) - \Gamma(j_{tF}|\omega_t)\right] \cdot \omega_t + \alpha_l^\tau \left[\Psi(j_{Et}|\tau_t, l) - \Psi(j_{Ft}|\tau_t, l)\right] \tau_t\end{aligned}$$

The terms $\pi_l' \left[\Gamma(j_{tE}|\omega_t) - \Gamma(j_{tF}|\omega_t)\right] \cdot \omega_t$ and α_j^τ are already identified by previous arguments. Average differences between these groups thus identify $\Psi(j_{Et}|\tau_t, l) - \Psi(j_{Ft}|\tau_t, l)$ exactly (one equation with one unknown). There are $\frac{J(J-1)}{2}$ such differences in J unknowns, meaning that Ψ is identified as long as $J \geq 3$. We can then extend the previous argument to $\tau_t \neq 1$.

Skill Prices: The remaining parameters governing average earnings are the skill prices r_{jt}. These are simply residuals of earnings net of already identified quantities.

For initial skill prices r_{j1}, consider comparisons originating from non-employment so that $\tau = 0$. Then, making the appeal to large numbers and exploiting the initial skill normalization, skill prices are just:

$$r_{j1} = \int_z \left(\bar{y}_{j1}(z) - \pi_j' \omega_1(z)\right) dF_z(z) = \int_z \bar{y}_{j1}(z) dF_z(z) - \pi_j' \iota_S \ \ \forall j$$

which also shows how the normalization pins down the location of skills relative to skill prices.

Remaining skill prices are computed by integrating over work histories conditional on working in industry j at time t. Formally:

$$r_{lt} = \bar{y}_{lt} - \pi_l' \mathbb{E}_{\mathscr{H}_{-t}}[\omega_{it}|j_{it} = l] - \alpha_l^\tau \mathbb{E}_{\mathscr{H}_{-t}}[\tau_{it}|j_{it} = l]$$

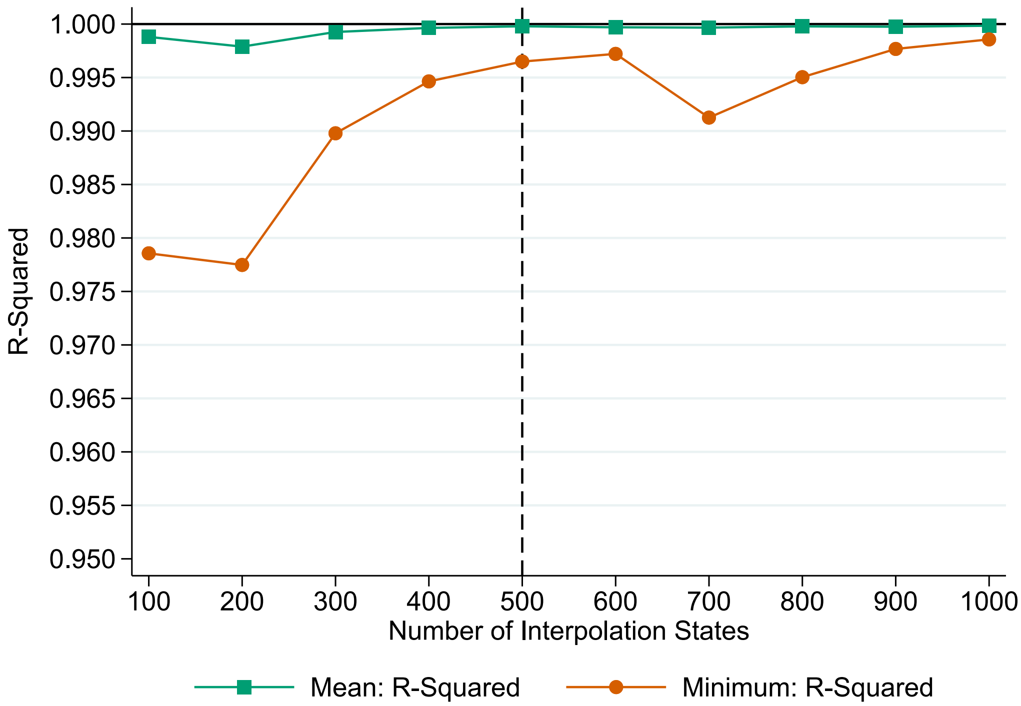
Distribution of η: We have made no assumptions about η other than mean independence. Since we now know all other parameters of the model, we can thus recover its distribution semi-parametrically:

$$\eta_{it} = y_{it} - r_{j_i,t} - \pi_{j_i}' \omega_i(\mathscr{H}_{-t}) - \alpha_{j_i}^\tau \tau_i(\mathscr{H}_{-t})$$

This shows that the model can in principle be much more flexible regarding the distribution of the errors than what is imposed in estimation. In particular, identification relies heavily on linearity, semi-parametric assumptions on the error terms, and having a sufficient overlap between choices and work histories. However, the arguments do not rely on parametric restrictions on the unobservables at all

D Estimation Appendix

Figure D1: Fit of the Value Function Interpolation and Sensitivity to Additional Interpolation States



Notes: This figure shows the fit of the value function interpolation, where the dashed line shows the number of states used for interpolation in estimation. I interpolate the value function separately for each age (30 periods from 25 to 54), graduation cohort (2 for 1994 and 1998 in estimation), last employment state (7 industries, non-employment, and the separation state), and worker type (4) for a total of 2,160 linear regressions. The orange (circles) line shows the minimum *R*-Squared over all these regressions while the teal (squares) line shows the average.

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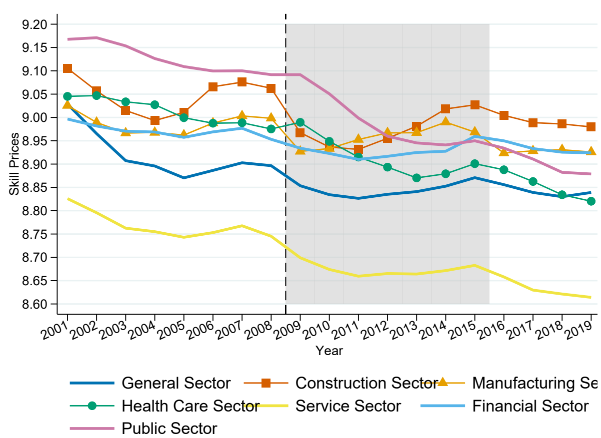
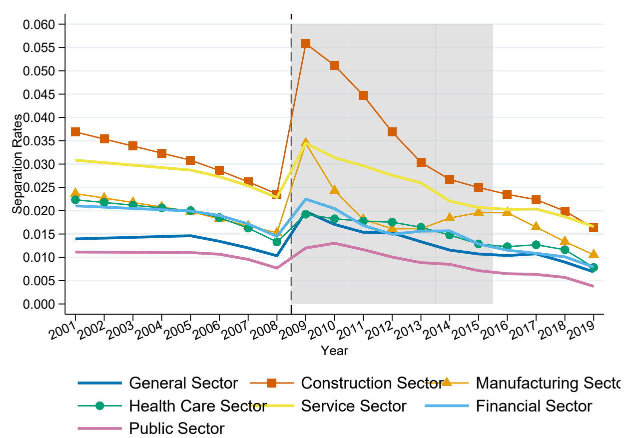
Figure D2: Skill Prices and Separation Rates - All Industries

(a) Skill Prices (Estimated)



(b) Separation Rates (Calibrated)



D.1 Algorithm to Evaluate NLLS Objective

An evaluation of Q^{NLLS} for a guess α_Y proceeds according to the following algorithm:

1. *Impose normalization*: Compute unrestricted $\tilde{\omega}_{1i}^{(s)}$ using α_Y for each i and s. Use these to compute average $\bar{\omega}_1^{(s)}$ by averaging in the population and use to force $\mathbb{E}[\omega_{1i}^{(s)}] = 1$ by setting $\omega_{1i}^{(s)} = \tilde{\omega}_{1i}^{(s)} / \bar{\omega}_1^{(s)}$.
2. *Evaluate human capital*: Compute $h_{it} = h\left(k_{it} | \Omega(\mathscr{H}_i^{-t}; \alpha_Y); \alpha_Y, \lambda_Y(\alpha_Y)\right)$ for all i and t
3. *Iterate over years*: Starting in year t with $r_{j,t-1}$ for each j and $\eta_{i,j_{i,t-1},t-1}$ for all i:
   (a) Compute skill prices using Equation 6.5
   (b) For each individual i:
      - Compute current idiosyncratic productivity: $\eta_{ijt} = y_{it} - r_{jt} - h_{it}$
      - Compute the current earnings residual: $\varphi_{ij,j_{i,t-1},t} = \eta_{ijt} - \rho^j_{j_{i,t-1}} \eta_{i,j_{i,t-1},t-1}$. Note that in the first period an agent works, $\varphi_{ij,j_{i,t-1},t} = \eta_{ij1}$.
4. *Compute objective*: Using Equation 6.4 by adding up $\varphi^2_{ij,j_{i,t-1},t}$

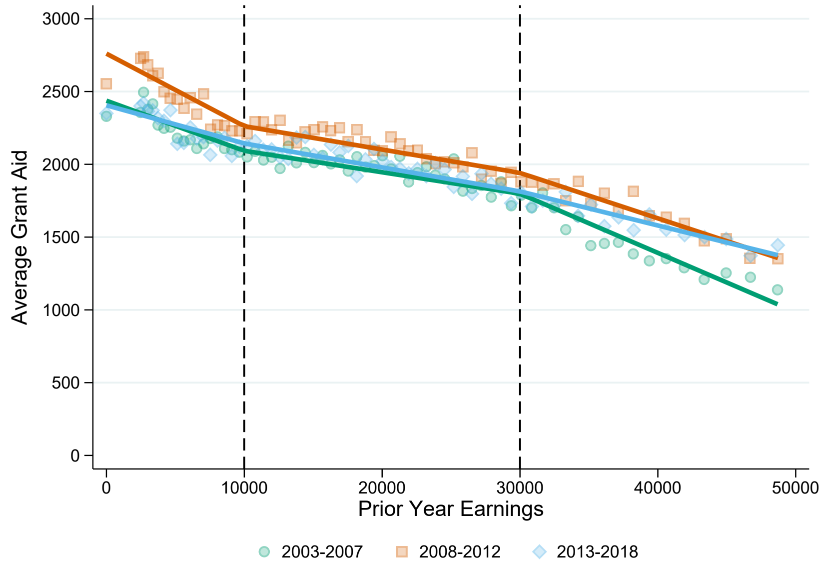
Estimates of choice-dependent variances of the shock process in terms of α_Y are:

$$\hat{\sigma}_j^{j-1}(\alpha_Y) = \sqrt{\frac{1}{N_{j,j_{-1}}} \sum_{(it) \text{ s.t. } j(k_{it})=j \text{ and } j(k_{i,t-1})=j_{-1}}^{N_{j,j_{-1}}} \left(y_{it} - y(k_{it} | \mathscr{H}_i^{-t}, q_i; \alpha_Y)\right)^2}$$

where the sum is over person-years working in industry j and $N_{j,j_{-1}}$ is the total ever working in j with activity j_{-1} at the start of the period. In practice, this is allowed to vary by the target industry j and by whether the individual remains in their current industry ($j(k_{it}) = j(k_{i,t-1})$), switches industries (voluntarily), or switches from non-employment (including an involuntary separation).

D.2 Estimated Financial Aid Schedules

Figure D3: Calibrated Financial Aid Schedules



D.3 Full Parameter Estimates

Table D1: Skill Weights, Skill Accumulation, and Match Accumulation Parameters: Π, Γ, and Ψ

	Skill 1	Skill 2	Skill 3	Specific Skill	Part-Time
A. Industry-Specific Return: $\pi_j^{(s)}$, $\alpha_j^{(\tau)}$, α_j^{PT}					
General	0.627	0.203	0.489	0.324	0.887
	(0.071)	(0.019)	(0.040)	(0.002)	(0.001)
Construction	0.561	0.136	0.470	0.311	0.887
	(0.065)	(0.020)	(0.040)	(0.003)	(0.001)
Manufacturing	0.601	0.212	0.463	0.320	0.887
	(0.069)	(0.018)	(0.039)	(0.002)	(0.001)
Health Care	0.647	0.190	0.232	0.328	0.887
	(0.069)	(0.018)	(0.034)	(0.002)	(0.001)
Services	0.672	0.069	0.484	0.361	0.887
	(0.072)	(0.014)	(0.041)	(0.002)	(0.001)
Financial	0.619	0.187	0.494	0.289	0.887
	(0.068)	(0.020)	(0.041)	(0.003)	(0.001)
Public Sector	0.608	0.173	0.220	0.344	0.887
	(0.061)	(0.019)	(0.032)	(0.002)	(0.001)
B. Learning-by-doing: $\gamma_{Work:j(k)}^{(s)}$					
Work in General	0.111	-0.051	-0.034		
	(0.010)	(0.009)	(0.005)		
Work in Construction	0.106	-0.148	-0.029		
	(0.010)	(0.025)	(0.007)		
Work in Manufacturing	0.088	-0.073	-0.015		
	(0.007)	(0.008)	(0.003)		
Work in Health Care	0.100	-0.040	-0.143		
	(0.009)	(0.010)	(0.011)		
Work in Services	0.050	-0.503	-0.028		
	(0.006)	(0.075)	(0.005)		
Work in Financial	0.065	-0.015	-0.011		
	(0.007)	(0.012)	(0.005)		
Work in Public Sector	0.105	-0.031	-0.137		
	(0.009)	(0.007)	(0.009)		
Work in Last Sector: $\gamma_{Accum}^{(\tau)}$				0.324	
				(0.002)	
C. Heterogeneity in Learning-by-doing: $\gamma_{Work:q}^{(s)}$					
D(Female-No College)	-0.014	-0.200	0.009		
	(0.003)	(0.034)	(0.004)		
D(Male-College)	0.023	0.021	0.008		
	(0.004)	(0.006)	(0.003)		
D(Female-College)	-0.012	-0.075	0.024		
	(0.003)	(0.012)	(0.004)		
D. Schooling: $\gamma_{School:f(k)}^{(s)}$					
Study in General	0.100	-0.198	-0.162		
	(0.022)	(0.069)	(0.028)		
Study in Technical	0.067	0.037	-0.031		
	(0.021)	(0.047)	(0.028)		
Study in Health Care	0.303	0.127	-0.963		
	(0.030)	(0.062)	(0.079)		
Study in Humanities	0.128	-0.001	-0.196		
	(0.021)	(0.052)	(0.036)		
Study in Business	0.116	-0.106	-0.043		
	(0.019)	(0.058)	(0.027)		
E. Heterogeneity in Schooling Returns: $\gamma_{School:q}^{(s)}$					
D(Female-No College)	-0.028	-0.141	-0.012		
	(0.021)	(0.060)	(0.033)		
D(Male-College)	-0.005	0.091	-0.052		
	(0.018)	(0.047)	(0.032)		
D(Female-College)	-0.009	-0.061	-0.032		
	(0.018)	(0.056)	(0.030)		
F. Other Accumulation Parameters:					
Depreciation: $\gamma_{Depr}^{(s)}$	0.032	0.000	0.007		
	(0.005)	(0.000)	(0.007)		
Diminishing Work Investments: $\gamma_{Dim:School}^{(s)}$, $\gamma_{Dim}^{(\tau)}$	1.189	0.000	0.051	0.311	
	(0.067)	(0.000)	(0.009)	(0.003)	
Diminishing School Investments: $\gamma_{Dim:School}^{(s)}$	2.005	1.983	0.001		
	(0.139)	(0.397)	(0.000)		
Loss from Voluntary Transition: $\gamma_{Vol}^{(\tau)}$				0.320	
				(0.002)	
Part-Time Share From Work: $\gamma^{PartTime}$					0.434
					(0.042)
G. Initial Conditions: $\gamma_{Z:1}^{(s)}$, $\gamma_{q:1}^{(s)}$					
D(General)	0.101	-0.003	0.022		
	(0.038)	(0.075)	(0.034)		
D(Construction)	0.318	0.147	0.052		
	(0.040)	(0.033)	(0.039)		
D(Manufacturing)	0.293	-0.417	0.172		
	(0.040)	(0.050)	(0.024)		
D(Health Care)	0.111	0.030	-0.030		
	(0.023)	(0.070)	(0.160)		
D(Services)	0.214	-0.141	-0.729		
	(0.054)	(0.083)	(0.117)		
D(Financial)	-0.081	0.088	-0.160		
	(0.071)	(0.069)	(0.070)		
D(Public Sector)	0.158	-0.043	0.404		
	(0.040)	(0.048)	(0.042)		
D(Female-No College)	0.478	0.339	-0.197		
	(0.051)	(0.041)	(0.046)		
D(Male-College)	0.154	0.377	-0.182		
	(0.038)	(0.042)	(0.046)		
D(Female-College)	0.088	-0.065	-0.207		
	(0.027)	(0.020)	(0.023)		

Table D2: Shock Process Parameters

	Remain	*EE Switch*	*EN Switch*	*Initial*
σ_j :General	0.275	0.399	0.643	0.487
	(0.001)	(0.002)	(0.002)	(0.003)
Construction	0.316	0.442	0.625	0.494
	(0.002)	(0.004)	(0.003)	(0.004)
Manufacturing	0.272	0.395	0.637	0.499
	(0.001)	(0.002)	(0.002)	(0.002)
Health Care	0.265	0.412	0.581	0.500
	(0.001)	(0.003)	(0.002)	(0.002)
Services	0.291	0.447	0.580	0.512
	(0.001)	(0.002)	(0.001)	(0.001)
Financial	0.255	0.379	0.578	0.438
	(0.001)	(0.003)	(0.003)	(0.003)
Public Sector	0.188	0.378	0.513	0.394
	(0.001)	(0.002)	(0.002)	(0.002)
ρ :	0.888	0.719	0.350	
	(0.001)	(0.002)	(0.003)	

Table D3: Choice Parameters

	Common	Difference: Female, No College	Difference: Male, College	Difference: Female, College
A. Action Utility: μ_q^k				
Work in General	-7.777	-0.047	0.064	0.013
	(0.279)	(0.013)	(0.010)	(0.013)
Work in Construction	-7.496	-0.324	-0.033	-0.329
	(0.276)	(0.013)	(0.011)	(0.013)
Work in Manufacturing	-7.539	-0.163	-0.054	-0.176
	(0.276)	(0.012)	(0.009)	(0.013)
Work in Health Care	-7.710	0.263	0.051	0.180
	(0.270)	(0.014)	(0.009)	(0.013)
Work in Services	-7.351	-0.035	-0.055	-0.137
	(0.265)	(0.010)	(0.009)	(0.012)
Work in Financial	-7.722	0.123	0.047	0.105
	(0.273)	(0.013)	(0.011)	(0.014)
Work in Public Sector	-7.492	0.019	-0.030	-0.020
	(0.272)	(0.014)	(0.010)	(0.013)
Study General	-3.308	-0.241	0.581	0.580
	(0.052)	(0.106)	(0.029)	(0.026)
Study Technical	-3.716	-1.439	0.452	-0.674
	(0.053)	(0.105)	(0.026)	(0.027)
Study Health Care	-3.536	-0.199	0.716	0.819
	(0.068)	(0.138)	(0.038)	(0.038)
Study Humanities	-4.534	-0.297	0.857	1.065
	(0.058)	(0.104)	(0.027)	(0.030)
Study Business	-4.264	-0.134	0.809	0.878
	(0.057)	(0.106)	(0.028)	(0.030)
Part-Time Study	0.547	0.593	-0.262	-0.074
	(0.039)	(0.094)	(0.016)	(0.022)
Full-Time Work $\times(\text{Age}-30)$	-0.006	-0.022	0.010	-0.005
	(0.003)	(0.001)	(0.001)	(0.001)
Full-Time Work $\times(\text{Age}-30)^2$	0.001	0.002	-0.000	0.001
	(0.000)	(0.000)	(0.000)	(0.000)
B. Elasticities:				
Preference for Log-Income: β_Y	0.738			
	(0.024)			
Sensitivity to Net Tuition: β_P	0.467			
	(0.016)			
C. Switching Costs: κ				
Origin: Non-Employed	1.401	0.011	0.053	0.056
	(0.007)	(0.002)	(0.001)	(0.002)
Origin: Employed	1.244			
	(0.004)			
Great Recession: Non-Employed	0.017			
	(0.001)			
Great Recession: Employed	0.058			
	(0.000)			
Target: Construction	0.227			
	(0.004)			
Target: Manufacturing	-0.012			
	(0.004)			
Target: Health Care	-0.064			
	(0.005)			
Target: Services	-0.359			
	(0.005)			
Target: Financial	0.100			
	(0.006)			
Target: Public Sector	0.092			
	(0.004)			
From Schooling	-0.301			
	(0.006)			
Into Schooling	0.396			
	(0.003)			