Reskilling, Upskilling, and the Role of Education in the Adjustment to Economic Shocks

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Abstract

One way workers can adapt to adverse shocks after entering the labor market is by returning to school later in life, a choice involving substantial opportunity costs in terms of foregone earnings and lost work experience. This paper uses administrative data on earnings and enrollment histories to estimate a dynamic model quantifying these tradeoffs. I first exploit variation from the Great Recession to show that adult workers respond to industry-level shocks by increasing community college enrollment, with heterogeneity across fields of study and industries playing a key role in driving enrollment. The model unpacks what these patterns imply for policies intended to increase worker earnings, such as targeted tuition subsidies. A key contribution of the framework is that it flexibly quantifies multidimensional skills using a data-driven approach, capturing interactions between fields of study and career pathways. A counterfactual tuition subsidy increases enrollment but results in returns that are negative on average, with substantial heterogeneity. Decomposing these returns emphasizes the importance of on-the-job work experience and aligning education with desired career transitions in the design of retraining policies.

Keywords: community colleges; retraining; fields of study; skill transferability; Great Recession
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1 Introduction

Education and career choices are made with uncertainty about future labor market conditions, potentially leaving some workers vulnerable to changes in the economy. 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] Studies of displaced workers (Jacobson et al. [1993]), recessions (Yagan [2019]), and exposure to import competition (Autor et al. [2014]) all find that the effects of such shocks persist throughout a worker's career. Policymakers seek to help impacted workers by promoting investments in training and reskilling programs[2] — most of which takes place at community colleges — as a means by which workers may adapt to economic change. This is a salient channel for many people: in 2018, 3.1 percent of U.S. adults between the ages of 30 and 55 were enrolled in public higher education.[3]

However, evidence on the earnings impacts of such training for adult workers remains mixed (Heckman et al. [1999], McCall et al. [2016], Card et al. [2018]), including in experimental evaluations (e.g. Fortson et al. [2021]). Even when positive effects are found, there is substantial heterogeneity across individual and program characteristics, with some benefiting workers while others do not (Jacobson et al. [2005], Jepsen et al. [2014], Stevens et al. [2019]). The payoff to training depends not only on whether workers return to school, but on what they study. At the same time, several studies show that human capital is multidimensional and that the imperfect transferability of skills is a key determinant of the incidence of labor market shocks (Neal [1995], Parent [2000], Gathmann and Schoenberg [2010]). When old skills do not transfer easily to new kinds of work, the benefits of later-life schooling likely depend on how newly acquired skills interact with desired work transitions. Understanding this interaction is essential for making sense of heterogeneous returns and tailoring policy to better align with workers' skills and career paths.

This paper studies who gains and who loses from later-life human capital investment, with the goal of identifying how retraining policies can be better targeted towards workers with the highest earnings gains. I focus on adult workers in Texas, for whom I have administrative data on

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

[2] A large share of training efforts in the United States operate through community college programs. Support at the federal level is provided via training accounts by the *Workforce Innovation and Opportunity Act* (*WIOA*), the *Trade Adjustment Assistance* (TAA), and formerly the *Trade Adjustment Assistance Community College and Career Training* (U.S. Department of Labor, Employment and Training Administration). See McCall et al. [2016] for a review of government-sponsored training programs in the United States and other countries. More recently, President Donald Trump's *AI Action Plan* recommends funding "rapid retraining for individuals impacted by AI-related job displacement" and the "integration of AI skill development into relevant programs, including career and technical education (CTE), workforce training, apprenticeships, and other federally supported skills initiatives." (White House [2025], U.S. Department of Labor [2025]).

[3] 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 ACS sample to Texas, the 30 to 55 enrollment rate increases to 3.5 percent, which is in line with the administrative data.

earnings and enrollment histories, and on one particular shock that triggered substantial reskilling — the Great Recession. Methodologically, I develop a novel empirical framework that models the heterogeneous returns to later-life education in terms of multidimensional skills. This approach captures complementarities between fields of study and work experience, linking the return to training to past and future career paths. The model is rich and carefully tailored to match patterns of selection that have been documented as important in the training literature (Heckman et al. [1999], McCall et al. [2016]). Using the framework, I ask: which workers take up and benefit from training through the public post-secondary education system? 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 such a policy to maximize earnings?

I begin the paper by documenting that students select into particular fields of study based on their prior work experience. Workers from the health care sector make up only 3.2 percent of enrollment in vocational technical degrees (e.g. welding) while making up 41.8 percent in health-related fields (e.g. nursing). Women are also nearly twice as likely as men to pursue community college training. I estimate returns to enrollment using matching estimators based on pre-enrollment earnings trajectories, finding low returns but substantial heterogeneity by fields of study and degree receipt. To examine how this heterogeneity drives responses to labor market shocks, I use an event study design that compares changes in enrollment between observably similar, narrowly-defined industries that are differentially exposed to the employment losses of the Great Recession. Workers in more negatively shocked industries respond by pursuing community college education: a one standard deviation increase in an industry's exposure to Great Recession employment losses increases the probability of enrollment by 0.37 percentage points, a 7.1 percent increase relative to the 2007 baseline. I find that workers from professional industries (e.g. finance and real estate) are most responsive to the shock. Moreover, about 40 percent of the overall enrollment effect is driven by enrollment in health-related fields, largely driven by workers reskilling from outside the health care industry.

This empirical evidence emphasizes the importance of community college training as a channel of worker adjustment and highlights both prior experience and fields of study as drivers of enrollment decisions. However, it has little to say about policy or which workers benefit most from this channel. To address this gap, I develop and estimate a partial equilibrium framework that quantifies the tradeoffs a worker faces in deciding to return to school. Relative to the empirical evidence, the model has two contributions. First, it quantifies the earnings gains from later-life schooling in terms of imperfectly transferable skills, measuring the specificity of human capital investments. Second, it predicts how choices respond under counterfactual environments, linking

the take-up of training with the earnings gains associated with uncertain future career pathways. A key feature of the framework is that I model human capital as a weighted sum of skills in the spirit of Lazear [2009], where an individual's time-varying skills receive industry-specific weights and evolve through choices of industry of employment and field of study. This structure allows workers to have comparative advantage across industries based on prior experience, which further shapes the gains from both fields of study and future work transitions. Agents differ in their preferences over industries and fields of study and dynamically respond to multiple sources of uncertainty — including job loss, persistent on-the-job earnings shocks, and aggregate changes in labor market frictions, policies, and industry conditions associated with the Great Recession.

Estimation of the skill process leverages the panel structure of administrative earnings data to quantify how a sequence of career and education decisions maps into earnings. The model directly incorporates mechanisms that can generate Ashenfelter [1978]-dip dynamics, such as job loss and on-the-job shocks to earnings. The crucial identifying assumption is that individuals do not select on within-period changes in the persistent error term in the earnings equation, conditional on the state defined by the model. The approach is conceptually related to AKM-style models (Abowd et al. [1999], Card et al. [2013]), dynamic frameworks such as Bonhomme et al. [2019], and matching estimators using lagged earnings trajectories that are often used to evaluate training programs (Heckman et al. [1998a], Dehejia and Wahba [1999]). This timing assumption aids greatly in tractability, permitting a two-step estimation procedure. It also delivers testable implications, as future choices should not affect current period earnings when conditioning on a model-implied state. The results of these tests indicate that the potential for residual bias appears to be limited. The model also replicates earnings trajectories around hard-to-match job separation and enrollment events, providing additional validation of the model.[4]

The results impart important lessons about the interaction between the labor market and later-life education. First, all else equal, returns from studying health have the potential to be high but are mostly relevant only 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 few gains 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 dy-

[4]My model allows for match effects based on observed work histories as well as for 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] which relaxes the assumption in Abowd et al. [1999] (AKM)-style analysis that workers do not sort on match effects. My framework differs from Bonhomme et al. [2019] in that it allows the entire past history of industry and schooling choices (and one lag of earnings) to affect current earnings but does not consider unobserved types. 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 trajectories (Heckman et al. [1998a], Dehejia and Wahba [1999], Card et al. [2018]).

namics. 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 relative to women. Fourth, I estimate large costs of switching sectors that are in line with the literature, but 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 (Adda and Dustmann [2023], Deming [2023]). Finally, workers are quite sensitive to price changes, even at the low levels of tuition seen in the data.

Counterfactual tuition subsidies show that workers are responsive to changes in tuition, but that training is not effective in raising earnings for the average worker at the margin of enrollment. However, these average effects mask substantial underlying heterogeneity. Specifically, I model the effects of a hypothetical surprise $1,000 reduction in the cost of community college that coincides with the onset of the Great Recession and decompose the returns to community college education. I find that this subsidy results in an increase in annual enrollment of 0.8 percentage points but an average earnings loss of 3.8 percent for those induced to enroll. Only 22.9 percent of those induced to enroll see earnings gains under the counterfactual.[5] Using the model to unpack this result indicates that those who gain would have experienced long periods out of work in the absence of the subsidy. By contrast, those who experience losses tend to be characterized by failed reskilling — these workers are induced by the subsidy to move out of their baseline sector but fail to see earnings gains from training. These losses are 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 imperfect transferability of skill investments — that some training is only relevant for certain industries — magnifies the negative effects from failing to secure a job in a target industry. In particular, despite having the highest potential earnings growth, subsidizing health care studies fares the worst in terms of earnings gains due to specificity of its skill investments.

Taken together, these results indicate that *training is no substitute for on-the-job work experience* and emphasize the important interaction between education and work transitions. Reskilling is potentially detrimental if it does not translate into a relevant job, which is especially true when

[5] A natural question is why forward-looking agents return to school if they experience negative average returns. Within the structure of my model, this will be driven by the estimates of the tuition elasticity and workers' preferences for schooling. These parameters could capture that workers are misinformed about the earnings value of college and would not go if they had better information (Jensen [2010], Hastings et al. [2015]). Alternatively, they could also reflect that schooling has returns not measured by earnings alone, such as an amenity value of studying. This paper focuses on a positive analysis of the distributional effects of community college training. It does not attempt to assess welfare or address inefficiencies that may justify government involvement. In this framework, lowering prices can only make people "better off" even if they see earnings declines.

acquired skills are highly specific. At the same time, this means that the population most likely to benefit from training is that which faces substantial difficulty returning to work and thus lose out on valuable on-the-job experience.

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]) and persist for up to 15 years (Schmieder et al. [2023]). It has long been a source of concern that individuals, especially low-skill workers, do not typically adjust by moving across labor markets in response to demand shocks (Bound and Holzer [2000], Yagan [2019]). It may also be that workers face substantial earnings penalties when making transitions to new types of work (Neal [1995], Parent [2000], Gathmann and Schoenberg [2010]), potentially hindering their ability to adjust to changes in labor demand. Given the evident difficulty that low-skill workers face in adjusting to shocks, training 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]). 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 technological change.[6] 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 also relates to the substantial literature on the return to later-life education, both in terms of active labor-market programs and community college training. Evaluations of government-sponsored training programs generally find mixed average effects with substantial heterogeneity by program type and participant characteristics [Heckman et al., 1999, McCall et al., 2016, Card et al., 2018].[7] Studies of community colleges tend to find positive but similarly heterogeneous

[6]Conversely, Charles et al. [2018] and Schanzenbach et al. [2023] find that enrollment declines in response to positive shocks to outside options, which is especially salient for the community college margin. A related literature shows that exposure to high unemployment at first-time enrollment causes individuals to select into different fields of study (Blom et al. [2021]). 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. [2016] 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.

[7]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

returns to degree receipt, typically using non-completers as comparisons for graduates (Jepsen et al. [2014], Belfield and Bailey [2017], Stevens et al. [2019], Minaya and Scott-Clayton [2020]).[8] Related research that focuses on displaced or unemployed workers – such as Jacobson et al. [2005] and Leung and Pei [2020] – finds positive effects but with some types of training having zero effect. Positive returns tend to be related to increased employment and post-enrollment industry switching. My framework builds on this literature by modeling the mechanisms behind these heterogeneous effects and the selection into post-schooling careers.

Finally, this paper contributes to an extensive literature that models selection into education (Willis and Rosen [1979], Heckman et al. [2018]) and life-cycle skill accumulation (Keane and Wolpin [1997], Keane et al. [2011]). Work on selection into schools for K-12 students (Walters [2018]) and college majors (Arcidiacono [2005]) shows that the type of person enrolling is an important driver of observed returns. Research has considered whether returns to college major are general or specific (Kinsler and Pavan [2015], Eckardt [2022]),[9] finding that high-return education choices are sometimes specific to certain types of work. This paper also relates to the life-cycle accumulation of specific skills (Roys and Taber [2019], Lise and Postel-Vinay [2020]). Applications of these models have shown that specific human capital determines the incidence of shocks, especially in the context of trade exposure (Dix-Carneiro [2014], Traiberman [2019]) or business cycles (Huckfeldt [2022], Grigsby [2022]).[10] Most related to this paper, Adda and Dustmann [2023] evaluate the return to early-life apprenticeships in Germany using a life-cycle model with multiple skills, finding complementarities between training and later on-the-job wage growth. However, no paper to my knowledge has focused such a model on the decision to *return* to school for mid-career workers.

The paper is organized as follows. Section 2 outlines data and motivating facts concerning enrollment in my sample and context. Section 3 examines how the Great Recession shock impacts enrollment choices for adult workers. Section 4 outlines the model of work and schooling choices. Section 5 discusses identification and the estimation approach. Section 6 presents model fit and key implications of the parameter estimates. Section 7 presents counterfactual exercises. Finally,

target in-demand sectors and provide assistance with job development and placement, show large positive effects (Katz et al. [2022]).

[8] Recently, Mountjoy [2022] uses the same administrative data from this paper in combination with a distance-based marginal treatment effect approach to estimate positive but highly heterogeneous returns, the latter pattern mirroring results from this paper. However, his analysis focuses on initial college enrollment. See also Kane and Rouse [1995] for an early evaluation of the returns to community college credits.

[9] See also Lemieux [2014] or Leighton and Speer [2020] for additional empirical evidence on the interaction between fields of study and the occupational specificity of skills.

[10] A related literature considers the process by which students learn about fixed but potentially multidimensional skills. See Miller [1985], Neal [1999], Papageorgiou [2014], Sanders [2014], Guvenen et al. [2020]. Most recently, Arcidiacono et al. [2024] embed these learning mechanisms in a dynamic model with initial post-secondary education investments. As the focus of this paper is on how adult workers adjust their known skills, I abstract from these learning considerations.

Section 8 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.[11] The THECB enrollment data comprise all Texas public colleges (from 1992 onward) and private non-profit colleges (from 2003 onward).[12] 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 colleges so as not to exclude short programs offered at traditionally 4-year colleges that may be similar to 2-year programs, although my focus on lower-skill workers results in more than 80 percent of enrollment in my baseline sample occurs at public 2-year institutions. 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.[13] Earnings are deflated to 2019 dollars and winsorized at the 99.9th percentile. The data contain granular measures of

[11] I am unable to use the distance-based variation from Mountjoy [2022] as adult workers move from their initial high school location within Texas, resulting in this instrument having little relevance as workers age.

[12] The analysis omits for-profit institutions. While an important focus of policy due to their high cost and rapid growth, publicly available data show that these programs account for a minority of adult enrollment and especially so in Texas. My calculations from the ACS show that the enrollment rate for those aged 30 to 55 in Texas in 2009 (which includes those attending graduate school) is 4.94 percent compared to 3.46 percent for public college enrollment, indicating that public institutions account for 76.7 percent of overall enrollment (for the whole U.S., this share is 70.0 percent). However, the ACS only distinguishes between private and public enrollment, and cannot separate 2-year and for-profit enrollment. Using the Integrated Post-secondary Education Data System (IPEDS) for those over the age of 25 in 2009 in Texas indicates that 2-year public colleges account for 56.6 percent of enrollment, 4-year public colleges account for 31.4 percent, for-profits account for 5.1 percent of enrollment, with the remainder being private not-for-profits.

[13] Missing earnings in UI data could indicate out-migration, working in jobs not covered by UI, or that the individual is out of the labor force. Fortunately, Texas is a state with the lowest out-migration rate of any state (Aisch et al. [2014]). Foote and Stange [2022] use cross-state earnings data to show that this results in minimal out-migration bias in estimates of college earnings premia in Texas. I later make several sample restrictions to further address these concerns and ensure my analysis is interpretable as conditional on the sample of low-skill workers with some attachment to the Texas labor market over the entire analysis period. I also compare the representatives of my baseline sample to the same cohorts born in Texas in the American Community Survey in Appendix Figure B.1. 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]).

industry of employment, which I aggregate into 5-digit North American Industry Classification System (NAICS) codes after some harmonization across years.[14] Additional details on data construction are provided in Appendix Section B.2.

2.2 Aggregate 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 A.8 reports the complete counts over various subgroups.[15]

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.*[16] 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.

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 higher magnitude than men. 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 specialization through different fields matters for these adult enrollees and shapes 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), which make up about half of total enrollment in 2007-

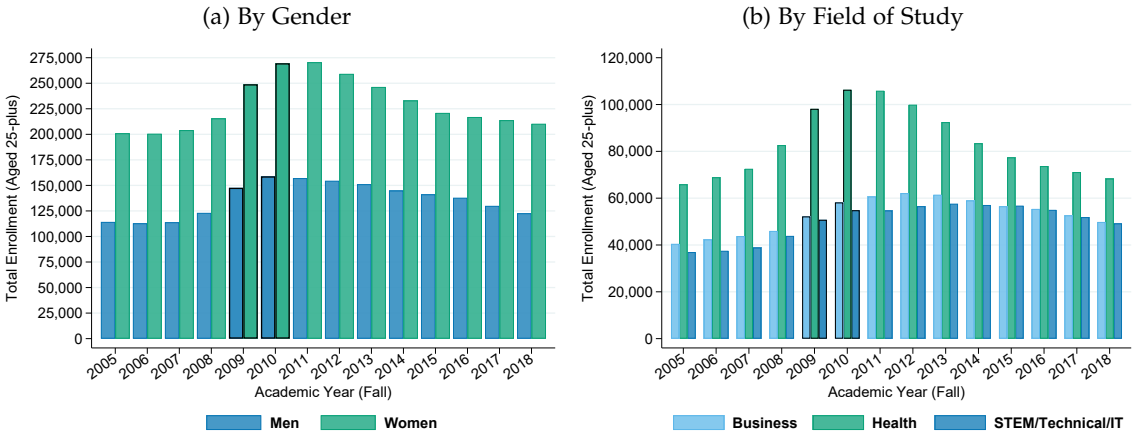
[14] The data do not contain firm, establishment, or unemployment insurance account information.

[15] Age 25-plus enrollees account for 34 percent of total enrollment in 2007-2008 (317,958 out of a total of 935,455). 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, meriting a focused study. See Barr and Turner [2013] for an excellent summary of the overall impacts of the Great Recession on American higher education more generally.

[16] The official dates of the Great Recession are between December 2007 and June 2009. However, there was a significant delay for the financial crisis to hit the labor market. Unemployment first rose above 5 percent in April 2008 and did not peak at 10 percent until October 2009. It also 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.

2008. Health degrees account for a large share of total enrollment: 22.8 percent of the total in 2007-2008 (72,548). They are also highly cyclical, increasing 46.5 percent to 106,289 in 2010-2011 before returning to low enrollment levels in 2017-2018 (71,112). Business and STEM[17] 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.[18]

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



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 and their aggregation into broad fields is outlined in Appendix B. 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 A.8 for complete results.

2.3 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 restrict to 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 that has 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 baseline sample is restricted to the 1994 to 1998 cohorts of Texas high school graduates who never attain advanced education degrees. These individuals are aged 29 to 33 in 2009 and 39 to 43 at the

[17]STEM is defined for this figure as combining Math/Engineering, Vocational Technical, and Information Technology fields. Field shares are broken out into more detail on my analysis sample in Figure 2.

[18]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).

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. The nature of the data is that I do not observe demographic information for individuals who neither enroll in the college nor K-12 system. 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 B.1 and comparisons with the American Community Survey are shown in Figure B.1.

2.4 Descriptive Patterns of Selection by Industry and Field of Study

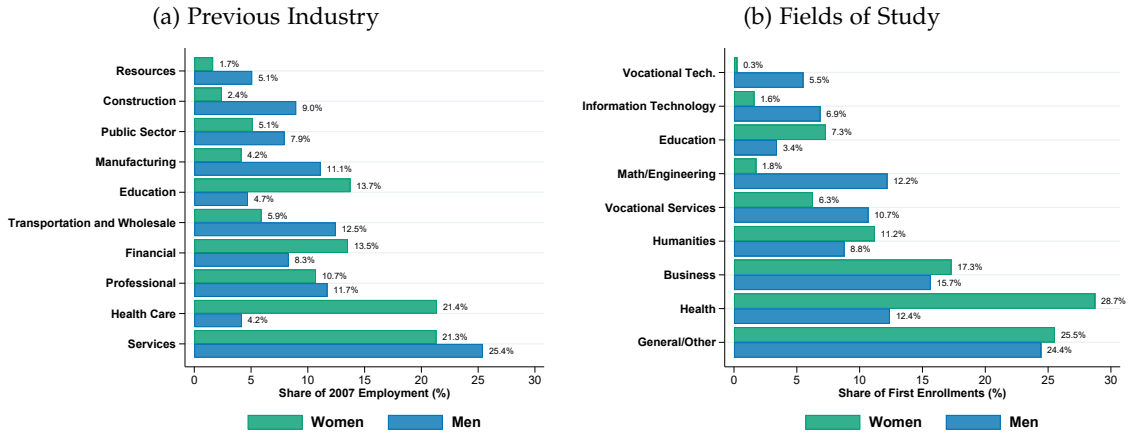
In Figure 2, I summarize the distributions of fields of study and industries of employment in the baseline sample, broken out by gender. A person's field of study is the field associated with their first enrollment spell begun after age 25. Industry is based on 2007 employment.

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 more likely to study health care than men and men are 6.9 times more likely to study math/engineering.

Selection into Field of Study by Prior Industry: *Table 1 shows that pathways from work to school depend 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.[19] While health care workers comprise 41.3 percent of enrollment in health fields, only 3.2 percent of enrollment in vocational technical fields and 4.7 percent in math/engineering comes from health care workers. In the latter two fields, workers from manufacturing make up 18.1 and 17.0 percent of enrollment, respectively. These numbers rise to above 40 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 reskilling and upskilling 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

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

Figure 2: Field of study and industry shares of enrollment



Notes: Both figures are computed on the baseline sample of $N = 247,973$. See Appendix Table B.1 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 B for details on how fields of study and industry codes were aggregated.

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 upskilling 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 (%)	Primary Industry (%)	Graduate (%)	Switch if Grad. (%)
A. By Field of Study						
General/Other	Health Care	17.4	36.6	18.6	6.5	38.9
Business	Financial	19.1	37.2	18.5	27.1	39.3
Humanities	Financial	12.6	43.2	9.6	41.4	49.8
Math/Engineering	Manufacturing	17.0	46.9	22.9	31.2	58.0
Health	Health Care	41.3	41.4	54.6	36.2	47.2
Vocational Tech.	Manufacturing	18.2	52.0	19.0	37.8	60.5
Vocational Services	Public Sector	31.8	41.2	37.9	32.4	47.6
Education	Education	40.5	33.8	50.6	13.8	47.8
Information Technology	Professional	17.8	42.6	19.4	25.9	44.6
B. By Overall Enrollment						
Non-Enrollee			30.5			
Enrollee			39.8		25.4	46.9

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 enrollment 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. Graduation is defined as receiving a degree within 5 years of enrollment.

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.* 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.[20] Some fields tend to be associated

[20]Comparing differences in these switching rates indicates that most is due to these large 1-digit industry changes. The

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 switch 5-digit industries. In contrast, for those studying vocational technical degrees, 52 percent will switch 1-digit industries.

Finally, there is an overall low probability of degree receipt within four years of enrollment, with an overall rate of 25.4 percent. The results on switching industry strengthen when looking at graduates, suggesting a link between degree receipt and post-industry switching. This pattern shows differences by field, with education showing the largest increase in switching for graduates but business and IT showing only modest differences.

2.5 Heterogeneity in the Observational Returns to Fields of Study

I now characterize how these patterns relate to earnings using simple matching estimators to construct an observationally identical comparison worker for each enrollee. Prior work shows that matching estimators using rich pre-treatment earnings trajectories can replicate experimental benchmarks (Heckman et al. [1998a], Dehejia and Wahba [1999]). I implement nearest-neighbor Mahalanobis matching to account for potentially heterogeneous treatments by year of enrollment, field of study, and future degree receipt. Details and additional results are provided in Appendix Section B.3.

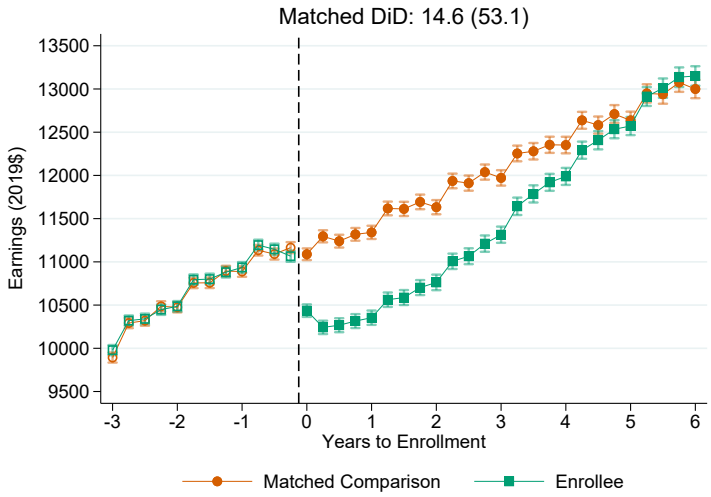
Figure 3 displays earnings trajectories for enrollees and matched comparisons, showing that there appears to be limited earnings gains on average. Enrollees and comparisons have overlapping earnings prior to enrollment, with enrollee earnings dropping sharply upon enrollment by about $500 (what is known as the "lock-in" effect). Over the course of the next six years, earnings between these two groups converge as enrollees catch up. The matched differences-in-differences estimate at six years post-enrollment, using two years pre-enrollment as the baseline, is an insignificant $14 (53.1) increase in earnings for enrollees.

While earnings impacts appear low on average, Table 2 shows there is substantial heterogeneity by field of study and degree receipt. The first column of panel A shows baseline earnings results. However, the rows in panel B show large differences by fields of study, where math/engineering, business, and health show earnings gains. Most other fields have returns that cannot be distinguished from zero, with general/other and humanities having negative returns.

There is also a large return to degree receipt, whose benefit differs by field of study. The third column shows degree receipt is associated with a $1,167 (114) increase in earnings relative to the comparisons, while enrollment without receiving a degree is associated with a $296 (60) earnings loss.

comparable numbers for 5-digit switching are 60 percent for enrollees and 48.5 percent 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.

Figure 3: Matching Estimates of Enrollment Effects



Notes: Plots total quarterly earnings, including zeros, for enrollees and matched comparisons in the baseline sample. See Appendix Section B.3 for details on the matching procedure and additional results.

The results across panel B show this is an important mediator for the fields observing positive returns. However, graduating with a health degree is associated with a $2,088 premium. However, enrolling in health without graduation is associated with a $501 penalty.

Finally, graduation is associated with a large increase in the probability of switching industries, mirroring patterns from Table 1. Graduates are 14.2pp more likely to switch on average, a very large increase relative to the non-graduate switching rate of 4.4pp and the switching rate of 39.8 percent reported in Table 1. This increase in switching shows some differences across fields, but is almost always much larger for graduates.

The structural model outlined in Section 4 will decompose these patterns into underlying skill components and modeling choices to identify responsiveness to policy. Although the framework does not explicitly incorporate graduation, its role should be kept in mind for interpreting results relating to post-schooling industry switching.

3 The Impact of the Great Recession on Adult Schooling Choices

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 one 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 existing literature on economic shocks and schooling decisions (e.g., Betts and McFarland [1995], Barrow and Davis [2012], Foote and Grosz [2019], Boustan et al.

Table 2: Heterogeneity in Matching Estimates by Field of Study and Graduation

	All		*Graduate within 4 years*			*Non-graduates*		
	Earnings	Employed	Earnings	Employed	Switch	Earnings	Employed	Switch
A. Unconditional								
All	14.6	-0.020***	1167.2***	-0.008*	0.142***	-295.5***	-0.023***	0.044***
	(53.1)	(0.002)	(113.9)	(0.004)	(0.008)	(59.8)	(0.002)	(0.004)
B. By Field of Study								
General/Other	-339.8***	-0.022***	557.2	-0.011	0.061*	-389.4***	-0.022***	0.031***
	(105.8)	(0.004)	(476.1)	(0.018)	(0.033)	(108.5)	(0.004)	(0.007)
Business	253.1*	-0.013***	754.0***	-0.009	0.124***	105.5	-0.014***	0.022**
	(131.0)	(0.005)	(253.0)	(0.009)	(0.021)	(152.2)	(0.005)	(0.011)
Humanities	-340.5**	-0.033***	231.9	-0.028***	0.142***	-654.6***	-0.035***	0.015
	(149.8)	(0.006)	(281.0)	(0.011)	(0.020)	(172.9)	(0.007)	(0.013)
Math/Engineering	1667.6***	-0.014*	4280.2***	-0.003	0.258***	772.1**	-0.018**	0.081***
	(333.4)	(0.008)	(599.0)	(0.014)	(0.037)	(393.1)	(0.009)	(0.021)
Health	239.2**	-0.025***	2088.7***	0.004	0.131***	-501.2***	-0.036***	0.066***
	(107.4)	(0.004)	(194.1)	(0.007)	(0.014)	(126.8)	(0.005)	(0.009)
Vocational Tech.	-16.8	-0.005	900.0	0.007	0.280***	-588.5	-0.012	0.092**
	(612.1)	(0.015)	(841.4)	(0.025)	(0.051)	(843.2)	(0.019)	(0.042)
Vocational Services	-132.1	-0.020***	-20.2	-0.025**	0.160***	-178.0	-0.018***	0.073***
	(157.0)	(0.006)	(269.6)	(0.010)	(0.023)	(191.8)	(0.006)	(0.014)
Education	-168.1	-0.008	119.6	0.024	0.203***	-194.8	-0.011	0.060***
	(149.6)	(0.007)	(514.0)	(0.032)	(0.049)	(156.4)	(0.007)	(0.013)
Information Technology	-496.3	-0.000	771.1	0.019	0.039	-861.4**	-0.006	0.028
	(364.8)	(0.009)	(655.0)	(0.019)	(0.046)	(429.4)	(0.010)	(0.023)

Notes: Presents difference-in-differences estimates of the return to enrollment. Graduates and non-graduates reflect whether the enrollee received any certificate within four years of enrollment. Switching is defined at the 1-digit level. See Appendix Section B.3 for details on the matching procedure and additional results. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[2022], Minaya et al. [2023]), leveraging the administrative data to probe 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 in the raw TWC data. I get similar results when defining exposure using data on sectoral employment outside Texas from the Statistics of U.S. Businesses, shown in Table A.10. An individual's exposure is defined based on their 5-digit industry of employment in 2007:Q4.[21]

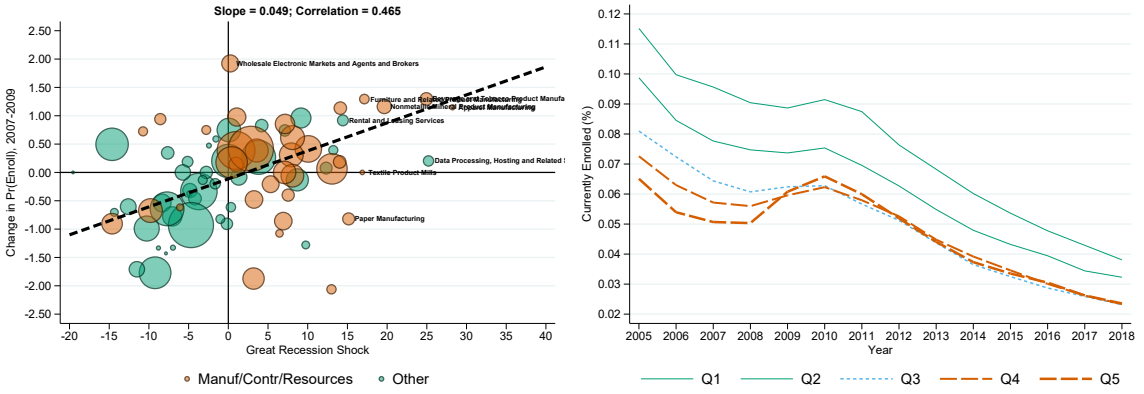
Figure 4 shows that industries that are more exposed to the Great Recession see increases in the rate of enrollment. This figure plots the raw variation of the exposure measure, aggregating up to the 3-digit NAICS-level. In particular, a 10 percentage point increase in exposure to the Great Re-

[21] To ensure attachment to this industry and a sufficient earnings history to define control variables, I restrict the analysis sample to 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 described in the sample restrictions exhibited in Appendix B.2.

cession is associated with about a 0.49 percentage point increase in the probability of enrollment. Sectors associated with manufacturing, construction, and resource extraction are especially hard hit, shown in orange.

Figure 4: Enrollment and Industry-Level Employment Shocks from the Great Recession

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



Notes: Both panels use data from the baseline sample. 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.

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 4, which plots enrollment rates by quintile of the shock measure, showing that the least shocked industries have higher baseline enrollment. Nevertheless, severely shocked industries have a clear break in trend driven by marked increases in enrollment. 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 are on similar trends in the absence of the Recession, comparing within-industry changes among similar individuals and industries. I also conduct several alternate analyses in the appendix, showing my findings that parallel trends likely hold and the findings are robust.[22]

[22]These results are shown in Table A.10. Specifically, I conduct a placebo analysis in the full sample assessing Great Recession exposure for baseline industry defined in 1997, showing that parallel trends are likely to hold. I also use an exposure measure using data on sectoral employment outside Texas from the Statistics of U.S. Businesses. I also use the

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

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 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 during pre-Recession years.

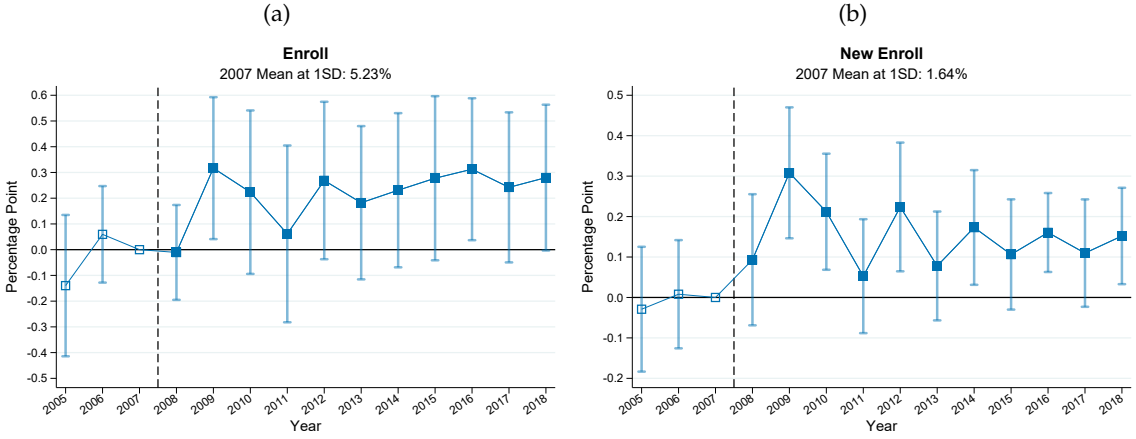
Enrollment Effects: *Figure 5a shows that individuals working in shocked industries look similar in terms of enrollment rates before the Great Recession and then increase enrollment after the start of the downturn.* A 1 standard deviation increase in exposure causes a 0.37pp increase in the probability of enrollment in 2009, representing a 7.1 percent increase off these shocked industries' baseline enrollment rates (measured at a 1 standard deviation).[24] 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 A.9.[25]

main sample to assess impacts on three-year industry transition probabilities, displayed in Appendix Figure A.17, where the transition probability is redefined relative to an industry in every year.

[23]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.

[24]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 industry experiences a 1.7 percent decline in employment with

Figure 5: Industry-Level Exposure Shock Event Study Results



Notes: Plots coefficient estimates of δ_y in Equation 3.1 and 95 percent confidence intervals, 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 industry 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 A.9 for point estimates and additional results.

New Enrollment Effects: *Figure 5b shows strong effects on new enrollment in exposed industries, indicating 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 or a 20 percent increase. Comparing to the overall enrollment effect, these results indicate that 90 percent of the increase in enrollment is made by new enrollees (0.33/0.37) rather than extending enrollment. These effects persist after the Recession ends as well.

Other Results: Looking at other outcomes reported in Appendix Table A.9, I find significant effects on graduation but only in 2010, indicating that some enrolling individuals complete degrees but not in large numbers. These qualitative 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 an exposure measure defined using

a standard deviation of 15.2 percent.

[25] Appendix Table A.9 also shows that the exposure measure captures deteriorating earnings 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.

employment losses outside of Texas. These results are shown in Appendix Table A.10.

3.3 Heterogeneity by Industry and Field of Study

Table 3 shows heterogeneity in responsiveness to shocks from the Great Recession by outcome and 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 A.12, exhibit similar magnitudes but are often imprecise at this granularity.

Heterogeneity by Industry: *Panel A of Table 3 shows that industry groups differ in their enrollment responses to the shocks of the Great Recession, with professionally-oriented industries being the most responsive.* This panel reports results that subset the sample to compare industries within the same broad category that differ in Great Recession exposure. Professional sectors (which include financial services and real estate) increase enrollment rates by 0.42 percentage points (or 10.5 percent off of the baseline for this group). Manufacturing and other 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 3 examines heterogeneity by field of study, showing that by far the biggest enrollment increase comes from health-related fields.* In this panel, columns indicate changes in the outcome into different fields of study. Enrollment in health increases by 0.094pp 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 highly-shocked industries. Comparing to the overall enrollment effect of 0.245pp in this sample (which combines 2009 and 2010) indicates that health studies account for 38 percent of the total enrollment effect. While imprecise, the comparable number for the baseline sample is a 0.136pp increase in health (a 48.2 percent effect). When looking at other fields of study, we see that all fields somewhat increase enrollment in response to the shock, with business and vocational services showing the largest responsiveness in both samples.

Heterogeneity by Field-Industry Pairs: *Looking at the interaction between field and industry shows that many workers use this as an opportunity to upskill while others use this as an opportunity to reskill, with the reskilling effect driven by moves into health care.* Appendix Table A.11 and Appendix Table A.12 report a full breakdown by industry and field of study combinations for the full and estimation sample, respectively. The response of production-oriented industries to studying health is large, representing 22 percent of the overall enrollment 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 for production workers 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. These latter results indicate selection into fields on the basis of past work experiences, suggesting upskilling at the same time as reskilling.

Table 3: 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. A complete breakdown of outcomes by industry groups reported in Appendix Table A.11 for the full sample and in Appendix Table A.12 for the baseline sample. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4 A Model of Adult Labor Supply and Schooling Choices

The results so far show that fields of study and past work experience play an important role in how workers respond to the shock of the Great Recession. While highlighting the importance of training and suggesting the multidimensional nature of human capital, 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 in those transitions. In order to shed light on these issues, I outline a structural model of a worker's joint choice of industry, 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 decomposition of life-cycle earnings. By incorporating dynamics, the model endogenizes the full pathway taken by workers.

Preliminaries: In each year t, individual i makes a choice $k \in \{1, ..., K\}$ in order to maximize their present discounted value of lifetime utility, which includes both earnings and non-pecuniary factors. Time is discrete. 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 also 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).[26] Let $j(k)$ and $f(k)$ denote the corresponding sector and field of study resulting from action k. As $J = 7$ and $F = 5$, there are $K = 1 + J + F + F \cdot J = 48$ actions. Denote $\mathscr{H}_i^{-t}$ as the *history* of individual i's work and schooling choices prior to period t. Workers enter the labor market at age 25 with initial conditions described below and make choices through age 55.[27]

Time-invariant worker heterogeneity comes through $q \in \{1, 2, 3, 4\}$ discrete worker types. These are observable demographic groups - defined as gender and observed college attendance before age 25. Each type q differs in their preferences and comparative advantage over work and schooling options.[28] As the skill process outlined below is quite rich, I focus on observable time-invariant heterogeneity for tractability.

Timing: The timing is summarized in Figure 6 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 previous industry, $j_{i,t-1}$. Upon a separation, workers lose job-specific skills and get shifted into non-employment. After separations are realized, workers 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 described in the following section.

4.1 Earnings and Human Capital Dynamics

Earnings: An individual i in period t making choice k to work in industry j (i.e, $j = j(k_{it}) > 0$) is modeled as having log-earnings with the following components:

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

[26] Specifically, 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 $f > 0$), both work in j and study in f part-time (j>0 and $f > 0$), or be 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.

[27] Age 55 is chosen as the terminal period since the focus is on education and earnings in a worker's 30s and 40s, and this is presumably far enough in the future not to affect payoffs at these earlier ages. There is virtually no schooling for workers in their 50s in the ACS.

[28] Agents are also differentiated by their graduation cohort. I often leave this as implicit for brevity, but in practice cohort or age is another discrete state in addition to time t and type q.

Skill prices r_{jt} are industry-by-time fixed effects that measure the return to human capital in industry j at time t, capturing time-varying industry conditions. These skill prices are reduced forms of equilibrium objects, and I do not model the determination of the non-stationary wage-setting equilibrium. The part-time penalty $\alpha^{PartTime}$ captures reduced labor supply while working and studying in the same period.

Transferable Skills: The approach to modeling human capital is quite general and nests multiple models. I adopt a skill weights approach in the spirit of Lazear [2009]. In this framework, skills are neither completely general nor entirely specific.[29] An important innovation relative to prior work (Yamaguchi [2012], Adda and Dustmann [2023]) is that I do not use observable measures of skills and instead adopt a fully data-driven approach based on observed transitions to inform the skill weights and accumulation process. This method captures components of human capital that may not measured in such data as well as enables me to tractably incorporate fields of study into a model of industry-specific human capital.

Earnings are an industry-specific weighting of $S = 3$ individual-specific latent skills.[30]. Individual i begins a period with latent skill $\omega_{it}^{(s)}$, which gets weight $\pi_j^{(s)}$ in industry j. Skill weights are restricted to be positive, $\pi_j^{(s)} > 0$, and time-invariant.[31] Based on the current vector of skills $\vec{\omega}_{it}$, a worker has comparative advantage over sectors as skills are semi-portable across industries. All else equal, workers prefer working in the sector that gives the highest weight to their skills.

Each skill is differentiated in its accumulation process in addition to its industry-specific weights. Skills grow deterministically, with current choice k impacting the future values of skills. Each skill s has a worker type-specific technology of accumulation, $\Gamma_q^{(s)}()$, such that:

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

The technology $\Gamma_q^{(s)}$ is interpretable as the percent growth in skill s and depends on both the precise choice of field of study f, choice of industry j, current level of skill $\omega_{it}^{(s)}$, and worker type q. Skills may depreciate at different rates in non-employment, exhibit diminished growth at higher levels of skill, and grow slower for someone who is working and studying at the same time. For brevity, the precise parametrization is shown in Equation D.1 in Appendix D.1.

[29] For example, if $S = J$ and $\Pi = I$, 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 with the aim of tractability and by the fact that the prior work on observable skills typically considers two or three dimensions. For example, Deming [2017] considers the returns to cognitive, non-cognitive, and social skills.

[30] I use the term latent in that the econometrician does not observe skills prior to estimation.

[31] A restriction of this model is that skill weights are time-invariant, meaning that the process by which past experience gets translated into human capital in each industry is constant. Some work 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}.

Job-Specific Skill: Job-specific skill τ_{ijt} captures a mix of industry tenure, search capital, and the returns to continuous employment. It is entirely lost upon a job separation and is not modified through schooling choices, only career transitions. This allows it to capture match effects with current employer, firm-specific human capital, and job-shopping dynamics in a reduced-form way (Bagger et al. [2014]).

This skill is allowed to grow both within and across periods, depending on whether the worker makes a voluntary or an involuntary transition across employers during the period. For this reason, it is interpretable as a search capital component that is unrelated to education and a precise work history, rather than a pure match or tenure component. If an individual experiences an involuntary separation from their previous job, $sep_{it} = 1$, τ is completely lost: $\tau_{ijt} = 0$. If an individual is not separated and makes a voluntary switch, τ grows within period according to $\tau_{ijt} = \gamma^{(\tau)}_{Vol}\tau_{i,j_{i,t-1},t}$. Then, between periods, τ grows according to the accumulation technology $\Psi(k|\tau_{ijt})$, which mirrors the form of $\Gamma^{(s)}_q$. These dynamics are summarized along with a precise parametrization in Appendix Section D.1.

Persistent Idiosyncratic Productivity: The structure on idiosyncratic productivity η_{ijt} allows for persistent heterogeneity in earnings, both weakening identification requirements and incorporating important selection dynamics. Idiosyncratic productivity η_{ijt} follows the AR(1) process:

$$\eta_{ijt} = \rho^{j}_{j_{i,t-1}}\eta_{i,j_{i,t-1},t-1} + \varphi_{i,j,j_{i,t-1},t} \tag{4.2}$$

where $\varphi_{i,j,j_{i,t-1},t} \underset{\text{i.i.d.}}{\sim} N(0, \sigma^{j}_{j_{i,t-1}})$.[32] The persistence parameters, ρ, and variance of the innovations, σ, both depend on chosen industry j as well as last activity $j_{i,t-1}$ through the type of work transition.[33] 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 (Ashenfelter [1978]).[34] This is

[32] 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.

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

[34] Specifically, individuals with negative η_{ijt} will respond by taking low-ρ actions while those with high η_{ijt} will take high-ρ actions. All else equal, individuals will be more likely to make a work transition in response to negative draws of $\varphi_{i,j,j_{i,t-1},t}$ and are less likely to move when they have high starting values of η_{ijt}. This will result in positive values to realized η_{ijt} over time. However, individuals will have to balance this motivation against potential changes in other

discussed in detail in Section 5.

Initial Conditions: As the main counterfactual is a surprise tuition subsidy that coincides with the Great Recession, initial conditions will not respond and are treated as exogenous. Observables prior to age 25 are used to parameterize initial skills as:

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

where z_i is a vector of these initial observables with $\gamma_{Z:1}^{(s)}$ a vector of coefficients for each skill s and dummies for worker type $\gamma_{q:1}^{(s)}$. 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 at age 23 or 24 (including none). I impose the normalization that $\mathbb{E}\left[\omega_{i1}^{(s)}\right] = 1$ in the population, which helps fix the location and scale of $\omega_{it}^{(s)}$, as discussed more in Appendix Section D.4. For other initial conditions, $j_{i,t-1}$ in $t = 1$ is set to the same recent industry of employment that determines z_i. At a parameter guess, initial specific skill $\tau_{i,j_{i,t-1},t}$ is computed by Equation D.4 based on observed tenure in that initial industry. The initial persistent shock is drawn independently with 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

A worker's choice is shaped by the state in which they start the period. In addition to previous work and school activities $j_{i,t-1}$ and $s_{i,t-1}$, there are also continuous states Ω_{it}. These continuous states are the current $S = 3$ transferable skills $\omega_{it}^{(s)}$, job-specific skill $\tau_{i,j_{i,t-1},t}$ in the starting industry, 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: Given realized preference and earnings shocks, ϵ and η, an agent of type q receives flow utility from taking action k in year t:

$$u_{qt}^k(j_{i,t-1}, s_{i,t-1}, \Omega_{it}; \vec{\epsilon}_t, \eta_{ijt}) = \underbrace{\mu_q^k(Age_{it})}_{\text{Preferences for Actions}} + \underbrace{\beta_Y y_t^k(\Omega_{it}, j_{i,t-1}; \eta_{ijt})}_{\text{Preference for Log-Earnings}} \tag{4.3}$$

$$- \underbrace{\beta_P Price_t^k(Y_{i,t-1})}_{\text{Sensitivity to Tuition Costs}} - \underbrace{C_{qt}^k\left(j_{i,t-1}, s_{i,t-1}\right)}_{\text{Switching Cost}} + \underbrace{\epsilon_t^k}_{\text{EV1}} \tag{4.4}$$

$$= \bar{u}_{qt}^k(j_{i,t-1}, s_{i,t-1}, \Omega_{it}; \eta_{ijt}) + \epsilon_t^k \tag{4.5}$$

which depends upon type-specific non-pecuniary benefits from taking action k, $\mu_q^k()$; preference for log-earnings, y_t^k; disutility from net tuition costs paid $Price_t^k$, varying by prior income and full- or part-time study; switching costs $C_{qt}^k()$; and the vector of extreme-value preference shocks, $\vec{\epsilon}_t$.

skills.

The worker type-specific function $\mu_k^q(Age_{it})$ consists of indicators for each industry, field of study, and for part-time study as well as quadratic slopes in age for being employed full-time.

Tuition and Financial Aid: I calibrate net tuition $Price_t^k(Y_{i,t-1})$ by taking public 2-year sticker prices in Texas from the Integrated Postsecondary Education Data System (IPEDS), accounting for differences in full and part-time tuition. I use financial aid data to model grant aid as a flexible function of the prior year's income $Y_{i,t-1}$. Details are provided in Appendix Section D.3.

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. If a worker makes choice k to switch industry (i.e., $j(k) \neq j_{i,t-1}$), they incur costs according to:

$$\ln C_{qt}^k\left(j_{i,t-1}, s_{i,t-1}\right) = \underbrace{\kappa^U U(j_{i,t-1}) + \kappa^E E(j_{i,t-1})}_{\textbf{Employment Status}} + \underbrace{\kappa_q}_{\textbf{Worker Type}} + \underbrace{\kappa_{j(k)}}_{\textbf{Target Industry}} + \underbrace{\kappa_{FromSchool} D\left[s_{i,t-1}=1\right]}_{\textbf{From School}} + \underbrace{\kappa_{GR}^U U(j_{i,t-1}) D\left[t \geq 2009, t \leq 2011\right] + \kappa_{GR}^E E(j_{i,t-1}) D\left[t \geq 2009, t \leq 2011\right]}_{\textbf{Business Cycle}} \quad (4.6)$$

The parameters $\kappa^{U(j_{-1})}$ and $\kappa^{E(j_{-1})}$ allow switching costs to vary by employment status after separations are realized. These are further allowed to vary over the business cycle through $\kappa_{GR(t)}^{E(j_{-1})}$ and $\kappa_{GR(t)}^{U(j_{-1})}$, increasing unexpectedly between 2009 and 2011. The parameters κ_j allow frictions to vary by target industry, measured 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 switching costs through $\kappa_{FromSchool}$, permitting training to act as a form of job search (Heckman and Smith [1999]). I also allow for switching costs into schooling to represent difficulties faced in returning to school that are not captured in tuition costs:

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

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 things happen upon separation. First, while workers 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. For simplicity,

aggregate separation rates are calibrated using the American Community Survey.[35]

For tractability, I treat involuntary separations as observed if the individual experiences a single quarter of non-employment. This assumption leverages the quarterly frequency of the data to enrich unemployment dynamics, but abstracts from sub-quarterly unobserved involuntary separations. These are captured by shocks to η_{ijt}. In the model, as τ_{ijt} is always lost whenever individuals enter non-employment, it does not matter for estimation whether a transition into non-employment starts with a voluntary or involuntary separation. In Figure 9, I show below that the model reasonably matches the earnings patterns of workers separated during the Great Recession.

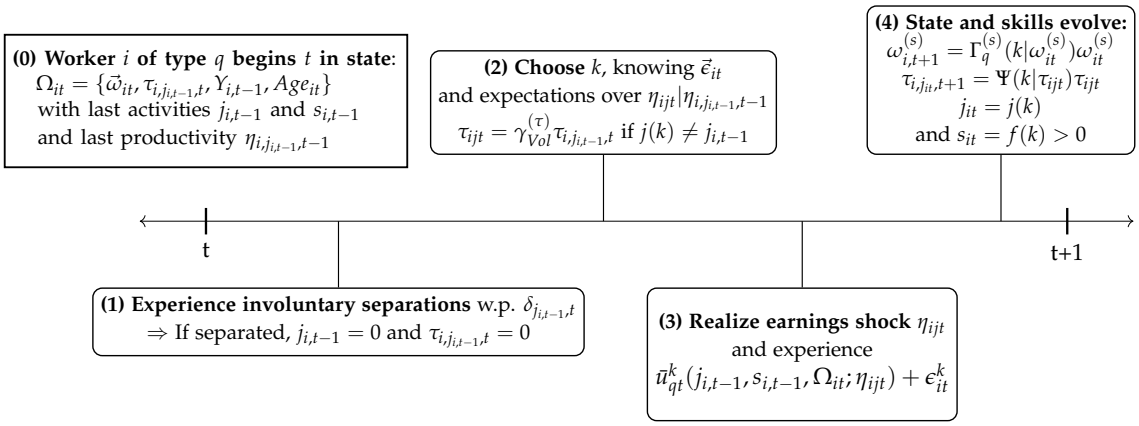
Beliefs on Aggregate States and Policy Regimes: I treat the Great Recession as a one-time, unanticipated shock. Agents are not myopic and use a forecasting rule for the aggregate states prior to the Recession. Practically, I linearly interpolate skill prices and separation rates for the years 2009 through 2015, which are estimated in a first step and assume agents use these interpolated paths to make their decisions prior to 2009. The approach is illustrated in Figure 10 for key industries. 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 estimation approach, 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 4.2. Similarly, let $\hat{\Omega}_q^k(\Omega_{it})$ be the future continuous states resulting from taking action k for worker type q. Net of logit shocks

[35] These are displayed in Figure 10(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 to form beliefs prior to the Recession.

Figure 6: Timing of one period of the model



$\vec{\epsilon}_t$, the value from taking action k at t for a worker of type q with $\hat{\eta}$ is:

$$v^k_{qt}(j_{i,t-1}, s_{i,t-1}, \Omega_{it}; \hat{\eta}) = \bar{u}^k_{qt}(j_{i,t-1}, s_{i,t-1}, \Omega_{it}; \hat{\eta}) + \underbrace{\delta_{j(k),t}\beta V_{q,t+1}\left(0, s(k), \hat{\eta}, \hat{\Omega}^k_q(\Omega_{it})\right) + \left(1 - \delta_{j(k),t}\right)\beta V_{q,t+1}\left(j(k), s(k), \hat{\eta}, \hat{\Omega}^k_q(\Omega_{it})\right)}_{\textbf{Expected Continuation Value}} \quad (4.7)$$

where $V_{q,t+1}()$ is 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 $\hat{\eta}$:[36]

$$\bar{v}^k_{qt}(j_{i,t-1}, s_{i,t-1}, \eta_{i,j_{i,t-1},t-1}, \Omega_{it}) = \int_{\hat{\eta}} v^k_{qt}(j_{i,t-1}, s_{i,t-1}, \Omega_{it}; \hat{\eta}) dF^k(\hat{\eta}|\eta_{i,j_{i,t-1},t-1}, j_{i,t-1}) \quad (4.8)$$

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

$$V_{qt}(j, s, \eta, \Omega) = \gamma_{Euler} + \log\left(\sum_k \exp\{\bar{v}^k_{qt}(j, s, \eta, \Omega)\}\right) \quad (4.9)$$

The full timing of the model is illustrated in Figure 6.

Solving the value function for this problem is difficult owing the large number of continuous states. I follow the tradition of Keane and Wolpin [1997] and solve the value-function through backwards iteration using regression interpolation on a set of sampled states. Details are provided in Appendix Section D.2.

[36] I use Gaussian-Quadrature with 5 nodes to evaluate this expectation when solving the model.

5 Identification and Estimation Strategy

Identification relies on panel data with fine-grained variation in earnings and work transitions. The main assumption is the conditional and mutual independence of time-varying unobservables, which breaks estimation into two steps. Importantly, the persistence in errors η_{ijt} and the generality of skills ω_{it} substantially weaken identification requirements while preserving tractability.

5.1 Margins of Selection and Implied Restrictions on Worker Mobility

The two most pressing concerns in estimating returns to training and education are (1) *ability bias* – that individuals may be selected on potential 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.[37] From the perspective of the model, levels of skills ω_{it} 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 shocks may drive an individual to enroll when this would not have been the optimal choice in prior periods.

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 a state:

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

where X_{it} is a conditioning set consisting of the entire sequence of past employment and schooling transitions $\mathscr{H}_i^{-t}$, prior earnings $Y_{i,t-1}$, determinants of initial conditions z_i, and the worker type q_i. These are allowed to drive selection as they determine an agent's current state in the model Ω_{it}. The moment condition 5.1 is implied by the following restriction on worker choices: $P_t(k_{it} = k|\varphi_{ij,j_{i,t-1},t}, X_{it}) = P_t(k_{it} = k|X_{it})$. This moment condition is therefore a timing assumption: individuals cannot select on φ, the within-period change in the error term in the earnings equation. However, due to the richness of the skill process and persistence in η_{ijt}, individuals' entire work and schooling histories as well as lagged earnings are allowed to drive selection in a general way.[38] Other papers, both structural and reduced form, make similar assumptions, for example, Card et al. [2013], Traiberman [2019], and Bonhomme et al. [2019].

[37] 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].

[38] There are two main alternatives to the timing assumption. First, one could allow agents to observe shocks prior to making their choice (as in Lee and Wolpin [2006] and Dix-Carneiro [2014]), which in practice relies on a combination of functional form and exclusion restriction assumptions. Second, one could impose more structure to estimate a search, matching, and bargaining model (e.g. Postel-Vinay and Robin [2002], Taber and Vejlin [2020], Huckfeldt [2022]). Both of these approaches would break the two-step estimation approach, make the current setup intractable, and distract from the main focus of the paper.

There are two upshots to the timing assumption given by Equation 5.1. First, the earnings equation is semiparametrically identified independently from the precise structure of the choice model. In fact, the full distribution of φ is revealed in the microdata for a given guess of parameters. Moreover, the structure on beliefs does not affect the results of the earnings model. Second, Equation 5.1 yields testable implications. In particular, workers stratified based on information from outside the conditioning set (k_{it}, X_{it}, t) should exhibit no differences in earnings, since individuals in the same conditioning set are in the same state and have the same expected earnings from making choice k under the model's structure. This assumption would be violated, for example, if there were unobserved worker types not accounted for in X_{it}. In that case, future choices would reveal information about the current unobserved type and indicate model misspecification.

This testable implication is assessed in Figure 7, which supports the notion that the estimates are purged of the most important sources of selection bias. I compare two individuals who should have identical earnings from the perspective of the model but differ in their *future enrollment choices*. Specifically, for each enrollment event, I find a matched comparison in the same period t having an identical conditioning set X_{it} and making the same current period choice k_{it} but who does not enroll two periods in the future.[39] The model predicts that enrollees and matched comparisons *should have identical earnings in the gray-shaded area* of Figure 7 at $t = -2$, but not necessarily $t = -1$ or $t = 0$ due to differing shocks or choices. There is only a small difference in earnings in this period on the order of \$964 in non-Recession years and \$802 in Recession years. This indicates that there may be a small amount of bias resulting from negative selection of enrollees, but overall indicates that the assumptions of the model are supported by the data.

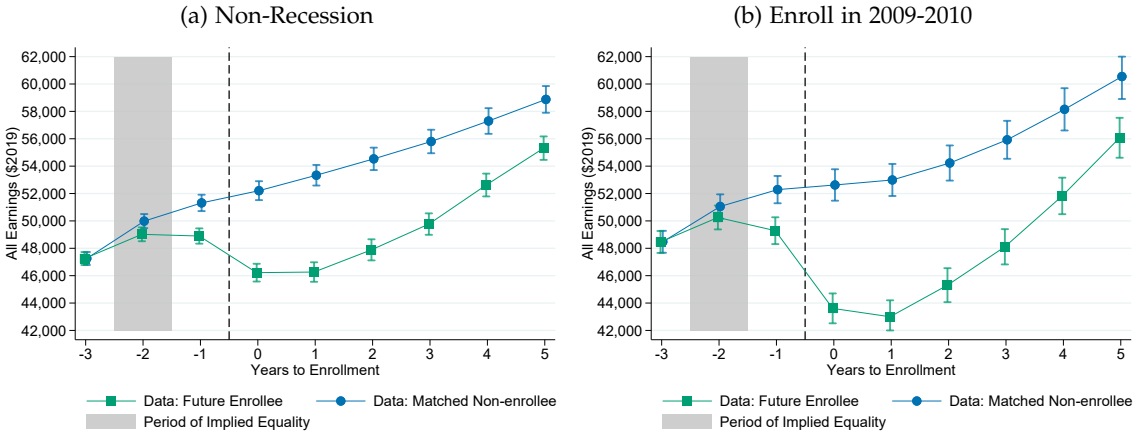
5.2 Additional Identification Details

Heuristic arguments summarizing identification of specific parameters are presented in Table 4 and discussed in detail in Appendix Section D.4. As is standard in dynamic discrete choice (Magnac and Thesmar [2002]), the discount factor is set to $\beta = 0.96$, flow utility is normalized to zero for non-employment at age 30, and the variance of preference shocks is fixed to 1.

Crucially, the identification of the latent skill process is obtained from within-history but across-industry comparisons of earnings, permitted by the assumption of deterministic skill growth and one normalization on each skill. This argument is discussed more thoroughly in Section D.4 and semiparametric identification proofs are given in Appendix C.

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

Figure 7: Check of Selection Assumptions



Notes: This figure uses observed earnings histories to check the implication of the independence of changes in time-varying unobservables, as implied by Equation 5.1. Specifically, future enrollees (at $t = 0$) are matched to a future 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 individual comparison with earnings within \$1,000 bandwidth of earnings in $t = -3$ (similar η_{t-1}). Conditional on these observables, the model predicts that individuals should have the same earnings in $t = -2$, which is highlighted in gray. Individuals may experience differing shocks and need not have the same earnings in $t = -1$ and beyond.

Table 4: 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 Shock Persistence: ρ_j	Within-industry, within-history covariance across lagged earnings
Idiosyncratic Shock Variance: σ_j	Within-industry, within-history variance 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	Duration/Frequency of industry switching in data
Switching Cost - From School: $\kappa_{S_{-1}}$	Duration/Frequency of sectoral switching out of enrollment
Switching Cost - Into School: $\kappa_{S(k)}$	Duration/Frequency of transitions into school not explained by price/aid

5.3 Estimation Approach

Estimation is through a maximum likelihood procedure that is separated into two steps. I provide an overview here, with the precise details of each step discussed in detail in Appendix Section D.5. The observed data in each period are log-earnings conditional on employment, y_{it}; observed work and schooling choices, k_{it}; and separations observed at the beginning of period t, sep_{it}. The econometrician also observes the time-invariant worker type q_i and covariates determining initial skills z_i. Recall that $\mathscr{H}_i^{-t}$ denotes the history for individual i.

Let θ_Y denote all parameters affecting the earnings process and θ_C denote the parameters governing transition probabilities. We seek to find values of $\theta = \{\theta_Y, \theta_C\}$ that maximize the likelihood of the observed histories:

$$L(\theta) = \prod_{i=1}^{N} \prod_{t=1}^{T_i} f\left(y_{it} | k_{it}, sep_{it}, \Omega(\mathscr{H}_i^{-t}; \theta_Y), q_i; \theta_Y\right) P\left(k_{it}, sep_{it} | \Omega(\mathscr{H}_i^{-t}; \theta_Y), q_i; \theta_Y, \theta_C\right) \tag{5.2}$$

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

$$l(\theta) = \underbrace{\sum_{i=1}^{N} \sum_{t=1}^{T_i} \log f\left(y_{it} | k_{it}, sep_{it}, \Omega(\mathscr{H}_i^{-t}; \theta_Y), q_i; \theta_Y\right)}_{\textbf{Step 1: Earnings and Human Capital Parameters}} + \underbrace{\sum_{i=1}^{N} \sum_{t=1}^{T_i} \log P\left(k_{it}, sep_{it} | \Omega(\mathscr{H}_i^{-t}; \theta_Y), q_i; \theta_Y, \theta_C\right)}_{\textbf{Step 2: Transition Parameters}} \tag{5.3}$$

Equation 5.3 shows that 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 observed current choice k_{it} and history $\mathscr{H}_i^{-t}$. In addition, the current state Ω is affected only by the worker's prior history $\mathscr{H}_i^{-t}$ and parameters governing earnings θ_Y. While we do not know a worker's skills ex-ante, they can be computed given a guess of θ_Y and observed $\mathscr{H}_i^{-t}$, an implication of deterministic skill growth.

In the first step, parameters of earnings and the skill process are estimated in a nonlinear least squares procedure, matching the sample analogue of the moment equation 5.1. Normality is then exploited to compute the variance of the shock φ across transitions. In the second step, choice parameters are estimated by maximizing the likelihood of observed transitions, conditioning on earnings parameters. This step, conducted outside the secure computing environment, matches smoothed conditional choice probabilities $P_{k|s}$ in the data with their model counterpart and necessitates solving the value function using regression interpolation.

The asymptotic variance-covariance matrix of parameters is computed using 100 nonparametric bootstrap samples. In the first step, individual panels are drawn with replacement to repeat-

edly estimate θ_Y and smoothed choice probabilities $P_{k|s}$, measuring the sampling covariance of these estimates. To compute standard errors on $\hat{\theta}_C$, the second-stage estimation is repeated for each bootstrap draw of earnings parameters $\hat{\theta}_Y^b$ and choice probabilities $\hat{P}_{k|s}^b$ estimated in the first step.

6 Estimation Results

Due to the large number of parameters, I focus on only discussing model fit and key implications. Complete parameter estimates are reported in Appendix Section D.6.

6.1 Model Fit and Validation

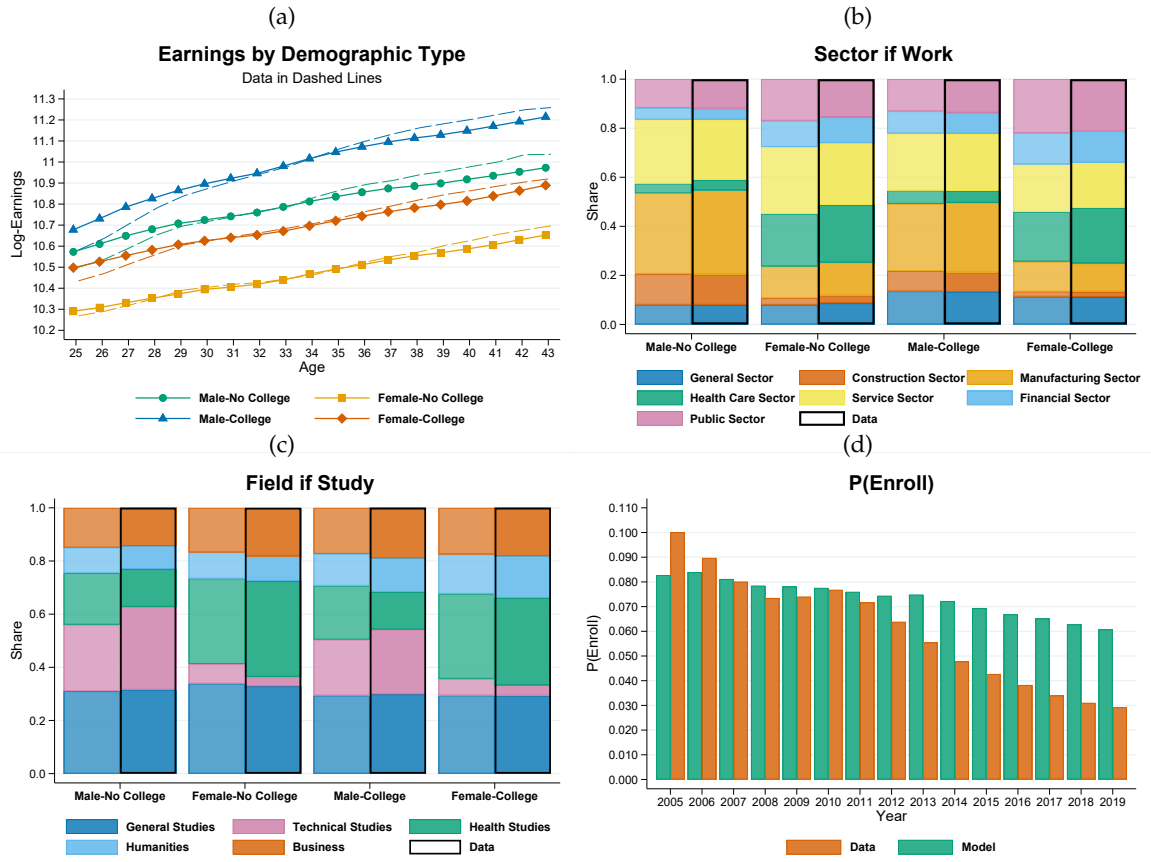
Figure 8 shows that the model fits basic patterns of the data quite well.[40] In Panels (a) to (c), shows that the model fits life-cycle earnings profiles and choices probabilities quite well. Importantly, the model is able to reproduce differences by gender and pre-labor market educational attainment 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 and some of the increase in enrollment during the Recession

Figure 9 shows that the model reproduces observed earnings dynamics around job separation during the Great Recession for both subsequent enrollees and non-enrollees. The model closely tracks pre-separation earnings for both groups, supporting the idea that it captures selection on the incidence of future shocks. It replicates the sharp earnings drop at separation, with small differences driven by different treatment of partial earnings in the data versus the model.[41] The model matches the recovery in earnings after job separation as well, which is a bit better for enrollees than non-enrollees. Appendix Figure A.18 shows the fit of the model for Recession enrollees without conditioning on job separation. Here, the model somewhat over-predicts pre-enrollment earnings, but nonetheless captures the broad trajectory of post-enrollment recovery. Overall, the model performs well in replicating earnings around these hard-to-match transition events, providing confidence in its ability to reasonably extrapolate away from the observed data.

[40] To assess the fit of the model, I simulate 1,000,000 worker histories at estimated parameters values, drawing initial conditions based on the observed values from finely grained cells. Specifically, 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.

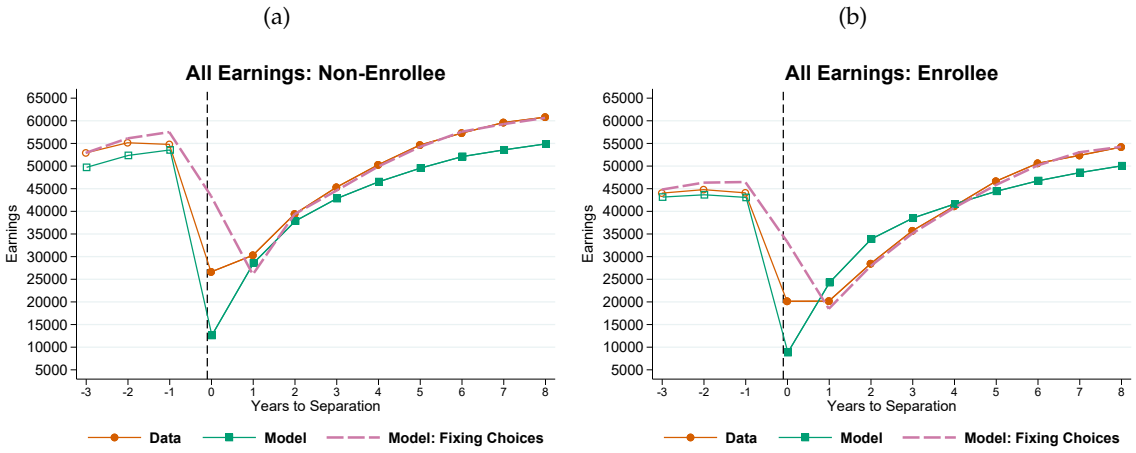
[41] In practice, separated workers in the data have some very low earnings in the data, whereas the model treats these workers as always having zero earnings.

Figure 8: 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) show 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.

Figure 9: Model Fit: Earnings of Workers Separated by Enrollment Take-up



Notes: Compares fit of total earnings, including zeros, between the baseline sample and simulations from the model of size N=1,000,000 . Total earnings include zeros. There are $N = 2,511$ displaced non-enrollees and $N = 10,976$ displaced enrollees. Displaced workers are those in the baseline sample who are employed for three years prior to an entry into non-employment in 2008 to 2010. Enrollees are defined as those enrolling in 2008 to 2010. Orange line (circles) shows the fit of the raw data and green lines (squares) show the fit of data simulated from the full model. The pink dashed line plots the fit of the earnings model holding choices fixed, accounting for idiosyncratic productivity using lagged errors by adding the $\rho\eta_{-1}$ for the appropriate transition (and $\sigma_\varphi^2/2$ to adjust for the level of earnings).

6.2 Characterization of the Skill Process

Skill Weights: Estimates of skill weights are shown in panel A of Table D.1. These results indicate that skill 1 tends to be general skill while 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, meaning that a one unit increase in skill 1 increases earnings by 55 percent to 67 percent across these sectors. A one unit increase in skill 2 has returns ranging from 7 percent in services to 21 percent for manufacturing. Skill 3 has returns ranging from 23 percent in health care and the public sector to about 49 percent in finance and the general sector.

Skill Accumulation: Parameters governing the skill accumulation process are shown in panels B to F of Table D.1, following the functional form of $\Gamma_q^{(s)}$ in Equation D.1. These estimates indicate that different choices build different skills, including the fact that some skills may depreciate.[42] For example, there is a 0.1 increase in the log-rate of accumulation of skill 1 for each period worked in health care whereas those studying health care have a 0.3 increase in this growth. Combined with the skill weights above, this indicates that earnings in the health sector are increased by past work in health by 6.6 percent[43], whereas studying health increases earnings by 22.2 percent through skill 1 alone, all else equal. The comparable numbers for skill 2 are -0.8 percent for health work

[42]Skills only depreciate fully in non-employment, so one can interpret this as a failure to gain skill relative to a constant depreciation rate.

[43]$100 \times (\exp\{-0.040\} - 1) \times 0.203$

and 2.8 percent for health study; skill 3 sees -6.5 percent for health work and -30.2 percent for health study. Note that these effects are normalized to men with no prior college and are changes relative prior earnings, not relative to an alternative reference action. The heterogeneous returns to work experience in Panel C of Table D.1 show that women tend to accumulate skills 1 and 2 slower than men but have some comparative advantage in accumulating skill 3. In contrast, men with prior college appear to more easily accumulate all skills through work. Panel F of Table D.1 shows that the rate at which skill investments diminish with skill levels is relatively constant for skill 3 and somewhat rapid for skills 1 and 2; for skill 1, investments from work are 70 percent less productive for 2 units versus 1 unit of skill. Panel F also shows that about 43 percent of part-time human capital investments come through work whereas 57 percent come 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. Finally, Panel G of Table D.1 shows initial skills as a function of pre-determined covariates.

Characterization of Skills: We can use the above patterns to construct a brief interpretation of the latent skills. Skill 1 tends to capture a general skill that cannot be modified later in life. Skill 2 tends to capture more specific technical investments where studying in health and technical fields have high returns, college educated men tend to have higher accumulation, 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, creating an opportunity cost of switching into those sectors in terms of lost skill.

Implied Transferability: To clarify how estimated parameters translate into earnings across the population, Tables 5 and 6 report implied one-year earnings growth using the ex-post distribution of skills in the baseline simulation, forcing individuals along specified transition paths. These returns are measured relative to the reference action of working full-time in an individual's prior industry and focus only on changes in the transferable skills ω_{it}. Table 5 highlights three key patterns for fields of study. First, only technical and health studies increase average earnings through skill accumulation; other fields yield negative returns relative to working. Second, while studying health has the highest return if subsequently transitioning into the health care and public sectors, it is highly specific and has negative earnings consequences in all other sectors. Finally, there is substantial heterogeneity in returns, with mean effects often small relative to their standard deviation. Table 6 focuses on work transitions, reinforcing the importance of the limited transferability of human capital. Earnings growth from skill accumulation is highest in the general, manufacturing, construction, and financial sectors. Skills tend to depreciate in the service sector. Similarly, work experience in the health and public sectors builds primarily sector-specific

skill.

Table 5: 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.

Table 6: 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.

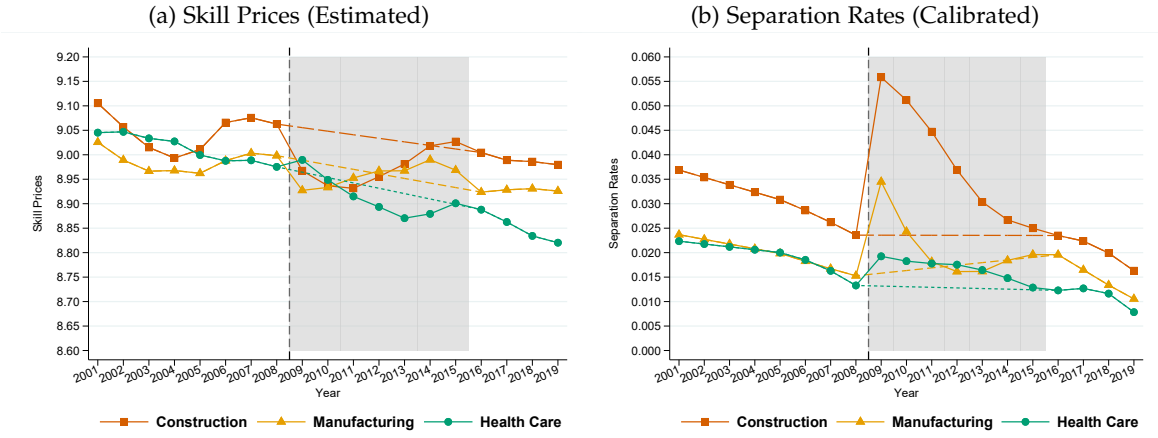
6.3 Other Parameters

Job-Specific Skill and Other Earnings Parameters: The fourth column of Table D.1 shows a high return to the job-specific skill. Panel A shows that each sector returns about 30 percent higher earnings for each unit of this skill. At one unit, this skill grows by about 6.9 percent — translating into 2 to 2.5 percent higher earnings depending on sector. On-the-job investments in this skill diminish quickly in levels. The skill grows across voluntary transitions by 2.1 percent, indicating an important role for search capital. The fifth column of Panel A shows that workers face about a

12 percent cut in earnings while enrolled relative to full-time, non-enrolled work due to reduced labor supply. Table D.2 shows that shocks to idiosyncratic productivity are quite persistent, with an autocorrelation parameter of 0.888 (0.001) and 0.719 (0.002) for those remaining or making voluntary transitions. Transitioning from non-employment has a low persistence parameter of 0.350 (0.003) and a much higher variance in shocks.

Aggregate Parameters: Industry-time varying separation rates and skill prices are shown for key industries in Figure 10 and for all industries in Appendix Figure D.2. Construction is the most affected by declines over the business cycle, seeing large reductions in the price of skill and increases in layoffs during the Great Recession. In contrast, health care has lower layoff rates and is less sensitive to the business cycle. Figure 10 also includes a graphical depiction of how beliefs about agents have biased beliefs. The dashed lines in this region show the agents' beliefs about aggregate states prior to the Recession.

Figure 10: Skill Prices and Separation Rates - Selected Industries



Notes: Plots estimated skill prices r_{jt} (see Equation 4.1) and calibrated separation rates δ_{jt} (see Equation 4.7) 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 D.2 for all industries.

Income Coefficient: Table D.3 shows a preference parameter for log-earnings of 0.738 (0.024).[44] This is a key parameter as it governs the degree of income maximization in the model.

Switching Costs: Panel C of Table D.3 shows the time-varying and heterogeneous switching cost parameters. The non-employed face switching costs that are 17 percent higher than the employed.[45] Sectors show structural differences in the job-offer rate. For example, switching into the service sector is 30 percent less costly in terms of utility than the general sector. Switching costs increase during the Recession and especially so for the employed workers, indicating increased

[44]For a comparable estimate, Ransom [2022] estimates 0.916 on expected log-earnings in a model of geographic mobility.
[45]Computed as $100 \times \left(\frac{\exp\{1.401\}}{\exp\{1.244\}} - 1\right)$

frictions for on-the-job search. Importantly, the estimates also indicate being currently in school lowers the switching cost by 26 percent. This provides an indirect role for schooling in increasing human capital: education helps workers transition into jobs where they may acquire further skills.

We can translate switching costs into dollar terms by comparing them to a present value increase in 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.[46] For comparison, Traiberman [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.[47]

Other Preference Parameters: The parameter governing sensitivity to tuition β_P is estimated to be 0.467 (0.016), indicating agents are quite responsive to reductions in tuition. Using the same conversion as for switching costs, this implies that individuals would need a present value increase in income of 2.6 percent in order to offset the current disutility of tuition payments, translating into a permanent increase in income of \$1,552 for the average worker. Finally, Table D.3 shows an important role for preference heterogeneity. Women tend to have higher preferences for working in health care and the financial sector, while relatively disliking construction and manufacturing.

6.4 Variance Decomposition of Earnings Components

Table 7 shows an ensemble decomposition of earnings with respect to each component of Equation 4.1 by broad age groups. This is conducted using the distribution of skills and choices in the microdata. The earnings model explains a high share of the variation in earnings – the implied R^2 at ages 30 to 34 is 0.744 or 0.268, depending on if we consider forecasts from lagged values of η. This persistent component captures about half of the variance in earnings, 47.6 percent. Each skill also explains a non-trivial share of the total earnings variance. The importance of skill 1 rises sharply as individuals age and that of skill 2 declines over age. The job specific skill τ is fairly constant at around 9 percent of the total variance in earnings.

Appendix Figure A.19 and Appendix Figure A.20 take a different approach and show the mean ex-post distribution of skill in simulated data. In particular, Appendix Figure A.20 shows the importance of skill 1 and the specific skill in determining earnings across sectors, while there

[46] 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

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

is sectoral sorting on skills 2 and 3. Since the persistent idiosyncratic productivity component is relatively small, this indicates that its large share of the variance from Table 7 comes from primarily *within-sector* differences.

Table 7: Ensemble Variance Decomposition of Earnings into Skill Components

	Total 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 $N =$. 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.

7 Counterfactual Exercises

7.1 Distributional Effects of Changes in Prices

I assess the effect of price changes by making an unexpected and permanent change in sticker prices that coincides with the shocks of the Great Recession to the labor market in 2009.[48] As it is a surprise, this counterfactual will not affect initial conditions or worker choices prior to the Great Recession. 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.[49]

Figure 11 shows the effect of these price changes[50] on enrollment between 2009 and 2015. Mirroring the discussion in Section 6.3, workers are quite sensitive to tuition prices. The model indicates that a $1,000 price decrease raises the annual propensity of workers to enroll by 0.8pp, with 2.9 percent ever enrolling. At the same time, there is also scope to substantially lower enrollment by raising prices — a $1,000 price increase lowers the annual enrollment rate by 1.3 percent.[51] For reference, the annual enrollment rate is 7.5 percent in the baseline simulation, indicating that these are substantial changes.

For those induced to change behavior, the model characterizes the *distribution* of earnings gains and losses, as shown in Figure 12. This figure plots changes in earnings between the baseline and counterfactual scenario, focusing on those induced to change behavior. Most individuals

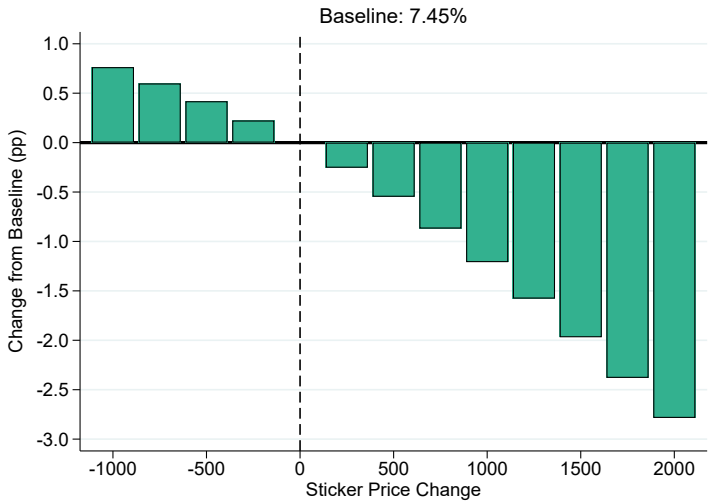
[48] To make individuals comparable across simulations, I fix realizations of random outcomes across simulations. These include the time-varying unobservables, such as innovations in idiosyncratic productivity φ, time-varying preferences ϵ, and outcomes of separations δ. I also fix the draws of the initial conditions.

[49] 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 similar results.

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

[51] The asymmetry between a price increase versus decrease is due to the fact that agents exposed to price increases and decreases are at different margins. In particular, individuals with some financial aid are less affected by price declines but will be affected by price increases.

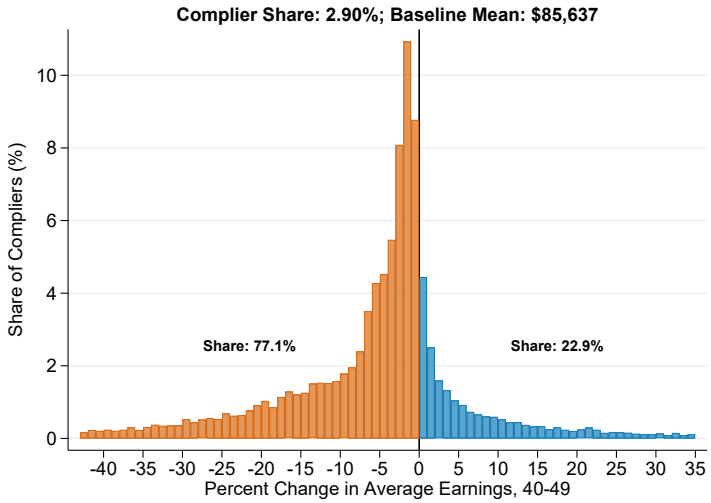
Figure 11: Enrollment Take-up by Surprise Tuition Subsidy Amount



Notes: This figure shows the changes in the annual probability of enrollment in 2009 and 2015 from an unexpected and permanent decrease or increase in the sticker in 2009. Each bar looks at differences of $250, comparing outcomes 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.

experience earnings losses from enrollment – only 22.9 percent of those enrolling due to the price cut see earnings increases and the average change in earnings for these compliers in -3.8 percent (median is -2.9 percent). These changes are clustered near zero but exhibit a long left-tail. While negative for the typical worker, the wide variation in earnings changes also indicates the potential for better targeting.

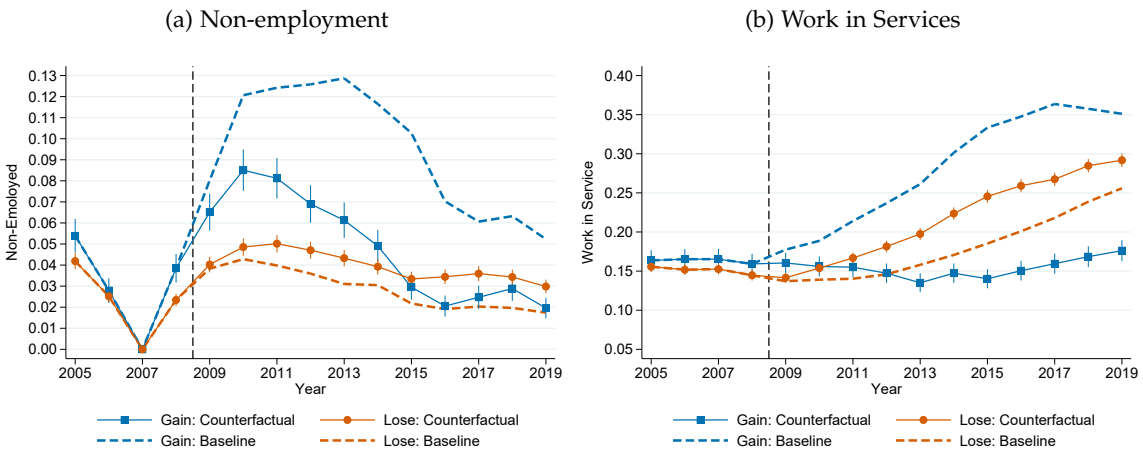
Figure 12: Distribution of Earnings Effects for those shifted by $1000 Tuition Subsidy



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.

Who are the workers who see the largest earnings gains? I investigate the drivers of the heterogeneity in Figure 12 by first characterizing the baseline and counterfactual pathways taken by 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). Figure 13 shows that those who see earnings gains are primarily characterized as having long non-employment spells in the baseline scenario and end up working in the service sector after the Recession, an industry characterized by low returns to skill but an easy job-finding rate. Under the counterfactual subsidy, this group sees a marked reduction in non-employment after 2009 of about 4pp and a very large reduction in the probability of working the service sector. In contrast, those who see losses have a slight increase in their post-Recession probability of non-employment and working in the service sector. Appendix Figure A.21 shows exhaustive comparisons of these baseline and counterfactual pathways.

Figure 13: Characterizing Pathways Taken by Winners and Losers

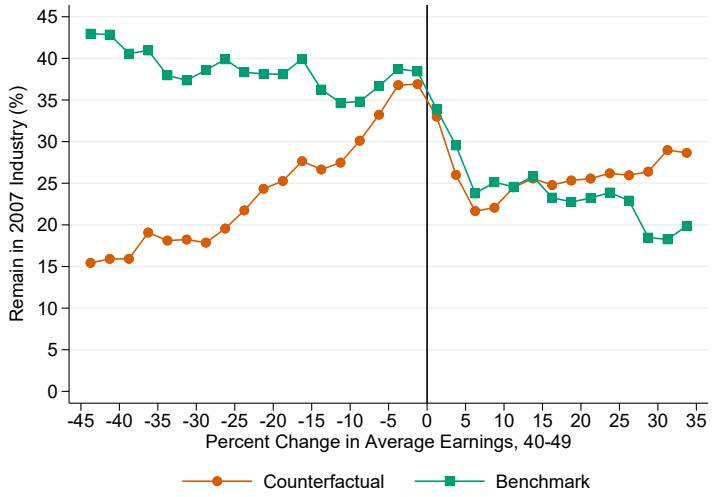


Notes: Plots history of variables for simulated individuals from Figure 12. Gain plots for those whose earnings increase by more than 5 percent; while losers are defined as earnings losses of more than 5 percent. Dashed lines plot these series under the baseline environment; solid lines plot for individuals in the counterfactual with price decreases. Error bars indicate simulation error. See Appendix Figure A.21 for additional outcomes.

Figure 14 examines how earnings changes relate to the probability of remaining in one's pre-Recession industry, holding individuals fixed along the same x-axis as in Figure 12. Those who see earnings losses are induced to move out of their baseline industry by the subsidy, with the rate of remaining in the baseline industry dropping from 40 percent to 20 percent. In contrast, those who benefit see almost no effect on this margin. If anything, those with very high earnings gains are more likely to remain in their baseline industry. However, these individuals have overall low probabilities of remaining at 25 percent, reinforcing the idea from Figure 13 that these workers

are forced out of their baseline careers and into non-employment.

Figure 14: Probability of Remaining in Baseline Industry by Earnings Change



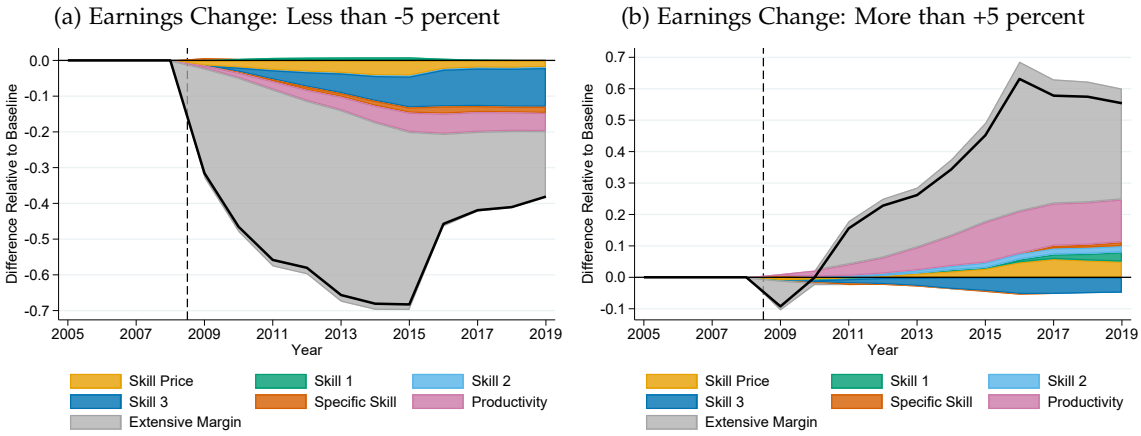
Notes: Plots the probability of remaining in 2007 industry in 2016, in the benchmark and counterfactual simulated data. Earnings changes are grouped into 2.5pp bins and smoothed over one neighbor in each direction.

Figure 15 decomposes changes in log-earnings into the components outlined in Equation 4.1.[52] 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, both winners and losers from the subsidy have lower values of skill 3 – the skill least rewarded in health care. Second, those who benefit have higher levels of skill prices and idiosyncratic productivity in later years, indicating that they are able to make more productive post-schooling work transitions. Importantly, skills 1 and 2, which are modified by schooling, increase but are a relatively small share of changes in earnings components. For these workers, education has primarily put them on a path to working in higher-return jobs, rather than purely building new skills. In contrast, those who lose earnings have lower values of all these components, indicating that returning to school has knocked them off the job ladder. These results indicate that when education works well, it can ease transitions back into the workforce. However, it may also divert workers from valuable on-the-job experience.

[52] I focus on log-earnings to keep the decomposition linear. A key issue is dealing with the extensive margin differences in earnings, since Figure 13 shows differences in participation are important. The extensive margin component of these decompositions reflect differences in participation holding average log-earnings conditional on participation to the baseline scenario: $\mathbb{E}[y^0|D^0=1]\cdot\left(P(D^1)-P(D^0)\right)$, where y^0 and D^0 are earnings and participation under the baseline scenario. This follows from the decomposition:

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

Figure 15: Decomposition of Sources of Earnings Gains and Losses



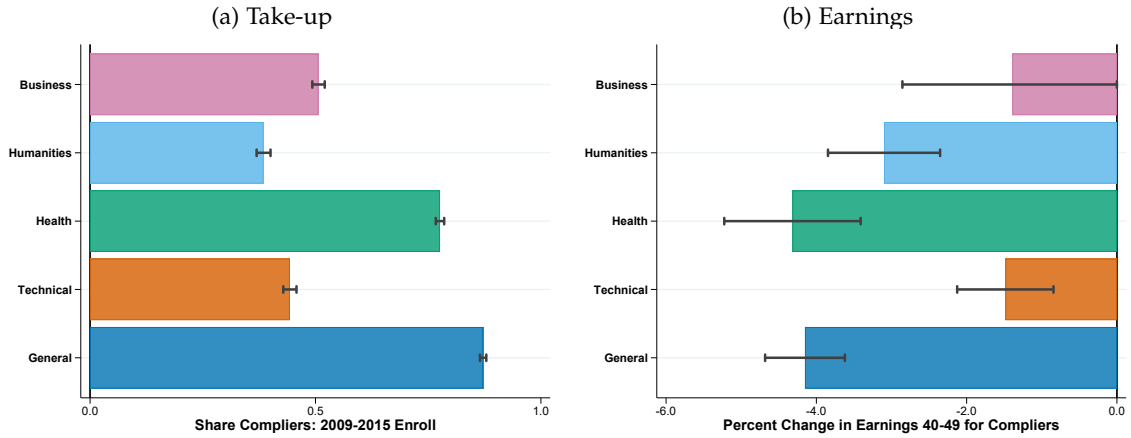
Notes: Decomposes difference in earnings between the baseline scenario and the counterfactual in terms of underlying model components.

7.2 Field-Specific Subsidies

Figure 16 investigates the potential for subsidies targeted towards specific fields to increase earnings. Each row in the figure is a different counterfactual that only reduces price for a specific field of study beginning in 2009. Fields differ substantially in both take-up as well as earnings impacts. Panel (a) shows the share of the data that are compliers with each field-specific subsidy. Health and general studies both result in the highest rates of take-up, mirroring the event study evidence. However, when looking at earnings effects in Panel (b), all fields have negative average effects. Health and general studies lead to larger earnings losses, while technical studies yields the least negative earnings losses. Business subsidies have effects on the order of technical studies but with a lot of uncertainty even in this large simulation.

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.

Figure 16: Take-up and Earnings Effects for Field-of-Study Specific Subsidies



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 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.

8 Conclusion

This paper studies the tradeoffs workers face when pursuing later-life human capital investment. The analysis combines administrative 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 to build new skills. 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 also addressing selection issues documented in the prior literature.

Not all workers should use education to adjust to shocks, and there is substantial nuance that determines the effectiveness of training. I find both that workers are very responsive to price reductions, but that the average worker who responds would face earnings declines. Reskilling can be risky if it does not translate into a job in the target sector and can be potentially harmful if it diverts individuals from valuable on-the-job experience. However, this also means that the population that benefits the most from schooling is workers who would have had long periods out of work and difficulty acquiring such experience in the absence of increased access to education. This may explain why studies that condition on displaced or unemployed workers find positive effects (e.g., Jacobson et al. [2005]). Policymakers should be careful when extrapolating results to the broader population. It may also explain why experimental evaluations of sectoral training programs see large returns (Katz et al. [2022]), but other experimental evaluations see disappointing results when workers do not match with targeted occupations (Fortson et al. [2021]).

The use of a structural model was necessary to uncover these insights due to the interaction between later-life education, work transitions, and skills. Several extensions could further enrich our understanding of these issues but are outside the scope of this paper, which focuses solely on a decomposition of the earnings gains from community college training. This paper does not deal directly with the general equilibrium implications of expanding access to education (Heckman et al. [1998b]), holding the path of labor demand fixed in counterfactuals as a reduced-form process. In addition, future research could seek to separate imperfect information about returns from preferences for schooling, which would require ex-ante surveys of worker beliefs (Hastings et al. [2015]).

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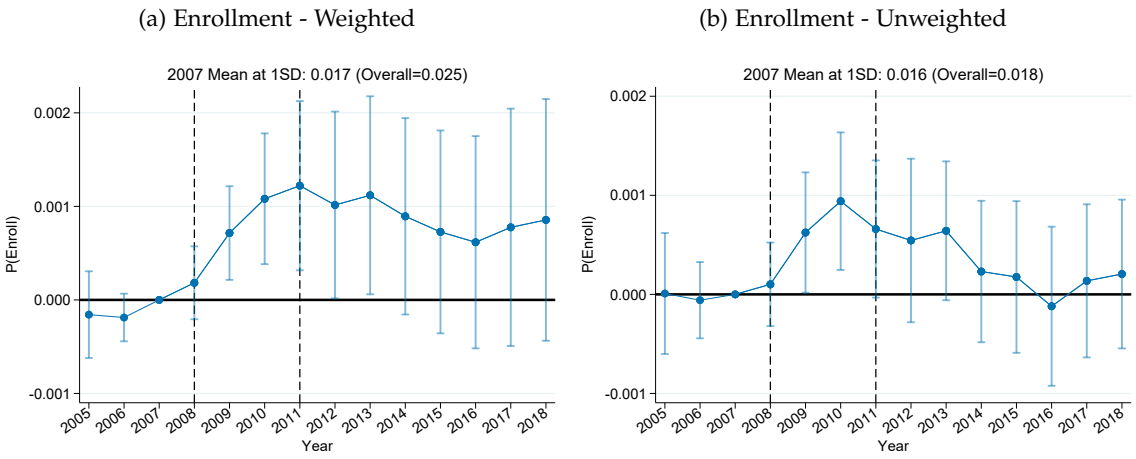
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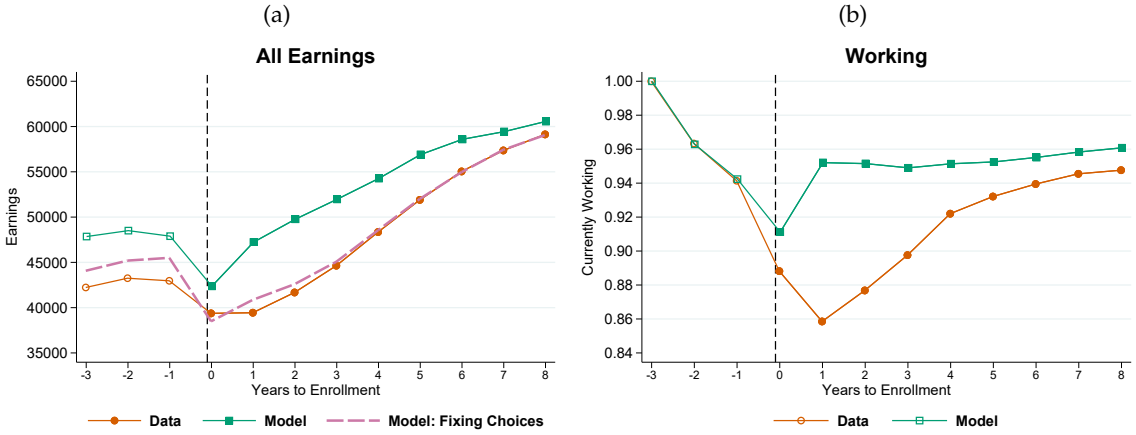
A Additional Figures and Tables

Figure A.17: Alternate Event Study: Great Recession Exposure on Industry-Level Enrollment Probabilities



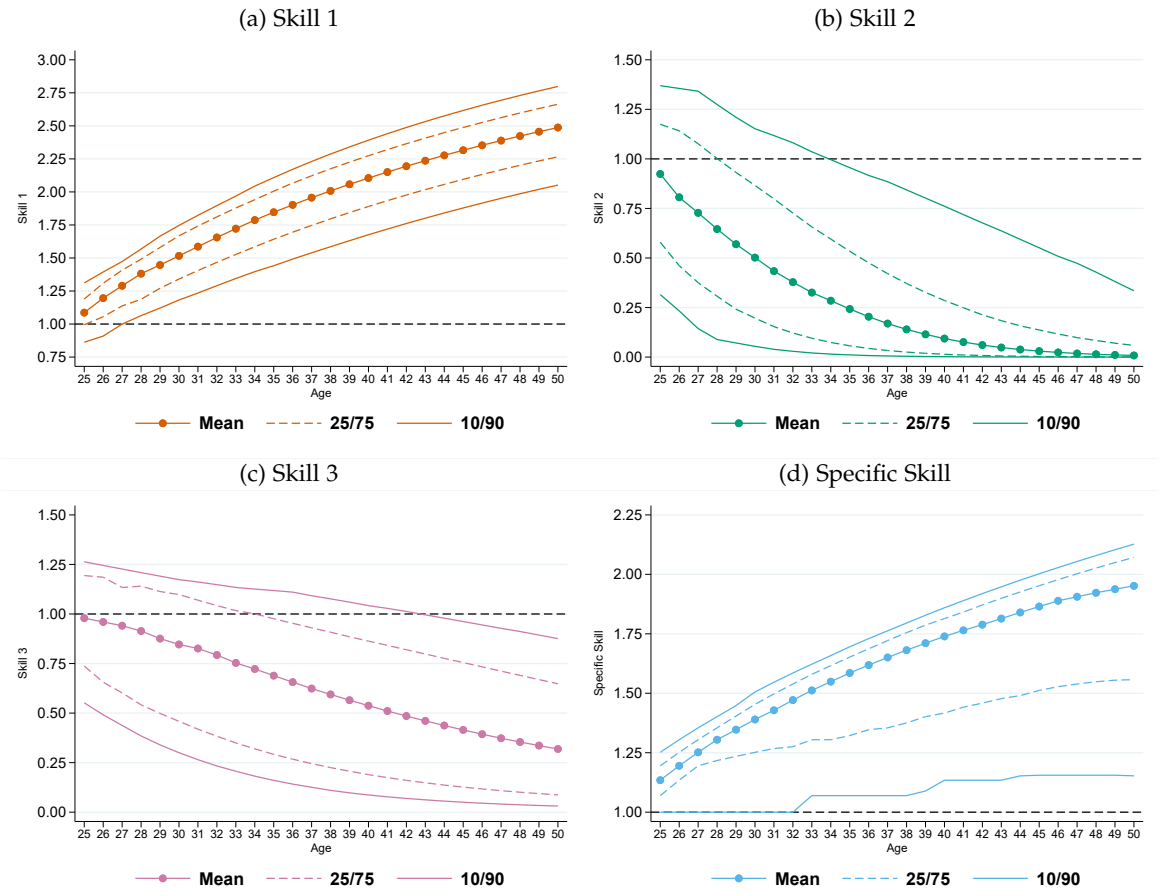
Notes: Plots coefficients and 95 percent confidence intervals from an event study analysis that focuses on changes in industry-level transition probabilities. For each 5-digit industry, using the full sample, I compute the probability that an individual who is working in the reference industry in quarter t is enrolled in $t+12$. Using this industry-time dataset of enrollment transitions, I then plot event study coefficients that interact year indicators with Great Recession exposure, controlling for industry fixed effects and overall time effects across industries.

Figure A.18: Model Fit: Earnings of Workers Enrolling in 2009 or 2010



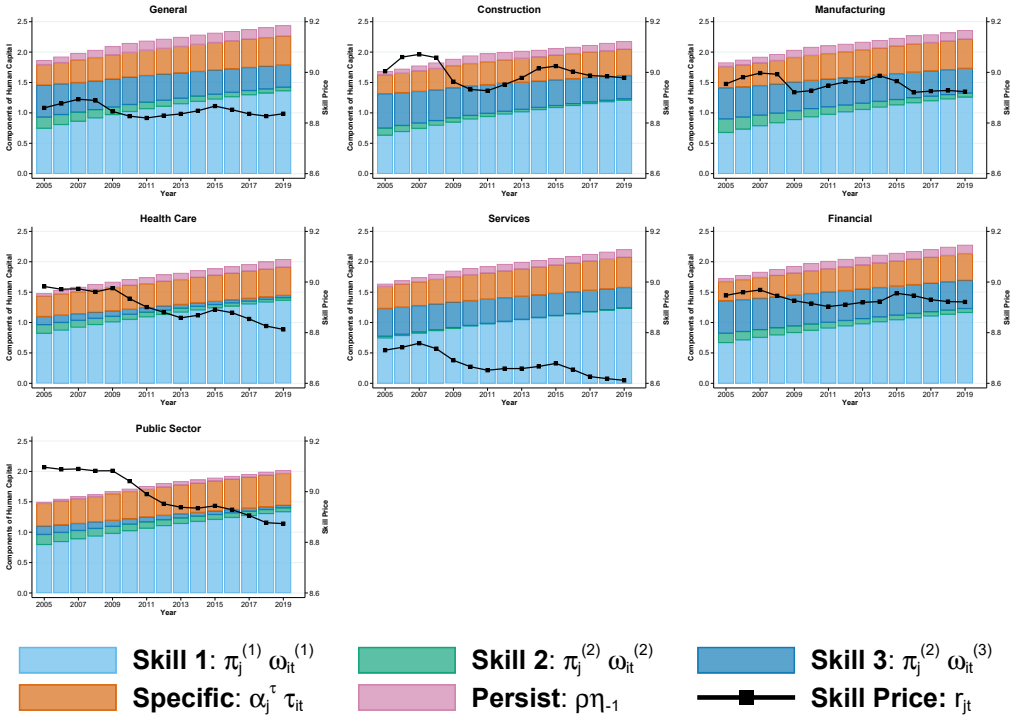
Notes: Share employed and total earnings, including zeros, for $N = 14,950$ workers in the baseline sample who enroll in 2009 or 2010 after not being enrolled in the prior three years and with some employment in year three prior to enrollment. Orange line (circles) shows the fit of the raw data, green lines (squares) show the fit of data simulated from the full model, pink (dashed) line shows the fit of the earnings model holding choices fixed to the path observed in the data. The pink dashed line plots the fit of the earnings model holding choices fixed, accounting for idiosyncratic productivity using lagged errors by adding the $\rho\eta_{-1}$ for the appropriate transition (and $\sigma_\varphi^2/2$ to adjust for the level of earnings).

Figure A.19: Marginal Distributions of Latent Skills by Age



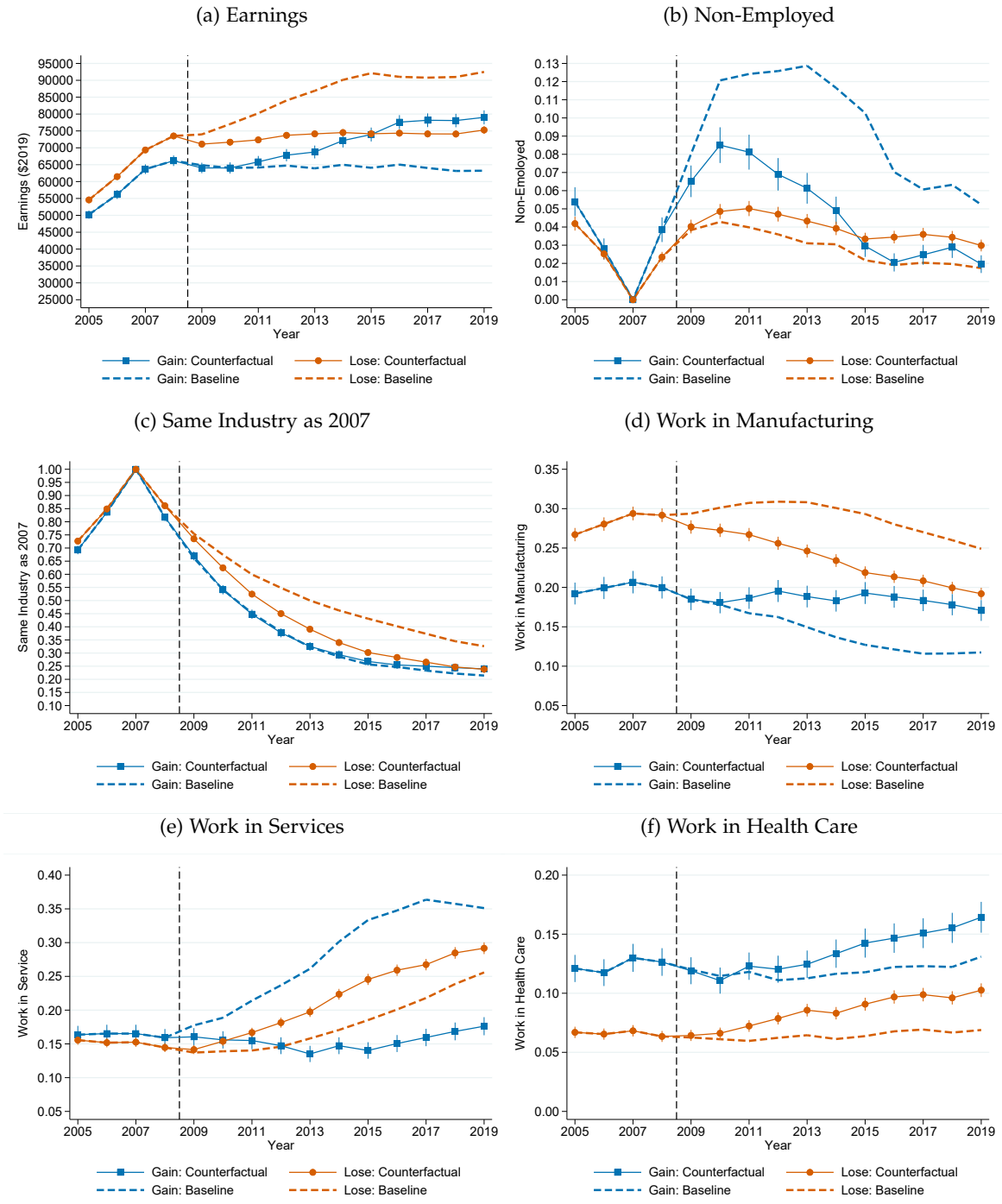
Notes: Plots the marginal distribution of each skill at each age in a simulated dataset of N =1,000,000 . At each age, the average, 10th, 25th, 75th, and 90th percentile of each skill is computed across all workers, without regard to labor force status.

Figure A.20: Mean Skill Components in Each Industry by Time



Notes: Plots mean earnings components in each industry and time using predicted earnings in the microdata.

Figure A.21: Summary of Pathways for those Induced to Enroll



Notes: Plots history of variables for simulated individuals from Figure 12. 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.

Table A.8: 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 show 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 A.9: Preferred Industry Exposure Estimates

	Baseline Sample				Full Sample			
	Enroll	New Enroll	Earnings	Graduate	Enroll	New Enroll	Earnings	Graduate
$Z(Shock)_j \times$ 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 A.10: Robustness of Industry Exposure Analysis

	External Shock		1997 Baseline		Alternate Controls I		Alternate Controls II	
	Enroll	New Enroll	Enroll	New Enroll	Enroll	New Enroll	Enroll	New Enroll
$Z(Shock)_j \times$ D(2005/1995)	-0.220*	0.002	-0.182**	-0.011	-0.140	-0.029	0.030	-0.013
	(0.114)	(0.067)	(0.072)	(0.023)	(0.140)	(0.079)	(0.135)	(0.080)
$Z(Shock)_j \times$ D(2006/1996)	-0.100	-0.005	-0.034	-0.000	0.060	0.008	0.051	0.029
	(0.094)	(0.073)	(0.032)	(0.022)	(0.095)	(0.068)	(0.091)	(0.073)
$Z(Shock)_j \times$ D(2008/1998)	-0.021	0.021	-0.009	-0.003	-0.011	0.093	0.044	0.114
	(0.079)	(0.079)	(0.032)	(0.025)	(0.094)	(0.082)	(0.097)	(0.086)
$Z(Shock)_j \times$ D(2009/1999)	0.287***	0.254***	0.007	0.015	0.317**	0.308***	0.303**	0.274***
	(0.109)	(0.077)	(0.060)	(0.042)	(0.140)	(0.082)	(0.144)	(0.086)
$Z(Shock)_j \times$ D(2010/2000)	0.216	0.085	0.015	-0.021	0.223	0.212***	0.162	0.200**
	(0.137)	(0.073)	(0.069)	(0.029)	(0.162)	(0.073)	(0.163)	(0.078)
$Z(Shock)_j \times$ D(2011/2001)	0.206	0.074	0.015	0.012	0.061	0.053	0.004	0.045
	(0.166)	(0.076)	(0.064)	(0.027)	(0.175)	(0.072)	(0.167)	(0.078)
$Z(Shock)_j \times$ D(2012/2002)	0.157	0.074	0.041	0.033	0.269*	0.224***	0.199	0.189**
	(0.165)	(0.070)	(0.068)	(0.028)	(0.156)	(0.081)	(0.155)	(0.080)
$Z(Shock)_j \times$ D(2013/2003)	0.181	0.049	0.098	0.037	0.182	0.078	0.048	0.043
	(0.145)	(0.063)	(0.075)	(0.029)	(0.152)	(0.068)	(0.152)	(0.070)
$Z(Shock)_j \times$ D(2014/2004)	0.168	0.078	0.085	0.021	0.231	0.173**	0.054	0.139*
	(0.174)	(0.063)	(0.079)	(0.028)	(0.152)	(0.072)	(0.147)	(0.074)
$Z(Shock)_j \times$ D(2015/2005)	0.189	0.050	0.088	0.014	0.278*	0.106	0.086	0.082
	(0.161)	(0.062)	(0.084)	(0.030)	(0.162)	(0.069)	(0.155)	(0.066)
$Z(Shock)_j \times$ D(2016/2006)	0.114	0.061	0.114	0.022	0.313**	0.161***	0.160	0.133**
	(0.167)	(0.062)	(0.084)	(0.027)	(0.140)	(0.050)	(0.132)	(0.052)
$Z(Shock)_j \times$ D(2017/2007)	0.126	0.090	0.114	0.024	0.242	0.110	0.032	0.067
	(0.164)	(0.063)	(0.088)	(0.029)	(0.148)	(0.068)	(0.134)	(0.063)
$Z(Shock)_j \times$ D(2018/2008)	0.179	0.093	0.164*	0.050*	0.280*	0.152**	0.076	0.123**
	(0.176)	(0.057)	(0.088)	(0.029)	(0.144)	(0.061)	(0.131)	(0.059)
2007 Outcome Mean	7.2	2.2			7.3	2.2	7.3	2.2
at 1 SD Z(Shock)	5.3	1.7			5.2	1.6	5.2	1.6
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 an 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 A.11: Heterogeneity by Field and Industry: Full Sample

	All	Production/Manufacturing	Services	Professional/Finance	Other
A. Main Outcomes					
Earnings	-3727.4***	-1627.4***	-1705.5***	-2627.1***	-4617.7***
	(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)	0.019	-0.035**	0.003	0.064**	0.018
	(0.013)	(0.015)	(0.031)	(0.025)	(0.025)
	[3.2%]	[-7.5%]	[0.5%]	[7.3%]	[4.3%]
Study Humanities (pp)	0.016	-0.001	-0.005	0.024	-0.035
	(0.017)	(0.008)	(0.015)	(0.038)	(0.025)
	[3.8%]	[-0.7%]	[-1.2%]	[4.1%]	[-7.8%]
Study Vocational Technical (pp)	0.011	0.051***	-0.012	0.019**	0.008
	(0.007)	(0.018)	(0.008)	(0.008)	(0.010)
	[9.5%]	[35.0%]	[-12.9%]	[42.3%]	[5.8%]
Study Math/Engineering (pp)	0.015	0.065***	0.019**	0.036	0.008
	(0.010)	(0.021)	(0.009)	(0.041)	(0.017)
	[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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.12: Heterogeneity by Field and Industry: Estimation Sample

	All	Production/Manufacturing	Services	Professional/Finance	Other
A. Main Outcomes					
Earnings	-2767.1***	-1631.8***	-1120.7***	-2737.5***	-3363.6***
	(490.371)	(551.962)	(298.325)	(499.714)	(1228.772)
	[-4.4%]	[-2.5%]	[-2.0%]	[-4.5%]	[-4.9%]
Enrolled (pp)	0.342**	0.404	0.082	0.708**	-0.029
	(0.160)	(0.348)	(0.262)	(0.323)	(0.325)
	[6.5%]	[7.6%]	[1.4%]	[10.4%]	[-0.9%]
New Enrollment (pp)	0.274***	0.204	0.108	0.367***	0.126
	(0.057)	(0.140)	(0.132)	(0.124)	(0.088)
	[16.7%]	[13.4%]	[5.8%]	[17.0%]	[11.0%]
B. Most Affected Fields					
Study Health (pp)	0.136*	0.146*	-0.146	0.196**	0.036
	(0.078)	(0.080)	(0.121)	(0.086)	(0.167)
	[48.2%]	[20.2%]	[-13.6%]	[26.5%]	[-4.9%]
Study Business (pp)	0.095*	0.030	0.118	0.151	0.060
	(0.049)	(0.097)	(0.092)	(0.114)	(0.059)
	[6.8%]	[2.3%]	[9.2%]	[8.0%]	[7.2%]
Study Information Technology (pp)	0.020	0.087	-0.002	0.014	0.026
	(0.020)	(0.054)	(0.048)	(0.042)	(0.034)
	[6.9%]	[32.5%]	[-0.7%]	[3.8%]	[13.2%]
Study Vocational Services (pp)	0.045	-0.004	0.005	-0.028	0.065
	(0.028)	(0.053)	(0.053)	(0.042)	(0.049)
	[14.1%]	[-1.8%]	[1.2%]	[-9.2%]	[17.5%]
Study Education (pp)	0.018	-0.009	0.084*	-0.018	0.001
	(0.018)	(0.022)	(0.043)	(0.046)	(0.034)
	[8.2%]	[-11.1%]	[36.8%]	[-6.9%]	[0.3%]
C. Other Fields					
Study General/Other (pp)	0.002	-0.010	0.080	0.230**	-0.085
	(0.062)	(0.101)	(0.162)	(0.102)	(0.111)
	[0.1%]	[-1.0%]	[6.9%]	[15.3%]	[-9.6%]
Study Humanities (pp)	0.009	0.059	-0.062	0.111	-0.092
	(0.039)	(0.056)	(0.096)	(0.116)	(0.057)
	[1.1%]	[12.0%]	[-7.4%]	[9.4%]	[-13.4%]
Study Vocational Technical (pp)	-0.004	0.046	-0.043	0.013	-0.004
	(0.017)	(0.069)	(0.031)	(0.023)	(0.026)
	[-2.4%]	[17.5%]	[-39.8%]	[23.7%]	[-1.9%]
Study Math/Engineering (pp)	0.023	0.060	0.048	0.038	-0.036
	(0.033)	(0.149)	(0.052)	(0.069)	(0.054)
	[3.8%]	[7.1%]	[10.5%]	[7.7%]	[-5.8%]
N (Industries)	561	142	130	79	210
N (Individuals)	189,073	15,282	41,803	41,923	90,065

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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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,[53] 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 demographics and complete labor market histories.

Baseline Sample: *This is a subsample of the previous panel of workers for which I have demographics and complete work histories, on which I conduct most if the 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) Are not observed to ever receive an advanced degree beyond the undergraduate level.

(e) Do 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 but are not observed to later receive degrees).

[53] 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.

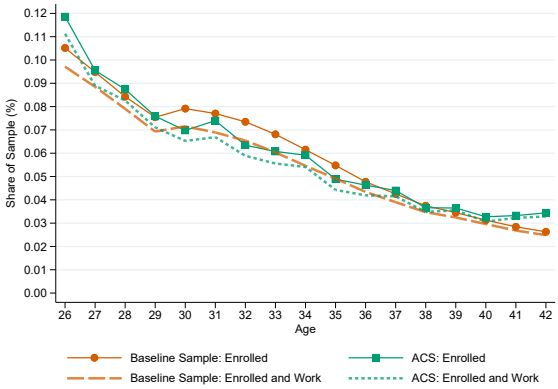
(g) Have one calendar year of 4 quarters of non-enrolled work between the ages of 25 and 30. This ensures that individuals choose an industry in this period.

This sample will range from ages 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.

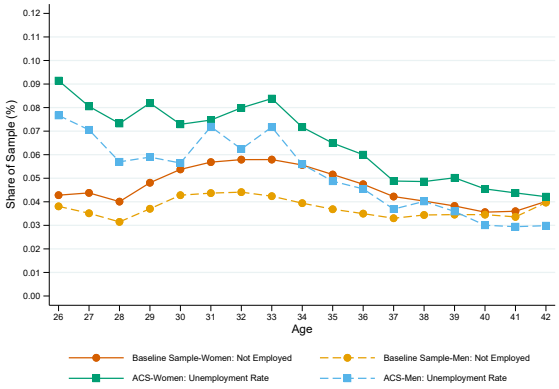
In Figure B.1, I compare the evolution of key variables for the baseline sample panel to cohorts of the same age range in the American Community Surveys. Figure B.1(a) shows that public college enrollment aligns almost exactly between the two samples. Figure B.1(b) shows unemployment and baseline sample non-employment differ in the early and mid-20s, likely due to restriction (f) above, but match well at later ages and in the decline over the life cycle.

Figure B.1: Comparison of Baseline ERC Sample with Statistics in the ACS

(a) Enrollment



(b) Non/un-employment



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 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 restrictions 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 non-employment shares 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. 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.

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 B.2.

I do some imputation to focus on the principal field of study associated with an enrollment spell. Many of the enrollment CIP codes are reported as general studies or as missing values, 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 period 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. I do some imputation based on CIP codes pursued throughout an entire spell and from degrees obtained. Details are available upon request.

Enrollment Timing: I 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 mapping roughly maps to that used in Jepsen et al. [2014]. For the fall and spring semesters, I divide completed hours equally between quarters. Enrollment at the annual level is defined as enrolling in any quarter.

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 transition analysis of Table 1 and matching estimator analysis of Section 2.5. 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.

Table B.1: 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

Table B.2: 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. Transporation 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

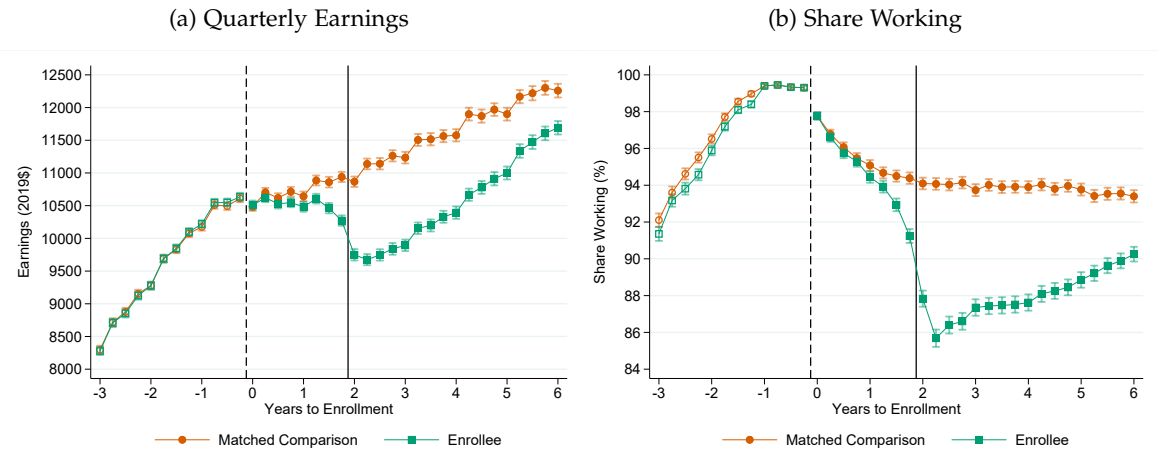
B.3 Additional Matching Estimates of Returns

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. Propensity score matching will balance covariates with respect to a target treatment, but it is possible there are additional balance issues when looking at different fields of study or subsequent outcomes we may wish to target. This leads me to this more flexible, but potentially

less efficient matching approach. Results are reported for the 22,594 enrollees and their matched comparisons for whom a control could be found.

Figure B.2 checks the quality of this matching procedure by shifting the enrollment date two years prior to actual enrollment. The earnings profiles for the enrollees and matched comparisons are almost exact through the placebo enrollment date. This indicates that the large lock-in effects measured in Figure 3 are not driven by mean reversion at the point we stop matching. Deviations between the two profiles start to appear about 3 to 4 quarters prior to the actual enrollment period. Table B.3 shows additional heterogeneity in matching estimators not reported in the main text.

Figure B.2: Matching Estimator: Placebo Check



Notes: This figure reproduces the matching procedure outlined in the notes to Figure 3, using a "fake" enrollment date two years prior to the actual enrollment quarter for each enrollee. This fake enrollment event is plotted as 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.

Table B.3: Heterogeneity in Matching Estimates

	Earnings	Employed	Earnings (if work)	Switch	Work in Health	Work in Manuf	Work in Services
A. Unconditional							
All	14.6	-0.020***	226.8***	0.065***	0.031***	-0.009***	-0.029***
	(53.1)	(0.002)	(49.6)	(0.004)	(0.003)	(0.003)	(0.003)
B. By Field of Study							
General/Other	-339.8***	-0.022***	-108.7	0.032***	0.012**	-0.021***	-0.005
	(105.8)	(0.004)	(99.4)	(0.007)	(0.005)	(0.005)	(0.006)
Business	253.1*	-0.013***	417.0***	0.045***	-0.009*	0.022***	-0.018**
	(131.0)	(0.005)	(118.7)	(0.010)	(0.005)	(0.007)	(0.007)
Humanities	-340.5**	-0.033***	-33.0	0.060***	-0.022***	-0.029***	-0.015*
	(149.8)	(0.006)	(136.1)	(0.011)	(0.007)	(0.007)	(0.008)
Math/Engineering	1667.6***	-0.014*	1869.2***	0.126***	-0.012	0.116***	-0.080***
	(333.4)	(0.008)	(319.3)	(0.019)	(0.007)	(0.016)	(0.014)
Health	239.2**	-0.025***	519.2***	0.085***	0.143***	-0.022***	-0.054***
	(107.4)	(0.004)	(100.0)	(0.007)	(0.007)	(0.004)	(0.005)
Vocational Tech.	-16.8	-0.005	-54.9	0.164***	-0.008	0.083***	-0.051**
	(612.1)	(0.015)	(594.7)	(0.033)	(0.010)	(0.029)	(0.025)
Vocational Services	-132.1	-0.020***	57.5	0.099***	-0.005	-0.041***	-0.028***
	(157.0)	(0.006)	(150.0)	(0.012)	(0.007)	(0.008)	(0.009)
Education	-168.1	-0.008	-117.1	0.073***	-0.001	-0.019***	-0.026***
	(149.6)	(0.007)	(127.4)	(0.012)	(0.007)	(0.007)	(0.009)
Information Technology	-496.3	-0.000	-465.7	0.030	-0.005	-0.022	-0.042**
	(364.8)	(0.009)	(349.6)	(0.020)	(0.009)	(0.016)	(0.017)
C. By Recession Enrollment							
GR Enroll	-6.9	-0.014***	149.6	0.074***	0.042***	-0.009	-0.030***
	(125.9)	(0.004)	(118.9)	(0.008)	(0.006)	(0.005)	(0.006)
Other Enroll	20.0	-0.021***	246.5***	0.063***	0.028***	-0.009***	-0.028***
	(58.5)	(0.002)	(54.4)	(0.004)	(0.003)	(0.003)	(0.003)
D. By Worker Type							
Male-No College	455.8*	-0.010	587.1**	0.102***	0.021**	0.004	-0.045***
	(273.3)	(0.009)	(258.6)	(0.019)	(0.008)	(0.016)	(0.014)
Female-No College	-81.2	-0.016**	35.5	0.034***	0.048***	-0.010	-0.014
	(131.8)	(0.007)	(117.6)	(0.012)	(0.011)	(0.007)	(0.009)
Male-Some College	-247.0**	-0.016***	-38.7	0.077***	0.020***	-0.017***	-0.033***
	(121.8)	(0.003)	(115.9)	(0.007)	(0.003)	(0.006)	(0.006)
Female-Some College	-92.7	-0.026***	149.1**	0.053***	0.035***	-0.007**	-0.028***
	(65.2)	(0.003)	(59.2)	(0.005)	(0.004)	(0.003)	(0.004)
Male-Prior Grad.	1683.9***	-0.001	1787.7***	0.125***	0.030***	0.002	-0.043***
	(358.8)	(0.008)	(340.2)	(0.019)	(0.009)	(0.015)	(0.013)
Female-Prior Grad.	576.6***	-0.014**	820.0***	0.074***	0.037***	-0.004	-0.019**
	(185.0)	(0.006)	(165.1)	(0.011)	(0.008)	(0.007)	(0.007)
E. By Race							
White	411.3***	-0.022***	674.2***	0.080***	0.034***	-0.003	-0.035***
	(83.2)	(0.003)	(78.2)	(0.005)	(0.004)	(0.004)	(0.004)
Black	-513.8***	-0.023***	-278.8***	0.047***	0.030***	-0.011*	-0.017***
	(107.7)	(0.005)	(96.8)	(0.009)	(0.007)	(0.006)	(0.007)
Hispanic	-271.4***	-0.017***	-123.5	0.053***	0.028***	-0.015***	-0.026***
	(86.7)	(0.003)	(80.9)	(0.006)	(0.004)	(0.004)	(0.005)
Other	411.2	-0.004	456.0	0.079***	0.038**	-0.006	-0.022
	(493.1)	(0.013)	(470.5)	(0.026)	(0.018)	(0.020)	(0.022)

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C Identification of the Skill Process

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 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 values, 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 ar-

guments 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 $\mathscr{H}_{-t}$ 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:

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

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 the 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 have 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 D.1 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 an 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 $\tau_t = 1$ (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:

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

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

D.1 Details of Model Parametrization

Transferable Skills: Equation D.1 below parameterizes the skill accumulation technology used in estimation:

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

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 more salient in finance than construction.

$\gamma^{PartTime} \in (0,1)$ 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, $\gamma_{Dim:School}^{(s)} > 0$ and $\gamma_{Dim:Work}^{(s)} > 0$ 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. Note that $\gamma_{School:f(k)}^{(s)}$, $\gamma_{Work:j(k)}^{(s)}$, $\gamma_{Work:q}^{(s)}$, and $\gamma_{School:q}^{(s)}$ are not sign-restricted, so individuals can lose skills from taking certain actions.

Specific Skills: Recall that job-specific skill is allowed to grow both within and across periods, depending on if the worker makes a voluntary or an involuntary transition across employers

during the period. Within-period growth in job-specific skill due to transitions is:

$$\tau_{ijt} = \begin{cases} 0 & \text{if } sep_{it} = 1 \quad \textbf{(involuntary separation)} \\ \gamma^{(\tau)}_{Vol}\tau_{i,j_{i,t-1},t} & \text{if } sep_{it} = 0 \text{ and } j(k) \neq j_{i,t-1} \quad \textbf{(voluntary switch)} \\ \tau_{i,j_{i,t-1},t} & \text{if } sep_{it} = 0 \text{ and } j(k) = j_{i,t-1} \quad \textbf{(remain)} \end{cases} \tag{D.2}$$

and the across-period growth follows:

$$\tau_{ij,t+1} = \begin{cases} 0 & \text{if } j(k) = 0 \quad \textbf{(non-employment)} \\ 1 & \text{if } \tau_{ijt} = 0 \text{ and } j(k) > 0 \quad \textbf{(entry-level employment)} \\ \Psi(k|\tau_{ijt})\tau_{ijt} & \text{if } \tau_{ijt} > 0 \text{ and } j(k) > 0 \quad \textbf{(experienced employment)} \end{cases} \tag{D.3}$$

where the function $\Psi(k|\tau)$ uses a functional form that mirrors the law of motion for transferable skills:

$$\log \Psi(k|\tau) = \gamma^{(\tau)}_{Accum} \exp\{-\gamma^{(\tau)}_{Dim}(\tau - 1)\} \tag{D.4}$$

D.2 Solving the Value Function using Regression Interpolation

Since I model the Great Recession as an unanticipated shock, 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 onwards, when agents are surprised). I also need to solve the model for each worker type q and graduation cohort. Moreover, the state space is large and has many continuous states, which poses an additional challenge. 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 backward recursion on a subset of possible states and approximate the value functions using regression interpolation.[54] 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

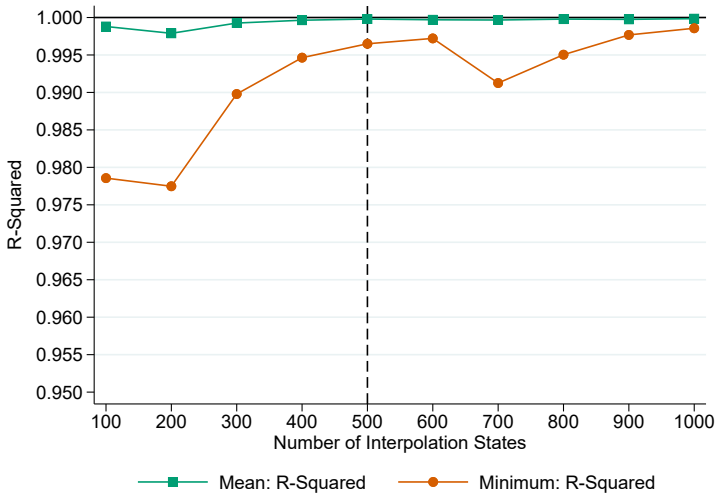
[54] Similar interpolation methods to quickly compute value functions through regression interpolation have been used in Keane and Wolpin [1997], Lee and Wolpin [2006], Sweeting [2013], Dix-Carneiro [2014], and Adda and Dustmann [2023].

continuous states in Ω, excluding Age_{it}.[55] 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, but pre-computing the design matrix for $x(\Omega, \eta, s)$ before evaluation makes this step quite fast.

In choosing the 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 first-step. 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, sampling a total of 500 points.

The approximation performs very well in practice, as shown in Appendix Figure D.1, where I vary the number of evaluation states on which to interpolate. In addition, the fact that the dynamic model fits choices quite well, as discussed in Section 6.1, provides further assurance that the interpolation is reasonable.

Figure D.1: Fit and Sensitivity of the Value Function



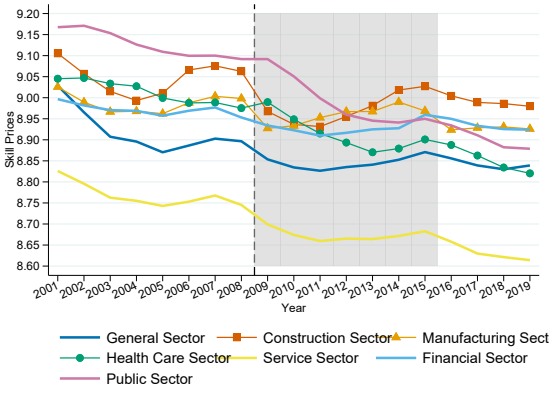
Notes: This figure shows the fit of the value function interpolation, where the dashed line shows the number of states used for interpolation in estimation. I interpolate the value function separately for each age (30 periods from 25 to 54), graduation cohort (2 for 1994 and 1998 in estimation), last 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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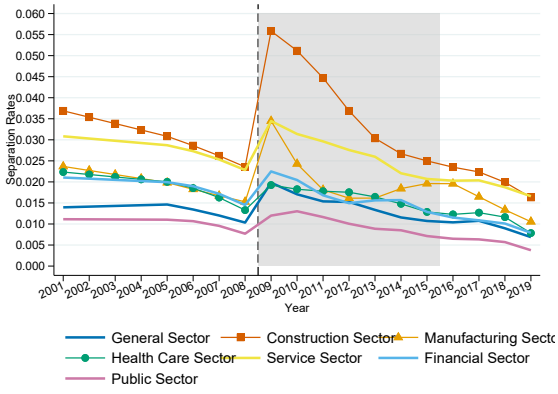
[55] Since I interpolate each cohort and time period separately, age is implicitly interacted with all coefficients as well.

Figure D.2: Skill Prices and Separation Rates - All Industries

(a) Skill Prices (Estimated)



(b) Separation Rates (Calibrated)



D.3 Calibrated Sticker Prices and Financial Aid Schedules

Sticker Prices: I sum 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 per-credit tuition costs reported on community college websites.

Financial Aid: 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 D.3. 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.

D.4 Detailed Discussion of Identification

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 $\pi_j^{(s)}$. Scale is

Figure D.3: Calibrated Financial Aid Schedules



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. 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.[56] Semi-parametric identification proofs are given in Appendix C. Implicit in these arguments is the assumption that there are enough transitions to identify the parameters.

Separation Rates, Switching Costs, and Flow Payoffs: Given earnings and skill parameters, which are estimated in a first step, transition probabilities can be non-parametrically identified from the data. I calibrate separation rates using annual transition rates from employment to unemployment by industry in the American Community Survey. As separation rates are known, this enables the inversion of CCPs to enable the identification of relative flow payoffs (Hotz and Miller [1993], Magnac and Thesmar [2002]). Once separation rates and the relative payoffs of actions in different states are identified, the probability of remaining in the same state pins down mean utilities while the probability of switching identifies mean utilities plus the switching costs.

Persistence and Shock Parameters: Shock parameters σ are identified by within-history, across-person variation in earnings. The persistence parameters ρ are identified from the degree to which this variation dies away within individuals. Specifically, as η is semi-parametrically identified, the

[56] 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. 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 $\tilde{\omega}^{(s)} = \frac{\omega^{(s)}}{\alpha}$.

estimation procedure observes how this object is related across periods at a guess of parameters.

Income Coefficient: The income coefficient β_Y 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. Moreover, since the Great Recession is a surprise, how workers respond to changes in industry conditions helps identify β_Y.

Tuition Coefficient: The sensitivity of individual choices to net tuition prices β_P 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 unexpected prior - how individuals of different potential financial aid shift enrollment decisions before and after the onset of the Great Recession aids in identification of this parameter.

D.5 Details on Estimation Procedure

Recall that θ_Y denotes parameters affecting the earnings process and θ_C denotes the parameters governing transition probabilities (utility, switching costs, etc.). It is useful to note that there are *auxiliary earnings parameters* α_Y that can be computed directly from the earnings microdata given a guess of θ_Y (e.g. skill prices, shock variances).

D.5.1 Estimation Procedure - Step 1: Earnings and Human Capital Parameters

The left part of the likelihood in Equation 5.3 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 θ_Y as the left side of the Equation 5.3 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 θ_Y, skill prices r_{jt} are simply recovered as averages 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 $\Omega(\mathscr{H}_i^{-t};\theta_Y)$, 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 4.2 can be rewritten as:

$$y_{it} = r_{jt} + h\left(k_{it}|\Omega(\mathscr{H}_i^{-t};\theta_Y);\theta_Y\right) + \rho_j^{j-1}\eta_{i,j_{-1},t-1} + \varphi_{ij,j_{i,t-1},t} = y(k_{it}|\mathscr{H}_i^{-t},q_i;\theta_Y) + \varphi_{ij,j_{i,t-1},t} \tag{D.5}$$

where r_{jt} is the skill price resulting from choice k_{it}, $h\left(k_{it}|\Omega(\mathscr{H}_i^{-t};\theta_Y);\theta_Y\right)$ 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 forecasted from the prior period's residual, and $\varphi_{ij,j_{i,t-1},t}$ is the contribution from independent shocks to idiosyncratic productivity.

The NLLS objective is defined as:

$$Q^{NLLS}(\theta_Y) = \frac{1}{2N}\sum_{i=1}^{N}\frac{1}{T_i}\sum_t\left(y_{it} - y(k_{it}|\mathscr{H}_i^{-t}, q_i;\theta_Y)\right)^2 = \frac{1}{2N}\sum_{i=1}^{N}\frac{1}{T_i}\sum_t \varphi_{ij,j_{i,t-1},t}^2 \tag{D.6}$$

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 in the main text.

Given a guess of θ_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:

$$\hat{r}_{jt} = \frac{1}{N_{jt}}\sum_{i \text{ s.t.} j(k_{it})=j}\left(y_{it} - h\left(k_{it}|\Omega(\mathscr{H}_i^{-t};\theta_Y);\theta_Y\right) + \rho_j^{j_{-1}}\eta_{i,j_{-1},t-1}\right) \tag{D.7}$$

Including an individual's productivity in the previous period in Equation D.6 and D.7 presents a computational challenge. This is not just a random effect — 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 $\varphi_{ij,j_{i,t-1},t}$.

Algorithm to Evaluate NLLS Objective: An evaluation of Q^{NLLS} for a guess θ_Y proceeds according to the following algorithm:

1. *Impose normalization*: Compute unrestricted $\tilde{\omega}_{1i}^{(s)}$ using θ_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 $h_{it} = h\left(k_{it}|\Omega(\mathscr{H}_i^{-t};\theta_Y);\theta_Y\right)$ 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 D.7
   (b) For each individual i:
      - Compute current idiosyncratic productivity: $\eta_{ijt} = y_{it} - r_{jt} - h_{it}$
      - Compute the current earnings residual: $\varphi_{ij,j_{i,t-1},t} = \eta_{ijt} - \rho_{j_{i,t-1}}^{j}\eta_{i,j_{i,t-1},t-1}$. Note that in the first period an agent works, $\varphi_{ij,j_{i,t-1},t} = \eta_{ij1}$.
4. *Compute objective*: Using Equation D.6 by adding up $\varphi_{ij,j_{i,t-1},t}^2$

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

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

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).

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 1,000 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.

D.5.2 Estimation Procedure - Step 2: Transition Parameters

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

$$Q^{CCP}(\theta_C|\hat{\theta}_Y) = \sum_{s=1}^{S} w_s \sum_{k=1}^{K} \hat{P}_{k|s}(\hat{\theta}_Y) \log P(k|\Omega_s, \hat{\theta}_Y, \theta_C) \tag{D.8}$$

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 D.8 is thus an approximation of the likelihood governing

choices in Equation 5.3.

Evaluating Equation D.8 requires solving the dynamic problem on each evaluation. This is because the history-dependence of skills and non-stationarity of the 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.[57]

There is then the issue of choosing states at which to evaluate the objective function D.8. I leverage the fact that the states are observed once θ_Y is estimated, picking states based on the observed distribution in the data. 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.

I maximize this likelihood using a Berndt-Hall-Hall-Hausman (BHHH) approximation of the true Hessian based on the outer-product of the score. As in the first-step estimation, I do a one direction line search for each parameter to assess global convergence.

[57] 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 between 1e-100 and 1-1e-100 to avoid negative or unusually large probabilities.

D.6 Full Parameter Estimates

Table D.1: 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: $\gamma_{Accum}^{(\tau)}$				0.067	
				(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	1.917	
	(0.067)	(0.000)	(0.009)	(0.109)	
Diminishing School Investments: $\gamma_{Dim:School}^{(s)}$	2.005	1.983	0.001		
	(0.139)	(0.397)	(0.000)		
Loss from Voluntary Transition: $\gamma_{Vol}^{(\tau)}$				1.021	
				(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 D.2: 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 D.3: 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)			