Learning the Major-Industry Mismatch

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Abstract

How do information frictions distort the choices of college majors and industries? This paper argues that uncertainty about individual's major-industry fit is a primary driver of mismatch and earnings dispersion among skilled workers. Using confidential Canadian administrative data linking education and employment histories, I establish three key facts. Firstly, mismatched individuals switch industries more. Secondly, on-the-job learning about major-industry match partially resolves the uncertainty. Thirdly, using a natural experiment that leverages LinkedIn's entry into Canada, I confirm that more information reduces mismatch. To quantify the aggregate consequences of these frictions, I develop a life-cycle directed search model with Bayesian learning where multidimensional skill individuals choose majors, industries, and climb the job ladder within an industry. The model is estimated to the Canadian economy and is consistent with the empirical facts. Imperfect information steers graduates to suboptimal majors, industries, and rungs on that ladder. Unresolved uncertainty about outside options, combined with search frictions, makes mismatch persistent. The model reveals that information frictions reduce average output by 25% at labor market entry. Counterfactuals show that improving the efficiency of this learning process not only raises aggregate output but also triggers a significant reallocation of talent, as majors with higher career uncertainty become more attractive.

Keywords: Industry Mismatch, Information Frictions, College Majors, Search Frictions, Job Ladders, Multidimensional Skills, Bayesian Learning

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1 Introduction

Are college graduates from a particular major working in their right industry? The allocation of talent is a cornerstone of economic growth, especially for high-skilled workers with a college degree[1]. How workers match with jobs has first-order consequences for aggregate output, productivity, and inequality (Bandiera et al., 2024). Yet, even within the same major, graduates face vastly different life outcomes, with earnings penalties for mismatch being well-documented (Andrews et al., 2022; Cassidy and Gaulke, 2023; Lindley and McIntosh, 2015; Robst, 2007). This raises key questions: What causes these outcome gaps, and can targeted interventions close them?

This paper finds that the primary driver is information friction about a worker's own skills. Conditional on an individual's major, graduates enter the labor market uncertain about which industry offers the best return for their skills. This uncertainty forces graduates into a dynamic trial-and-error learning process. Workers receive noisy signals about their skill in the industry they join, and dynamically decide whether to stay or switch industries based on updated information. This process generates a large and persistent mismatch. Some workers find their most productive industry quickly, while others sort through a series of poor or mediocre matches. Crucially, these labor market uncertainties also shape ex-ante educational choices, influencing a student's decision of what to study. To support this finding, I provide extensive empirical evidence and develop a novel framework of directed search incorporating educational and labor market choices.

I begin by documenting key facts about labor-market dynamics and sorting patterns of college graduates. I use a unique Canadian administrative panel linking the employment records of all post-secondary graduates studied and worked in Canada to their detailed educational histories. I further enrich this dataset by matching it with unemployment insurance records and high school grades when available. This comprehensive data allows me to establish several stylized facts about labor market and earnings dynamics, which provide direct evidence of on-the-job learning under significant information frictions.

I construct a measure of major-industry match quality at the individual level using the residual from a population-level earnings regression. I ask how unexplained workers' earnings affect their labor market outcomes[2]. This measure reveals a striking, U-shaped relationship with the probability of switching industries, even after conditioning on col-

[1] In this paper, I focus on bachelor's degrees and higher, using "college" and "university" interchangeably. Differences between colleges and universities are not the focus of this paper and remain for future research.

[2] Although focusing on different topics, this idea is inspired by the revealed preference approach of Sorkin (2018) in ranking jobs and how residual wages tells important information about job loss (Baley et al., 2022).

lege major. While it is intuitive that matches with large negative residuals are more likely to dissolve, the crucial finding is that matches with large positive residuals also end at a higher rate. This symmetrical response to large earnings deviation points directly to information friction and suggests both workers and firms correct poor matches.

The dynamics of mismatch over time highlight industry-specific learning. The variance of mismatches decreases with industry tenure, as good matches are confirmed and poor ones are dissolved. However, this learning does not transfer across industries. In fact, the overall mismatch variance nearly doubles in 14 years after graduation. Together, the two opposing trends indicate that switching industries resets the learning process. The intensity of switching varies across majors. Graduates from majors like Arts and Humanities exhibit persistently higher switching rates than those from majors like Education, implying that choosing a major is also choosing a level of career uncertainty.

Further supporting the learning mechanism, I show that these patterns cannot be a story about innate ability. Using 12th-grade test scores to proxy for pre-college ability, I find that while higher ability predicts sorting into specific majors, it does not predict a better initial industry match.

To provide causal evidence for information availability shaping labor market outcomes, I use a Difference-in-Differences design to estimate the effect of LinkedIn's 2009 entry into Canada to outcome of new graduates. My identification strategy compares graduates from majors with higher career path uncertainty (Business and Law), who were more likely to be affected by the introduction of LinkedIn, to those from majors with more structured career paths (Engineering and Construction), who were plausibly less affected. LinkedIn improves information on career opportunities. First, it improves initial matches, reducing first-year mismatch by 0.25 standard deviations. Scond, it accelerates the correction of poor initial choices, enabling mismatched workers to leave for a better fit four months sooner. These results provide causal evidence that greater information access leads to more efficient labor market sorting, both by improving the initial allocation of talent and by expediting the dissolution of poor matches.

To formalize and quantify the cost of information frictions evident by the empirical facts, I develop a life-cycle directed search model with uncertainties (Menzio et al., 2016; Baley et al., 2022), a one-time college major choice (Arcidiacono et al., 2012), and industry mobility (Carrillo-Tudela et al., 2022). The model features three main components.

First, individuals with heterogeneous innate abilities choose majors with different labor market prospects, subject to Frechet preference shocks. Majors differ in their prior for industry-specific skills, productivity terms, and skill requirements. This choice of majors reflects the uncertainty associated with each major, as individuals only observe a prior of the major specific skill distribution. Consider, for example, a high-ability individual who chooses to major in mechanical engineering over history, anticipating better career prospects.

Second, workers direct their job search to a specific industry and job rung, defined by its skill requirement, within that industry, subject to under- and over-qualification penalties. Workers trade off between higher output gain and expected mismatch, given their current belief about their industry-specific skills. For instance, the high-ability worker with a mechanical engineering degree may begin in an entry-level construction role, expecting average skills in that industry.

Third, while employed, workers receive noisy signals about their true skills in the industry. The belief updating on their industry-specific skills follow standard Bayesian updating. They then decide whether to climb the job ladder, stay, or switch based on updated beliefs. The mechanical engineer in construction might receive a positive signal that prompts a promotion or a negative signal that could lead to separation if staying is less valuable than the outside option.

I solve the model using Block Recursive Equilibrium (BRE) techniques (Menzio and Shi, 2010) to handle the high-dimensional state space from multidimensional skills and learning. This approach can cleanly charaterize the allocation of workers across majors, industries, and rungs independent of the aggregate distribution of workers and firms.

This model is innovative in several respects: it jointly incorporates multidimensional skill matching, dynamic industry and job rung choices, and learning under imperfect information about industry-specific skills. Relative to the extensive literature on incorporating search fricitons and mismatch in the labor market[3], I include life-cycle educational choices that are endogenously determined by the level of uncertainties faced in the labor market. There are four key insights from this model.

First, imperfect information, or uncertainty, steers graduates of a given major into suboptimal industries and job rungs within industries. Importantly, uncertainty exists both about the current industry and outside options. Therefore, information friction in this economy never fully resolves. Workers only learn about their current industry-specific skills and not about outside options beyond the unemployment benefits.

Second, unresolved uncertainty regarding outside options and search frictions makes the mismatch persistent. Longer industry tenure leads to self-selection: good matches

[3]See recent review paper Wright et al. (2021) that discusses extensively the theoretical progress.

remain, poor matches exit. Separation decisions depend on noisy signals: if a signal falls below a threshold set by the major-specific prior, the worker exits. Since beliefs reset to prior upon switching, workers with poor skills across industries tend to switch repeatedly and never settle in one industry. Conversely, workers with strong industry-specific skills across all industries may settle prematurely in suboptimal industries without further exploration.

Thirdly, information friction and learning speed alter educational choices. If learning is slow, workers choose majors with a more controlled yield, which have lower variance and a lower mean. If people can quickly discover their type, they will be more willing to pick majors with more varied outcomes.

Lastly, individuals tend to choose the industry that offers the highest average pay for their major. This industry may not actually be the best fit. Since each person sees the same prior before matching, ex-ante, the highest average pay industry looks most attractive, and people believe they'll achieve the highest yield there.

I calibrate the model using Canadian administrative data via the Generalized Method of Moments. The calibrated model quantitatively replicates the key stylized facts from the empirical analysis. It generates the observed sorting of students into majors by ability and of workers with different majors into industries, including the heterogeneity in sorting frictions across different majors. Crucially, the model also accounts for the U-shaped relationship between earnings residuals and industry switching, alongside providing the divergent paths of mismatch variance declining within an industry but rising over a career. This close alignment between the model's predictions and the data provides strong validation for the proposed on-the-job learning mechanism and the role of information frictions.

I first quantify the productivity loss from information frictions by comparing the baseline economy to a first-best benchmark with perfect information. I decompose this loss in two steps. First, holding major choices fixed, I eliminate all post-entry uncertainty about industry-specific skills. Second, I allow individuals to re-optimize their major choices given this perfect information. The model reveals substantial output gaps. Relative to the perfect-information benchmark, average output per employee is 25% lower in the baseline at entry and narrows with continuous industry tenure to roughly 12% after 30 years. This persistent loss reflects the limits of on-the-job learning; workers only discover their match quality in their current industry, leaving their potential in outside options unresolved. The model shows a key behavioral response: workers compensate for weak industry matches by climbing the internal job ladder more aggressively. Fearing the high cost of resetting their beliefs by switching industries, workers overvalue "good-enough" matches, leading them to underexperiment across different sectors.

In a different counterfactual exercise, I show how the efficiency of learning shapes educational choices. I increase the precision of the signals workers receive on the job, which accelerates the correction of poor matches. A four-fold increase in signal precision raises steady-state output per worker by 3% but triggers a significant reallocation of talent across majors. Majors with higher career uncertainty attracts more students, as faster learning reduces the cost of exploring one's fit. This effect is particularly pronounced among high-ability individuals. Conversely, an opposite exercise that prevents learning by making signals infinitely noisy pushes students into majors with low outcome variance, as they seek to avoid the risk of bad matches entirely.

Literature Review This paper bridges three strands of literature. First, I build on studies of earnings heterogeneity among college graduates. Second, I add to the understanding of labor market mismatch. Third, I advance life-cycle directed search models by incorporating a Bayesian learning mechanism to analyze information frictions.

First, I build on the literature documenting substantial earnings heterogeneity among college graduates, even within the same major[4] (Andrews et al., 2022). The literature attributes this earnings variation to several factors: changing skill prices (Altonji et al., 2014), value-added differences across majors (Kim et al., 2015; Andrews et al., 2017; Bleemer and Mehta, 2022; Hastings et al., 2013) and institutions (Murnane et al., 2024), and cohort-specific conditions at labor market entry (Altonji et al., 2016; Liu et al., 2016; Oreopoulos et al., 2012; von Wachter, 2020). A shared conclusion is that these observable characteristics, while significant, do not fully explain the diverse outcomes of college graduates. Crucially, this literature focuses on between-major differences, whereas my paper identifies a powerful mechanism for the significant within-major heterogeneity: skill mismatch driven by information frictions[5] in the labor market for industry-specific skills[6]. Methodologically, where prior work is largely empirical, I contribute by combining causal evidence with a structural model to quantify the aggregate consequences of this friction.

[4]For comprehensive reviews of the college major choice literature, see Oreopoulos and Petronijevic (2013) and Altonji et al. (2016), confirming significant financial benefits of a college degree and substantial variation in earnings across fields.

[5]Information channel has been extensively studied on understanding how multiple stages of post-secondary studies are decided. See, for example, Hastings et al. (2016) for major choices and Kerr et al. (2020) for institution selection.

[6]Industry premium has long been recognized as an important source of earnings heterogeneity Krueger and Summers (1988), with especially enthusiasm towards industry-specific human capital (Neal, 1995). Bleemer and Mehta (2022) highlights the importance of industry in explaining earnings premium for better-paid majors.

Second, I contribute to the literature on labor market mismatch[7] by identifying information frictions as a key driver of the under-explored major-industry dimension. Prior work has largely focused on the worker-occupation link, using either standardized test scores against O*NET requirements (Guvenen et al., 2020; Baley et al., 2022; Bandiera et al., 2024) or survey data on job relevance (Robst, 2007; Lindley and McIntosh, 2015; Cassidy and Gaulke, 2023). By explicitly modeling the ex-ante educational choice, I distinguish vertical sorting on an occupational ladder[8] from the more nuanced, horizontal sorting across industries. This perspective is critical for understanding why an engineering graduate's earnings differ substantially between the Finance and Information sectors. To isolate this channel, I model skills as ex-ante industry-specific (Baley et al., 2022)—not as idiosyncratic match-quality shocks (Menzio and Shi, 2011)—and use a directed search framework to abstract from exogenous frictions (Lise and Postel-Vinay, 2020; Lindenlaub and Postel-Vinay, 2023). Methodologically, I advance the work on information frictions as a mechanism for mismatch (Jovanovic, 1979; Baley et al., 2022)[9] by providing both causal evidence and a structural estimation. My framework is the first to then link these post-graduation labor market frictions back to ex-ante educational choices, showing how the prospect of learning and mismatch risk shapes human capital investment.

Third, I advance the literature on search and matching by developing a tractable life-cycle model that links educational choice to labor market sorting. I make three theoretical contributions. First, I synthesize a life-cycle framework (Menzio et al., 2016; Papageorgiou, 2014) with directed search and multidimensional learning a la Jovanovic (1979). This setup moves beyond the uni-dimensional learning in Groes et al. (2015) and, distinct from Baley et al. (2022), embeds a rich learning mechanism within a life-cycle framework where search is directed across industries. Second, and most critically, I embed this rich search and learning process within an irreversible educational choice framework (Arcidiacono et al., 2012; Flinn and Mullins, 2015). This is my central innovation, as it allows me to analyze how the prospect of future labor market frictions distorts students' ex-ante major choices. This link has been previously underexplored. Finally, the model identifies a novel, acyclical mechanism for scarring. Whereas the literature emphasizes cyclical shocks (Altonji et al., 2016; Liu et al., 2016), my framework quantifies how persistent

[7] Literature on mismatch is vast, and the definition of mismatch varies. Some look at mismatch as misalignment between vacancies and unemployed workers (Faberman and Mazumder, 2012; Şahin et al., 2014), while some look at mismatch as misalignment between worker skills and job requirements (Guvenen et al., 2020). In this paper, I focus mostly on the latter but incorporate employment transitions as key outcomes to look at.

[8] Occupation sorting shapes earnings dynamics both generally (Kambourov and Manovskii, 2009) and over the business cycle (Huckfeldt, 2022; Carrillo-Tudela and Visschers, 2023).

[9] Existing work has shown how information affects pre-college major choice (e.g., Qiu (2025)), labor market search more broadly (Conlon et al. (2018); Bradley and Mann (2024)), and how technology influences job search behavior Autor (2001).

penalties on careers and aggregate productivity (Bandiera et al., 2024) arise purely from initial major-industry mismatch. The framework is tractable and well-suited to study various educational and labor market policies.

The rest of the paper is organized as follows. Section 2 describes the data and presents motivating empirical patterns. Section 3 provides causal evidence on the role of information frictions in improving labor market outcomes. Section 4 introduces the theoretical model, and Section 5 discusses the estimation strategy, while Section 6 explores counterfactual scenarios. Finally, Section 7 concludes.

2 Data and Motivating Trends

2.1 Data Description

I first describe the data used in this paper briefly. I use unique Canadian administrative data from the Education and Labour Market Longitudinal Platform (ELMLP) provided by Statistics Canada. The ELMLP brings together several datasets that enable the study of labor market outcomes for postsecondary students in Canada. The main dataset contains the universe of registration information for all post-secondary attendees in Canada from 2009 to 2021, with partial coverage starting from 2004. In this paper, I combine four datasets within this platform:

1. The Postsecondary Student Information System (PSIS) provides data on major (up to 6-digit CIP code), institution, province of residence, and graduation year for all postsecondary students in Canada from 2005 to 2021. Majors are classified using CIP codes at various levels of detail: for example, 2-digit codes such as *Business, Management, Marketing, and Related Support Services (52)* vs. *Health Professions and Related Programs (51)*; 4-digit codes such as *52.03 (Accounting and Related Services)* vs. *52.08 (Finance and Financial Management Services)*; and 6-digit codes such as *52.0801 (Finance, General)* vs. *52.0807 (Investments and Securities)*. The main analysis uses 2- or 4-digit CIP codes to balance group size and detail, further separating large fields (such as splitting CIP *52* into *52.03 Accounting*, *52.08 Finance*, etc) where enrollment counts justify. All group separations are based on the number of students within each finer category.

2. The T1 Family File (T1FF) contains individual tax records from 2000 to 2021, providing annual data on basic worker characteristics, wage and self-employment earn-

ings, and industry of employment (up to 3-digit NAICS code). For example, industries are classified as *517 (Telecommunications)* or *518 (Data Processing, Hosting, and Related Services)*, allowing for analysis of industry switching at a detailed yet meaningful level.

3. The Employment Insurance Status Vector (EISV) offers details on unemployment spells, including the reason for job separation for each filing. Therefore, multiple spells within the same year will be recorded separately. This information is available to those who applied to Employment Insurance, regardless of their eligibility.

4. The Ontario 9/12 high school file contains grade 12 course performance in Mathematics and Language for a subset of students who attended public high school in Ontario between 2013 and 2016. Both Mathematics and Language classes at the grade 12 level are required for high school students to obtain the high school diploma.

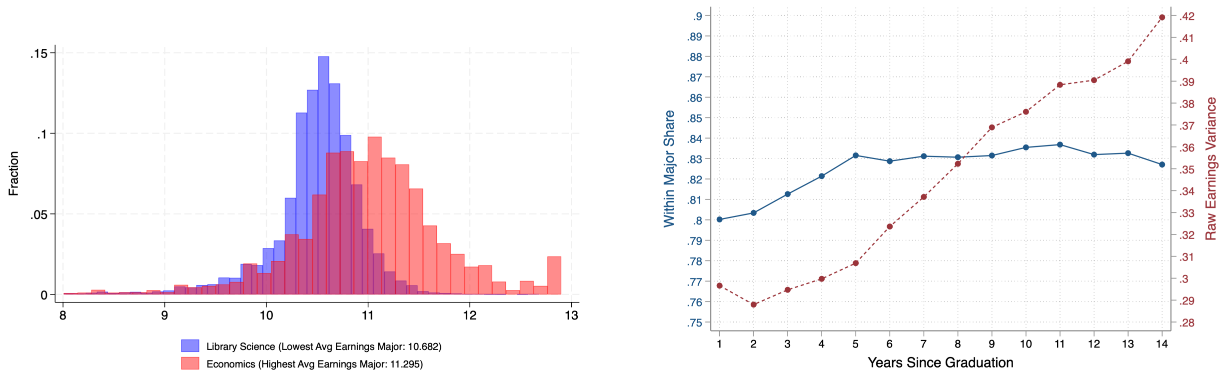
The main sample used in the analysis focuses on individuals who obtained a terminal bachelor's degree and were aged 18 to 35 at graduation. Throughout the analysis, I use the term "college graduates" to refer to these individuals. I only include terminal degrees to avoid contamination of returning to schooling reflected as poor labor market performance. I track these graduates longitudinally from their year of graduation through the latest year available. The results presented in the empirical section are robust to include students who obtain a bachelor's degree or higher, or to include all graduates from terminal post-secondary institutions. In fact, including more groups makes the results quantitatively more significant. Detailed descriptions of each dataset and sample limitations are provided in Appendix A.5.

2.2 Large Heterogeneity within College Majors

I first establish a rather surprising empirical fact that prefaces this paper: there exists massive and persistent heterogeneity in earnings among college graduates within the same major. Figure 1a illustrates this point by plotting the earnings distributions for the highest- and lowest-earning college majors in the U.S. The distributions overlap significantly.

To illustrate this more directly, following Song et al. (2019), I decompose total earnings variance and find that over 80% of it arises from differences among graduates from the same major. This variance rises to 96% when residualized by institution and gender.

This massive and persistent within-major variance, shown in Figure 1b, suggests systematic and implicit forces shaping earnings differences among college graduates beyond the choice of major. Section B.1 provides more details on this decomposition and robustness checks.



(a) Overlapped Dist. of log earnings

(b) Total variance decomposition

Figure 1: Earnings distributions and total variance decomposition

Notes. Panel (a) plots density distribution of log annual earnings for the majors with the highest and lowest mean earnings using National Survey of College Graduates from U.S. for young graduate aged between 25 to 35. The sample only include full-time workers and are selected exactly as in Altonji et al. (2014). Panel (b) reports the within-major and between-major shares of total earnings variance computed separately for each cohort c and years since graduation t. Across cohorts and years, the within-major share exceeds 80% and remains stable over t. The figure plots the time trend for the cohort graduated in 2010. The total earnings variance increased roughly from 0.3 to 0.42 in the first 14 years post-graduation, shown by the dotted green line using the right axis. See Section B.1 for more details regarding the variance decomposition.

2.3 Switching Patterns and Earnings Deviation

To investigate the drivers of earnings heterogeneity within fields of study, I construct a measure of individual-industry match quality, conditional on a graduate's major. This measure captures the component of an individual's earnings that deviates from the level predicted by their observable characteristics, thereby quantifying the match quality between a worker and their industry. Because I use population data for all Canadian college graduates, this procedure is a decomposition rather than an estimation, which avoids common econometric issues like measurement error.

I use this measure to document three key empirical facts: (1) mismatch predicts industry separations; (2) mismatch is resolved through industry-specific tenure, consistent with a model of learning; and (3) the intensity of this uncertainty varies systematically by major.

Capturing Match Quality I consider the difference between the actual earnings of an individual and the predicted earnings based on a mincerian-type regression as a measure of match quality. The intuition is that after controlling for a rich set of observable characteristics, the residual earnings component reflects the unobserved quality of the match between an individual and their employed industry at time t. At the definition stage, I will be agnostic about the source of such variation and whether the sign or the magnitude of this variation has any economic interpretation. It will become clear as I demonstrate and describe the motivating facts that a value closer to 0 is more stable, thus a better match.

The main specification is as follows:

$$\log(y_{ijmct}) = \alpha_i + \beta_{mj} + \gamma_{jt} + \xi_{mt} + \delta_{mj\tau} + f(\text{age}) + \epsilon_{ijmct} \tag{1}$$

where y_{ijmct} is the total earnings of individual i employed in industry j, graduated from major m and cohort c in year t, with industry tenure τ_{ijt}. The model includes individual fixed effects α_i, a major-specific industry fixed effect β_{mj}, industry-time fixed effect γ_{jt}, major-industry specific tenure profiles $\delta_{mj\tau}$, and a polynomial time trend $f(\text{age})$ that includes age, age squared, and age cubed. Standard errors are clustered at the individual level. While I cannot directly share the regression table due to data confidentiality, the R-squared of this regression is 0.5383.

This comprehensive specification accounts for key determinants of individual earnings, including time-invariant individual heterogeneity, and detailed, major-specific returns to industry experience, among other controls. Controlling for institution-time fixed effects does not change any of the results listed below. Institutions in Canada are mostly public with similar tuition fees, and the explanation power of institution fixed effects is small. I omit it in the main specification for parsimony.

I denote the earnings deviation, or the residuals from this comprehensive regression, as Mismatch, M_{it}. More precisely,

$$M_{it} \equiv \widehat{\epsilon_{ijmct}} = \log(y_{ijmct}) - \log(\widehat{y_{ijmct}}) \tag{2}$$

By construction, $M_{it} > 0$ implies that individual i is earning more than predicted by their observables at time t; similarly, $M_{it} < 0$ implies this individual earns less. Note M_{it} is denoted only with i and t because given a year and an individual, the industry, major, and cohort are determined. The subsequent facts will validate that a value of M_{it} close to zero represents a stable, high-quality match.

2.4 Stylized Facts on Match Quality and Labor Market Dynamics

I now show that this measure of mismatch is strongly correlated with workers' career progression, employment stability, and industry sorting over lifetime.

2.4.1 Fact 1: Higher Mismatch Is Associated With a Greater Probability of Industry Separation

I first focus on the correlation between the deviation of earnings to industry switching probability in the next year. I binned the earnings residuals in quintiles and calculated the share of industry switchers, both experiencing unemployment (EUE transitions) and not (EE transitions), without conditioning on whether they land a job in the next year. The relationship of interest is whether voluntary and involuntary separations are correlated with the quality of matches in previous employment.

The relationship between past mismatch, $M_{i,t-1}$, and subsequent industry switching is strikingly U-shaped. As shown in Figure 2, higher magnitudes of $M_{i,t-1}$, regardless of the sign, are associated with a higher probability of switching industries in the next year. In contrast, workers whose earnings are close to their predicted value, $M_{it} \approx 0$, are the least likely to switch industries. Calculating the average layoff share for the same binned group of earnings deviation results in a similar pattern.

Together, these two patterns yield two key insights. First, both firms and workers correct bad matches ex-post. This suggests that a large mismatch is costly for both parties, leading to separations initiated by either the worker (industry switching patterns) or the firm (layoff patterns).

Second, the very existence of these poor matches, which dissolve more quickly, suggests that it is difficult for workers and firms to assess match quality before the match. Firms and workers would only form "good" matches in the center of the distribution if information were perfectly known beforehand. The matches formed at the two extremes indicate a process of trial and error, and the high separation rates at the two extremes are evidence of the market correcting matching errors that are only revealed on the job.

From these results, I hypothesize that M_{it} captures an idea of qualification for individuals with industry j at time t. A negative M_{it} indicates that individual i is overqualified at

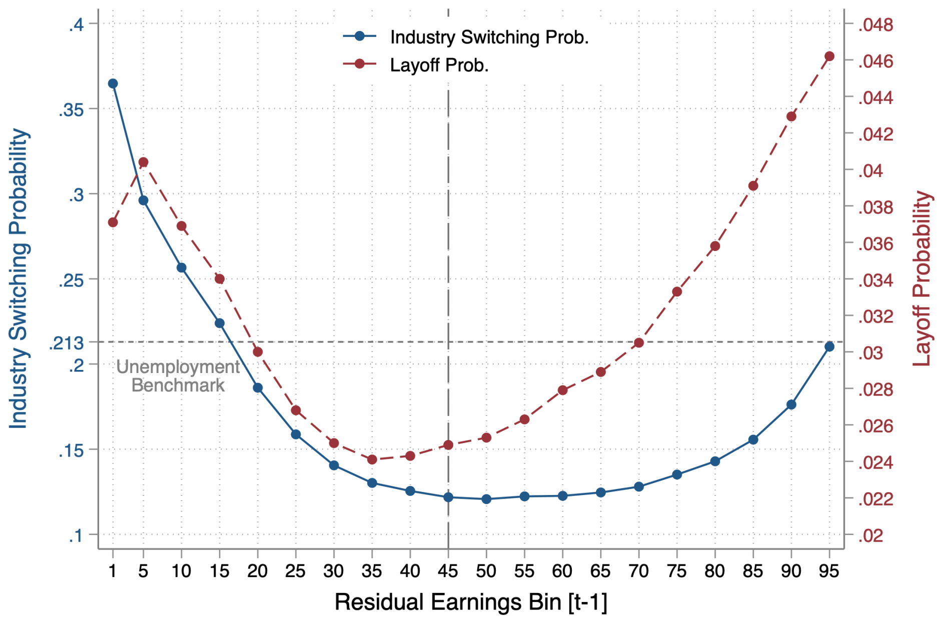


Figure 2: Industry Switching and Layoff Probability by $M_{i,t-1}$

Notes: The left axis (blue line) shows the industry switching probability, including EE (employment-to-employment) and EUE (employment-unemployment-employment) transitions. The right axis (red line) displays the layoff probability from the job, as recorded in the Employment Insurance dataset. The unemployment benchmark line indicates the industry switching rate for individuals who experienced unemployment (UE). Residual earnings ($M_{i,t-1}$) are binned into quintiles (each bin represents 5 percentiles); bin 45 includes the group with residuals equal to zero.

year t, providing more incentive to endogeneously switch to a different industry. Consequently, firms might find a frustrated and unhappy worker unfit for the job and lay them off. Whereas a positive M_{it} is associated with underqualification, and it is in the best interest of the firm to lay off that worker in search of a more productive worker, and for the worker themselves to locate to a more suitable job for their skills. This bilateral consensus on which matches to keep will support a key assumption of the market structure in the model.

2.4.2 Fact 2: The Variance of Mismatch Declines With Industry Tenure and Increases With Years Since Graduation

From Fact 1, I establish that M_{it} is a good measure of match quality, with values near 0 being better than large deviations from 0. I have not yet established any potential mechanism that could help individuals and firms self-select out of a bad match and confirm that the current match is good enough. The hypothesis I bring in this paper is that workers have imperfect information about their qualifications for each industry and take time to learn about the qualifications.

To test that hypothesis, I look at the variance of M_{it}. The intuition is that if individuals learn about their match quality over time, the uncertainty surrounding it should decrease. Through which key mechanism does the uncertainty decrease depend on subgroup behavior differences over time.

The data strongly suggest that workers learn about their match quality over time. As shown in Figure 3, the variance of M_{it} falls by 58% within the first five years of continuous industry tenure. This suggests that as workers accumulate experience in an industry, poor matches are either improved or dissolved, leading to a convergence of outcomes among industry stayers.

Critically, the learning process appears to be industry-specific. In sharp contrast to the effect of tenure, the variance of M_{it} rises steadily during the entire duration of early careers of the workers (see the right axis). Read together, these opposing trends imply that learning does not generalize across industries; when a worker switches, the learning process resets. This dynamic of trial, error, and industry-specific learning helps explain why significant earnings disparities can persist long after graduation.

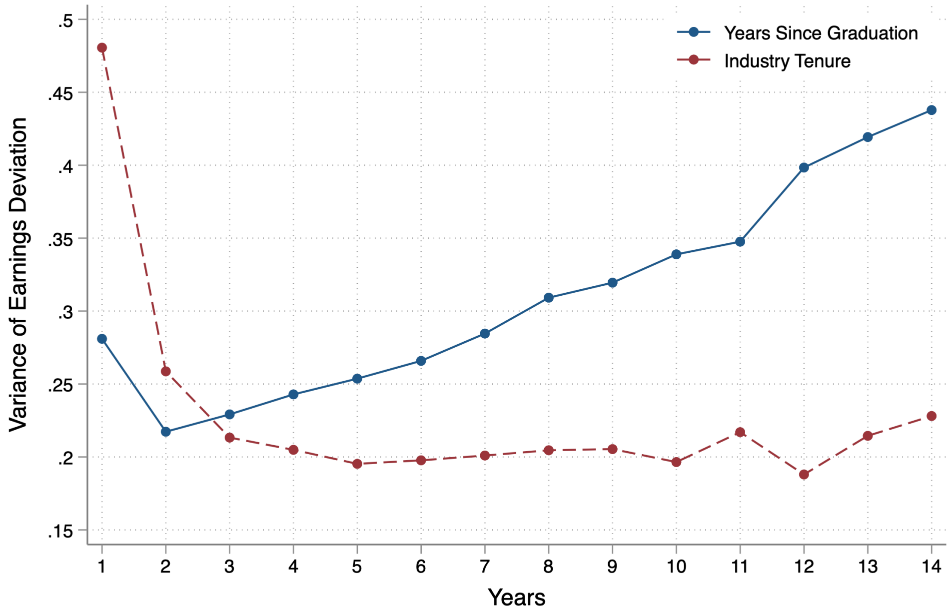


Figure 3: Variance of M_{it} Trend over Industry Tenure and Time Since Graduation

Notes: The variance of the earnings residual M_{it} is calculated cross-sectionally for each year, across all individuals from different cohorts. The blue solid line shows the variance by years since graduation, while the red dotted line shows the variance by years of continuous industry tenure.

2.4.3 Fact 3: Major Choice Corresponds to a Choice of Career Mobility and Uncertainty

I now turn to investigate whether the intensity of this "search and learn" process varies systematically by fields of study. This is evident in Figure 4, which shows that the choice of the major could also be an implicit choice about the degree of labor market uncertainty a graduate will face.

Since the CIP codes are a much finer description of the majors, and we are limited by reporting criteria from using administrative data, to demonstrate heterogeneities across majors with transition paths, I aggregated to a coarser 1-digit ISCED-F major codes (with a total of 10 majors) and looked at the transition shares for each major during the early and late careers. I define early careers as the first 5 years after graduation and late careers as the 9th-14th years after graduation. Figure 4 shows that the transition shares vary systematically by college majors.

Graduates from more generalist majors, such as Arts and Humanities and Social Sciences, exhibit the lowest stability and the highest rates of industry switching during continuous employment. Their career paths involve more "shopping around", suggesting they face a wider, more uncertain set of industry match qualities. Surprisingly, this heightened mobility persists, as they continue to exhibit a lower industry staying rate even at the 9th-14th year after graduation. This intensive switching represents a prolonged engagement in the "search and learn" process detailed in Fact 2, compared to some other majors, where graduates must repeatedly reset their industry-specific experience to find a suitable career throughout their lifetime.

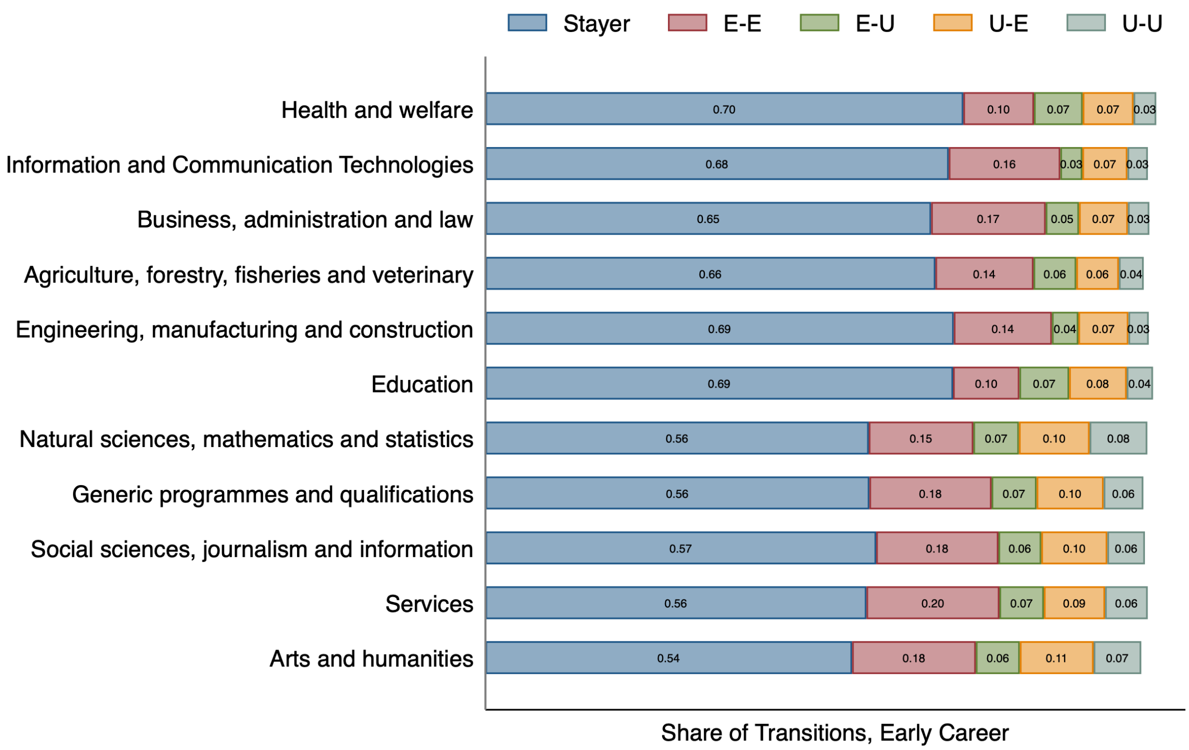


Figure 4: Early Career Transition Patterns by Major

Notes: Majors are grouped at the 1-digit ISCED-F code, using the standard crosswalk from Statistics Canada to map between 4-digit ISCED-F and 6-digit CIP codes. Early career refers to the first five years after graduation, while late career stayers are defined as those with 9–14 years of experience but still show substantial major heterogeneity, as seen in Figure 12. Majors are ranked from top to bottom using averaged earnings in the early career years in descending order, with "Health and welfare" earning the highest on average, and "Arts and humanities" the lowest. Each row does not sum to one because exits from the labor market are allowed; the observed exit rate is used to discipline the exit rate in the quantitative model. The numbers in the bars represent the shares of individuals in each group. All transitions are characterized at the 3-digit industry NAICS code level.

2.4.4 Ruling Out Mechanical Effects

A natural concern is whether the documented patterns are statistical artifacts of the estimation method rather than evidence of mismatch and economic learning. Here, I argue why this is not the case.

By construction, the OLS residuals have a mean of zero over the full estimation sample and are uncorrelated with the included regressors, such as tenure. However, these properties do not mechanically generate the patterns I observe.

First of all, the OLS framework makes no prediction that individuals with large absolute residuals at any given time should be more likely to switch industries in the subsequent year. This U-shaped relationship is a behavioral pattern similar to the notion of the U-shape of occupational mobility, where both underqualified workers and overqualified workers have a higher occupational switching rate (Groes et al., 2015). This U-shaped relationship between the level of mismatch and the decision to change industries is not an econometric byproduct. While serial correlation is clearly present from the empirical evidence, it merely reflects the persistence of match quality over time, something I expected. For example, a standard autoregressive process on the error term, e.g., an AR(1), simply implies that a positive shock is likely to be followed by another positive shock. It does not mechanically predict that individuals with very large shocks, either positive or negative, will have a higher probability of exiting the state, which is the industry in my setting, altogether. The observed fact that large, persistent mismatches trigger separations corresponds to the interpretation of the learning mechanism in economic structures, not a statistical tautology.

Similarly, OLS does not guarantee the variance for the subsample of "industry stayers" to decline with tenure. The sharp drop in variance for this group, especially when contrasted with the rising variance for the full sample of graduates, points to a powerful selection and learning mechanism unique to continuous employment, and not a general property of residuals. Moreover, one might argue that this is merely tenure-dependent heteroskedasticity, reflecting that the variance of the true unobserved error term differs across groups. This critique, however, is not a rebuttal but rather a statistical reframing of my central economic argument. The hypothesis is that tenure facilitates learning, which reduces uncertainty about the quality of the match in the current employment. If match quality is a key component of the unobserved error term, then a reduction in uncertainty is a reduction in the error variance for that individual. Therefore, tenure-dependent heteroskedasticity is precisely the statistical property one would expect from an economic model of learning.

Taken together, all empirical results from this section paint a clear and coherent picture. The labor market for recent graduates is characterized by significant information friction regarding their individual-industry specific match quality/productivity. The persistence of mismatch, the U-shaped separation patterns, and the heterogeneity across majors all underscore the importance of this learning mechanism in shaping career paths.

2.5 Ability Predicts Major Choice but Not Industry Match Quality

I have shown that large earnings variation exists within major-industry cells. Next, I test the primary alternative explanation: are these variations driven by pre-existing differences in inherent ability, rather than post-entry learning? The central hypothesis is that if the mismatch we characterized and observed in the previous section is merely a proxy for unobserved ability, then a direct measure of pre-market ability should predict better matches. To assess this, I use the selected cohorts of Ontario public high schoolers from the dataset. The results show that, while ability predicts major choice, it does not predict match quality.

There are no aptitude test scores available to directly measure inherent ability in our data. Therefore, I use administrative data on Grade 12 Mathematics and Language course grades for the subset of students from Ontario high schools graduating in 2013/2014 to 2015/2016. These grades serve as a good proxy for pre-college ability. We know the specific courses these students took and their corresponding letter grades for Language and each Math course. In Ontario, students must complete Grade 12 courses in both Mathematics (which can be broadly characterized by two difficulty levels) and language (English or French). Critically, universities make admission decisions based on Grade 12 first-semester and second-semester midterm marks. While offers are conditional on final performance, the sorting process is based on this interim, and therefore noisy, signal of ability. In this analysis, I use the final, realized Grade 12 marks as the proxy for ability, which provides a more precise and comprehensive measure than the grades used in university admission decisions.

I test whether this ability measure predicts sorting into better majors and labor market matches. I use average earnings of college majors as the ranking basis, as is standard. For labor market matches, I use two measures: (1) employment in a major's top-paying industry and (2) the magnitude of the mismatch, $|M_{it}|$. I estimate the following specification:

$$Y_{it} = \alpha + \beta_g \text{GradeGroup}_i + \delta \text{Control}_{it} + \gamma_m + \epsilon_{it} \tag{3}$$

Table 1 presents the results, proceeding in two clear steps.

First, column (1) shows that higher grades in Mathematics and Languages are linked

Table 1: Sorting Patterns between Inherent Ability and Outcomes

	(1)	(2)	(3)
Dependent variable:	Avg Major Earnings	$\mathbb{I}${Top 1 Industry}	Earnings Deviation
(Math, Lang) = (A, A)	0.034***	0.013	0.007
	(-7.45)	(-1.34)	(-1.61)
(Math, Lang) = (A, B)	0.030***	-0.004	-0.000
	(-7.00)	(-0.44)	(-0.04)
(Math, Lang) = (A, C)	0.029***	-0.014	-0.004
	(-4.56)	(-1.08)	(-0.66)
(Math, Lang) = (B, A)	0.014**	-0.003	0.010
	(-2.79)	(-0.28)	(-1.88)
(Math, Lang) = (B, B)	0.010**	0.008	0.001
	(-2.58)	(-1.09)	(-0.27)
(Math, Lang) = (B, C)	0.009*	0.001	-0.008
	(-1.97)	(-0.16)	(-1.77)
(Math, Lang) = (C, A)	-0.013	0.038**	0.024**
	(-1.83)	(-2.65)	(-3.20)
(Math, Lang) = (C, B)	-0.007	0.019*	-0.004
	(-1.62)	(-2.38)	(-0.96)
(Math, Lang) = (C, C)	—	—	—
Female	-0.023***	-0.010*	
	(-10.62)	(-2.23)	
Constant	9.433***	0.004	0.183***
	(-151.45)	(-0.03)	(-27.31)
Controls	Yes	Yes	No
Major FE	No	Yes	No
N	16,000	41,000	41,000
R^2	0.319	0.070	0.001
F	386.3	4.868	5.163

Notes: Coefficients with t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. The base group is students with a letter grade of C in both Mathematics and Language. Students must complete a 12th grade course in both subjects, hence each student could be characterized by a pair of grades (Math, Lang). Control variables include university graduation year, university institution, years since graduation, number of difficult math courses, gender, and high school graduation year. The top 1 industry is ranked by average earnings among graduates of a given major at the population level. Results are robust to alternative definitions of "top" industries, such as using the first quartile of average earnings or rankings based on major-industry fixed effects obtained from Equation 1. Column (1) is estimated at the individual level, since each person chooses their major only once. Columns (2) and (3) are estimated at the individual-year level, as they track outcomes for each year after university graduation. Depending on the year each individual graduates, I can observe them for different numbers of years. The sample size reflects the total number of observations across all years.

to choosing majors with higher average pay. Consequently, this validates that high school letter grades can predict educational choices, as theory suggests. Furthermore, ability sorting occurs between inherent ability and major choices.

Second, I test whether this same ability measure predicts a better subsequent industry match. Columns (2) and (3) show that it does not. High school grades have almost no predictive power for whether individuals are employed in their major's top-paying industry in the first two years after university or in an industry with lower mismatch. Additional robustness checks are in the Appendix B.6 Table 12.

This finding is clear and powerful: high school performance predicts sorting into better-paid majors but does not predict the quality of industry matches within those majors. High-ability individuals are just as likely as others to begin in poor matches, showing that underlying ability does not drive mismatches. These points strongly suggest a systematic barrier of information frictions that prevents the positive assortative matching of talent to industries. Another subtle implication is the effect on distribution to welfare changes. Since sorting is imperfect, the distributional effects of resolving information frictions in the labor market are substantial.

3 Further Identifying Information Friction

The prior sections establish that unexplained earnings variations are substantial, persistent, and linked to career mobility, which is consistent with a model of learning under uncertainty. In this section, I turn to direct causal evidence by testing whether an exogenous increase in labor market information for the options for each individual can causally affect match quality and alter career dynamics for recent graduates. Specifically, I exploit the 2009 entry of LinkedIn into Canada as a natural experiment, applying a difference-in-differences (DiD) strategy to compare majors with varying exposure to LinkedIn before and after its introduction.

3.1 Empirical Strategy

Institutional Background Before discussing the empirical strategy in detail, I briefly summarize the relevant features of LinkedIn's platform and its expansion into Canada. These features are critical to understanding the exogenous shock used for identification. LinkedIn is a professional, employment-focused social media platform used "to exchange information, ideas and opportunities" (see initial launch screenshot in 14). The company began operating in the US in 2003 and quickly expanded internationally. Today, it has over 28 million users in Canada. Of those, 66.6% are between 18 and 34 (World Population Review, 2025), which aligns exactly with the main sample of our analysis.

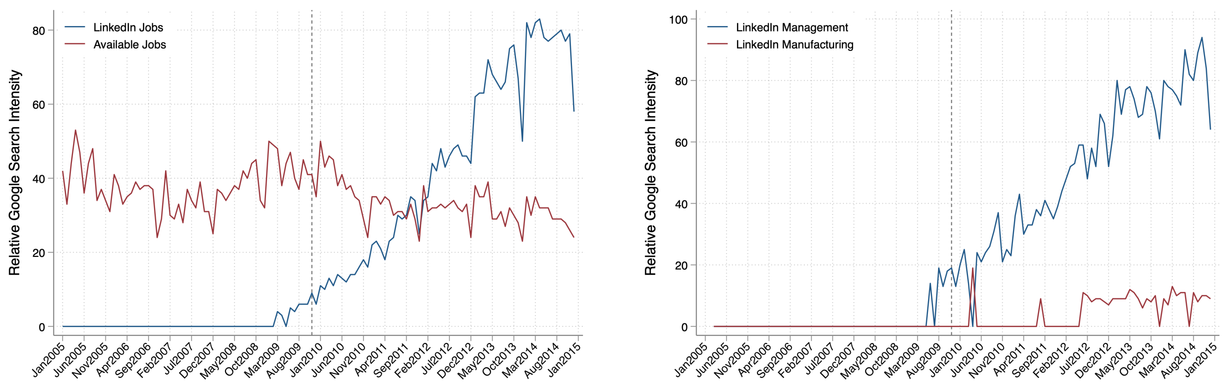
LinkedIn officially began operating in Canada on November 11th, 2009 by launching the website "ca.linkedin.com". The company set up its Toronto office on June 16th, 2010. Before this date, Canadians could create accounts, but the platform's regional sorting made it far less effective for the Canadian market[10]. Figure 5a uses Google Trends data to show the interest in LinkedIn in Canada. It compares multiple keywords.[11] A grey dashed vertical line indicates LinkedIn's launch in Canada. The figure shows that the Canadian search interest for "LinkedIn Jobs" was non-existent before 2009 but grew rapidly thereafter, quickly surpassing generic searches for "Available Jobs". Given this sharp, sudden increase in the interest in finding job opportunities on LinkedIn, I define the post-treatment period as starting with the 2010 graduation cohort. The 2009 cohort is the base.

Crucially, LinkedIn is fundamentally structured around industries, which is central to this paper's focus on industry-level sorting. The platform prompts users to select a primary industry and uses this information to filter and present candidates to recruiters. This feature was present at launch, as shown in early interface screenshots (see Appendix B.6). This structure provides graduates with a more transparent and current view of the labor market. It also makes career options more visible and comparable. The main channel of influence is the reduction of market-level uncertainty about the broader set of career opportunities.LinkedIn provides example career progressions found on other users' pages and job descriptions for each posting.

Justifying the Treatment and Control Groups Having established the institutional context of LinkedIn's entry into Canada, it is crucial to justify the selection of treatment and control groups for the DiD analysis. The credibility of this design relies on the argument that LinkedIn's introduction had a different effect across majors. Through multiple confirmations, I argue that graduates from business majors (ISCED code 4: *Business, Administration and Law*) were more exposed to the platform than graduates from engineering majors (ISCED code 7: *Engineering, Manufacturing and Construction*).

[10] See the bottom of the Figure 14 for a screenshot of the website as it appeared when first published.

[11] The magnitude of Google Trends is a relative measure of search interest on a 0 — 100 scale. Here, 100 is the peak popularity during a specific time and region. A value of 50 means the term is half as popular, and a value of 0 means not enough data. I also included a comparison in Figure 15 between "LinkedIn," "Indeed," and "Traffic" to show LinkedIn's large popularity in Canada.



(a) LinkedIn Jobs vs Available Jobs

(b) Management vs Manufacturing

Figure 5: Relative Google Search Intensity in Canada for LinkedIn Related Keywords.

Notes: Both figures display Google Trends data limited to Canada. Panel (a) compares the relative magnitude of search interest between the keywords “Available Jobs” and “LinkedIn Jobs”. Panel (b) compares “LinkedIn Management” and “LinkedIn Manufacturing”, approximating jobs targeted by business versus engineering graduates. LinkedIn Engineering keywords primarily refer to software engineering, so they are excluded since the sample omits software engineers. The dotted vertical gray line marks November 2009, when LinkedIn Canada launched. Values are relative within each panel and cannot be compared across panels for intensity.

There are two sets of evidence. First, Figure 5b presents the Google Trends results comparing the two related keywords for the business graduates and new engineers. It shows that the search intensity for “LinkedIn Management” grew qualitatively identical to “LinkedIn” in Canada, whereas “LinkedIn Manufacturing” barely had any effect.

Second, early in its expansion, LinkedIn’s network and job postings were heavily skewed toward business, sales, and management roles. Technical and engineering positions, except for software-related jobs, were less common. Often, they were limited to management tracks.[12]

These two pieces of evidence demonstrate that LinkedIn’s initial value proposition was concentrated in the business domain, making business majors the natural treatment group, and engineering majors a credible control group.

To further strengthen the validity of the treatment and control groups and ensure a clean comparison, I further refine the sample. I exclude individuals with software engineering majors, as they are typically employed as computer scientists rather than traditional engineers. I also remove graduates with Finance or Accounting and Finance majors, since the 2009 recession disproportionately affected the financial industry, where most of these graduates work. I address the confounding effects of the 2008-2009 Recession directly in the next section. Finally, I restrict the earnings outcome to the first year

[12] Appendix B.6 contains pages of actual screenshots from the LinkedIn Canada site in early 2010 via Wayback Machine. The job postings are much more focused on management roles in engineering categories, whereas business graduates see postings that closely match their majors.

after graduation. This avoids complications from differences in graduation timing, such as working part-time, full-time, or holding a temporary job. I also focus on comparing cohorts, not individuals, to avoid confounding from different labor market experiences. The final sample is a cross-sectional comparison of cohorts of individuals, such as marketing graduates in 2008 and those in 2012. Table 2 presents the shares of treatment and control groups by post period.

Eliminating Potential Effect from Recession A primary threat to identification is the effect of the Great Recession. Though Canada was less affected than the US, the downturn still impacted financial markets. To reduce the recession's potential effect, I take two steps. First, I restrict the analysis to graduates from Alberta universities who stayed and work in Alberta. Alberta's economy focuses more on the energy sector than finance, insulating it from most crisis shocks. Second, I control for remaining local business cycle effects. Specifically, I use the industry-year unemployment rate ($\text{UnemploymentRate}_{jc}$), measured as the share of individuals who separated to unemployment from the previous year for each industry.

Table 2: Shares (%) by Treatment and Post

	Post		
Treatment	0	1	Total
Control: Engineering	14%	19%	33%
Treatment: Business	25%	42%	67%
Total	39%	61%	100%

Now we are ready to estimate the specification. I estimate the causal effect of information using the following Difference-in-Differences specification:

$$Y_{imjc} = \alpha + \beta \text{Post}_c \cdot \text{Treatment}_{imjc} + \lambda_c + \lambda_m + \lambda_j + \text{UnemploymentRate}_{jc} + \epsilon_{imjc} \quad (4)$$

where Y_{imjc} is the outcome variable for an individual i chose to be in major m, graduated in cohort c and go on to be employed in industry j. Post_c is a binary indicator for the post-treatment period, which is 1 if the individual graduated in 2010 or later. HighInfo_{imjc} is a binary indicator for being in majors that are more exposed to LinkedIn, as defined previously. The coefficient β captures the differential changes in the outcomes between the treatment and control groups after being exposed to more information. We further control for cohort fixed effects λ_c, major fixed effects λ_m at the two-digit CIP code level, and industry fixed effects λ_j at the two-digit NAICS code level to account for common time trends as well as initial heterogeneity across cohorts, majors, and industries. We include the unemployment rate at the industry-year level $\text{UnemploymentRate}_{jc}$ to control for the business cycle effect. ϵ_{imjc} is the i.i.d error term, clustered at the major-industry level.

The main outcomes of interest are the individual-level deviation from expected earnings, the duration in the first industry after graduation (measured in years), the probability of being laid off or receiving Employment Insurance, and whether the individual ever switches industry.

Event Study Framework To assess the dynamics of the treatment effect and ensure the robustness of the previous estimation, I also estimate a dynamic event study framework, as shown in Equation 5, with cohort 2009 as the base.

$$Y_{imjc} = \alpha + \sum_{\tau=-5,\tau\neq-1}^{4} \beta_\tau \text{Post}_{2010+k} \cdot \text{Treatment}_{imjc} + \lambda_m + \lambda_j + \text{UnemploymentRate}_{jc} + \epsilon_{imjc} \quad (5)$$

Identifying Assumption The key identifying assumption for coefficients β_τ is that, conditional on controls, the outcomes for business and engineering graduates would have followed parallel trends in the absence of LinkedIn. The event study allows me to test this: the pre-treatment coefficients β_τ should be statistically insignificant around 0 for τ between 2005 and 2009. All outcomes of interest have flat and insignificant pre-trends, providing strong support for this assumption. See the event study plot in Appendix B.6.

3.2 Empirical Findings

Because I cannot observe which specific graduates used LinkedIn, the DiD specification estimates an Intent-to-Treat (ITT) effect. The estimates capture the impact of graduating with a major that gained improved access to the platform, not the effect of using the platform itself. Under the standard assumption of monotonicity, where the introduction of LinkedIn did not cause anyone to stop using it, the ITT effect provides a lower bound for the average treatment effect on the "compliers", graduates who were induced to use

LinkedIn because of its Canadian launch. Therefore, the true effect of the platform on its users is likely even larger than the estimates presented here.

Table 3 presents the main DiD results from estimating Equation 4. The results tell a cohesive story about how information frictions operate, a story best understood through the lens of two distinct types of uncertainty: a learnable uncertainty about the productivity or quality of one's current match, and a market-level uncertainty about the value of outside options. LinkedIn primarily impacts the latter, as it is a platform providing market-level information and information regarding outside options for graduates with business-related majors. Specifically, better information shapes career outcomes, demonstrated primarily through three outcomes: improving initial search, accelerating the correction of bad matches, and increasing productive mobility.

Table 3: Difference in Differences Point Estimates

	(1)	(2)	(3)	(4)	(5)
Dependent variable	Earnings Deviation	First Ind. Duration Before Switching	Ever Switched	Ever Received EI	Ever Laid Off
Post × Treatment	-0.245***	-0.324***	0.0423**	-0.0751***	-0.0358**
	(-6.19)	(-3.50)	(-3.08)	(-4.71)	(-2.76)
Post	0.170***	-0.335***	-0.0884***	-0.0906***	0.0134
	(-4.18)	(-4.17)	(-7.61)	(-6.71)	(-1.22)
Treatment	-0.166***	-0.240	-0.0194	-0.0201	-0.139
	(-4.96)	(-0.33)	(-0.17)	(-0.15)	(-1.28)
Unemp. Rate$_{jt}$	2.290***	-3.738**	0.728***	-0.179**	-0.0382
	(-11.89)	(-3.23)	(-12.32)	(-2.60)	(-0.68)
Cohort FE	No	Yes	Yes	Yes	Yes
Major FE	No	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes
N	19,000	15,000	19,000	19,000	19,000
R^2	0.051	0.057	0.030	0.026	0.004

Notes: Coefficients with t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. The total number of observations is rounded to the nearest 1,000 to satisfy reporting guidelines. The outcomes for columns (3) to (5) are binary and defined at the individual level throughout the entire observation window. Again, as described above, the sample is excluded at the individual level, and the earnings outcome is restricted to the first year after graduation.

Improving Initial Match Quality The platform's primary effect is to reduce uncertainty about the set of available jobs, allowing for better initial choices. Column (1) of Table 3 shows that for treated majors, the initial absolute earnings mismatch M_{it} decreases by 0.245 standard deviations after the arrival of LinkedIn. This suggests that the platform improved search efficiency, allowing graduates to find better-fitting jobs straight out of university. The effect is immediate and persistent, as shown by the event study in Figure 17a. This suggests that by making outside options more transparent, LinkedIn improved search efficiency, allowing graduates to find better-fitting jobs from the start. This does not change the on-the-job learning process itself, but it provides a much better starting point.

Accelerated Correction of Bad Matches and Career Sorting. LinkedIn's impact on career further highlights its role in resolving uncertainty about outside options, not the current employment.

First, better information allows for a faster correction of mistakes. Column (2) shows that, conditional on switching industries, treated graduates stay 0.324 fewer years nearly four months) in their first industry. This suggests that when an industry match is revealed to be poor through on-the-job experience, reduced uncertainty about the existence of better alternatives allows graduates to act on that knowledge and enables them to switch out of a bad match sooner if they are in one.

Second, better information encourages productive mobility: by reducing uncertainty in outside options, LinkedIn reduces the likelihood of graduates getting "stuck" in mediocre but acceptable jobs. Column (3) suggests that the improved transparency of outside options provided by LinkedIn allowed business graduates to recognize better opportunities outside their current employment, resulting in a 4.3 percentage point higher probability of ever switching industries. Reassuringly, this increased mobility leads to better outcomes. According to columns (4) and (5), the graduates were 7.5 percentage points less likely to receive EI and 3.6 percentage points less likely to be laid off, indicating they ultimately sort into more stable, higher-quality matches.

Finally, a survival analysis confirms this mechanism. The duration in the first industry is a censored variable, as it can only be measured for individuals who eventually switch industries. We estimate a Cox proportional hazards model using the same control variables and clustering as in the previous section. While the overall hazard rate of switching rises, for individuals who are already in a good initial match, defined as within the bottom 25th percentile of absolute mismatch, the hazard rate of switching decreases by 10% before and after the policy for the treated group relative to the control group. This synthesizes the story perfectly: clarifying market-level uncertainty allows workers to confidently leave bad or mediocre jobs sooner and empowers them to recognize and commit to good jobs more quickly.

Summary Notes The empirical evidence paints a clear picture of a labor market shaped by significant information frictions. While these facts identify the core mechanism and highlight its large impact on the labor market, a structural model is necessary to quantify its aggregate consequences and conduct counterfactual analysis. The empirical findings directly inform the model's structure in several ways.

First, the observed U-shaped industry switching patterns based on previous match quality motivate a model with ex-ante unknown match quality. Workers and firms do not fully understand the match results, which can lead to a loss in output. Second, the opposing trends in mismatch variance over tenure versus number of years in the labor market reveal industry-specific learning: learning happens only while employed and resets upon industry switches. Third, heterogeneity across majors in labor market transition outcomes suggests that major choices should capture varying levels of information frictions. Finally, the fact that innate ability fails to predict match quality indicates that this uncertainty is universal, independent of innate ability.

The LinkedIn experiment shows two key types of information frictions to model. First, workers face uncertainty about their fit with jobs in their industry, which they learn over time. Second, there is steady uncertainty about outside options by major, which does not resolve with experience. LinkedIn helped by lowering this second uncertainty for some majors, speeding up exits from poor matches, and improving career sorting. These insights guide the structural model in the next section. I am now ready to set up the model.

4 Model

I now develop a theoretical model of search, learning, and college major choices to explain the above empirical patterns of industry mobility and earnings inequality. The main mechanisms we are interested in exploring are the effect of learning interacting with labour market frictions.

4.1 Environment

Time is continuous and infinite. The labor market in this model is similar to Baley et al. (2022) and Carrillo-Tudela and Visschers (2023).

Demography There is a fixed measure of individuals that evolves as in a perpetual youth model à la Blanchard (1985) where workers exit with an exogenous rate ν. Exiting workers of all periods are replaced by the same measure of new entrants starting from period 0. Individuals are born with inherent ability p that is observed perfectly by the individuals (and firms once they enter the labor market).

Labor Market Belief Individuals receive a vector of industry specific skills after graduating from a certain major. This vector is unknown to the individuals, but they can learn the value for the industry they are employed in with noisy signals. I will explain these in detail in section 4.2.

Labor Market The labor market consists of perfectly segmented submarkets, denoted by

$$(m, p, j, a, \Sigma, r) \in \mathbb{N}^3 \times \mathbb{R}^2 \times \mathbb{N}$$

which represents the major, worker innate ability, industry, current mean belief, current belief variance, and level of job rung, respectively. Workers are born with heterogeneous innate ability p. Before a worker enters into the labor market, they choose a major m. Only (j, a, Σ, r) can be changed by the worker while they are in the labor market.

Major Choice Individuals choose a major m one period before the beginning of their life. This irreversible choice is made by drawing from a distribution of preferences over majors and an expected lifetime utility from each major. Each individual enters the labor market unemployed. More details are described in section 4.3.

Production Technology. Firms have log linear production technology using only labor as input. The production function explicitly requires specific skill to be met in order to produce output without any penalty. There are two types of production skill requirements: (1) the job ladder, chosen mutually by the firm and the worker, and (2) additional skill requirements that are common to all major-industry pairs in the economy. Thus, my model predicted mismatch will originate from the negative (not enough skill) or positive (too much skill) deviations from the required skill level. The production function is given by:

$$\ln y = \ln A_{mp} + \eta(r\phi) - \frac{1}{2}\Big(\lambda_+(r)[r\phi - pa]_+^2 + \lambda_-(r)[r\phi - pa]_-^2\Big) \tag{6}$$

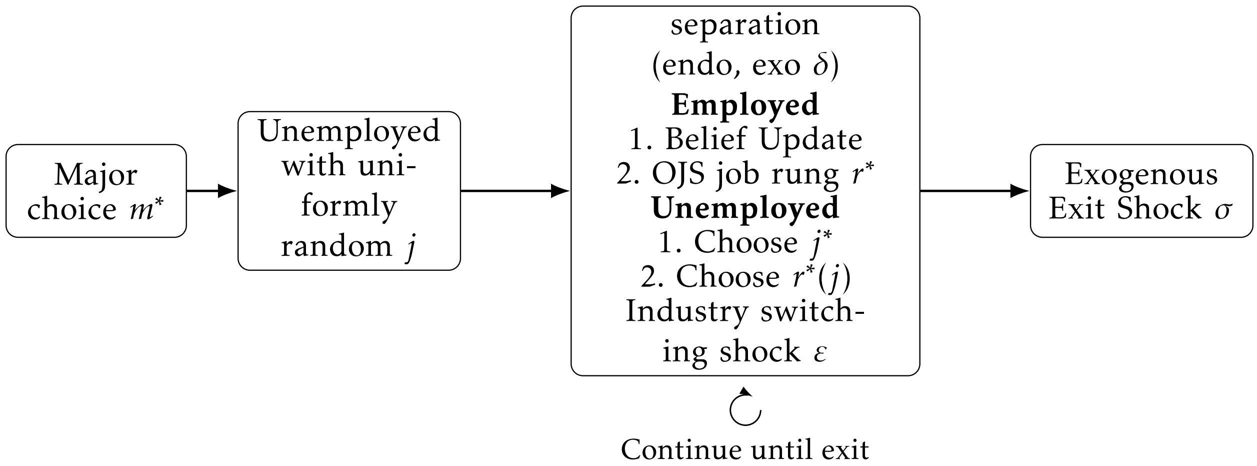


Figure 6: Illustrative Flow diagram of the life cycle of an individual in the model

Short Summary. To illustrate intuitively, Figure 6 provides a succinct flow chart of the model from birth to exit. Each individual, born with an innate ability p, starts their life by choosing a major m. They then enter the labor market unemployed in an industry j randomly uniformly. After entering the labor market, they will navigate the labor market frictions, learning, and job ladder climbing until they receive an exogenous exit shock σ and exit the labor market permanently. While in the labor market, individuals transition between employment and unemployment states, as summarized in Figure 7. For illustration purpose, I omit exogenous shocks of separation and industry switching in the flow chart.

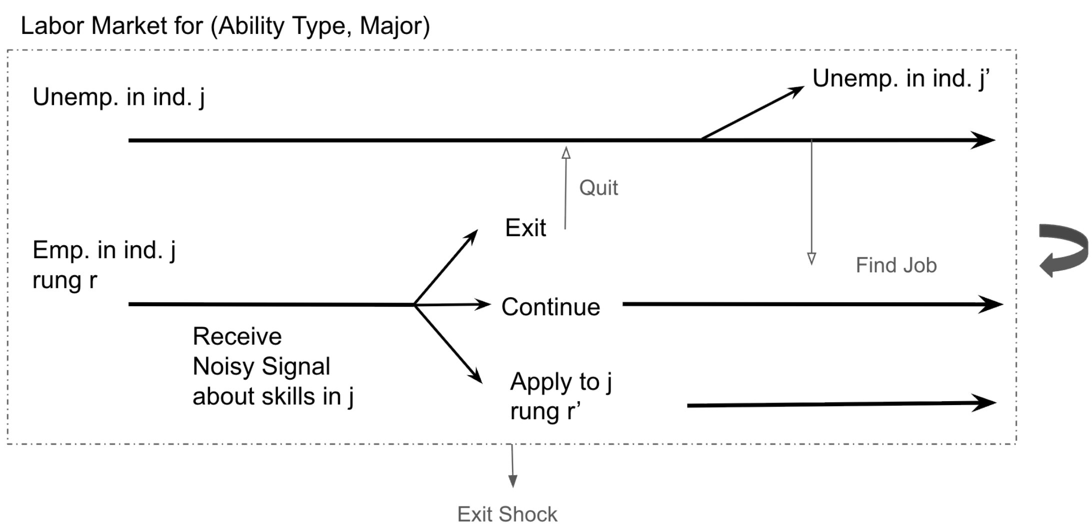


Figure 7: Illustration of Labor Market Transitions Absent Exogenous Shocks

4.2 Belief Dynamics

All beliefs are public information to both workers and firms. For each individual graduating from major m, all graduates have the same prior $a_{ijm} \sim N(a_{m0}, \Sigma_{m0})$. These beliefs are updated during the production stage when firms and workers update their belief about the unobserved part of the utilitized skill, $a_{i,j}$, conditional on the observed utilitized skill p_i and the college major m_i of the worker. The updating process is on the basis of the noisy signal $l_{i,j}$ and assumed to be following a continuous time Normal-Normal Bayesian updating process.

$$d\ l_{i,j}(t) = a_{i,j}dt + \mu dW_{i,j}(t) \tag{7}$$

where $W_{i,j}(t)$ is a standard Brownian motion.

Let $\hat{a}_{i,j}$ be the posterior mean of the unobserved skill $a_{i,j}$ and $\Sigma_{i,j}$ be the posterior variance. Such assumed process implies that the posterior moments follow a diffusion given by the standard Kalman-Bucy filter.

$$d\hat{a}_{i,j}(t) = \frac{\Sigma_{i,j}}{\mu^2}d\ l_{i,j}(t) - \hat{a}_{i,j}dt \tag{8}$$

$$d\Sigma_{i,j}(t) = -\left(\frac{\Sigma_{i,j}}{\mu}\right)^2 dt \tag{9}$$

4.3 Major Choice

Each new cohort has the same measure as the exiting cohort, with each individual drawing an innate ability type p from the distribution $F_p(\tilde{p})$. For simplicity, I assume all graduates begin their careers by randomly entering unemployment in an industry j, with probability determined by the major-specific industry shares. In addition, each individual i experiences a Frechet-distributed preference shock $k_{im} \sim \exp(-k^{-\nu})$ over majors m. Therefore, individuals choose majors to maximize their expected lifetime utility, starting from unemployment with initial beliefs. Individuals are randomly allocated to an industry j with probability ξ_j. This expected lifetime utility is denoted by $\bar{\mathcal{U}}(m,p)$.

The major choice problem can be written as follows:

$$\max_m k_{im}\bar{\mathcal{U}}(m,p) \tag{10}$$

$$\text{s.t. } \bar{\mathcal{U}}(m,p) = \sum_j \xi_j U(m,p,j,a_{m0},\Sigma_{m0}) \tag{11}$$

Since k_{im} is a Frechet distributed preference shock, the major choice problem can be solved analytically to yield an ability p specific major share $s_m(p)$:

$$s_m(p) = \frac{\overline{\mathcal{U}}(m,p)^{\nu}}{\sum_{m'=1}^{M}\overline{\mathcal{U}(m',p)}^{\nu}} \tag{12}$$

4.4 Vacant Match Value Functions

The value of an unfilled vacancy created by a firm in submarket is:

$$V_t(m,p,j,\hat{a},\Sigma,r) = -c(m,p) + \max_x q(\theta_t(m,p,j,\hat{a},\Sigma,r))\{J_t(m,p,j,\hat{a},\Sigma,r) - x\} \tag{13}$$

where x is the promised lifetime utility contracted by this vacancy. Note that because the contract is at lifetime utility, vacancy creation does not involve any expectation terms of future utility. In equilibrium with free entry, I have the following Free-Entry Condition:

$$\frac{p(\theta)}{\theta}\Big(J_t(m,p,j,\hat{a},\Sigma,r) - x\Big) = c(m,p) \tag{14}$$

The above condition creates a mapping between market tightness and firm surplus, and the intersection with the worker value function will determine the equilibrium market tightness. Below when I set out the unemployed and employed match value functions, I will omit submarket index m and p for cleaner notation since they are not a choice variable anymore at the labor market stage. The implication is workers cannot change their major once they enter the labor market and their innate ability is fixed once they are born.

4.5 Unemployed Matches

Unemployed workers receive flow benefit b and choose optimal job rung r and contract x. They are matched in their chosen submarket with probability $p(\theta_t(j,\hat{a}_j,\Sigma,r))$. At Poisson rate ϵ, workers experience an exogenous industry switch, resetting their beliefs.

$$\begin{aligned}(\rho+\sigma)U_t(j,\hat{a}_j,\Sigma) = b + &\max_{x,r}\Big\{p(\theta_t(j,\hat{a}_j,\Sigma,r))\Big[x - U_t(j,\hat{a}_j,\Sigma)\Big]\Big\} \\ &+ \epsilon\Big[\sum_j p_j U_t(k,a_{m0},\Sigma_{m0}) - U_t(j,\hat{a}_j,\Sigma)\Big]\end{aligned} \tag{15}$$

Moreover, workers can endogenously switch to a different industry if optimal. Including endogenous switching by workers, the maximization problem is:

$$\mathcal{U}_t(j,\hat{a}_j,\Sigma) = \max\{\max_k U_t(k,a_{m0},\Sigma_{m0}), U_t(j,\hat{a}_j,\Sigma)\} \tag{16}$$

Unemployed individuals can search across all industries $k \in J$ and for the industry j they are currently unemployed in, they could optimally choose which job rung r to apply for.

4.6 Workers Value Functions

The worker's Bellman equation for a worker in industry j with current belief $\hat{a}_j$ and Σ is laid out in Equation 17.

$$\begin{aligned}(\rho+\sigma)J_t^{\text{act}}(j,\hat{a}_j,\Sigma,r) = &\, e^{\eta(r\phi_{mj})}\mathbb{E}\Big[e^{-\max\{(r\phi_{mj})-pa_j,0\}}\Big] \\ &+ \Lambda_t(j,\hat{a}_j,\Sigma,r) \\ &+ \max_{x',r'}\Big\{\kappa p(\theta_t(j,\hat{a}_j,\Sigma,r'))\Big(x' - J_t(j,\hat{a}_j,\Sigma,r')\Big)\Big\} \\ &+ \delta\Big(\mathcal{U}_t(j,\hat{a}_j,\Sigma) - J_t(j,\hat{a}_j,\Sigma,r)\Big) \\ &+ \epsilon\left(\sum_k p_k \mathcal{U}_t(k,\hat{a}_{m0},\Sigma_{m0}) - J_t(j,\hat{a}_j,\Sigma,r)\right)\end{aligned} \tag{17}$$

The first term corresponds to the expectation over flow output y. The second term summarizes the impact of learning to match value, which is any changes to J_t as a result of time as in Equation 18. Appendix C.3.1 provides details in discretizing this learning process.

$$\Lambda \equiv \frac{\partial J}{\partial t} = \frac{\partial}{\partial \Sigma}\left(\frac{\Sigma}{\mu}\right)^2 + \frac{1}{2}\left(\frac{\Sigma}{\mu}\right)^2 \frac{\partial J}{\partial a^2} \tag{18}$$

The third term summarizes the net gain from on-the-job search, where employed individuals can search at rate κ on another lifetime utility contract x and job rung r within the same industry j. The fourth term is the net loss from exogenous separation, and the last term summarizes exogenous switching shock to another industry and start with the initial belief. At each instance, workers can endogenously separate into unemployment whenever it is mutually beneficial for both firms and workers as shown in Menzio and Shi (2011). Therefore, the unconditional maximization problem can be expressed as:

$$J_t(\omega_k^r) = \max\left\{J_t^{\text{act}}(\omega_k^r), \mathcal{U}_t(\omega_k)\right\} \tag{19}$$

Note that individuals are not allowed to endogenously switch industries while employed. Should they want to switch to a different industry, they must first separate into unemployment and then re-enter the labor market in the new industry.

4.7 Wages Without Commitment by Workers

The computation of wages follows closely the results established in Schaal (2017). In particular, I adopt the unique wage scheme such that the equilibrium search policy completely coincides with the ones established in the previous setup. Let w_t denote the wage offered to workers in period t, and W_t be the expected lifetime utility. In a competitive labor market where contracts are complete and transferable as assumed in my environment, all rents are driven out, and the firm in equilibrium receives no profit. Therefore, entering firms choose a contract that minimizes the per-hiring cost for each individual, which is the difference between the contract utility posted, x, and the expected cost of posting that vacancy before filled, $\frac{c}{q(\theta)}$.

4.8 Equilibrium

The equilibrium in the labor market that I focus on is the Block Recursive Equilibrium (established in Menzio and Shi (2010, 2011)) and can be defined as follows, conditional on the major and innate ability of the worker:

- A market tightness function $\theta : \mathcal{J} \times \mathcal{A} \times \mathcal{S} \times \mathcal{R} \rightarrow \mathbb{R}_+$
- Unmatched value functions $U : \mathcal{J} \times \mathcal{A} \times \mathcal{S} \rightarrow \mathbb{R}$
- Matched value function $J : \mathcal{J} \times \mathcal{A} \times \mathcal{S} \times \mathcal{R} \rightarrow \mathbb{R}$

such that these functions satisfy the following requirements:

1. All functions are independent of aggregate states
2. Bellman equations are satisfied for all values taken by the functions
3. Firms have free entry condition

Then, after solving the labor market equilibrium, I can solve for the optimal major allocation of workers by utilizing the nice properties of Frechet distributed preference shocks. The equilibrium major allocation is given by the following equation:

$$s_m(p) = \frac{\overline{\mathcal{U}^*}(m,p)^{\nu}}{\sum_{m'=1}^{M} \overline{\mathcal{U}^*(m',p)}^{\nu}} \tag{20}$$

I discuss the computation of steady state distribution of workers in the next subsection.

4.9 Kolmogorov Forward Equation

The setup of the Kolmogorov Forward Equations is fairly standard, with slight modifications to incorporate learning, directed search across industries, on-the-job ladder climbing, and exogenous entry and exit of the population.

Let me begin after workers have already chosen their majors. At this point, each individual treats their own major and ability type as given. Therefore, all transitions occur between submarkets denoted by (j, a_j, Σ_j), given the major and ability (m, p).

Let $p_U(\cdot)$ and $p_E(\cdot)$ denote the job finding rates for unemployed and employed workers, respectively, as specified by the model. The Kolmogorov Forward Equation (KFE) can then be defined as follows.

Active Employment The distribution over active employment, $\Gamma_t(k, \hat{a}_k, \Sigma_k, r)$, is characterized by the following PDE:

$$\begin{aligned}\dot{\Gamma}_t(k,\hat{a}_k,\Sigma_k,r) = \dot{\Gamma}_t^{\text{Learn}}(k,\hat{a}_k,\Sigma_k,r) + \dot{\Gamma}_t^{\text{EE}}(k,\hat{a}_k,\Sigma_k,r) + \dot{\Gamma}_t^{\text{UE}}(k,\hat{a}_k,\Sigma_k,r) \\ - \dot{\Gamma}_t^{\text{EU}}(k,\hat{a}_k,\Sigma_k,r) - \dot{\Gamma}_t^{\text{Exit}}\end{aligned} \tag{21}$$

The first term, $\dot{\Gamma}_t^{\text{Learn}}(k, \hat{a}_k, \Sigma_k, r)$, captures net changes due to learning about ability and moving to a different submarket as beliefs are updated. In the quantitative estimation, I use forward differences with a boundary condition of 0 to approximate the first derivative, and central differences with Dirichlet boundary conditions for the second derivative. This term reflects the impact of learning for job stayers; thus, $\dot{\Gamma}_t^{\text{Learn}}$ only concerns changes in Σ_k and $\hat{a}_k$, while keeping industry j and job rung r fixed.

$$\dot{\Gamma}_t^{\text{Learn}}\Big(k, \hat{a}_k, \Sigma_k, r\Big) = \left(\frac{\partial}{\partial \Sigma} + \frac{1}{2}\frac{\partial^2}{\partial \hat{a}^2}\right)\left[\left(\frac{\Sigma}{\mu}\right)^2 \Gamma_t\Big(k, \hat{a}_k, \Sigma_k, r\Big)\right] \tag{22}$$

The second term, $\dot{\Gamma}_t^{\text{EE}}(k, \hat{a}_k, \Sigma_k, r)$, captures net changes from on-the-job search transitions within the same industry but across different job rungs. Thus, Γ_t^{EE} only involves changes in job rung r, keeping industry k and beliefs $(\hat{a}_k, \Sigma_k)$ fixed.

$$\dot{\Gamma}_t^{\text{EE}}\Big(k, \hat{a}_k, \Sigma_k, r\Big) = -p_E\Big(k, \hat{a}_k, \Sigma_k, r, z\Big)\Gamma_t\Big(k, \hat{a}_k, \Sigma_k, r\Big) + \sum_{r' \in R} p_E\Big(\hat{a}_k, \Sigma_k, r', z\Big)\Gamma_t\Big(\hat{a}_k, \Sigma_k, r'\Big)\mathbf{1}_{r' \to r\ (\hat{a}_k, \Sigma_k, z)}. \tag{23}$$

The third term, $\dot{\Gamma}_t^{\text{UE}}(k, \hat{a}_k, \Sigma_k, r)$, captures transitions from unemployment to employment within the same industry k. This change only includes individuals who successfully match with a job while unemployed, and thus depends on the unemployment distribution Υ_t.

$$\dot{\Gamma}_t^{\text{UE}}\Big(k, \hat{a}_k, \Sigma_k, r\Big) = p_U\Big(k, \hat{a}_k, \Sigma_k, r, z\Big)\Upsilon_t\Big(k, \hat{a}_k, \Sigma_k, r\Big)\mathbf{1}_{r \to r^*\ (\hat{a}_k, \Sigma_k, z)} \tag{24}$$

The fourth term, $\dot{\Gamma}_t^{\text{EU}}(k, \hat{a}_k, \Sigma_k, r)$, captures both endogenous and exogenous transitions from employment to unemployment. Specifically, it includes exogenous separation shocks and endogenous separation choices. For endogenous separations, the outflow rate is ∞ as long as $\Gamma_t\Big(\hat{a}_k, \Sigma_k, r\Big) \neq 0$, so the only possible limit is $\Gamma_t\Big(\hat{a}_k, \Sigma_k, r\Big) = 0$ for those states. In quantitative estimation, I approximate this limit with a large but finite π. This term captures the loss of job rung r, but individuals remain in the same industry k with beliefs $(\hat{a}_k, \Sigma_k)$.

$$\dot{\Gamma}_t^{\text{EU}}\Big(k,\hat{a}_k,\Sigma_k,r\Big)=\Big(\delta+\lim_{\pi\to\infty}\pi\,\chi^{\text{sep}}\Big(\hat{a}_k,\Sigma_k,r,z\Big)\Big)\Gamma_t\Big(\hat{a}_k,\Sigma_k,r\Big) \tag{25}$$

The fifth term captures exogenous switching and exiting from the labor market. This term represents a total loss of state: individuals lose their current industry, beliefs, and job rung. There is no inflow from exogenous switching, as I assume exogenous switching only leads to unemployment in the new state space.

$$\dot{\Gamma}_t^{\text{Exit}}(k,\hat{a}_k,\Sigma_k,r)=(\epsilon+\sigma)\Gamma_t(k,\hat{a}_k,\Sigma_k,r) \tag{26}$$

The last term captures the exogenous allocation of newborn workers into the labor market. I assume they are randomly assigned to an initial industry k with initial beliefs.

Unemployed Workers The distribution over unemployed workers, $\Upsilon_t(\omega_k)$, is characterized by the following PDE:

$$\dot{\Upsilon}_t(\omega_k)=\dot{\Upsilon}_t^{\text{Switch}}(\omega_k)+\dot{\Upsilon}_t^{EU}(\omega_k)-\dot{\Upsilon}_t^{UE}(\omega_k)-\dot{\Upsilon}_t^{\text{Exit}}(\omega_k) \tag{27}$$

Here, $\dot{\Upsilon}_t^{\text{Switch}}(\omega_k)$ denotes net changes in the unemployment distribution due to exogenous and endogenous industry switching. Unlike the employment distribution, the unemployment distribution tracks both outflows at Poisson rate ϵ from the current state and inflows from all other state spaces to the state with reset beliefs, specifically from industries $j\neq k$ at rate $\epsilon p_{k|j}$.

$$\begin{aligned}\dot{\Upsilon}_t^{\text{Switch}}(k,\hat{a}_k,\Sigma_k)=&-\Big(\epsilon+\lim_{\pi\to\infty}\pi\rho^{\text{switch}}(k,\hat{a}_k,\Sigma_k)\Big)\Upsilon_t(k,\hat{a}_k,\Sigma_k)\\&+\sum_{j\neq k}\int\int\Big[\epsilon p_{k|j}+\lim_{\pi\to\infty}\pi\rho^{\text{new}}(j,a',\Sigma')\Big]d(a',\Sigma')\Upsilon_t(j,a',\Sigma')\cdot\mathbf{1}\{(a_k,\Sigma_k)=(a_0,S_0)\}\end{aligned} \tag{28}$$

Here, $\rho^{\text{switch}}(\omega_k)\in\{0,1\}$ is the policy function indicating whether it is optimal for individuals to switch industries, i.e., $\exists\ j$ s.t. $U_t(\omega_k)<U_t(\omega_j)$. The first term of $\dot{\Upsilon}_t^{\text{Switch}}(\omega_k)$ captures those switching out of the current state to a different industry, while the second term captures individuals switching from other industries into industry k, both exoge-

nously and endogenously. The distributional change due to employment-unemployment transitions is given by

$$\dot{\Upsilon}_t^{EU}(k, \hat{a}_k, \Sigma_k) = \int \dot{\Gamma}_t^{EU}(k, \hat{a}_k, \Sigma_k, r)dr + \sum_{j \neq k} \int \int \int p_{k|j} \epsilon \Gamma_t(j, a', \Sigma', r) d(a', \Sigma', r) \cdot \mathbf{1}\{(a_k, \Sigma_k) = (a_0, S_0)\} \tag{29}$$

The first term of $\dot{\Upsilon}_t^{EU}(\omega_k)$ sums over all possible transitions to unemployment in the current industry k, and the second term captures all individuals who exogenously switch from other industries while employed. The distributional change due to unemployment-employment transitions from successful job finding is given by:

$$\dot{\Upsilon}_t^{UE}(\omega_k) = p_U(\omega_k)\Upsilon_t(\omega_k) \tag{30}$$

Lastly, the exogenous exit rate is:

$$\dot{\Upsilon}_t^{\text{Exit}}(k, \hat{a}_k, \Sigma_k, r) = \sigma \Upsilon_t(k, \hat{a}_k, \Sigma_k, r) \tag{31}$$

The transition matrix is then constructed as:

$$\text{TM} = \begin{bmatrix} \dot{\Gamma}_{\text{Learn}} - \dot{\Gamma}_{\text{EU}} + \dot{\Gamma}_{\text{EE}} - \dot{\Gamma}_{\text{Exit}} & \dot{\Gamma}_{\text{UE}} \\ \dot{\Upsilon}_{\text{EU}} & \dot{\Upsilon}_{\text{Switch}} - \dot{\Upsilon}_{\text{UE}} - \dot{\Upsilon}_t^{\text{Exit}} \end{bmatrix} \tag{32}$$

Note that the sum of each column (source) is not zero by construction, due to exogenous exits. Given exogenous entries of the same size, I solve for the ergodic distribution from the following equation:

$$\mathbf{TM} \cdot \mathbf{g} = \mathbf{Newborn} \tag{33}$$

where **g** is the ergodic distribution of workers across all states, and **Newborn** is the distribution of new entrants into each state of the labor market. Note that everyone enters the labor market as unemployed; there is no mass of newborns for employed states. Since there are no transitions between (m, p) once chosen, I can solve for the ergodic distribution for each (m, p) pair separately and then stack them together to improve computational efficiency.

A key observation regarding the equilibrium and the optimal choices of job rungs are as follows:

Proposition 1. *Given the production function in Equation (6), the optimal job choice $r^*(m, j, a, \Sigma)$ is unique and increasing in the belief of ability $\hat{a}$.*

Appendix C.1 provides detailed proof of the propositions and Appendix C.2 describes the strategy to compute the equilibrium.

5 Estimation

I estimate the model using a coarser characterization of college majors and industries than in the empirical section, both for computational reasons and to facilitate a clearer interpretation of the mechanisms and quantification of effects.

For college majors, I first aggregate CIP codes to the 1-digit ISCED codes. I then select the top three majors with the highest share of graduates: Social Sciences, Business, and Engineering. For industries, I group the 3-digit NAICS codes to the 2-digit level and combine the primary sectors (Agriculture, Forestry, Fishing and Hunting; Mining, Quarrying, and Oil and Gas Extraction; Utilities; Construction; and Manufacturing) into one category called the Primary Sector. I then select the top three industries that hire the most graduates from these majors: Finance, Public Administration, and the Primary Sector. For inherent abilities, I use high school letter grades in Math and Language courses to group students. Based on the minimum criteria for a bachelor's degree in Canada, I restrict my attention to students who have either an A in both Math and Language or at least a B in both subjects. I consider two ability groups: high ability (AA) and low ability (AB, BA, BB). In total, I have two groups of students choosing among three majors and sorting into three industries in the labor market. More details regarding the estimation data are provided in Appendix D.

5.1 Estimation Strategy

Assigned Model Parameters I parameterize the model at an annual frequency, consistent with the data. I set the discount rate ρ to $\log(1.05)$ to match a 5% annual discount rate. The relative search intensity of employed workers, κ, is set to 0.5, consistent with the relative search effort documented in Faberman et al. (2022) and Holzer (1987). The annual exit probability is set to ensure an average working life of 45 years. This value is also a lower bound for the observed labor market exit rates for each major, as shown in Figure 4. I set the exogenous industry switching rates, $p_{k|j}$, to be uniform across all industries. I do not target observed industry transitions because they are driven by many factors not present in the model, such as firm-specific shocks and geographic moves. Targeting these transitions would force the model to overstate the importance of exogenous shocks, biasing the results. The distribution of innate ability, w_p, is taken directly from the observed grade distribution in the data. Table 4 summarizes the assigned parameters.

Table 4: Assigned Parameters

Parameter	Description	Value	Source
ρ	Discount rate	log (1.05)	Annual 5% interest
κ	Switching cost	0.5000	Faberman et al. (2022)
σ	Per-period exit probability	0.0222	Average 45 years of working
w_p	Distribution over p from the economy	[0.2411, 0.7589]	Normalized share of grade distribution
$p_{k\|j}$	Transition probability between industries k to j		Exogenous; Uniform

For the set of potential task complexities $\mathcal{R}$, I use a 6-point grid over $[0, 2]$, normalized by the standard deviation of the initial prior mean, $\widehat{a_{m0}}$. Importantly, I include $r = 0$ as an entry-level rung to ensure that new graduates can find a match in any industry. I approximate beliefs about worker skills using a 120-point grid for the mean, $\hat{a}$, spanning six standard deviations around $\widehat{a_{m0}}$, and a 20-point grid for the variance, Σ, over $[0, 1]$, also normalized by the initial variance. I verified that the results are robust to using finer grids.

Estimated Parameters I estimate the remaining parameters jointly using the Simulated Method of Moments (SMM). All model moments are computed from the model's ergodic distribution. To keep the estimation tractable, I impose structure on parameters that vary across the state space, reducing the number of parameters while preserving key information. Table 5 summarizes the estimated parameters.

For the vacancy posting cost, $c(m, p)$, I assume it is constant across majors and abilities. Similarly, I assume a single, economy-wide utility from non-employment, b. I further impose structure on the major-industry specific productivity requirement, ϕ_{mj}, and the major-ability specific productivity term, A_{mp} (see Appendix D.2 for details). These parameters are identified using **major-industry and major-ability employment shares**,

Table 5: Estimated Parameters

A: Estimated Parameters		
Parameter	**Description**	**Value**
δ	Separation rate	0.073
c	Vacancy posting cost	0.376
γ	Matching function parameter	1.45
η	Returns to skill	0.33
b	Unemployment utility	0.65
ν	Preference parameter for majors	5.09
ε	Exogenous career switching rate	0.017
μ	Learning rate	9.23
λ_+	Penalty on overqualification	0.66
λ_-	Penalty on underqualification	0.97

B: Parameters Varying Across Majors, Abilities, and Industries		
Parameter	**Description**	**Value**
A_{mp}	Major–Ability productivity	
k_{1m}		-0.06
A_p		[1.61, 1.68]
ϕ_{mj}	Major–Industry requirement	
$\bar{\phi}_j$		[0.98,1.7,0.78]
β_m		-0.03
$\hat{a}_{m0}$	Major-specific initial belief about ability	[0.28,0.1,0.41]
Σ_{m0}	Major-specific initial variance of belief	[0.25,0.49,0.55]

respectively.

Before matching them to the model, I residualize all earnings data by regressing log earnings on institution, city of residence, and citizenship indicators to remove variation from sources absent in my model. Since I am using tax data, I cannot distinguish between unemployment and non-participation. I therefore treat all non-employed individuals as a single state, which I refer to as non-employment (N).

I briefly summarize the mapping between the key parameters and their targeted moments below. More details are provided in Appendix D.

Following the literature, I target worker flows into and out of non-employment to identify the exogenous separation rate, δ, and the vacancy creation cost, c. I pin down the utility from non-employment, b, by targeting a replacement ratio of 0.4 from Shimer (2004). The parameters governing over- and under-qualification penalty, λ_+ and λ_- are estimated by targeting the job-switching rates of workers with positive and negative mismatch values. The returns to skill, η, is identified using the ratio of the variance to the mean of earnings. Finally, major-specific preference parameters are estimated by targeting the observed shares of graduates in each major.

The key parameters for the model are the two sets of parameters that govern the learning process and the information frictions present in the labour market. Specifically, they are the signal noise μ, and the major-specific initial belief distributions $\{a_{m0}, S_{m0}\}$ for each major m. I outline the estimation strategy for these parameters next. In the model, μ governs the speed at which individuals converge from the initial belief to the true match value. A higher μ indicates that individuals receive noisier signals and take longer to learn the true match value. To estimate μ, I use the empirical pattern of how mismatch declines with industry tenure. The intuition is that the number of years it takes individuals, on average, to become less varied in match quality should indicate how fast learning occurs. Conditional on the learning speed, the mean of the initial distribution determines the expected outside option of leaving the current industry. The higher this mean is, the more likely individuals are to switch industries. To avoid any interaction effect between learning and the mean a_{m0}, I use the empirical industry switching rate between the first and second years after college graduation. When all individuals have noisy beliefs, the switching rate should be determined mostly by the expected outside option, which is determined by a_{m0}. The variance of the initial belief distribution captures how dispersed individuals are around a_{m0}. Therefore, when individuals have accurate beliefs, the mass that remains determines the size of the variance. See Figure 18 for an illustration. Given the mean belief a_{m0}, endogenous industry switching is now completely captured by the variation from S_{m0}.

5.2 Baseline Economy Estimation Results

The baseline economy is estimated using the procedure described above. Table 6 compares the targeted moments in the data and the model. The model does a reasonably well job at matching the baseline economy.

Table 6: Targeted Moments

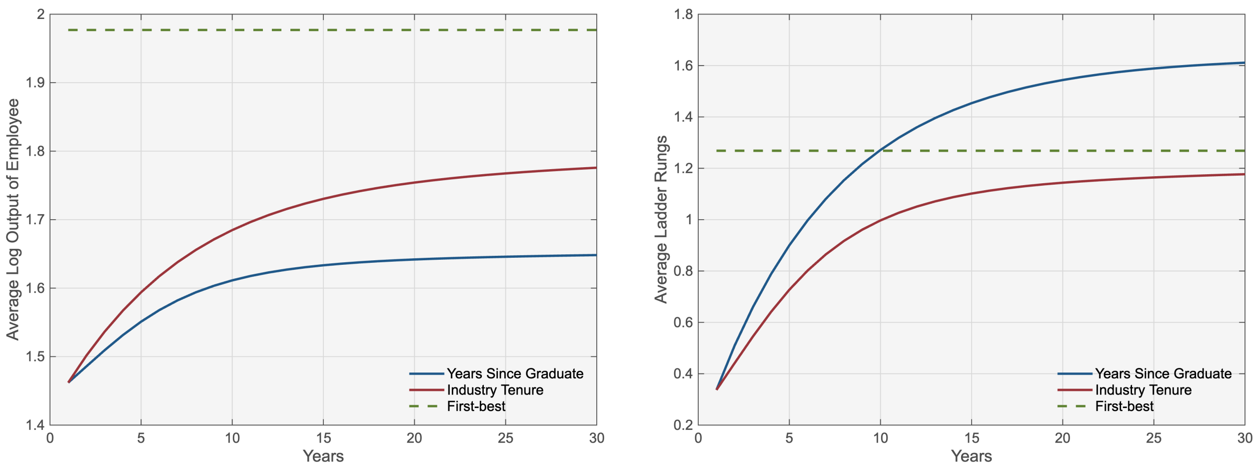
Moment	**Data**	**Model**
Within-major share	0.96	0.85
Within-major btw-ind. share	0.08	0.09
NE rate (yearly)	0.63	0.51
EN rate (yearly)	0.07	0.09
Industry Switching Rate (Year 1)		
Social Science	0.13	0.08
Engineering	0.11	0.06
Business	0.11	0.12
Industry Staying Rate (Year 6)		
Social Science	0.42	0.65
Engineering	0.50	0.74
Business	0.55	0.49
Var(mismatch) ratio yr8/yr2	1.42	0.96
Var(mismatch) at y5	0.25	0.19
Replacement rate ($b/E[y]$)	0.40	0.40
$Var(y)/E[y \mid E]$	0.03	0.03
share m1–p1	0.28	0.37

Employment Shares (Majors × Industries)

	Data			Model		
	Primary	**Finance**	**Public**	**Primary**	**Finance**	**Public**
Social Science	0.28	0.12	0.18	0.37	0.15	0.15
Engineering	0.23	0.03	0.15	0.07	0.05	0.08
Business	0.08	0.15	0.10	0.12	0.11	0.11

6 Counterfactual Analysis

Characterizing the First Best Economy I start by characterizing the first-best economy, which serves as an idealized benchmark absent any information frictions. To construct this counterfactual, I hold major choices from the baseline economy fixed. I then assign individuals to their most productive industry-rung pair based on their true industry-specific skills, $\{a_{ij}\}\ \forall j \in J$. In this scenario, individuals know their true skills from the start. They sort into their optimal positions, facing only search and matching frictions. Figure 8 compares the average output per employee and average job rung in this first-best economy to the baseline. It tracks a new cohort of workers over the first 30 years of their career.



(a) Average Output

(b) Average Rung

Figure 8: First Best Economy: Average Output and Rung

The results in Figure 8 reveal the significant and persistent costs of these information frictions. Panel 8a shows that average output in the baseline economy starts substantially below the first-best benchmark, represented by the green dotted line. Output in the baseline never fully converges with the benchmark. The green line is constant, reflecting the immediate optimal assignment of workers in a world without skill uncertainty. The red line, which tracks “industry stayers” who likely found a good-enough initial match, illustrates that even these workers underperform relative to the benchmark. This persistent gap arises because the cost and uncertainty of switching lead some to settle in “good enough” but ultimately suboptimal industries. The gap between the stayers (red line) and the full cohort average (blue line) quantifies the additional output loss from workers who start in poor matches and engage in costly learning over time.

The distortions are also evident in workers’ career progression, as shown in Panel 8b.

On average, the cohort climbs to higher job rungs than is optimal in the first-best case. This pattern reveals a key compensatory mechanism. To make up for a poor industry match, workers climb higher on the internal job ladder than they otherwise would. In contrast, "industry stayers", being in better industry matches, have less need for this compensatory climbing. Their average rung remains closer to the efficient first-best level. This overshooting of the optimal rung is a clear and interesting distortionary consequence of the initial mismatch caused by information frictions. Another key implication is that the higher the job rung is, the less likely one is to separate from their suboptimal job. This results in a persistent mismatch.

The model suggests two types of policy interventions could affect these outcomes. First, accelerating the learning process would enable workers to recognize good matches and move out of poor matches more rapidly, steepening initial productivity gains for the cohort. Second, increasing the transparency of outside opportunities would help workers avoid settling for suboptimal positions, thus narrowing the output gap relative to the first-best scenario. In the next subsection, I examine the specific effects of these interventions in detail.

6.1 Varying the Speed of Learning

To quantify the importance of learning in the model, I conduct two counterfactual experiments that alter the speed at which individuals learn about their major-specific abilities. The key parameter controlling this speed is the signal noise, μ. By varying μ, I can simulate economies with faster and slower learning, isolating its effect on sorting and aggregate outcomes.

The baseline economy is characterized by a high estimated value of μ, indicating that individuals learn relatively slowly about their true industry fit. Starting from this baseline, I simulate two scenarios:

Higher Speed of Learning I consider a counterfactual economy where individuals learn four times faster. This is implemented by setting the signal noise parameter $\mu_{\text{fast}} = \frac{1}{4}\mu_{\text{baseline}}$ and recalculate the equilibrium without recalibrating. In this scenario, the signals individuals receive about their productivity are much more informative, allowing for a quicker resolution of uncertainty regarding their initial beliefs.

No Learning In this scenario, I effectively eliminate learning. This is achieved by setting μ to a very large value, which makes productivity signals almost entirely uninformative. Under this calibration, an individual would learn only about 1% of their true match value after a 45-year career, making their choices heavily dependent on their initial priors.

Figure 9: Major Share Allocation Difference

Figure 9 illustrates the steady-state changes in major allocation for both high- and low-ability individuals under the two learning scenarios, relative to the baseline. The results highlight that the speed of learning is a crucial determinant of sorting, particularly by reallocating talent away from majors with low initial belief uncertainty.

In the fast-learning scenario, there is a significant reallocation of students out of Social Science and into Engineering and Business. This effect is particularly strong for high-ability individuals, who see a nearly 15% decrease in Social Science enrollment and a greater than 10% increase in Engineering enrollment. This reallocation is explained by the model's initial parameter estimates. My estimates show that individuals begin with high uncertainty as shown by large variance, Σ_{m0} about their ability in Engineering and Business, but are relatively certain about their Social Science ability. Faster learning allows individuals to quickly resolve the uncertainty in high-variance majors. High-ability individuals, upon receiving informative signals, discover they are a good fit for Engineering and Business and thus move away from the more certain but less productive for them, Social Science major.

Conversely, in the no-learning scenario, the opposite occurs. Lacking informative signals, individuals must rely on their initial priors. The high uncertainty associated with Engineering and Business becomes a deterrent. Consequently, individuals sort into the major they are most certain about: Social Science. This leads to an increase in the share of Social Science majors and a decrease in Engineering and Business majors for both ability groups.

Table 7: Equilibrium Outcomes: Steady State

	Mean Output per Worker	**Unemployed Mass**
Baseline	1.6352	0.24549
Fast Learn	1.6889	0.44639
No Learn	1.6240	0.27250

Table 7 shows the impact of learning speed on steady-state outcomes and the transitional dynamics of output. It reveals that faster learning leads to a higher mean output per worker compared to the baseline. This productivity gain stems from improved talent allocation; individuals sort more efficiently into majors where they are genuinely more productive. However, this improved sorting comes at the cost of higher unemployment. Faster learning reveals low matches more quickly, leading more individuals to become unemployed as they search for a better fit. The "No Learn" economy, by contrast, has the lowest output per worker as poor sorting hinders productivity.

Table 8: Output Gap to Baseline (%)

	Year 1	**Year 10**	**Year 20**	**Year 30**
Fast Learn	6.10%	1.93%	1.02%	0.73%

Table 8 examines the output gap between the "Fast Learn" scenario and the baseline over time. We can see that faster learning makes initial output significantly higher towards the first-best scenario. This initial surge is driven by the immediate reallocation of the existing workforce based on more informative signals. However, as time progresses, the output gap narrows. This convergence occurs because, over time, even in the baseline scenario, individuals gradually learn about their true abilities and sort more efficiently. Moreover, the outside options remain uncertain and unchanged across both scenarios, limiting the long-term return to faster learning. Thus, while accelerating learning yields substantial short-term productivity gains, its long-term effects are more muted as the economy naturally moves towards better sorting over time.

7 Conclusion

This paper investigates how information frictions distort the allocation of college graduates to industries, leading to costly and persistent mismatch. I argue that uncertainty about individual-industry skill fit is a primary driver of this misallocation. Graduates enter the labor market with uncertain information through a process of trial and error, and learn about their productivity over time. This dynamic learning process generates a substantial and lasting mismatch.

My empirical analysis, using confidential Canadian administrative data, establishes three key facts supporting this mechanism. First, there is a striking U-shaped relationship between a worker's earnings residual—my measure of mismatch—and their probability of switching industries, indicating that both over- and under-performance lead to separations. Second, this mismatch uncertainty is resolved through industry-specific tenure, but the learning does not transfer across industries, forcing switchers to restart the process. Third, the choice of major is also an implicit choice about the degree of career uncertainty one is willing to face. I provide causal evidence for this mechanism by exploiting the entry of LinkedIn into Canada as a natural experiment. A difference-in-differences design shows that improved access to labor market information led to better initial matches, faster correction of poor matches, and more productive career mobility.

To quantify the aggregate costs of these frictions, I develop and calibrate a life-cycle directed search model with Bayesian learning, major choice, and on-the-job search. The model reveals that information frictions are costly: average output per worker at labor market entry is 25% below the level in a first-best economy with perfect information. This gap narrows but persists over the career, as unresolved uncertainty about outside options leads workers to remain in suboptimal but "good-enough" matches. Counterfactual exercises demonstrate that policies accelerating the learning process could significantly reallocate talent toward majors with higher initial uncertainty but also higher potential returns, particularly for high-ability individuals.

The findings underscore the economic value of institutions that reduce information frictions. From a policy perspective, they suggest that interventions aimed at improving career guidance could generate substantial welfare gains, especially since students are responsive to public information about earnings (Wiswall and Zafar, 2015). The framework also opens several avenues for future research. While the literature has established that students self-select into majors based on expected returns (Kirkebøen et al., 2016), my model introduces career uncertainty as a key, distinct dimension of this choice. Future work could explore how this uncertainty interacts with pre-existing differences in risk preferences (Patnaik et al., 2020) or access to informal information networks—often correlated with gender or socioeconomic background—to provide a richer narrative for sorting patterns (Qiu, 2025). Furthermore, the model's learning mechanism offers a natural laboratory for studying other labor market dynamics, such as the persistent scarring effects of graduating into a recession (Kahn, 2010; von Wachter, 2020) or the role of firm-level heterogeneity in resolving match uncertainty. The large quantitative cost of mismatch identified in this paper demonstrates the critical importance of integrating information frictions and learning into models of educational choice and the market for high-skilled labor.

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A Data Description and Cleaning

A.1 Post Secondary Student Information System (PSIS) Data

Description The PSIS contains information on all students who have attended a post-secondary institution in Canada from the academic year 2009 onwards. Each cohort graduated in 2009 onwards has roughly 450,000 graduates. The PSIS also contains students from 2002 to 2008, inclusive. But these are inherited from Enhanced Student Information System (ESIS), which does not contain the universe of Canadian post-secondary students and have limited comparability to later standardized PSIS. The number of observations is approximately one-fourth of the cohorts graduated in 2009 onwards.

We use the PSIS dataset to obtain information on individuals' post-secondary educational information. This dataset is constructed directly from administrative data obtained from each institution in Canada. Each institution must submit basic information to Statistics Canada each year for each registered student regardless of graduation. Therefore, the dataset is comprehensive and covers all students who have attended a post-secondary institution in Canada starting from 2009. This data contains an annual record for each student registered that year. In particular, the dataset contains information on the student's major (standardized by Statistics Canada to the CIP codes), the institution attended, the credentials obtained, enrollment year, and an indicator of graduation. However, it does not contain information on courses and grades.

The main variables used for analysis from the PSIS are (1) majors, coded by the CIP system; (2) the year of graduation, denoted by cohorts. The main variables used for analysis from the T1FF are (1) the industry of employment, coded by the NAIC, (2) the total earnings in the tax year, and (3) parental total earnings. The PSIS contains demographic information for each student such as age, gender, province of residence, and citizenship status.

A.2 T1 Family File (T1FF) Data

Description The T1 Family File (T1FF) contains individual tax return data, from 2000 to 2021. The T1FF contained in ELMLP contains all the students enrolled in the PSIS and ever filed taxes in Canada.

The main variables used for analysis from the T1FF are (1) the industry of employment, coded by the NAIC and derived from the business registration information, and (2) the total earnings and wages in the tax year. The T1FF also contains detailed information on the individual and family characteristics for tax purposes. All wages, earnings, and benefits are deflated to 2002 dollars using the Consumer Price Index.

A.3 Ontario 9 to 12 (ON 9 to 12) Data

Description The Ontario 9 to 12 (ON 9 to 12) dataset contains administrative information submitted by institutions to the Ontario Government in accordance to regulations. This dataset includes information on basic student demographics and detailed information on the highschool each student attended. Specifically, we used the subset that contains the entries regarding information from 12th grade, which includes whether and which Mathematics courses taken, and letter grades for each Math course taken and the Language course taken.

The main variable used for the analysis is the level of difficulty of the Mathematics courses taken, and the highest letter grade achieved within the level of difficulty. The level of difficulty is coded as 1 for Math Courses that are more advanced versus 0 for less advanced courses. The advancement of the courses are governed by the recomendation of the Ontario Ministry of Education. We excluded special education and adult education individuals and limit the analysis to those who graduated from a bachelor's degree between 2018 to 2020.

A.4 EISV Data for Unemployment Benefits

Description The Employment Insurance Status Vector (EISV) data contains information on the unemployment insurance benefits received by individuals in Canada for each application. Therefore, individuals can have multiple entries in a year if they applied for unemployment benefits multiple times. The EISV data contains information, among others, on the reason for unemployment, the duration of unemployment benefits received, and the amount of benefits received.

For EISV data, we use only the sample that could be linkable to the T1FF data via the ELMLP. The EISV data contains information on the unemployment insurance benefits received by individuals in Canada. The main variables used for analysis from the EISV are the reason for unemployment and the duration of unemployment benefits received. We use this information to define layoffs and exclude parental leave from the definition of unemployment.

A.5 Estimation Sample and Restrictions

We subset the PSIS dataset as follows. We include only the highest degree for each graduate - we followed the process recommended by Statistics Canada in identifying the highest degree. If multiple degrees are obtained within the same year, we exclude the students who studied in not-for-credit programs or military-specific programs (These are roughly 2000 students in total). We include only graduates aged 18 to 35 at the year of graduation. We also exclude the students who are not in the T1FF subset. These are graduates who never filed any taxes in Canada, which is a direct indication that they did not stay in Canada after graduation at all. We further exclude individuals who are disabled or unemployed for the entire duration of the analysis (unemployment defined below).

Conflicting Information across Datasets Any conflicting information recorded in both datasets is resolved using the T1FF tax files. Since we are interested in tracking individuals, we exclude anyone who filed taxes for fewer than two years after graduation. Each individual is assigned a unique identifier to enable linkage across years and datasets.

Employment Status We define employment status for individuals by imputing from the tax records. An individual is considered employed if they have positive salary income in the tax year. Individuals are classified as self-employed if their share of self-employment income is greater than 0.5. An individual is considered to have worked if they are either self-employed, employed, or both. Self-employment is treated as a separate industry in the analysis. Due to incentives to file taxes even when not in the labor force in Canada for benefits, unemployment must be defined separately. Individuals are classified as unemployed if they have annual income lower than 8,000 CAD, or if they received more than 8,000 CAD in employment insurance benefits. Therefore, we can observe employment, unemployment, and non-employment.

Corrections to Industry Coding Individuals are coded to the industry based on the NAIC code of the employer. For some years and some individuals, this information is missing. In these cases, we first use the secondary industry code recorded in the dataset if possible. If not, we use the industry code of the employer in the previous year if the individual is employed in the year. If the industry code is also missing for the previous year's entry for that individual, we use the industry code of the following year. If the individual is self-employed, we will overwrite the industry code, regardless of whether there is an entry, with the self-employment code.

Switchers All switchers in this analysis are defined with respect to industries. Switchers include both EE switchers (individuals who remain continuously employed but switch industries) and EUE switchers (individuals who experience an employment gap and then switch industries). As long as an individual switches industries between two employment records, they are considered a switcher.

Analysis Level Selection The industry NAIC code in the dataset is at the 3-digit level, and the CIP code is at the 6-digit level. To ensure sufficiently large subcategories to track over time, we primarily use the 2-digit CIP code and the 3-digit NAIC code. As a supplementary analysis, we also use the 4-digit CIP codes, and the results remain qualitatively the same.

B Empirical Results Appendix

B.1 Earnings Variances Within College Major

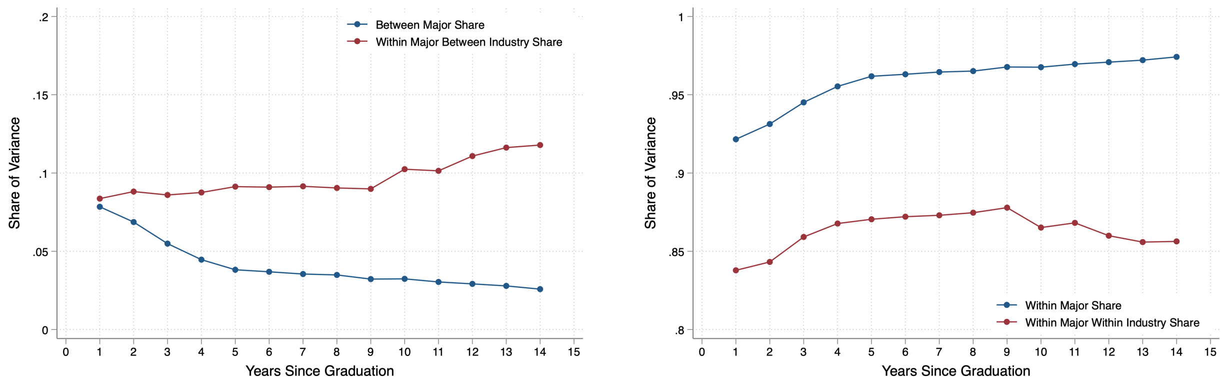
We begin our analysis by examining changes in the variation of total earnings. Since our earnings data are obtained from tax records, total earnings are defined as the sum of all taxable income, including both business and employment income. We use total earnings because self-employment is considered as one of the industries, allowing us to evaluate outcomes for a broader set of college graduates. All analyses of earnings inequality are conducted at the cohort level and repeated for each cohort.

I decompose the variance of log earnings for each year since graduation, t, and for each cohort, c, into between- and within-major components. Here, n_m and $\overline{w}_m$ represent the share of individuals in major m and their corresponding average earnings, while $\overline{w}$ represents the average earnings of the entire economy. The within-major component dominates, accounting for roughly 90% of the total variance. This suggests that most of the variance among these post-secondary graduates arises not from the major they studied but from other factors within the major.

$$\begin{aligned} \mathrm{Var}(y_{ijmct}|c,t) &= \underbrace{\mathrm{Var}(y_{ijmct}-\bar{y}_{mct})}_{80\%}+\underbrace{\mathrm{Var}(\bar{y}_{mct}-\bar{y}_{ct})}_{20\%} \\ &= \sum_m n_m\cdot(\overline{w}_m-\overline{w})^2+\sum_m n_m\cdot(w_{im}-\overline{w}_m)^2 \end{aligned} \tag{34}$$

Further decomposing the within-major component into between- and within-industry components reveals that major-industry matches explain more variance than the major alone. In this decomposition, n_{mj} and $\overline{w}_{mj}$ represent the share of individuals in major m and industry j and their corresponding average earnings.

$$\begin{aligned} \mathrm{Var}(y_{ijmct}|c,t) &= \mathrm{Var}(y_{ijmct}-\bar{y}_{jmct})+\mathrm{Var}(\bar{y}_{jmct}-\bar{y}_{mct})+\mathrm{Var}(\bar{y}_{mct}-\bar{y}_{ct}) \\ &= \sum_m n_m\cdot(\overline{w}_m-\overline{w})^2+\sum_m n_m\cdot\left(\sum_j n_{mj}\cdot\left(\overline{w}_{mj}-\overline{w}_j\right)^2+\sum_j n_{mj}\cdot\mathrm{Var}(w_{imj})\right) \end{aligned} \tag{35}$$



(a) Between-major variance share (b) Within-major variance share

Figure 10: Shares of between-major and within-major variance over time

Outlier Majors in Variance Decomposition As shown in equation 34, the between-major variance at the aggregate level is effectively the summation of the deviations of average earnings for each major from the cohort's average earnings, weighted by the relative size of the major. Therefore, it is important to understand if there exist outliers that drive the results. I observe that the weighted between-major variance is quite persistent, and the contributions among majors are generally similar, with one notable exception: medical doctors after residency (CIP 60). These doctors after residency (approximately 150 individuals per cohort) exihibit a very large between-major variance component. Consequently, I exclude these individuals from the analysis. The numbers reported above already account for the exclusion of medical doctors.

For other majors, the within-major variance completely dominates with some having interesting trends over time given a cohort. For example, in business (CIP 52), within-major variance is low in the first year after graduation but increases over time, while its between-major variance is steadily small. In contrast, some majors, such as health-related fields (CIP 51), display the opposite trend. Additionally, some majors, such as engineering (CIP 14), have within-major variances that are highly sensitive to business cycles. Despite these fluctuations, the between-major variance remains remarkably stable across cohorts and majors.

Individual Persistence Given the large within-major, within-industry variance, I further examined individual earnings persistence over the entire observation period. If individual earnings variances are highly persistent, this suggests that significant skill differences or other individual-level factors, not captured by major or industry, may contribute to the observed within-major and within-industry variance, reducing their prominence.

To investigate this, I first calculate the average lifetime earnings for each individual by summing their annual earnings and averaging over the years they are employed. I then take the log of these average earnings at the cohort-major level. The variance of these log earnings is comparable in magnitude to the within-major variances, effectively smoothing out individual annual shocks. These substantial variances, similar to the within-major variances, indicate that individual earnings are highly persistent over time. When I include unemployed years in the calculations, the variances increase significantly.

B.2 Supplementary Variance Decomposition Results

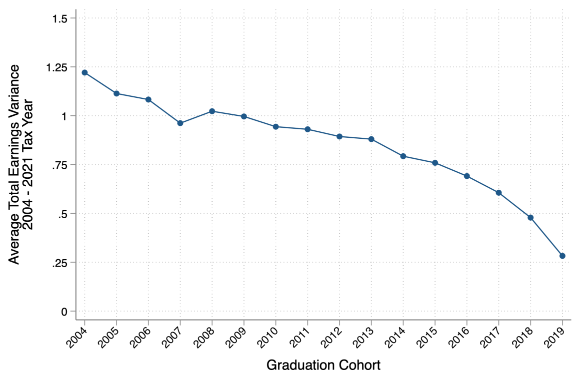
Figure 11a plots the time trend for the average total variance of raw log earnings for each cohort, pooling all years since graduation available together. This trend is biased downwards towards later cohorts because they only have the earlier results, which have less variations among graduates.

Individual Persistence Given the large within-major within-industry variance, I further looked at individual level persistence. If the individual variances are very persistent, then the indication is that there might be large skill differences or other factors at the individual level that are not captured by the major or industry.

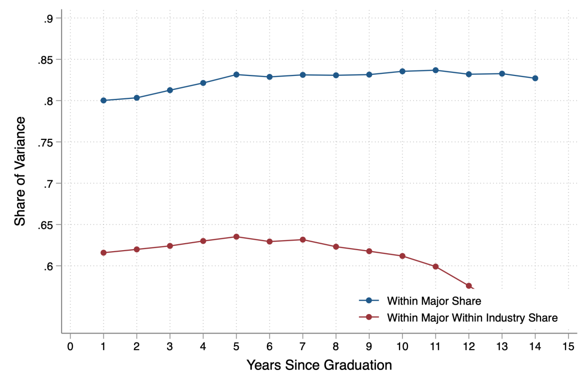
In order to do so, I first calculate the average life-time earnings for each individual by summing up earnings and averaging out on years that they are employed. I then take the log of the average of these earnings at the cohort-major level. The variance of the log earnings is comparable as the within major variances smoothing out individual annual shocks. The variances are very large and are similar to the within-major variances, suggesting that the individual earnings are very persistent. The variances computed by including unemployed years are much larger.

B.2.1 Supplementary Raw Variance Decomposition

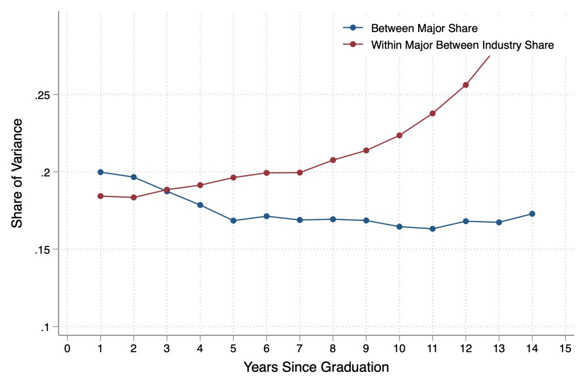
Figure 11 presents supplementary results for the raw variance decomposition. Figures 11b and 11c show the share of within-major variance and between-major variance in total variance, respectively. The patterns are similar to those in Figure 1b, but the within-major variance is slightly lower, and the between-major variance is slightly higher.



(a) Variance Decomposition of Log Earnings for College Graduates



(b) Share of within-major variance



(c) Share of between-major variance

Figure 11: Supplementary Raw Variance Decomposition: (a) Variance Decomposition of Log Earnings for College Graduates, (b) Share of within-major variance, (c) Share of between-major variance.

B.3 Earnings Mismatch Definition and Supplementary Results

An alternative way to residualize the earnings is without interacting tenure terms with industry and majors. Our results remain robust when using Equation 36.

$$\log(y_{ijmct}) = \alpha_i + \delta_{mj} + \gamma_{jt} + \xi_{mt} + f(c) + \epsilon_{ijmct} \tag{36}$$

B.4 Supplementary Facts from National Graduate Survey

The supplementary data to cross-validate the administrative data is the National Survey of College Graduates from the U.S. used in Altonji et al. (2014). These surveys are cross-

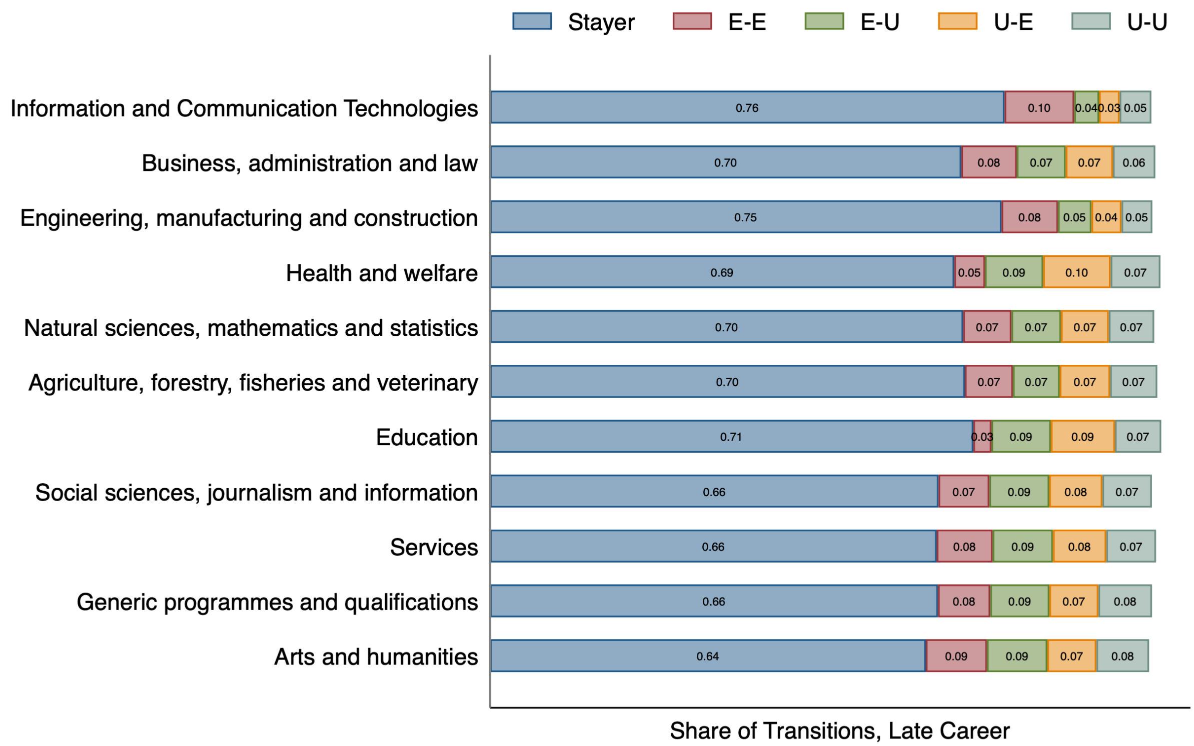
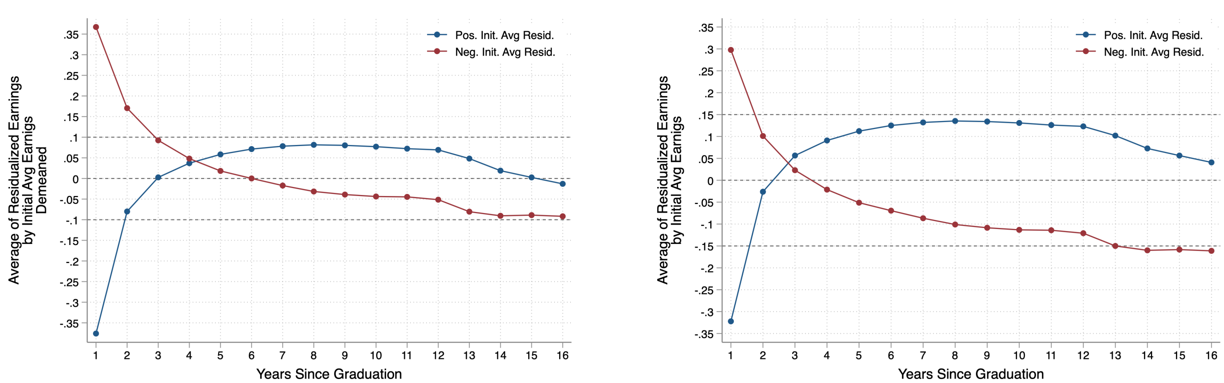


Figure 12: Late Career



(a) Average M_{it} by Tenure, Raw

(b) Average M_{it} by Time

Figure 13: Average M_{it} by Tenure and by Time, Raw

sectional that includes individuals with at least a bachelor's degree, sampled from the American Community Survey during the reference week of the survey year. There are three waves of survey that are used in their paper, which are: 1993, 2003, and 2010. I will only be using the waves 2003 and 2010 since the 1993 wave does not record individual's industry. The results are weighted to reflect the entire population of college graduates in the US as of each survey year.

I obtained the data from the authors' published replication file. Therefore, the following analysis is based on the same data selection criteria, focusing on full-time workers aged 25–55. Since graduation year is unavailable for most individuals in the survey, I assume that each person graduated at age 22. This graduation year proxy is applied to all individuals because, even when graduation year is reported, most of the reported values are implausible.

B.4.1 Variance Decomposition

The first step to benchmark is the fact about the earnings inequality within college graduates lies primarily within college majors. Since this is a survey, I modified equation 34 and equation 35 to include survey weights. Moreover, since the sample size of the survey cannot support slicing it at the cohort-age-major-industry level, I group the cohort into 9 groups: graduating between 1960 - 1970; 1970 - 1975; 1975 - 1980; 1980 - 1985; 1985 - 1990; 1990 - 1995; 1995 - 2000; 2000 - 2005; 2005 - 2009. I also group age into 6 groups: 25-30; 30-35; 35-40; 40-45; 45-50; 50-55. In this subsection specifically, t and c are the cohort and age group, respectively.

Raw Variance Changes I compute the raw variance by first calculating the variance for each c and t and then pooling across the surveys to obtain a view over the entire lifetime. See Table 9 for the results. The results indicate that within-group variance dominates for all age groups, while between-group variance remains relatively constant. In contrast, total variance increases drastically over time. This pattern is consistent with the findings from the Canadian administrative data.

Further Variance Decomposition Within Major Similar to equation 35, I can further decompose the earnings variance within majors into within- and between-industry components. Table 10 presents the results. The importance of industries within a major is consistently much larger than the between-major variance. Since the survey also includes

Table 9: Variance Decomposition by Age Group

Age Group	25	30	35	40	45	50
Within Variance	0.3328	0.3623	0.4339	0.4910	0.5157	0.5256
Within Share (%)	92.39%	92.44%	92.36%	92.19%	91.33%	93.05%
Between Variance	0.0273	0.0297	0.0359	0.0416	0.0489	0.0392
Between Share (%)	7.61%	7.56%	7.64%	7.81%	8.67%	6.95%
Total Variance	0.3601	0.3920	0.4697	0.5325	0.5646	0.5648

occupation information, I compare the decomposition between industry and occupation.

Table 10: Detailed Variance Decomposition by Age Group

Age Group	25	30	35	40	45	50
Within Major Within Industry Var	0.2553	0.2652	0.3173	0.3511	0.3709	0.4014
Within Major Within Industry Share (%)	70.69%	67.71%	67.47%	65.93%	65.55%	70.99%
Within Major Between Industry Var	0.0761	0.0966	0.1150	0.1368	0.1423	0.1209
Within Major Between Industry Share (%)	21.27%	24.58%	24.56%	25.68%	25.31%	21.46%
Between Major Var	0.0273	0.0297	0.0359	0.0416	0.0489	0.0392
Between Major Share (%)	7.61%	7.56%	7.64%	7.81%	8.67%	6.95%
Total Variance	0.3601	0.3920	0.4697	0.5325	0.5646	0.5648

Table 11 shows the results when I further decompose the within-major variance into within- and between-occupation variances. The results indicate that the importance of industry and occupation are of similar magnitudes. Thus, I can confidently focus on industry decomposition in the administrative data and consider the mismatch between industry and college major as a significant source of earnings inequality in the model. All other sections of the paper will be based on the Canadian administrative data.

Table 11: Variance Decomposition by Age Group: Majors vs. Occupations

Age Group	25	30	35	40	45	50
Within M. Within Occ. Var	0.2366	0.2492	0.2885	0.3153	0.3316	0.3546
Within M. Within Occ. Share (%)	65.57%	63.59%	61.36%	59.22%	58.69%	62.77%
Within M. Between Occ. Var	0.0948	0.1126	0.1438	0.1726	0.1815	0.1677
Within M. Between Occ. Share (%)	26.39%	28.70%	30.66%	32.40%	32.17%	29.69%
Between Major Var	0.0273	0.0297	0.0359	0.0416	0.0489	0.0392
Between Major Share (%)	7.61%	7.56%	7.64%	7.81%	8.67%	6.95%
Total Variance	0.3601	0.3920	0.4697	0.5325	0.5646	0.5648

B.5 Robustness Results for Ontario Highschoolers

The full regression table results for the Ontario highschoolers is in Table 12.

Table 12: Sorting Patterns between Inherent Ability and Outcomes

	(1)	(2)	(3)	(4)
Dependent variable:	Ind. Quartile	M–J FE	Neg Dev.	Pos Dev.
Math==C#Lang==B	0.0129	-0.00138	-0.00312	-0.00542
	(-0.66)	(-0.36)	(-0.42)	(-1.06)
Math==C#Lang==A	0.0409	-0.000831	0.0296*	0.0194*
	(-1.19)	(-0.12)	(-2.22)	(-2.20)
Math==B#Lang==C	-0.0300	-0.0102*	-0.00813	-0.00937
	(-1.36)	(-2.36)	(-0.96)	(-1.64)
Math==B#Lang==B	-0.00668	-0.00355	-0.00160	0.00159
	(-0.36)	(-0.97)	(-0.23)	(-0.34)
Math==B#Lang==A	-0.0127	-0.0108*	0.0143	0.00559
	(-0.53)	(-2.29)	(-1.60)	(-0.93)
Math==A#Lang==C	-0.0922**	-0.0207***	-0.00993	-0.00329
	(-2.99)	(-3.42)	(-0.81)	(-0.43)
Math==A#Lang==B	-0.0332	-0.00730	-0.00322	-0.000436
	(-1.58)	(-1.76)	(-0.41)	(-0.08)
Math==A#Lang==A	0.0212	-0.00531	0.0161	0.000695
	(-0.93)	(-1.19)	(-1.93)	(-0.13)
female	-0.0241*	-0.00680**		
	(-2.12)	(-3.03)		
_cons	2.452***	0.0719	0.171***	0.192***
	(-7.83)	(-1.17)	(-14.76)	(-23.86)
N	41,000	41,000	16,000	25,000
R^2	0.100	0.036	0.002	0.001
Adj. R^2	0.095	0.031	0.001	0.001
F	2.355	13.11	3.094	2.987

Notes: Coefficients with t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

B.6 LinkedIn Identification Supplementary Results

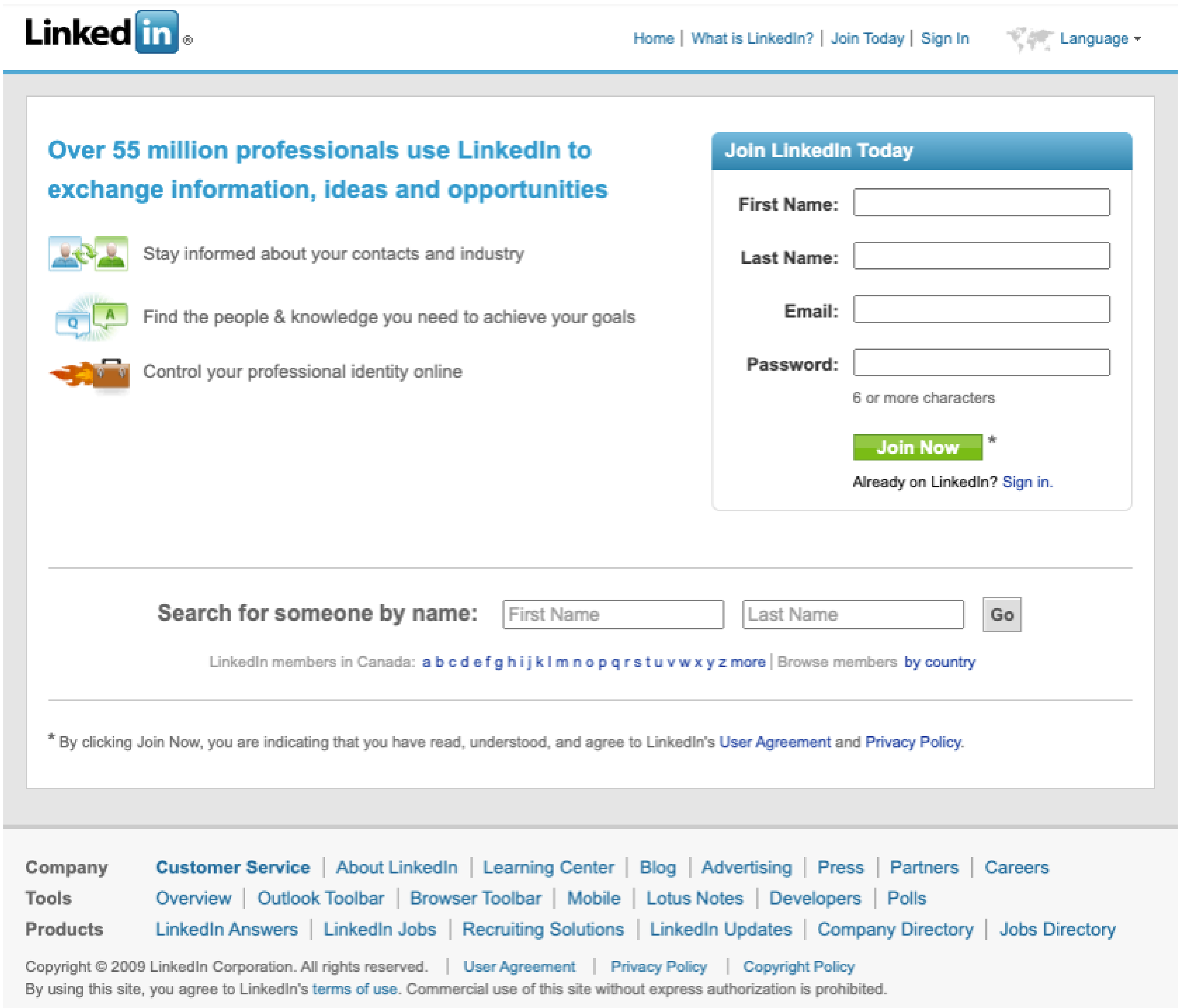


Figure 14: Snapshot of the LinkedIn Canada website when it first launched on Nov 11th, 2009

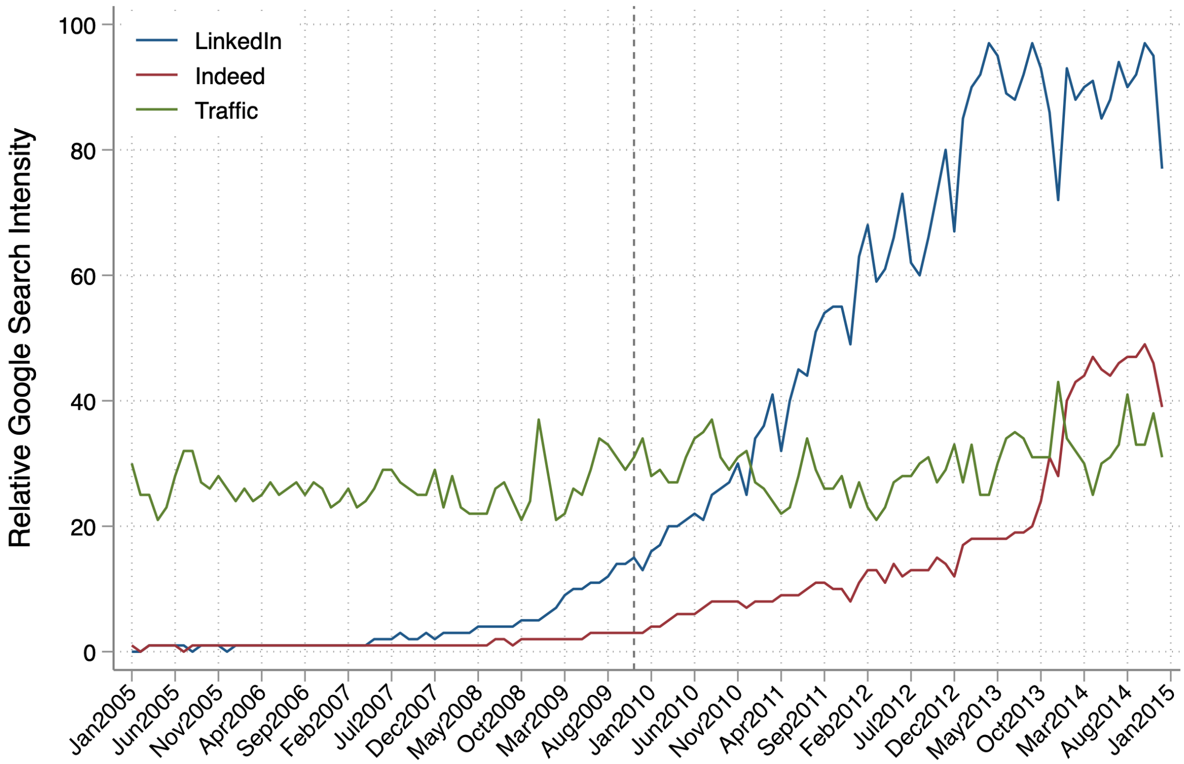


Figure 15: Google Trends comparison between LinkedIn, Indeed, and general web traffic


Browse Jobs by Industry

Accounting Industry Jobs
Apparel, Fashion Jobs
Automotive Jobs
Aviation, Aerospace Jobs
Banking, Mortgage Jobs
Biotechnology, Greentech Jobs
Chemicals Jobs
Civil Engineering Jobs
Computer Games Jobs
Computer Hardware Jobs
Computer Networking Jobs
Computer Software, Engineering Jobs
Computer, Network Security Jobs
Construction Jobs
Consumer Electronics Jobs
Consumer Goods Jobs
Defense, Space Jobs
Education Management Jobs
Electrical, Electronic Manufacturing Jobs
Entertainment, Movie Production, Film Production Jobs
Environmental Services Jobs
Financial Services Jobs
Food, Beverages Jobs
Health, Wellness, Fitness Jobs
Higher Education, Acadamia, Universities Jobs
Hospital, Health Care, Medicine, Nursing Jobs
Hospitality Jobs
Human Resources, HR Jobs
Industrial Automation Jobs
Information Services Jobs
Information Technology, Services, IT Jobs
Insurance Jobs
Internet, Web2.0, Startups, Social Networking Jobs
Logistics, Supply Chain, Procurement Jobs
Management Consulting Jobs
Marketing, Advertising, Sales, Business Development, BD Jobs
Mechanical or Industrial Engineering Jobs
Medical Equipment Jobs
Mining, Metals Jobs
Non-Profit Organization Management Jobs
Oil, Energy, Solar, Greentech Jobs
Online Publishing Jobs
Pharmaceuticals Jobs
Real Estate, Mortgage Jobs
Retail Industry Jobs
Semiconductors Jobs
Staffing, Recruiting, Headhunting, Executive Search, Sourcing Jobs
Telecommunications, Wireless, Mobile Jobs
Transportation, Trucking, Railroad Jobs
Utilities Jobs

Figure 16: Screenshot of the LinkedIn jobs page on April 28, 2012

LinkedIn

Not a user? Join Now

Jobs Directory

Engineering Jobs

Jobs Directory > Engineering Jobs

Active Directory SME at Lockheed Martin in Washington D.C.

Architect at Microsoft in Seattle

Audio Programmer at Neversoft Entertainment in Los Angeles

Automotive Equipment Installation Management Plant Engineering at The PAC Group in Other Region

Avaya Senior Systems Engineer at Lantana Communications in Dallas, Fort Worth

Avaya Solution Architect at BrantTel Networks in Toronto, Canada

Build and Release Master at MuleSoft Inc in San Francisco Bay Area

Build Release Engineer at Kakai Inc in San Francisco Bay Area

CampusVue Administrator at Bridgepoint Education in San Diego

Communications Network Engineer at CELTIQ LLC in Washington D.C.

Compiler Lead at Adobe Systems in Boston

Consultant Software Engineer Database Architect at RSA The Security Division of EMC in Boston

Consumer User Interface UI Engineer OpenGL Qt C Linux at Cisco Systems in San Francisco Bay Area

Cost Manager at Parsons in Other Region

Data Center Manager at Microsoft in Chicago

Data Systems Software Engineer at Intelius in Seattle

Database Engineer IV at VeriSign in Washington D.C.

Design Engineer at NORESCO in Washington D.C.

Development Manager Platform Team at Infoblox in San Francisco Bay Area

Director Of Program Managment at Microsoft in Other Region

Director of Research Engineering Packet Network Technologies at Ericsson in San Francisco Bay Area

Do you toast your Pop tarts at oogalabs in San Francisco Bay Area

Electrical Design Engineer at Gentex Corporation in Grand Rapids, Michigan

Electrical Engineer at Universal Avionics Systems Corporation in Atlanta

Electrical Planning Engineering Specialist at Volkswagen Group of America in Chattanooga, Tennessee

Embedded Linux Platform Engineer at Cisco Systems in San Francisco Bay Area

Energy Utility Specialist at Volkswagen Group of America in Chattanooga, Tennessee

Engineer II Sr Engineer Cell Culture Manufacturing Science Technology at Genentech Inc in San Diego

Engineer II Sr Engineer Purification Manufacturing Science Technology at Genentech Inc in San Diego

Engineering Director Small Steam Turbines at Alstom Power in Zurich, Switzerland

Enterprise Architect Systems Engineer at Image Matters LLC in Washington D.C.

Estmiating Manager at Russell Construction in Davenport, Iowa

Facility Manager at MAX Environmental Technologies Inc in Pittsburgh

Federal Project Manager at I Q Staffing Solutions Inc in Minneapolis-St. Paul

Front End Web Developer at hi5 in San Francisco Bay Area

Global Technology Supply Manager at Cisco Systems in San Francisco Bay Area

Graphics Software Engineer at Intel in San Francisco Bay Area

I V Project Lead LTE eNB Verification at Nokia Siemens Networks in Dallas, Fort Worth

Instrumentation Technician at Genentech in San Diego

IT Technologist with Apache Tomcat Skills at MuleSoft Inc in San Francisco Bay Area

Java Applications Development Engineer at Research In Motion in San Francisco Bay Area

Java Developer Web Design at Medsphere Systems Corporation in San Diego

Java Engineer at Sportvision in San Francisco Bay Area

Java Engineer Master Data Management at Teradata in San Diego

Java Programmer at Stratify in San Francisco Bay Area

JIT Compiler Engineer at Adobe Systems in Boston

Junior to Intermediate Internet Software Engineers at CSN Stores in Boston

Laboratory Engineering Specialist at Volkswagen Group of America in Chattanooga, Tennessee

Lead Java Engineer 845 at Wavestaff in New York City

LEAD PROCESS ENGINEER GOLD MILL HEAP LEACH AND POX EXPERIENCE TORONTO AREA at PeopleFind Inc in Toronto, Canada

Lead Software Test Engineer at Citrix Systems in Miami, Fort Lauderdale

Leader Water Geospatial Asset Management at The City of Calgary in Calgary, Canada

Linux Software Engineer at Intel in Portland, Oregon

Loss Prevention Engineer at Saudi Aramco in Other Region

Mac Lead Developer at YouSendIt in San Francisco Bay Area

Manager of Engineering exciting small growing company designing electro mechanical systems at GNR in Tampa, St. Petersburg, Florida

Manager Reliability Physics Device Packaging at First Solar in Toledo, Ohio

Manufacturing Eng Product Manager at BridgeWave Communications in San Francisco Bay Area

Manufacturing Technical Specialist III Sr Engineer at Genentech Inc in San Francisco Bay Area

Material Flow Engineering Specialist at Volkswagen Group of America in Chattanooga, Tennessee

Mechanical Hardware Engineering Manager at Cisco Systems in San Francisco Bay Area

Memory Management Engineer at Adobe Systems in San Francisco Bay Area

Memory Software Developer at Research In Motion in Kitchener, Canada

Metallurgist at Alcoa in Bellingham, Washington

MicroStrategy Architech at LowerMyBills com in Los Angeles

Mobile Client Architect at NETWORKS IN MOTION in Los Angeles

Mobile Product Architect at Silicon Image in San Francisco Bay Area

Modeling Engineer at Rive Technology in New York City

NET SQL Web Application Developer at Americaneagle com in Chicago

Network Design Capacity Engineer at Time Warner Cable Business Class in San Diego

Network Engineer at Tower Research Capital in New York City

Nuclear Criticality Safety Engineer at Nuclear Safety Associates in Johnson City, Tennessee

PCB Designer at Lynk Labs Inc in Chicago

Perfomance Engineer at Adobe Systems in San Francisco Bay Area

Peripheral Hardware Engineering Manager at Cisco Systems in San Francisco Bay Area

Physical Design Consultant at Synopsys in San Francisco Bay Area

Pre integration Manual Test Engineer at Red Hat in Other Region

Principal Bioprocess Consultant Engineer at Biopharm Services in Hemel Hempstead, United Kingdom

Principal Engineer CAPA at Baxter Healthcare in Chicago

Principal FPGA Design Engineer at Networking Start Up in San Francisco Bay Area

Principal Release Engineer at Citysearch com in Los Angeles

Principal Security Engineer at RSA The Security Division of EMC in Boston

Principal Software Engineer LinkedIn Communication System at LinkedIn in San Francisco Bay Area

Product Development Architect at Fluke Networks in Washington D.C.

Product Engineer 3 4 at Acumed in Portland, Oregon

Product Manager Orthopaedic at Materialise in Brussels, Belgium

Product Marketing Manager at SunPower Corporation in San Francisco Bay Area

Product Support Specialist at Stratify in San Francisco Bay Area

Production Data Solutions Engineer at Genentech in San Francisco Bay Area

Professional Services Consultant at Coit Staffing in San Francisco Bay Area

Program Manager at YouSendIt in San Francisco Bay Area

Project Cost Estimator at INVISTA in Houston, Texas

QA Automation Engineer at Citysearch com in Los Angeles

QA Entry Level Engineering Internship MUST currently be a student and live in the area at Chegg Inc in San Francisco Bay Area

Quality Engineering Member of Technical Staff at Salesforce com in San Francisco Bay Area

R D Project Engineer at C S Wholesale Grocers in Boston

Rectifier Firmware Engineer at Lineage Power in Dallas, Fort Worth

RF Engineer at Laird Technologies in Boston

RMA Technician at Silver Spring Networks in San Francisco Bay Area

RF Software Developer at Research In Motion in Ottawa, Canada

LinkedIn

Not a user? Join Now

Jobs Directory

Marketing Jobs

Jobs Directory > Marketing Jobs

Account Executive at The Internet Advertising Institute in New York City

Account Manager at YouCast Corp in New York City

Account Manager for Health Insurance Pharma at Acxiom in Little Rock, Arkansas

Account Specialist at Mesirow Financial in Chicago

Ad Agency Account Executive at Eleventh Hour in Los Angeles

Affiliate Manager at CM Recruiting Confidential in San Francisco Bay Area

Analyst Online Sales Operations French Dublin at Facebook in Other Region

Analyst Online Sales Operations Nordics Dublin at Facebook in Other Region

Assistant Marketing Manager 2 at E J Gallo Winery in Modesto, California

Associate Brand Manager Soup Salad Dressings Sauces at Bay Valley Foods in Pittsburgh

Associate Creative Director Copywriter at Denali Marketing in Minneapolis-St. Paul

Associate Marketing Manager at The McGraw Hill Companies in New York City

B2B Sports Marketing Manager at 888 com in London, United Kingdom

BPS Software solutions US Sales Marketing Manager at Biopharm Services in Hemel Hempstead, United Kingdom

Brand Manager at HSN in Tampa, St. Petersburg, Florida

Brand Manager at HSN in Tampa, St. Petersburg, Florida

Brand Marketing Product Manager or Senior at Kraft Canada Inc in Toronto, Canada

Citi Cards Value Product Strategy Director at Citigroup in New York City

Communicatie Specialist at Athlon Car Lease in Utrecht, Netherlands

Communication Specialist at Bacardi Martini B V Geneva Branch in Geneva, Switzerland

COMMUNICATIONS PUBLIC AFFAIRS ADVISOR at CAA Niagara in Ontario, Canada

Content Marketing Strategist Creator at Intronis in Boston

Corporate Copywriter at Littelfuse in Chicago

Country Product Manager at EF Education AG in Zurich, Switzerland

Customer and Sales Information Analyst at Dean Machinery Co in Kansas City, Missouri

Customer Marketing Manater at The Burke Group in Ontario, Canada

Database Marketer at liveBooks in San Francisco Bay Area

Digital Marketing Multiple Openings at Spirent Communications in Los Angeles

Digital Sales Manager at The Onion in Chicago

Dir Communications for Pres Fin Planning Retirement Wealth Strategies Chief Mktg Officer at Ameriprise Financial Services Inc in Minneapolis-St. Paul

Director Brand Consumer Advocate at Raley s in Sacramento, California

Director Citi Cards Chairman Hilton Product Strategy at Citigroup in New York City

Director Communications at Nexterra Systems Corporation in Vancouver, Canada

Director Database Analytics at National Pen in San Diego

Director Digital Marketing Glendale CA or White Plains NY at Disney Publishing Worldwide in New York City

Director Direct to Customer Sales at Wolters Kluwer Health Pharma Solutions in Philadelphia

Director Emerging Digital Channels at Citigroup in New York City

Director Enterprise Marketing at TheLadders com in New York City

DIRECTOR M86 SECURITY LABS at M86 Security in Los Angeles

Director New Product Development at Express Scripts in St. Louis

Director of Business Operations at ContextWeb in New York City

Director of Communications Nielsen Telecom at The Nielsen Company in New York City

Director of CRM at Electronic Arts in San Francisco Bay Area

DIRECTOR OF DIGITAL ONLINE STRATEGY at Columbia College in Chicago

Director of Product Management at CodeRyte in Washington D.C.

Director Online Marketing at Corporate Executive Board in Washington D.C.

Director Product Manager at Bush Industries in Jamestown, New York

Director Regional Brands Snuff Richmond VA at Swedish Match in Richmond, Virginia

Embedded SW Lead Developer at Mentor Graphics in San Francisco Bay Area

EMEA Online Partner Marketing Executive at Expedia in London, United Kingdom

Executive Communications Director at Yahoo in San Francisco Bay Area

Global Category Specialist Manger Services at Welch Allyn in Syracuse, New York

GM Travelocity ca at Travelocity com in Toronto, Canada

Graphic Designer at Acumed in Portland, Oregon

Head of Player Marketing at PartyGaming in Other Region

Human Resources Director at Panduit Corp in Other Region

Interaction Designer at Express Scripts in St. Louis

Manager Global Trade Marketing at The Rockport Company in Boston

Manager of Solutions Services Marketing at ServiceSource in San Francisco Bay Area

Market Segment Manager at Sigma Aldrich in St. Louis

Marketing Campaigns Intern at Space Time Insight in San Francisco Bay Area

Marketing Coordinator at Manufacturing and Marketing Co in Boston

Marketing Director for Luxury Men s Accessories Brand at Couture Staff in New York City

Marketing Intern at Hire Ed Solutions in New York City

Marketing Manager at FoodShouldTasteGood in Boston

Marketing Manager at Mesirow Financial in Chicago

Marketing Manager at Rezolve Group Inc in Boston

Marketing Manager at Thomson Reuters in Minneapolis-St. Paul

Marketing Manager Digital Solutions at Cengage Learning in San Francisco Bay Area

Marketing Manager Media Buyer SEM at CM Recruiting Confidential in San Francisco Bay Area

Marketing Performance Analyst at Vonage in New York City

Director of Marketing at AppNexus in New York City

Director of Online Customer Experience Strategy at Citigroup in New York City

Director of Web Marketing and Social Media at Aquire in Dallas, Fort Worth

Director Online Sales and Marketing Strategy at Citigroup in New York City

Director Products and Services Marketing at Ingersoll Rand in Indianapolis, Indiana

E commerce Merchandiser at Sears Holdings Corporation in Chicago

EMEA Marketing Director at Expedia in London, United Kingdom

Emerging Markets Investment Bank Seeks HR or Recruiting Specialist at Nova Capital Partners LLC in New York City

Experienced Project Manager at Taphandles Inc in Seattle

Global Alliance Marketing Manager Microsoft at Novell in Seattle

Global Market Research Manager at Blizzard Entertainment in Los Angeles

Google Marketing and Communications Opportunities at Google in New York City

Head of On Line Marketing at Connect Distribution in Other Region

Head of PPC at Stickyeyes in Leeds, United Kingdom

Inside Sales Marketing Executive at Quest Computing Ltd in Other Region

Interactive Marketing Coordinator at SunGard in Philadelphia

Manager Healthcare Communications International and Emerging Markets at Philips in Eindhoven, Netherlands

Market Development Manager Responsable D veloppement des march s at EXFO in Quebec, Canada

Marketing Automation Manager at Sophos in Boston

Marketing Communications Manager at ForeScout Technologies in San Francisco Bay Area

Marketing Director at Greene Resources in Richmond, Virginia

Marketing Director Other Positions in Marketing at IMImobile in Other Region

Marketing Manager at Air2Web in Atlanta

Marketing Manager at Lineage Power in Dallas, Fort Worth

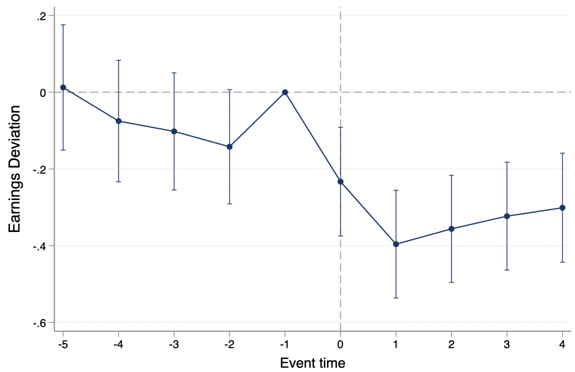
Marketing Manager at Overtone in San Francisco Bay Area

Marketing Manager at SunGard in New York City

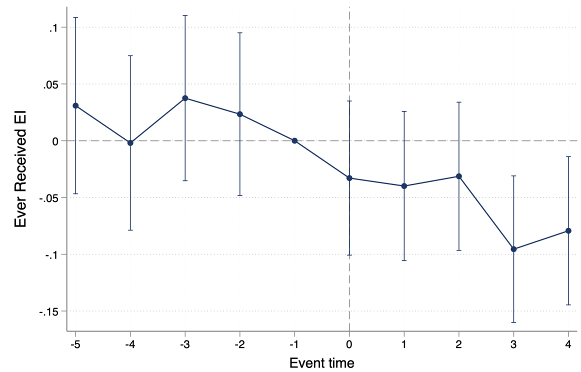
Marketing Manager Breast Cancer Molecular Diagnostics Portfolio at Agendia Inc in Los Angeles

Marketing Manager Director Asia at Xoom Corporation in San Francisco Bay Area

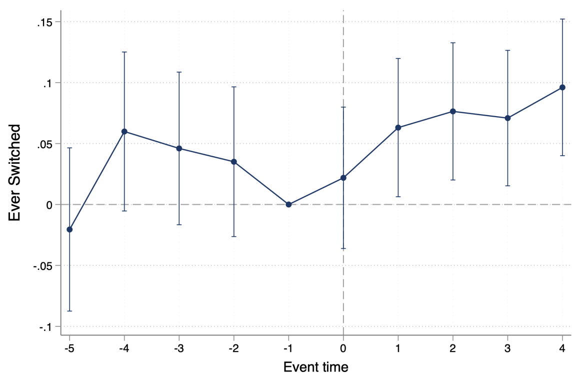
Marketing Managers at Mead Johnson Nutrition in Amsterdam, Netherlands



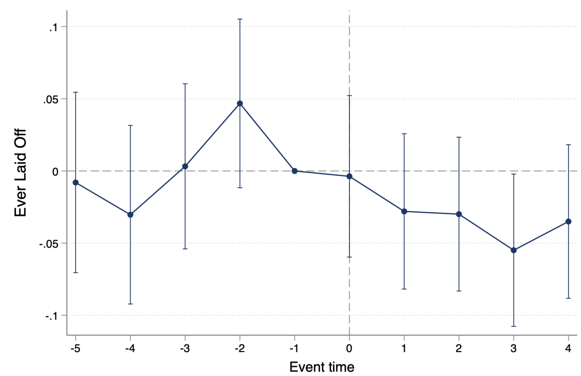
(a) Earnings Deviation



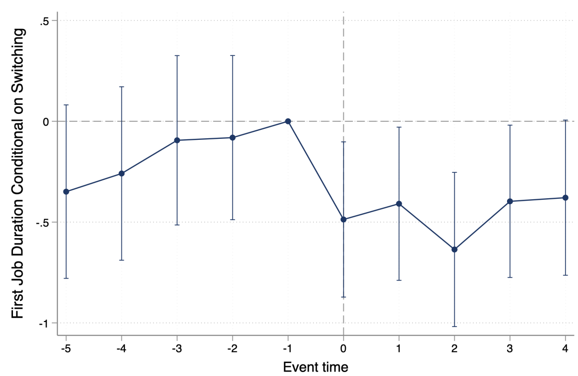
(b) Probability of receiving EI



(c) Probability of ever switching jobs



(d) Probability of ever being laid off



(e) Duration of initial industry employment (conditional on switching)

Figure 17: Event study: (a) Earnings deviation, (b) probability of receiving EI, (c) probability of ever switching jobs, (d) probability of ever being laid off, and (e) duration of initial industry employment by cohort.

The full regression table results for the event study is in Table 13. Other event study plots are included in Figures 17.

Table 13: Event-Study DID by Graduation Cohort

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	First Job Duration Before Switching	Ever Switched	Ever Received EI	Ever Laid Off	Earnings Deviation
1.Treatment#2005.grad_year	-0.349	-0.0205	0.0309	-0.00797	0.0125
	(-1.59)	(-0.60)	(-0.78)	(-0.25)	(-0.15)
1.Treatment#2006.grad_year	-0.259	0.0599	-0.00196	-0.0303	-0.0751
	(-1.18)	(-1.80)	(-0.05)	(-0.96)	(-0.93)
1.Treatment#2007.grad_year	-0.0943	0.0460	0.0375	0.00321	-0.102
	(-0.44)	(-1.44)	(-1.01)	(-0.11)	(-1.31)
1.Treatment#2008.grad_year	-0.0810	0.0351	0.0234	0.0468	-0.142
	(-0.39)	(-1.12)	(-0.64)	(-1.57)	(-1.87)
1.Treatment#2009.grad_year	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)
1.Treatment#2010.grad_year	-0.487*	0.0219	-0.0329	-0.00371	-0.233**
	(-2.48)	(-0.74)	(-0.95)	(-0.13)	(-3.22)
1.Treatment#2011.grad_year	-0.409*	0.0631*	-0.0399	-0.0280	-0.396***
	(-2.11)	(-2.18)	(-1.19)	(-1.02)	(-5.53)
1.Treatment#2012.grad_year	-0.636**	0.0764**	-0.0313	-0.0299	-0.356***
	(-3.26)	(-2.66)	(-0.94)	(-1.10)	(-5.00)
1.Treatment#2013.grad_year	-0.397*	0.0709*	-0.0955**	-0.0549*	-0.323***
	(-2.06)	(-2.50)	(-2.90)	(-2.04)	(-4.50)
1.Treatment#2014.grad_year	-0.379	0.0961***	-0.0793*	-0.0350	-0.301***
	(-1.93)	(-3.36)	(-2.38)	(-1.29)	(-4.15)
unemp_rate_jt	-6.182***	0.801***	-0.172*	-0.0174	1.898***
	(-3.75)	(-13.12)	(-2.43)	(-0.30)	(-8.91)
N	15,000	19,000	19,000	19,000	19,000
R^2	0.061	0.037	0.035	0.006	0.054
Adj. R^2	0.058	0.035	0.033	0.005	0.053

Notes: Coefficients with t-statistics in parentheses. Base cohort is 2009 (= 0). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

C Model Details

C.1 Single–Peakedness and Single–Crossing of Rung Choice

Setup and notation Fix a major m, industry j, and ability p. The job ladder has rungs $r \in \{0, 1, \dots, \bar{r}\}$. For simplicity, we will assume a continuous choice $r \in [0, \bar{r}]$ in the interior. The discrete case follows by projection onto the nearest integer, and all results hold by applying the Topkis Theorem to the discrete lattice $\{0, 1, \dots, \bar{r}\}$.

Let $\phi \equiv \phi_{mj} > 0$ denote the major-industry requirement, and $(\hat{a}, \Sigma)$ the belief state about match-specific skill a with $a \mid \mathcal{I} \sim \mathcal{N}(\hat{a}, \Sigma)$. As in the text, the flow technology, introduced in Equation 6, is copied here for convenience:

$$\ln y = \ln A_{mp} + \eta\,(r\phi) \;-\; \tfrac{1}{2}\Big(\lambda_+(r)[r\phi - pa]_+^2 + \lambda_-(r)[r\phi - pa]_-^2\Big)$$

The expected output given the belief state is then

$$\mathbb{E}[y \mid \hat{a}, \Sigma] = A_{mp}\, e^{\eta r\phi}\, H_r(\zeta), \qquad \zeta := r\phi - p\hat{a}, \quad s^2 := p^2\Sigma,$$

with

$$H_r(\zeta) \;=\; \mathbb{E}_{Z\sim\mathcal{N}(0,s^2)}\Big[\exp\Big(-\tfrac{1}{2}(\lambda_+(r)[\zeta+Z]_+^2 + \lambda_-(r)[\zeta+Z]_-^2)\Big)\Big]$$

Throughout we assume $\lambda_+(r), \lambda_-(r) \geq 0$ where in the interior rungs both are strictly positive. At the boundary, we assume agents cannot be underqualified is at the lowest rung, and can not be overqualified if at the highest rung. That boundary condition is expressed as:

$$\lambda_+(0) = 0, \qquad \lambda_-(\bar{r}) = 0, \qquad \lambda_\pm(r) > 0 \quad \text{o.w.}$$

The assumption of such boundary being only rung specific and not affected my ϕ is without loss of generality. Also note that since log is an strictly increasing function, the maximizer of $\mathbb{E}[y \mid \hat{a}, \Sigma]$ is the same as that of $\ln\mathbb{E}[y \mid \hat{a}, \Sigma]$. Define $\ell(r, \hat{a}) \;:=\; \ln\mathbb{E}[y \mid \hat{a}, \Sigma]$. We will build out results mostly in terms of ℓ. Our main results build on the lemma below, which establish the log concavity and unimodality of H_r, our expectation term.

Lemma 1 (Log–concavity of H_r). *For any fixed r, the function $H_r : \mathbb{R} \to \mathbb{R}_+$ is log–concave in m. If $\lambda_+(r) > 0$ and $\lambda_-(r) > 0$, then $\ln H_r$ is strictly concave and differentiable with $(\ln H_r)''(m) < 0$ for all m.*

Proof. Let $V(z) \equiv \frac{1}{2}(\lambda_+(r)[z]_+^2 + \lambda_-(r)[z]_-^2)$. Then $H_r(\zeta) = \int_{\mathbb{R}} \exp(-V(z))\phi_s(z-\zeta)\,dz$, where ϕ_s is the density of $\mathcal{N}(0, s^2)$.

Since $V(z)$ is convex in z, $\exp(-V(z))$ is log-concave and minimized at $z = 0$. Then, the gaussian kernal $\phi_s(z-\zeta)$ is also log-concave jointly in (z, ζ). Therefore, the product of two log-concave functions is also log-concave in (z, ζ). By Prékopa's theorem, the integral of a log-concave function over z is log-concave in ζ. Thus, $H_r(\zeta)$ is log-concave in ζ and maximized at $\zeta = 0$. □

From Lemma 1, it follows directly that $(\ln H_r)'(\zeta)$ is strictly decreasing in ζ. Since

$H_r(\zeta)$ decays at least as fast as a Gaussian in both tails, we have the following lemma:

Lemma 2 (Tails of $(\ln H_r)'$)**.** *If $\lambda_+(r) > 0$ and $\lambda_-(r) > 0$, then*

$$(\ln H_r)'(\zeta) \to +\infty \qquad \text{as } \zeta \to -\infty,$$
$$(\ln H_r)'(\zeta) \to -\infty \qquad \text{as } \zeta \to +\infty.$$

If $\lambda_+(r) = 0$, then

$$(\ln H_r)'(\zeta) \to 0 \qquad \text{as } \zeta \to -\infty.$$

If $\lambda_-(r) = 0$, then

$$(\ln H_r)'(\zeta) \to 0 \qquad \text{as } \zeta \to +\infty.$$

Now that we have established the properties of H_r, we can proceed to prove the main propositions.

Proposition 2 (Single–peakedness in r)**.** *For any fixed $(m, p, j, \hat{a}, \Sigma)$ and $\eta > 0$, the function $\ell(r, \hat{a})$ is concave in r and has a unique maximizer $r^*(\hat{a})$. The unique maximizer $r^*(\hat{a})$ is characterized by:*

$$\ln H_r'(r^*\phi - p\hat{a}) = -\eta$$

Proof. The proof follows directly from Lemma 1 and Lemma 2. The partial derivative of ℓ with respect to r is given by

$$\frac{\partial \ell}{\partial r} = \eta\phi + (\ln H_r)'(\zeta, \Sigma)$$

and the second derivative is given by

$$\frac{\partial^2 \ell}{\partial r^2} = \phi^2 (\ln H_r)''(\zeta, \Sigma) \leq 0$$

Then, by the two lemmas established above, $\ell(r, \hat{a})$ is concave in r and has a unique maximizer $r^*(\hat{a})$ given by the first order condition. □

Proposition 2 establishes that for any fixed belief state $(\hat{a}, \Sigma)$, the worker's choice of job rung r is single-peaked and uniquely maximized at $r^*(\hat{a})$. Next, we show that the optimal rung choice is monotone in the belief about match-specific skill $\hat{a}$: i.e., higher $\hat{a}$ leads to weakly higher $r^*(\hat{a})$.

Proposition 3 (Monotone Sorting of Rung Choice)**.** *$\ell(r,\hat{a})$ has increasing differences in $(r,\hat{a})$ and consequently the argmax correspondence $\hat{a} \mapsto r^*(\hat{a})$ is (weakly) increasing.*

Proof. Observe that the cross-partial derivative of ℓ with respect to r and $\hat{a}$ is non-negative:

$$\frac{\partial^2 \ell}{\partial r \partial \hat{a}} = -p\phi(\ln H_r)''(\zeta,\Sigma) \geq 0$$

Therefore, $\ell(r,\hat{a})$ has increasing differences in $(r,\hat{a})$. By Topkis's theorem, the argmax correspondence $\hat{a} \mapsto r^*(\hat{a})$ is (weakly) increasing. □

The single crossing property of log output in $(r,\hat{a})$ says that high match quality workers choose weakly higher rungs. Such sorting force plays a key role in the model's predictions about learning and mobility, and the effect of removing information frictions on the aggregate match quality. If the penalty function is symmetric, we can obtain a closed form solution for the optimal rung choice.

Proposition 4 (Closed form under symmetry)**.** *If $\lambda_+(r) = \lambda_-(r) = \lambda > 0$ for the rung under consideration, then*

$$H_r(\zeta) = (1+\lambda s^2)^{-1/2} \exp\left(-\frac{\lambda \zeta^2}{2(1+\lambda s^2)}\right)$$

with first derivative,

$$(\ln H_r)'(\zeta) = -\frac{\lambda}{1+\lambda s^2}\zeta$$

Then, the unique optimal mismatch level is:

$$\zeta^* = \frac{1+\lambda s^2}{\lambda}\eta$$

and the unique continuous maximizer solves

$$r^*(\hat{a};\Sigma) = \frac{p\hat{a}}{\phi} + \frac{\eta}{\phi}\left(\frac{1}{\lambda} + p^2\Sigma\right)$$

The results in Proposition 4 directly follows from simple algebraic manipulation. The next proposition establishes the comparative statics of the optimal rung choice with respect to the belief state $(\hat{a},\Sigma)$ and the penalty parameters η, λ.

Proposition 5 (Comparative Statics of Optimal Rung Choice)**.** *The optimal rung choice $r^*(\hat{a};\Sigma)$ is strictly increasing in $\hat{a}$, Σ and η, and strictly decreasing in λ.*

Proof. The proof follows directly from the closed form solution in Proposition 4. The comparative statics are given by:

$$\frac{\partial r^*}{\partial \hat{a}} = \frac{p}{\phi} > 0, \quad \frac{\partial r^*}{\partial \Sigma} = \frac{\eta p^2}{\phi} > 0, \quad \frac{\partial r^*}{\partial \eta} = \frac{1}{\phi}\left(\frac{1}{\lambda} + p^2\Sigma\right) > 0, \quad \frac{\partial r^*}{\partial \lambda} = -\frac{\eta}{\phi}\frac{1}{\lambda^2} < 0$$

□

Discussion of the Asymetric Case The symmetric penalty assumption in Proposition 4 is for analytical convenience and to obtain a closed form solution for the optimal rung choice. When penalty is not symmetric, our updated $H_r(\zeta)$ is in Equation 37 and there is no closed form solution for the optimal choices. However, since our Lemma 1 holds for any $\lambda_+(r), \lambda_-(r) \geq 0$, all the other propositions hold without the symmetry assumption. In particular, since $(\ln H_r)'(\zeta)$ is strictly decreasing in ζ from $(-\infty, \infty)$, it must crosses $-\eta\phi$ exactly once, and therefore the optimal rung choice is still unique.

$$H_r(\zeta) = \frac{\exp\left(-\frac{\lambda_+\zeta^2}{2(1+\lambda_+ s^2)}\right)}{\sqrt{1+\lambda_+ s^2}}\Phi\left(\frac{\zeta}{\sqrt{1+\lambda_+ s^2}}\right) + \frac{\exp\left(-\frac{\lambda_-\zeta^2}{2(1+\lambda_- s^2)}\right)}{\sqrt{1+\lambda_- s^2}}\Phi\left(-\frac{\zeta}{\sqrt{1+\lambda_- s^2}}\right) \tag{37}$$

C.1.1 Effect of Uncertainty on Output and Match Value

The previous section discussed the effect of some parameters, including uncertainty Σ, on the optimal rung choice and optimal mismatch level ζ^*. Here we expand the analysis to the effect of uncertainty on expected output and match value. Let us still consider the symmetric penalty case, observe that the effect of uncertainty on expected output is given by:

$$\frac{\partial \mathbb{E}[y \mid \hat{a}, \Sigma]}{\partial \Sigma} \equiv \mathbb{E}[y \mid \hat{a}, \Sigma] \cdot \frac{\partial \ell}{\partial \Sigma} = \mathbb{E}[y \mid \hat{a}, \Sigma] \cdot \frac{p^2\lambda}{2(1+\lambda s^2)^2}\left(\lambda\zeta^2 - (1+\lambda s^2)\right) \tag{38}$$

Note whether the effect is positive or negative depends only on the term $\lambda\zeta^2 - (1+\lambda s^2)$. The results are summarized in the following corollary:

Corollary 6 (Effect of Uncertainty on Expected Output)**.** *The effect of uncertainty Σ on expected output $\mathbb{E}[y \mid \hat{a}, \Sigma]$ depends on the mismatch level ζ as follows:*

- *If $\zeta^2 > \frac{1}{\lambda} + s^2$, then $\frac{\partial \mathbb{E}[y|\hat{a},\Sigma]}{\partial \Sigma} > 0$. In this case, higher uncertainty increases expected output.*

- *If* $\zeta^2 < \frac{1}{\lambda} + s^2$*, then* $\frac{\partial \mathbb{E}[y|\hat{a},\Sigma]}{\partial \Sigma} < 0$*. In this case, higher uncertainty decreases expected output.*

- *If* $\zeta^2 = \frac{1}{\lambda} + s^2$*, then* $\frac{\partial \mathbb{E}[y|\hat{a},\Sigma]}{\partial \Sigma} = 0$*. In this case, expected output is invariant to uncertainty.*

And at the optimal mismatch level $\zeta^* = \frac{1+\lambda s^2}{\lambda}\eta$, the effect of uncertainty can be summarized as follows:

Corollary 7 (Condition for Positive Effect of Uncertainty on Expected Output)**.** *At the optimal mismatch level* $\zeta^* = \frac{1+\lambda s^2}{\lambda}\eta$*, the effect of uncertainty* Σ *on expected output* $\mathbb{E}[y \mid \hat{a}, \Sigma]$ *is positive if and only if:*

$$\eta^2 > \frac{\lambda}{1 + \lambda s^2}$$

In this case, higher uncertainty increases expected output.

However, from Equation 18, the effect of reducing uncertainty deterministically increases match value J at the rate of $\frac{\Sigma^2}{\mu^2}$. Therefore, the global effect to the match value J from uncertainty Σ is the sum of the two effects above and is more nuanced.

C.2 Equilibrium Characterization

The steps to numerically solve and characterize the Block Recursive Equilibrium of the model are as follows:

1. Initialize parameters

2. Given the parameters, solve for the Hamilton-Jacobi-Bellman equations equilibrium value functions

3. Given the optimal value functions and policy functions, compute the optimal allocation of workers with p ability to their optimal majors (This is computed as shares of workers in each major given their ability p due to Frechet distribution of preferences)

4. For each major-ability pair:

   (a) Set up and discretize the Kolmogorov forward equations and back out the transition matrix of workers for each state space

(b) Given the transition matrix, solve for the ergodic (steady state) distribution of workers for each state space, normalize to mass 1 within each major-ability pair

5. Stack all the steady state distributions of workers across all major-ability pairs

    - Normalize the distribution such that the share of workers in each major by ability is equal to the shares computed in step 3

C.3 Computation Notes for Ergodic Distribution

C.3.1 Discretizing Learning

Recall the effect of learning to value function is the changes in value function J with respect to time t.

$$\Lambda = \underbrace{\frac{\partial}{\partial \Sigma}\left(\frac{\Sigma}{\sigma}\right)^2}_{\text{drift in } \Sigma} + \underbrace{\frac{1}{2}\left(\frac{\Sigma}{\sigma}\right)^2 \frac{\partial \Gamma}{\partial a^2}}_{\text{diffusion in } a} \tag{39}$$

We discretize this by using conservative flux on non-uniform grid. Specifically, for the variance of belief, since we mandate it to always decrease over time, i.e. individuals can only become more and more accurate on their belief about skills, we use an upwind scheme. We use the standard Kalman-Bucy filter with drift term $\left(\frac{\Sigma}{\sigma}\right)^2$. Define this drift term as D for cleaner notation.

$$[\partial_\Sigma (D\Gamma)]_i \approx -\frac{D_i}{\Delta \Sigma_i}\Gamma_i + \frac{D_{i+1}}{\Delta \Sigma_{i+1}}\Gamma_{i+1} \tag{40}$$

where since our mean belief could fluctuate both up and down, we use a central differencing scheme.

$$\frac{1}{2}\partial_a\Big(D\,\partial_a\Gamma\Big)\Big|_i \approx \frac{D_{i+\frac{1}{2}}}{\Delta a_{i+\frac{1}{2}}\,\Delta a_i}\Gamma_{i+1} - \left(\frac{D_{i+\frac{1}{2}}}{\Delta a_{i+\frac{1}{2}}\,\Delta a_i}\right)\Gamma_i + \frac{D_{i-\frac{1}{2}}}{\Delta a_{i-\frac{1}{2}}\,\Delta a_i}\Gamma_{i-1} - \left(\frac{D_{i-\frac{1}{2}}}{\Delta a_{i-\frac{1}{2}}\,\Delta a_i}\right)\Gamma_i \tag{41}$$

To ensure this scheme works on non-uniform grid, we weight the drift by neighbouring values:

$$D_{i\pm\frac{1}{2}} = \frac{1}{2}(D_i + D_{i\pm1}) \text{ and } \Delta a_{i+\frac{1}{2}} = \frac{1}{2}(\Delta a_i + \Delta a_{i\pm1}) \tag{42}$$

C.3.2 Conservation of Mass in Transition Matrix

Following convention, we define the transition matrix with sources as columns and destinations as rows. For each employed source column e:

$$\sum_{x\in\text{E-rows}} \Gamma^{\text{learn}}_{x,e} + \sum_{x\in\text{E-rows}} \Gamma^{\text{ee}}_{x,e} + \Gamma^{\text{eu}}_{e,e} + \sum_{u\in\text{U-rows}} \Upsilon^{\text{eu}}_{u,e} = 0 \tag{43}$$

Specifically, Γ^{learn} and Γ^{ee} are conservative in its source by construction, meaning their mass is conserved within their own block. $\Gamma^{\text{eu}}_{e,e}$ and Υ^{eu} must add up to zero for each source e since their inflows and outflows must balance with mass $(\delta+\varepsilon)+\lim_{\pi\to\infty}\mathbf{1}\{\text{separation}\}\cdot\pi$.

Similarly, for each unemployed source column u:

$$\sum_{x\in\text{E-rows}} \Gamma^{\text{ue}}_{x,u} + \sum_{y\in\text{U-rows}} \Upsilon^{\text{uu}}_{y,u} = 0 \tag{44}$$

The conservation of mass within the unemployment blocks says individuals must either remain unemployed or transition to employment.

Since in our setup, we have exogenous shock on exiting the economy, and this shock affects everyone at the same rate, we can simply subtract that rate from the diagonal entries of the transition matrix at the end at once. Therefore, each column sums to $-\sigma$.

D Estimation Appendix

D.1 Estimation Data

D.1.1 Naics 2 digit

There are a total of 20 industries at the 2-digit NAICS code level. We include self-employment and code it as 99 for industry code. For estimation, we aggregate the following:

- **Primary Sector**:

- 11 – Agriculture, Forestry, Fishing and Hunting
- 21 – Mining, Quarrying, and Oil and Gas Extraction
- 22 – Utilities
- 23 – Construction
- 31-33 – Manufacturing

- **Finance**:
  - 51 – Information and Cultural Industries
  - 52 – Finance and Insurance
- **Public Administration**:
  - 91 – Public Administration

D.1.2 ISCED description

In the estimation, we first aggregate the CIP codes to the 1-digit ISCED codes to classify college majors. Below is the description of each code.

0. Generic programmes
1. Education
2. Arts and Humanities
3. Social sciences, journalism, and information
4. Business, administration, and law
5. Natural sciences, mathematics, and statistics
6. Information and Communication Technologies (ICTs)
7. Engineering, manufacturing, and construction
8. Agriculture, forestry, fisheries, and veterinary
9. Health and welfare
10. Services

Then, we select the top three majors with the highest share of graduates. They are [3] Social Sciences, Journalism, and Information, [4] Business, Administration, and Law, and [7] Engineering, Manufacturing, and Construction.

D.1.3 Ability Level

Ability level is approximated by 12th grade math and language scores from the information submitted by Ontario public high school students. Students took at least one math and one language course in their final year of high school. However, they are allowed to take more than one math courses (and they normally do to boost their chances of getting into a good university program).

We categorize students into 5 mutually exclusive groups based on their math and language letter grades. We restrict our sample to only individuals who receives a language grade and a math grade higher than a C. Out of the sample of Ontario public high school students included in the ELMLP platform, a total of 51.9% of students are included in the analysis. The groups are defined as follows:

1. Moderate achievement: One of Math and Language letter grades is B
2. High achievement: Both Math and Language letter grades are A

D.2 Estimation Structures and Details

Major-Ability Specific Productivity For the major-ability specific productivity term A_{mp}, I decompose it into a linear combination of an ability-specific term A_p and a linear coefficient α_p that scales with the ranking of the major, based on the ranking of the share of major m in ability p.

$$A_{mp} = \bar{A}_p + \alpha \cdot \text{rank}_{mp} \tag{45}$$

Major-Industry specific productivity requirement A key set of parameter that is empirically driven is the major-industry specific productivity requirement ϕ_{mj}. This parameter captures the specific skill requirements for each major-industry pair and is crucial for understanding the matching process in the labor market. However, with 11 majors and 21 industries, it is challenging to estimate all ϕ_{mj} parameters directly from the data. I provide some structure to reduce the number of parameters to estimate while preserving key information.

First, I use the major-industry specific fixed effect obtained from Equation 1 to obtain a major-industry specific ranking. A high ranking indicates a higher skill requirement for that major-industry pair, therefore the hardest to enter but highest return if not penalized. With that, I consider a major specific linear relationship of entry barriers as described in Equation 46. Note, this ranking is not the same as the ranking of major-ability specific production A_{mp} in Equation 45.

$$\phi_{mj} = \bar{\phi}_j + \beta \cdot \text{rank}_{mj} \tag{46}$$

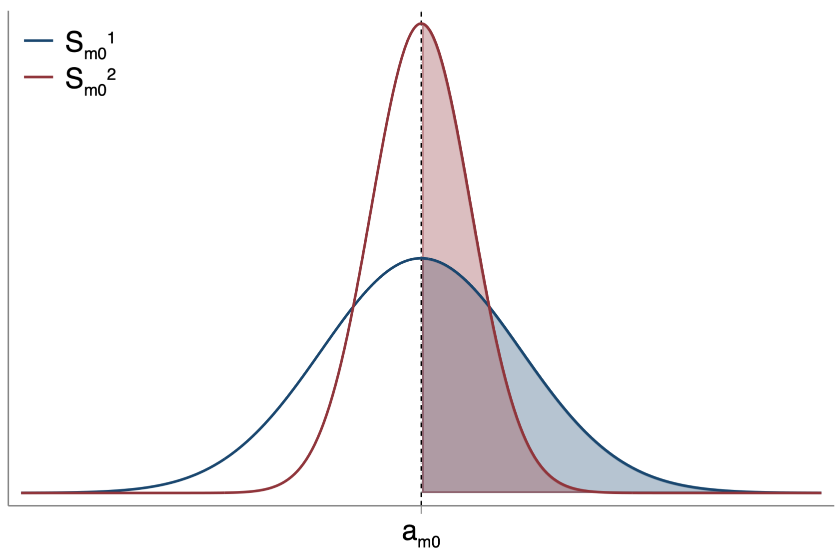


Figure 18: Illustration of the initial belief distribution and learning process.

D.3 Estimation Note

To compute the model moments for transitions over time, we take advantage of the model's steady-state properties. After constructing the transition matrix generator, we can track how a newborn cohort evolves by using the matrix exponential function. Specifically, if we denote the transition matrix generator as Q, then the distribution over states evolves after t periods is given by:

$$p(t) = e^{Qt} p(0) \tag{47}$$

This approach allows us to efficiently compute the distribution of individuals across states at any time t without simulating each individual's path. Note that our $\mathbb{TM}$ from Section 4.9 corresponds to Q here. Furthermore, to compute these dynamics efficiently on a large, sparse state space as introduced in the model, we use the backward Euler method. For a small time step Δt, the backward Euler method approximates the matrix exponential as follows:

$$\frac{p_{t+\Delta} - p_t}{\Delta} = Q p_{t+\Delta} \quad \Longrightarrow \quad p_{t+\Delta} = (I - \Delta Q)^{-1} p_t \tag{48}$$

and t/Δ successive steps yield the approximation to the exponential $[(I - \Delta Q)^{-1}]^{t/\Delta} \approx e^{Qt}$.

As long as Δt is sufficiently small, this approximation is both accurate and A-stable (even if some transitions are large/fast, the method remains stable). Although our model is estimated at the annual frequency, we use a monthly time step in the backward Euler method to ensure accuracy. This also helps us match the model to the data on transitions. In the model, individuals cannot switch industries while employed; to switch industries, they must first enter a brief period of unemployment. Since time is continuous, individuals in the model can transition very quickly. In the data, we observe high industry-switching rates between any two consecutive years. By using a smaller time step and excluding short unemployment spells, we can better approximate the annual transition rates observed in the data.

Assumptions in Using the Backward Euler Method For the backward Euler method to be valid, we need the following assumptions to hold:

1. The transition matrix generator Q is time-invariant. This holds in our model since we estimated it in steady state.

2. Q has to be a valid generator with non-negative off-diagonal elements, negative diagonal elements, and rows summing to the leak rate (our exogenous exit rate σ). This guarantees that there will never be negative probabilities creating by inverting. This also holds in our model.

3. The time step Δt must be sufficiently small to ensure the stability and accuracy of the backward Euler method. In our implementation, we use a monthly time step to achieve this.

We define two sets of industry EE transitions. The first set is path strict, i.e. individuals

E Comparative Statics

Consider the three majors, two abilities, and three industries described earlier. I obtained the rankings from empirical shares of major-ability pairs and empirical earnings rankings of major-industry pairs. With 1 as the highest rank (highest average earnings) and 3 as the lowest, Table 14 summarizes the rankings for major-industry pairs.

	Primary Sector	Finance, Insurance, and Information	Public Administration
Social Sciences, Journalism, and Information	3	2	1
Engineering, Manufacturing, and Construction	1	2	3
Business, Administration, and Law	2	3	1

Table 14: Empirical employment share rankings of major-industry pairs (1 = highest, 3 = lowest).

Rows correspond to majors ($m = 1, 2, 3$), columns to industries ($j = 1, 2, 3$). Similarly, Table 15 summarizes the rankings for major-ability pairs.

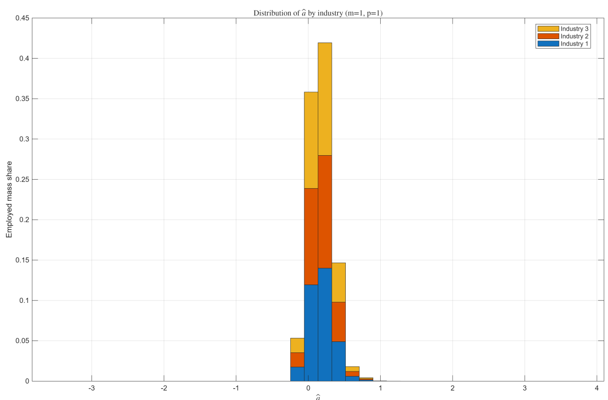
	Social Sciences, Journalism, and Information	Engineering, Manufacturing, and Construction	Business, Administration, and Law
Low Ability	2	3	1
High Ability	1	2	3

Table 15: Empirical share rankings of major-ability pairs (1 = highest, 3 = lowest).

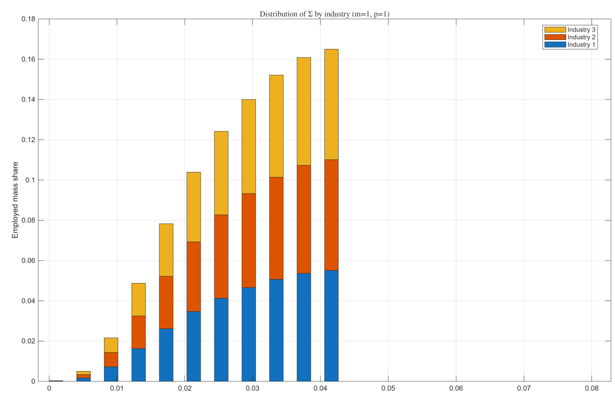
E.1 Comparative Statics Results

This subsection presents comparative statics results to show how changes in key parameters affect model outcomes. I highlight how the model's additional features, relative to Baley et al. (2022), influence the results.

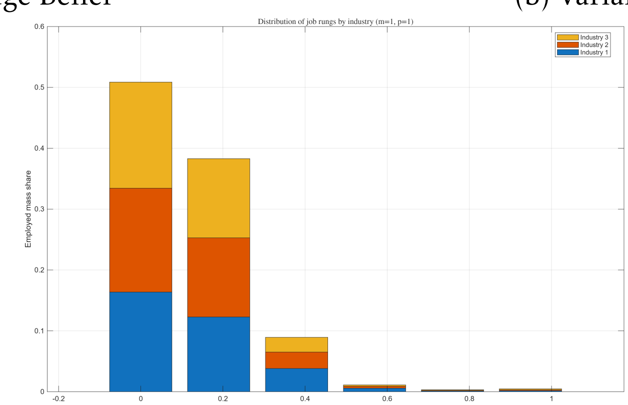
I first describe the steady-state outcomes of the baseline model. The average skill belief is slightly below the initial value (sometimes even slightly negative). There are substantial differences between the perpetual youth and infinitely lived agent settings. The steady-state distribution of belief variances is lower for infinitely lived agents. If agents exit the economy due to an exogenous shock, beliefs become much more dispersed. As predicted, higher-ability individuals end up in higher ranks regardless of industry. Figure 20 shows the steady-state distributions of average beliefs, variances of beliefs, and optimal job rungs for the baseline calibration for the less productive major and lower innate ability. In contrast to the clustering at lower rungs, when I shift to a more productive major and higher ability, the steady-state distribution of average beliefs is slightly more dispersed, but the optimal job rung is much more concentrated at higher rungs. Since individuals exit the economy stochastically, there is not enough time to learn, and individuals end up with more dispersed beliefs in all cases.



(a) Average Belief

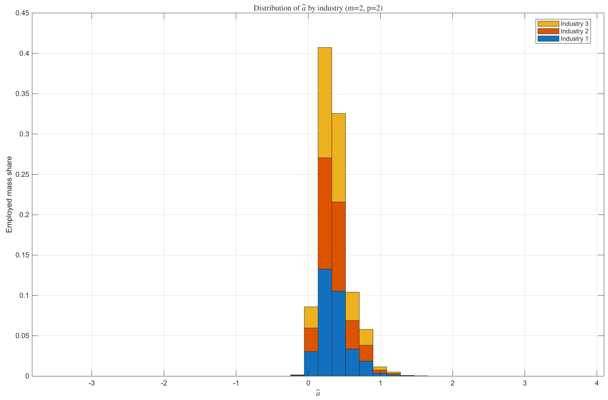


(b) Variance of Belief

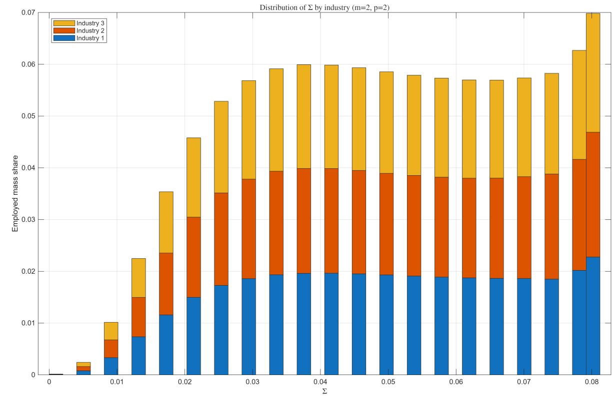


(c) Optimal Job Rung

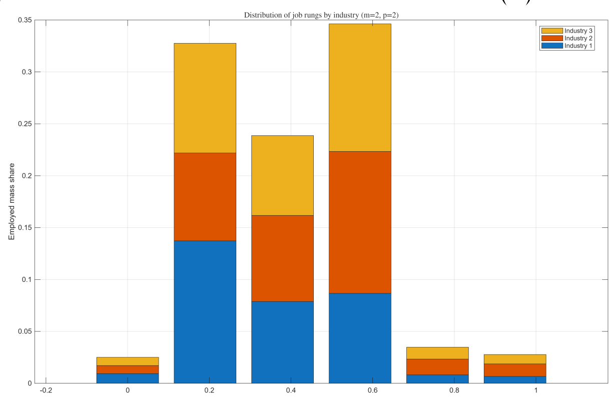
Figure 19: Steady-state distributions, Baseline Calibration, Low Productive Major and Low Ability



(a) Average Belief



(b) Variance of Belief

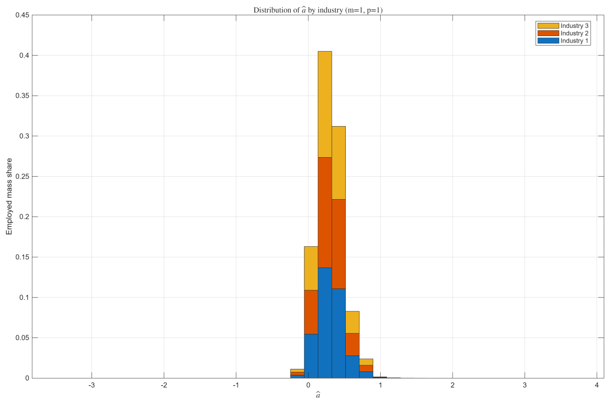


(c) Optimal Job Rung

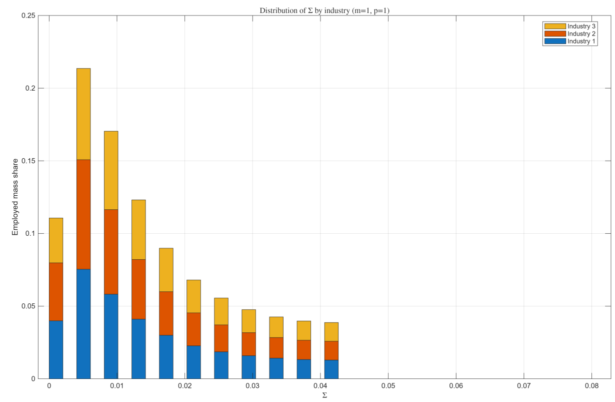
Figure 20: Steady-state distributions, Baseline Calibration, High Productive Major and High Ability

Lifespan of Agents A key aspect of the model is the perpetual youth setting. This assumption is crucial for mapping the model to the data, as new cohorts enter each year and I observe large differences in transition dynamics as cohorts age. However, most of the literature on directed search with learning assumes infinitely lived agents. This distinction leads to less accurate learning in the steady state, as agents do not have enough time to learn their true ability. Therefore, this small difference leads to large differences in the steady state distributions of variances of beliefs, leading to more dispersed earnings, as observed from the data.

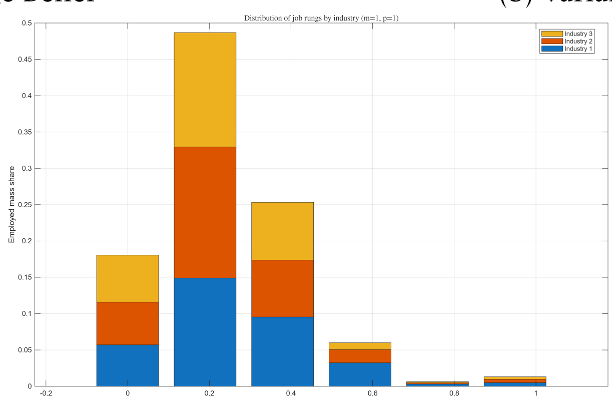
Learning Process In this model, three key factors govern each agent's learning process: the first two moments of the initial belief distribution $(\hat{a}_{m0}, \Sigma_{m0})$ and the learning rate μ. Examining the production function (Equation 6) and the value of the match (Equation 17), I see that $\frac{\partial y}{\partial \hat{a}_{m0}} > 0$, $\frac{\partial r^*}{\partial \hat{a}_{m0}} > 0$, and $\frac{\partial \phi_{mj}}{\partial \hat{a}_{m0}} > 0$. Thus, a higher initial belief $\hat{a}_{m0}$ leads to a higher expected value from entering that industry and a greater steady-state share of



(a) Average Belief



(b) Variance of Belief



(c) Optimal Job Rung

Figure 21: Steady-state distributions, Infinitely Lived Agents

workers in that submarket. The initial variance Σ_{m0} has a more nuanced effect. When the mean is close to the productivity requirement $\phi_{mj}r$, higher variance reduces the probability of meeting the requirement, lowering the optimal job rung r^* and shifting workers to industries with lower requirements, resulting in lower earnings. If the mean is well above the requirement, higher variance has little effect.

The more interesting effect is from the learning rate μ. The rate of learning governs how quickly agents converge to their true ability. A larger μ means a noisier signal, which in turn leads to slower learning. This parameter is estimated by looking at the speed of convergence of earnings variance. A higher μ leads to more persistent mismatch and a higher steady-state variance of beliefs, resulting in more dispersed earnings.