How IT Specialized Majors Pay Off: Evidence from an IT Industry Shock *

Tianze Liu †

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Abstract

This paper examines how IT-specific shocks affect the career paths of workers with specialized IT skills. Using comprehensive administrative data on fields of education, earnings, and employment from the Swedish dotcom boom-bust of 2000, I show how the sector-specific cycle influenced the labor market outcomes of IT-specialized college graduates and incumbent workers by comparing them to workers from other fields. During the boom years, IT-specialized entrants earned a significant initial earnings premium. However, only two years later, following an IT stock market collapse and a surge in bankruptcies, this pattern reversed, and IT entrants earned less than other graduates. During the bust, many more IT graduates found employment in other industries, earning lower salaries within these industries. After the initial shock, however, earnings recovered very rapidly, leaving only marginal earnings scars after 5–10 years. The sectoral recession, however, had a lasting impact on the career paths of IT specialists, as much of their earnings recovery took place outside the IT sector in high-paying roles within non-IT occupations and industries. Unlike entrants, incumbents largely remained within the IT sector but shifted toward lower-premium firms within the industry. Overall, the results suggest that the occupational flexibility of IT entrants enables long-term economic resilience to sector-specific shocks despite a massive initial impact, while incumbent IT workers absorb the shocks by sliding down the firm ladder rather than changing sectors.

JEL-codes: E32, J30, I23, I26
Keywords: College major returns, Industry shocks, the dotcom bubble

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†Department of Economics and Uppsala Center for Labor Studies, Uppsala University (email: tianze.liu@nek.uu.se).

1 Introduction

The information technology (IT) sector is critical for economic growth and innovation[1]. However, the sector experiences significant volatility. Technological breakthroughs often lead to capital inflows, which drive wage increases and worker reallocation. When returns on investment fall short of expectations, capital flows out of the IT sector, ultimately resulting in sector downturns. Similar patterns were repeated in events like the AI winter, the dotcom bubble, and the recent widespread layoffs in the tech sector [2]. This inherent volatility not only affects the industry's performance but also has profound implications for the workforce, particularly those with specialized IT skills.

Although the effects of general economic recessions are well documented, it is less clear how an industry-specific shock affects workers with specialized skills. This paper addresses this gap by examining how a very large IT-industry shock affects workers with IT-specialized college majors. The answer is not straightforward: on the one hand, previous research suggests that high-skill college majors often provide a buffer against economic downturns by securing good initial placements due to the limited supply of their skills (Oreopoulos et al., 2012; Altonji et al., 2016); on the other hand, cyclical mismatches between industries and majors are common during recessions and can be costly, particularly for new graduates (Liu et al., 2016).

IT majors, among the highest paid fields, can provide skills that remain in demand in unaffected sectors following a shock in the IT industry. However, a sudden demand shock in the industry where IT specialists are primarily employed could lead to misallocation across industries due to labor market frictions. Furthermore, these impacts may vary between less experienced and more experienced workers, depending on their accumulation of industry-specific human capital and differing job search behavior (Eriksson, 1991; Bloemen, 2005). For example, more experienced workers may be less mobile because of the difficulty in giving up the industry-specific skills they have accumulated, while younger workers, even if they face setbacks early in their careers, might recover through more frequent job searches and by acquiring skills in other industries.

[1]For example, previous studies have shown the contribution of IT industry and IT skills on economic growth (Oliner and Sichel, 2000; Jorgenson, 2001), productivity (Sandra E. Black et al., 2001; Brynjolfsson and Hitt, 2003; Dale W. Jorgenson et al., 2008), and innovation (Müller et al., 2012; Chen and Kim, 2023).

[2]See, for example,"Tech layoffs in 2024: A timeline", *Computer World*, 2024

In this paper, I use comprehensive Swedish administrative data to examine how the dotcom shock of 2000 affected returns to IT majors. The shock originated from the collapse in the stock market, which caused bankruptcies and a contraction in employment in the IT sector. I focus on both entrants (who graduated during the dotcom cycle) and incumbents (who graduated before the dotcom boom) by comparing earnings gaps between IT and other fields. College majors serve as an ideal measurement for a worker's skill specialization because the vast majority of students in Sweden choose their field of study *before* entering college, making this decision less endogenous to labor market conditions. Additionally, the IT industry is a highly skilled sector[3], making it a suitable case for analyzing the labor market dynamics of highly educated workers with specialized skills during economic shocks. Sweden, with its highly developed IT sector and comprehensive administrative data, provides an ideal setting to examine the effects of the dotcom cycle.

To the best of my knowledge, this is the first study to document the returns to IT college majors for the population of college-educated workers during an IT industry cycle. The substantial variation in returns following the industry shock provides an opportunity to explore the underlying mechanisms driving these changes in greater detail. Inspired by Altonji and Zhong (2021), I posit that the returns to IT majors stem both from employment in high-paying industries and from IT-specific skills within those industries. This idea is closely related to a large body of labor economics literature that decomposes earnings differences into rents associated with industries or firms, on one hand, and individual-specific returns within these industries or firms, on the other[4]. To empirically disentangle these two sources of returns, I apply a decomposition framework conceptually related to the AKM model of Abowd et al. (1999), allowing for a clear distinction between industry-wide premium effects and within-industry returns attributable to IT majors.

My findings reveal significant effects of the dotcom shock for IT-specialized workers, showing that even a short-lived adverse industry demand shock can have profound effects on skilled workers' labor market outcomes. Both labor market entrants and experienced workers were affected, but the nature of the effects differed dramatically with career experience.

[3]According to the U.S. Bureau of Labor Statistics, 66 percent of IT workers in the United States held a bachelor's or master's degree in 2001. Similarly, over 40 percent of workers in the Swedish IT sector had a bachelor's degree or higher in the same year.

[4]For example, Card et al. (2023) decompose worker-related components and industry-specific components, while Card et al. (2013) examine the role of firm premiums and individual productivity in determining wages.

When studying recent graduates, I track graduation cohorts in IT-specialized fields and compare their trajectories to graduates from other fields. Conceptually, the identification is similar to the large number of studies in the literature on graduating during a recession (see references below) although I rely on a sectoral shock instead of regional unemployment rates. A potential concern is that students may be more mobile across sectors than across regions, but I use data on student grades to show that selection on general abilities is unrelated to the cycle. Rich Swedish administrative data allows me to compare students with similar ninth-grade GPA who graduated from the same high school, attended the same college, and belonged to the same cohort, but who differed in their choice of IT majors versus other fields of study. The identification comes from the sharp timing of the dotcom boom and bust, which generates quasi-random variation in labor market conditions for different graduating cohorts.

I find that graduating during the bust years of the dotcom cycle led to significant short-term adverse effects for IT majors. Specifically, there was an initial gap of 27 log points in earnings returns compared to boom cohorts. This initial loss is primarily driven by negative returns within non-IT industries, as bust cohorts were forced to find employment outside the IT sector due to the sharp contraction in IT employment opportunities. The share of IT specialists working in the IT sector plummeted from about 60 percent for the 2000 cohort to approximately 20 percent for the 2003 cohort. This sharp decline indicates a significant contraction in IT sector employment opportunities for new graduates. Jointly, these short-run results indicate that the skills of IT graduates are highly specialized and closely tied to the IT sector—when the sector collapses, graduates are forced to relocate to other industries and suffer substantial earnings losses as a consequence.

In the medium to long run, the results are remarkably different. The earnings recovery for bust cohorts is fast, narrowing the initial gap to just 6 log points after 10 years. Although the long-term earnings losses associated with entering during a sector-specific recession were mild, the experience had large and lasting impacts on other aspects of their career trajectories. Bust cohorts remained much less likely to work in the IT sector even in the long run, with their IT sector employment probabilities persisting at 15 percentage points lower a decade later. Among those remaining in non-IT sectors, most do not transition into IT occupations; instead, their earnings recovery occurs through mobility into other higher-paying, non-IT occupations. This recovery indicates a very fast accumulation of a broader set of skills by the IT graduates.

The second part of my empirical analysis focus on incumbent workers who entered the labor market before the boom years. These workers were affected as well, but effects exhibit a very different pattern compared to entrants. Their overall returns to IT majors decline sharply by about 16 log points from the boom to the bust years. Using models with individual fixed effects and time-varying returns to industries, and to IT-majors within these industries, I show that the decrease is driven by both a devaluation of IT skills within industries and a reduction in industry premiums. In contrast to the entrants, the incumbents resiliently remained within the IT sector, despite falling industry-level wage premia. Instead, their employment shifted towards lower-premium firms within the industry, which explains most of the within-industry earnings decline.

My analysis merges perspectives from three different literatures, describing the impact of graduating in a recession, the economic consequences of field choice, and the impact of sectoral economic shocks, respectively. This is the first paper to analyze how graduating with industry-specialized skills during an industry cycle affects students' short- and long-term earnings and career paths. Identification relies on graduation timing during major industry shocks, following a method similar to Engdahl et al. (2022). I find that graduates from bust cohorts experienced severe initial adverse effects but recovered in the longer run. This is consistent with the effects of graduating during a general recession, as documented in the existing literature (Van Den Berge, 2018; Schwandt and von Wachter, 2019). I add to this strand of literature by demonstrating that IT college majors, as high-return majors, are more severely impacted by industry-specific shocks than other majors, highlighting a larger degree of uncertainty compared to business cycle recessions (Oreopoulos et al., 2012; Altonji et al., 2016). However, IT graduates also exhibit a unique ability to recover by leveraging their skills across industries to mitigate the initial skill mismatch (Liu et al., 2016). Although they experience greater initial adverse effects, their recovery is relatively faster compared to previous findings.

This paper also contributes to the emerging literature on the returns to college majors by highlighting the variability of payoffs in response to fluctuating demand for specific skills. Previous studies have focused on the average treatment effects of the field of study (Kirkeboen et al., 2016), economics major (Bleemer and Mehta, 2022), or the distributional and career effects of majors (Andrews et al., 2024). My results show that the high returns to IT majors can be disrupted by a sudden demand shock, even turning negative, which underscores the importance of considering the dynamic nature of returns to these skills, especially when they are highly specialized. Therefore, this paper is also linked to studies on the returns to college major specificity. Leighton and Speer (2020) and Martin (2022) find that majors with greater specificity tend to earn more early in their careers, but this advantage gradually declines with experience. Similarly, Deming and Noray (2020) shows that the premiums of applied majors (including IT majors) follow a declining pattern due to faster skill obsolescence. The finding on IT major returns within industries turn to negative in the late stage of career is consistent with these results. Furthermore, Altonji et al. (2012) demonstrates that computer and IT majors have the highest returns among all majors, based on 2009 ACS data. In this paper, I shed light on the mechanisms behind such high returns by decomposing them into the payoffs within industries and across industries.

Lastly, this paper provides new insights into the consequences of industry shocks. Walker (2013) studies the transitional costs across industries following environmental regulations, while Ellingsen and Espegren (2022) show that petroleum workers in Norway experienced sharp earnings losses after transitioning to other sectors due to a crude oil price shock. Using the same oil shock, Lorentzen (2024) finds that workers in destination sectors receiving displaced petroleum workers experienced slower earnings growth and a higher probability of exiting the industry. Kline (2008) demonstrates that workers were reallocated to the oil and gas field services industry after a spike in crude oil prices. I extend this literature by focusing a shock affecting high-skilled workers and by estimating the effects on entrants as well as incumbents. The closest reference is Hombert and Matray (2023), which examines a similar shock in France and finds that ICT sector entrants during the boom years faced long-term losses due to faster skill obsolescence. My study focuses on a very different set of mechanisms as I rely on pre-determined IT skills instead of IT-sector employment. This approach allows me to study the process of entry into the sector, which I show to be strongly related to the cycle, and to contrast the patterns for graduates and incumbent workers.

Overall, my results provide new evidence on how IT-specialized workers adjust to the significant shocks typical of the IT industry. IT graduates enter the labor market with sector-specific skills, making them highly sensitive to short-term sectoral demand. While the results align with the view that IT skills depreciate quickly if not utilized, young IT workers adapt by transitioning to other industries and occupations, demonstrating their ability to acquire alternative skills. Thus, young IT-specialized workers show resilience to large sectoral fluctuations, particularly in terms of earnings, despite their initial sensitivity. In contrast, more experienced workers tend to remain in the industry, absorbing the shock with lower earnings and declining firm quality, rather than switching industries.

The remainder of the paper is structured as follows: Section 2 describes the background. Section 3 explains data, and methodology. Sections 4 and 5 present findings for entrant workers and incumbent workers, respectively. The final section concludes.

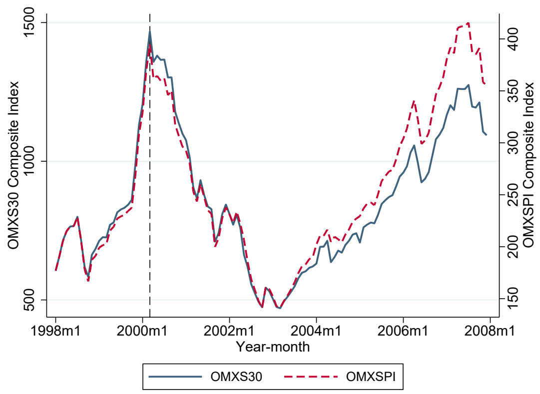
2 The Dotcom Bubble and its Impact on Sweden's IT Industry

The dotcom bubble was a period of excessive speculation in the late 1990s, driven by the rapid growth of internet-based companies. This speculative bubble peaked in March 2000, with stock indices like the OMXS30 and the OMXSPI in Sweden reaching unprecedented levels (Panel (a) of Figure 1). In Sweden, the OMXSPI stock market index surged by approximately 400 percent, while in the US, the Nasdaq Composite rose by 800 percent during the same period (Brown et al., 2009). This global stock market growth was largely fueled by high expectations for the future of the internet and digital technologies.

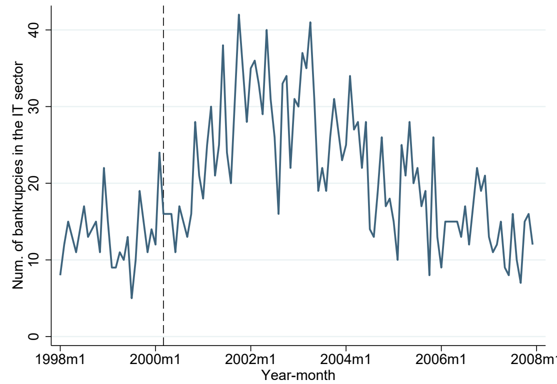
The crash that followed in 2000 led to a significant market correction, severely affecting IT firms worldwide, including those in Sweden. As shown in Panel (b) of Figure 1, the number of bankruptcies in Sweden's IT sector increased sharply in the aftermath of the stock market crash. Many firms that had expanded rapidly during the boom were unable to sustain operations when investment dried up, leading to widespread closures and financial instability in the sector (Kogut, 2003).

The effects of the dotcom bust extended beyond firm closures, deeply impacting the labor market. Panel (c) of Figure 1 illustrates the decline in IT sector employment relative to the total labor force in Sweden. The rapid hiring in the late 1990s, driven by high-growth expectations, came to a halt, resulting in layoffs and a notable decline in IT employment share following the crash. Many workers displaced from the IT sector were forced to seek opportunities in other industries, exacerbating the overall unemployment rate (Maican, 2012).

Sweden's experience during the dotcom cycle closely mirrored that of the United States, where the stock market also suffered a major correction, with indices losing nearly two-thirds of their value (Kogut, 2003). This is in contrast to the UK and Germany, where the market decline was less severe, with indices dropping by



(a) Stock market shocks: OMXS30 & OMXSPI



(b) Num. of bankruptcies in the IT sector

(c) IT sector employment share

Figure 1. The Dotcom Bubble and its Economic Impact

Notes: Panel (a) presents the OMXS30 and OMXPI stock market indices, where the OMXS30 is a market-capitalization-weighted index of the 30 most-traded stocks, and the OMXPI represents all stocks listed on the Nasdaq OMX Stockholm stock exchange. Panel (b) illustrates the number of bankruptcies in Sweden's IT sector. Panel (c) shows the IT sector's employment rate relative to the total labor force. The vertical lines mark March 2000 and the year 2001, corresponding to the peak of the dot-com bubble.

only half. The similarity between the US and Swedish market downturns suggests that the IT sector's composition in Sweden closely resembled that of the US, with both countries having a higher share of IT firms that were disproportionately affected by the bubble and subsequent crash. This parallel reinforces the relevance of Sweden as a case study, with potential implications and insights that are applicable to the US context.

3 Data and Method

3.1 Data

Main Analysis Data and Sample Construction

This study utilizes comprehensive Swedish administrative employment data, mainly from the *Louise* dataset and educational registers. These datasets offer detailed labor market information, including annual employer-employee records, pretax earnings, and industry affiliations. Additionally, they provide rich worker characteristics, such as 4-digit fields of study, highest educational attainment, ninth-grade GPA, high school and college attended, birth year, and gender.

The primary analysis focuses on college-educated workers, defined as those whose highest educational attainment is a bachelor's degree. This restriction serves two purposes: firstly, it concentrates on majors highly specific to the IT sector, such as computer science, which are predominantly offered at the bachelor's level. Secondly, it facilitates more direct comparisons with extant literature focusing on college-educated workers.

I define IT-specialized majors using 3-digit field indicators, which includes the following majors: Computer Science, General (480); Computer and Systems Sciences (481); Computer, Other/Unspecified Education (489); and Electronics, Computer Engineering, and Automation (523). For the primary analysis, I employ a binary treatment variable to facilitate result interpretation.

To validate this classification quantitatively, I analyze both the distribution of graduates across industries within these majors and the content they are taught in college, as detailed in Appendix A.1. First, I calculate the share of graduates from each 3-digit major employed in the IT industry between 1990 and 1997. Second, I examine the proportion of IT-specialized courses within each major's curriculum, using administrative data on course registrations from 1993 to 2007. The majors identified as IT-specialized consistently rank at the top in terms of both employment rates in the IT industry and the share of IT-related courses in their curricula.

Earnings data, sourced from the Swedish Employment Register, represent annual gross cash salary income. These figures have been adjusted to 2000-level Swedish Krona for consistency. The analysis primarily employs the natural logarithm of annual earnings. Following Edin and Fredrikson (2000), individuals whose annual labor income falls below the threshold for qualifying for public pensions (approximately 37,000 SEK in the year 2000) are excluded. However, this consequently omits some completely unemployed spells from the analysis.

A worker's graduation year is defined as the year of highest educational attainment, which also delineates graduation cohorts. Observations predating an individual's graduation year are excluded from the analysis. Potential work experience is calculated as the difference between the graduation year and the current calendar year. Individuals who completed their highest level of education before the age of 20 or after the age of 30 are omitted.

The IT sector is defined using the Swedish Standard Industrial Classification (SNI), standardized to the 2002 codes using firm-level crosswalks. Specifically, the IT sector corresponds to the 2-digit industry "computer and related activities" (SNI2002 72). To align with previous research on industrial premiums (Philippon and Reshef, 2012; Böhm et al., 2023), the farming and public sectors are excluded from the sample.

To examine effects on labor market entrants, the study concentrates on cohorts graduating between 1998 and 2007, with data extending to 2018 to capture long-term implications. Ninth-grade GPA, an important proxy for academic ability, is largely available for the entrant sample. Due to changes in the test scoring system during the sample period, these scores are converted to percentile rankings within each cohort for consistency. Incumbent workers are defined as those who graduated prior to 1998. The analysis of incumbent workers focuses on the decade from 1998 to 2007, encompassing the complete boom-bust cycle of the IT industry while avoiding the confounding effects of severe financial crises in the early 1990s and post-2008 periods.

Data on Wages, Firms and Occupations

To complement the main analysis and provide insights into occupational and firm-level dynamics, I utilize data from the Wage Structure Statistics for the Private Sector (Lönestrukturstatistik för privat sektor), a comprehensive survey conducted by Statistics Sweden. This dataset offers detailed information on wages, occupations, and employers, allowing for a more nuanced examination of the IT industry shock's effects.

The survey employs a stratified random sampling method, with establishments as the primary sampling units. The sample is stratified by industry sector and firm size, resulting in approximately 530 strata. While the survey covers about 8,700 firms, it is designed to capture data on over one million individuals, representing approximately 50 percent of private sector employees. While larger firms (500+ employees) are fully surveyed, smaller firms are sampled at lower rates, potentially underrepresenting startups that may be particularly relevant in the early stages of IT industry development.

The wage data in this survey is comprehensive, including both time-based and performance-based pay. It encompasses fixed salaries, fixed supplements, piecework performance, and variable components such as commissions and bonuses. Occupational information is coded according to the Standard for Swedish Occupational Classification (SSYK96), which I harmonized across the sample period by translating more recent classifications (SSYK2012) into SSYK96 and aggregating to the 3-digit level for consistency. The IT occupations are defined as "Computing professionals" and "Computer associate professionals". Finally, I merged this occupational, wage, and employer information into my main analysis sample. The merged dataset covers approximately 30 percent of the individuals in the main sample.

The main reason for using the population dataset Louise for the main analysis, rather than this dataset, is the smaller sampling proportion of small firms in the latter. Since small firms likely represent a significant share of the IT industry during the study period, relying solely on samples with firm information would introduce selection bias when estimating returns for IT majors. Specifically, within small firms, IT firms or IT occupations might offer a larger wage premium compared to others. Excluding these firms could lead to an underestimation of returns for IT majors. Figure A2 shows the relationship between returns to IT majors (in log wages) and firm size, demonstrating a clear negative correlation. Workers in smaller firms (size classes 1-4) enjoy an average advantage of 6 to 13 log points, while those in larger firms (classes 5-8) exhibit returns ranging from -2 to 5 log points.

3.2 Empirical Methods

Event study analysis

I estimate the effects of IT majors on log earnings and IT sector employment for entrants using an event study analysis. For each cohort graduating in different phase of the dotcom cycle, I run the following econometric model separately:

$$y_{it} = \beta_t S_{m(i)} + \gamma_t + Z_i \Phi + \epsilon_{it} \tag{1}$$

where y_{it} denotes the outcome of interest for individual i in year t from the specific cohort. $S_{m(i)}$ is a binary variable equal to 1 for graduates from IT majors and 0 otherwise. Z_i includes various time-invariant controls: gender, ninth-grade GPA, high school fixed effects, and college fixed effects. ϵ_{it} represents the error term. The coefficient of interest, β_t, measures the returns of being an IT specialist in year t for that specific cohort, relative to the variation in outcomes for generalists from the baseline year to year t, as captured by year fixed effects γ_t.

If the controls and fixed effects account for the non-random selection of IT majors versus other majors, β_t reflects the causal return to IT majors. While this is a strong assumption, the inclusion of comprehensive controls and fixed effects in the model bolsters the credibility of the estimated effects. Specifically, ninth-grade GPA serves as a proxy for pre-college academic ability, capturing individual differences that might influence both major choice and earnings. Reassuringly, my results show that the compulsory school grades of IT graduates do not change in any meaningful way during the recession. High school fixed effects control for variations in educational quality and resources across different schools, adjusting for the influence of secondary education environments. College fixed effects account for differences in institutional quality, peer groups, and networking opportunities that could impact employment prospects. Controlling for sex addresses potential gender disparities in education and employment. Overall, this comparison is among students from the same cohort, high school, college, and gender, with similar pre-college academic performance.

Decomposition of returns to IT-specialized majors

To further dissect the returns to IT-specialized majors, I augment the previous model by incorporating industry-by-year fixed effects. The modified econometric specification is:

$$y_{it} = \lambda_t S_{m(i)} + \phi_{j(i),t} + \gamma_t + Z_i \Phi + \epsilon_{it} \tag{2}$$

The key additions to this model are λ_t and $\phi_{j(i),t}$. The coefficient λ_t captures the within-industry returns to IT majors in year t, reflecting the average earnings difference between IT specialists and generalists working within the same industry. This measures how much more (or less) IT majors earn compared to their peers in the same industry, after accounting for observable characteristics and overall industry trends. The term $\phi_{j(i),t}$ represents industry-by-year fixed effects, capturing the industry-specific earnings premiums and sorting that vary over time. It accounts for factors such as industrial demand shocks or industrial technology advancements that affect earnings across entire industries in a given year.

This decomposition parallels the framework of the AKM model, which separates wages into components attributable to individual workers and firms. Similarly, in my model, $\lambda_t S_{m(i)}$ captures the effect of IT majors (akin to worker characteristics), while $\phi_{j(i),t}$ reflects industry-specific premiums and endogenous sorting (analogous to firm effects in the AKM model). However, a key difference is that the AKM model includes individual fixed effects to account for unobserved heterogeneity, whereas my model relies on returns to IT majors and observed individual characteristics. This approach allows for a clear decomposition of earnings into within-industry returns to IT majors and industry-wide premiums without requiring worker mobility across sectors.

The specifications for incumbents

A similar specification to equation (1) is used to estimate the effects of IT majors for incumbent workers. However, due to the absence of key control variables for many incumbents, such as pre-college academic performance and detailed educational institutions, I adjust the model to include individual fixed effects to account for unobserved individual characteristics, along with an interaction between gender and a quadratic age profile. This specification focuses on capturing changes in the returns to IT majors over time, with 1998 serving as the reference year [5].

For the decomposition analysis of returns to IT majors among incumbent workers, I incorporate individual fixed effects in a similar manner. This allows for the

[5] I perform several robustness checks on the specification choice. The main results remain consistent across specifications, as shown in Figure A5 and Table A6.

decomposition of the observed changes in returns into different channels—such as within-industry returns and industry-wide premiums—while controlling for unobserved individual heterogeneity. The focus is on understanding the relative importance of each channel in explaining the temporal changes in returns to IT majors.

Estimation of occupational and firm premiums

To further investigate the effects of IT specialization on various labor market outcomes, I examine how IT specialists move across differently paid occupations and firms. This analysis requires estimating occupation and firm-specific wage premiums. I employ the AKM model to disentangle the contributions of individual and employer characteristics to wage variation. Following Card et al. (2013), I estimate a wage equation that includes individual fixed effects, firm (or occupation) fixed effects, year fixed effects, and time-varying individual characteristics (mainly gender interacted with quadratic age profile).

The estimated firm (or occupation) effects are used as outcome variables in the main regressions to examine how IT specialists sort into firms and occupations compared to generalists. As mentioned earlier, the data on wages, firms, and occupations in Sweden are sampled, so the sample used for this estimation differs from that in the main analysis. This approach helps to clarify the mechanisms behind sorting into different paying firms and occupations.

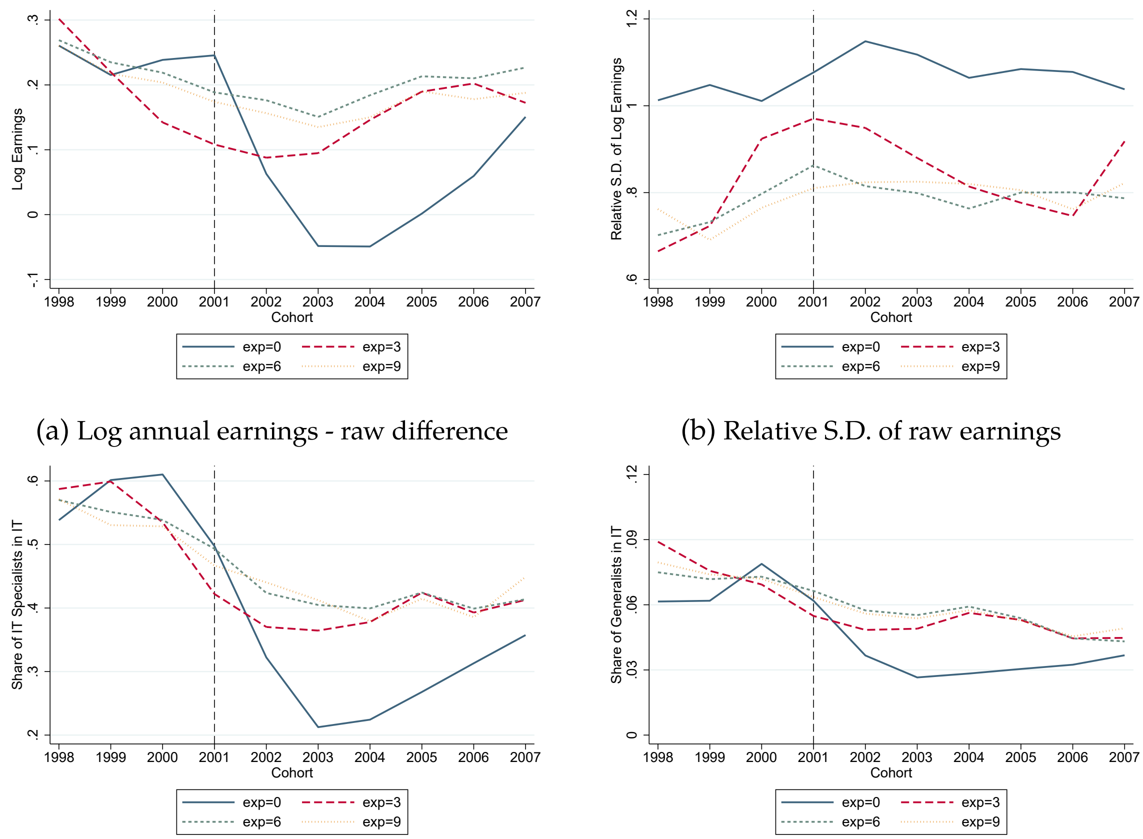
4 The Effects on Entrant Workers

4.1 Average labor market outcomes of IT-specialized graduates

Figure 2 presents a descriptive overview of various labor market outcomes for IT specialists who entered the workforce between 1998 and 2007, capturing the effects of the dotcom boom and subsequent bust in diffrent phases of their career.

Panel (a) illustrates the raw earnings difference of IT specialists relative to generalists across different cohorts and levels of experience. For the bust cohorts (1998-2001), IT specialists enjoyed a substantial initial earnings advantage averagely, particularly pronounced for new entrants. However, this advantage sharply declined for cohorts graduating after 2001, with the 2003-2004 cohorts experiencing near parity or even slight disadvantages in earnings upon entry. The premium rebounds for more recent cohorts, suggesting a cyclical pattern in the valuation of IT skills. The gap tends to narrow with experience for all cohorts, indicating some convergence in earnings over time.

Panel (b) reveals the relative variability in earnings for IT specialists. The standard deviation of log earnings for IT specialists relative to generalists increased markedly for cohorts graduating immediately after the dotcom bust, particularly for new graduates. This heightened variability persists for several cohorts, suggesting increased uncertainty and heterogeneity in outcomes for IT specialists during the post-bust period. The trend is less pronounced with experience, while bust cohorts have a persistent higher dispersion than boom cohorts.



(a) Log annual earnings - raw difference

(b) Relative S.D. of raw earnings

(c) Share of IT majors employed in IT sector

(d) Share of other majors employed in IT sector

Figure 2. Average Labor Market Outcomes of Entrant IT Specialists and Generalists by Graduation Cohort

Notes: The figure shows average labor market outcomes for IT specialists and generalists across graduation cohorts from 1998 to 2007. Panel (a) displays the average difference in log earnings between IT specialists and generalists for different years of potential experience. Panel (b) presents the relative standard deviation of log earnings for IT specialists compared to generalists. Panel (c) and (d) show the share of IT specialists and generalists working in the IT sector for different years of potential experience. Different lines represent different years of potential experience (0, 3, 6, and 9 years). The vertical dashed line at 2001 in each panel marks the burst of the dotcom bubble.

The sectoral allocation of IT specialists, depicted in Panel (c), demonstrates a dramatic shift following the dotcom bust. The share of IT specialists working in the IT sector plummeted from about 60 percent for the 2000 cohort to approximately 20 percent for the 2003 cohort (exp=0 line). This sharp decline indicates a significant contraction in IT sector employment opportunities for new graduates. Notably, the recovery in IT sector employment for subsequent cohorts is gradual and incomplete, suggesting persistent structural changes in the labor market for IT skills.

Panel (d) illustrates the decline in the share of generalist graduates employed in the IT sector across different cohorts and experience levels. Before the 2001 dotcom bust, around 6-9 percent of generalists were employed in IT, indicating steady demand for non-specialized skills. However, following the bust, the share of new graduates (exp=0) employed in IT drops significantly, bottoming out at 3 percent for the 2003 cohort. Although the share of experienced generalists stabilizes more quickly, it never returns to boom levels.

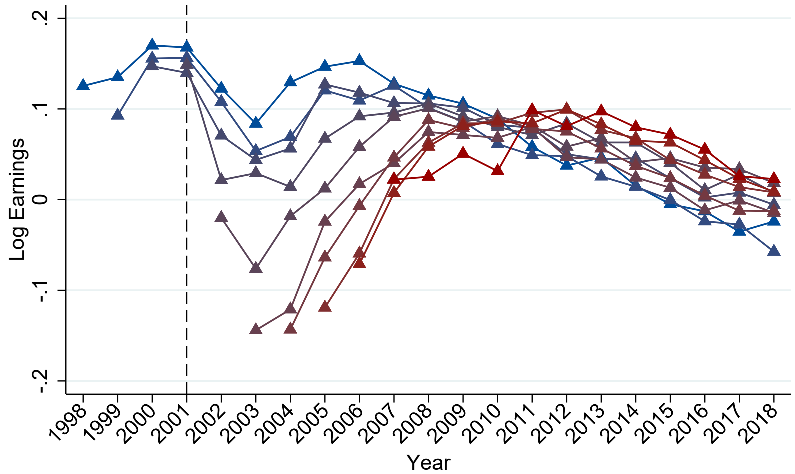
4.2 Regression Analysis of Returns to IT Majors for Entrants

This subsection presents the regression results on labor market outcomes for IT graduates across boom and bust cohorts. The analysis reveals significant heterogeneity in outcomes based on graduation timing, providing insights into how industry shocks affect entrants with industry specialized human capital. Importantly, the regression models control for ninth-grade GPA, high school, and college fixed effects. These controls mitigate concerns about self-selection into IT majors or compositional changes among cohorts, allowing me to isolate the effects of graduating at different stages of the IT industry cycle.

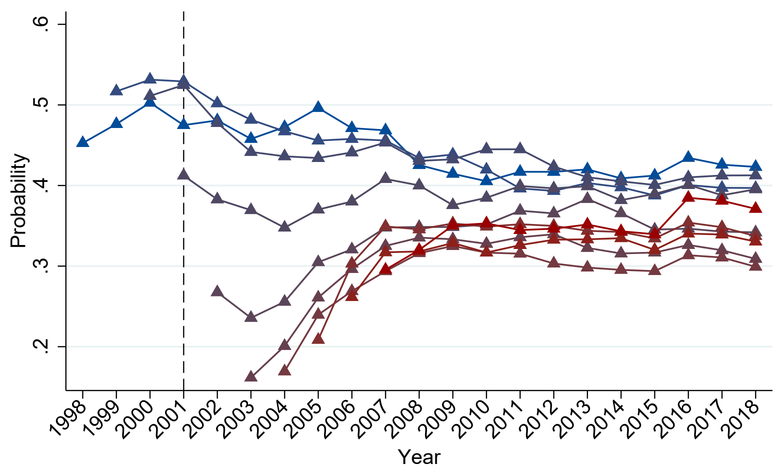
The effects on earnings

Figure 3 (a) illustrates the evolution of returns to IT majors in log earnings over time, with each line representing a different cohort based on graduation year [6]. The blue lines correspond to earlier cohorts, while the red lines depict more recent cohorts. This visual allows for a clear distinction in IT major premiums based on the timing of entry into the labor market, which is especially important given the major shocks affecting the IT industry during the early 2000s.

[6] All estimates with standard errors are reported in Panel (a) of Table A4.



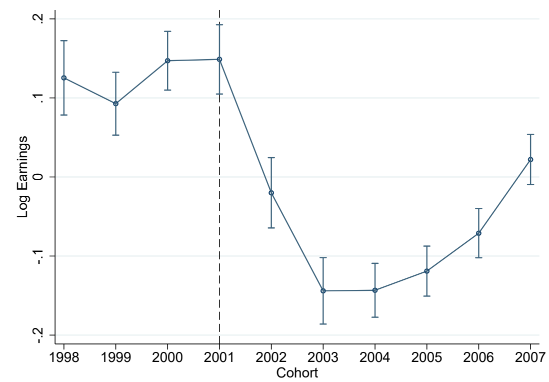
(a) Estimated effects of IT majors on log earnings



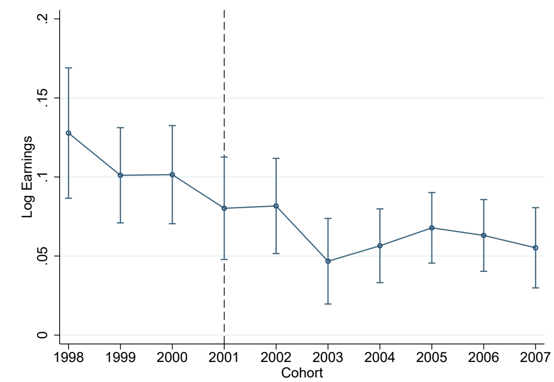
(b) Estimated effects of IT majors on IT sector employment

Figure 3. Labor Market Outcomes of Entrant IT Specialists by Graduation Cohort

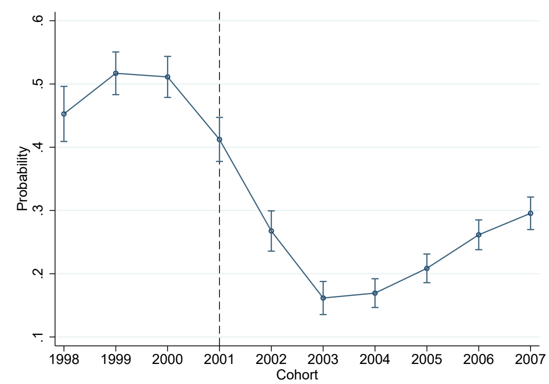
Notes: This figure presents estimates for different college graduation cohorts from 1998 to 2007. Panel (a) shows the estimated returns to IT-specialized majors on log earnings over time for each cohort. Panel (b) illustrates the estimated probability of working in the IT sector for IT specialists compared to generalists for each cohort. The x-axis represents years from 1998 to 2018, allowing for up to 20 years of follow-up for each cohort. The vertical dashed line at 2001 indicates the dot-com bubble burst. The analysis sample consists of college workers who graduated between 1998 and 2007. Estimates are derived from regressions controlling for year, sex, 9th-grade GPA, and high school and college fixed effects. 95% confidence intervals are omitted for clarity. Different colors represent different graduation cohorts.



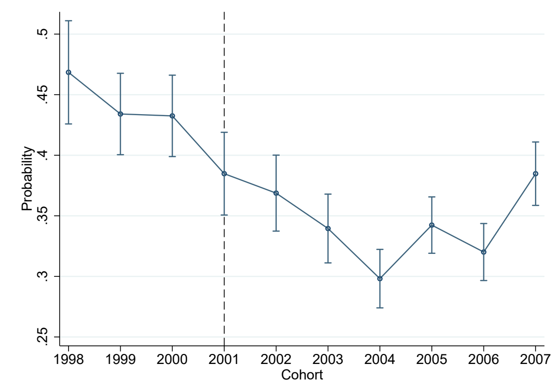
(a) Log earnings (0 exp)



(b) Log earnings (9 exp)



(c) Prob. of IT sector employment (0 exp)



(d) Prob. of IT sector employment (9 exp)

Figure 4. Labor Market Outcomes for IT Specialists by Graduation Cohort and Experience

Notes: This figure presents estimates of returns to IT majors for different graduation cohorts (1998-2007) at 0 and 9 years of potential experience. Panel (a) and (b) show log earnings differentials between IT specialists and generalists across cohorts. Panel (c) and (d) show the probability differential of working in the IT sector. The x-axis represents graduation cohorts. The vertical dashed line at 2001 indicates the dotcom bubble burst. The analysis sample consists of college workers who graduated between 1998 and 2007. Estimates are derived from regressions controlling for years, sex, 9th-grade GPA, and high school and college fixed effects. 95% confidence intervals are reported.

The figure shows that the initial labor market conditions vary significantly across cohorts. The earlier cohorts start with higher returns when they enter the labor market, benefiting from the economic boom before the crash. In contrast, the more recent cohorts, entering the workforce post-crash, begin with substantially lower and negative returns. The initial gaps between these cohorts reflect the immediate impact of the dotcom bust, with the shock particularly detrimental to recent graduates.

The figure emphasizes the differential impact of the dotcom shock based on workers' experience levels. The shock's effects are particularly pronounced for recent entrants, as evidenced by the steep drop in IT major premiums for cohorts entering after 2001. In contrast, earlier cohorts, who had already established themselves in the labor market, experienced a more muted decline in their premiums. This divergence highlights how industry-specific shocks can disproportionately affect new labor market entrants while having less severe, though still noticeable, effects on more experienced workers. This finding underscores the importance of career timing in shaping long-term IT major premiums for specialized graduates. The effects on worekrs who entered the labor market before the boom years are further discussed in Section 5.

Over time, however, the returns to IT majors for all cohorts tend to converge, although small differences persist, especially for those who entered during bust years. This convergence is evident in Figure 3 (a), where the lines representing different cohorts begin to align as workers gain more experience. For the cohorts that entered during the boom years, the initially high earnings premiums diminish slightly over time, while for the bust cohorts, the negative or negligible premiums observed at entry improve steadily with experience. By the tenth year after graduation, the earnings of IT specialists across cohorts converge to within a few percentage points of each other. This pattern suggests that while the initial labor market conditions significantly affect early career earnings, their impact attenuates over time as workers accumulate experience and adapt to the labor market.

Figure 4 presents results from the same specification but focuses on specific years in the career trajectory and includes significance levels. Figure 4 (a) focuses on the initial year IT-specialized graduates entered the labor market, along with significance levels. Graduates from the 1998–2001 cohorts initially enjoyed substantial IT major premiums, ranging from 10 to 15 log points. In contrast, cohorts graduating after the dotcom crash (2002–2004) faced significantly lower or even negative returns, with some premiums dropping as low as -12 log points. This sharp contrast underscores the immediate and severe impact of the dotcom bust on IT-specialized graduates, even after controlling for pre-college academic performance and the quality of educational institutions. Notably, these IT major premiums exhibit strong evidence of convergence over time, with bust cohorts gradually recovering much of their initial losses. The difference in returns between boom and bust cohorts narrows from 27 to 5 log points after 9 years (Panel (c) of Figure 4).

The effects on IT sector employment

Figure 3 (b) illustrates regression results on the probability of IT sector employment for IT-specialized graduates, showing distinct patterns across different cohorts [7]. Earlier cohorts consistently demonstrate a higher and more stable probability of employment within the IT sector. In contrast, later cohorts, particularly those graduating after the dotcom crash, face considerably lower probabilities of working in the IT sector initially. This divergence mirrors the patterns seen in earnings returns, where boom cohorts benefitted from better initial market conditions, while bust cohorts struggled to establish a foothold in the IT industry.

One of the most striking observations is the long-term gap between the boom and bust cohorts. Even though the probability of IT sector employment increases for bust cohorts over time, they never fully recover to the levels seen among earlier graduates. This suggests that the initial labor market shock during the bust years had a lasting effect, pushing many IT-specialized graduates into other industries or fields. This persistent gap highlights the strong path dependence of early career placements for IT specialists. Graduates entering the workforce during favorable periods are more likely to remain within the IT sector throughout their careers. Meanwhile, those entering during adverse conditions face more challenges securing IT sector employment and may be forced to explore alternative career paths outside the industry, even as labor market conditions improve.

Figure 4 narrows the focus to specific career stages, offering a closer look at early and mid-career outcomes with significance levels included.Figure 4 (b) reveals a sharp decline in the probability of IT sector employment for post-2001 cohorts during their initial years, with employment probabilities falling from peaks of around 50 percentage points to lows below 20 percentage points. Panel (d) of Figure 4 further underscores the persistence of this gap, showing a 15 percentage point difference in IT sector employment probabilities between boom and bust cohorts even

[7] All estimates with standard errors are reported in Panel (b) of Table A5.

after 9 years of experience. This highlights the lasting effects of initial labor market conditions on sector-specific career trajectories.

4.3 Robustness Analysis

Robustness to compositional change across cohorts

In studying the returns to IT majors for new labor market entrants, it is crucial to account for potential changes across cohorts. Specifically, two concerns arise that could bias the estimates of returns if not properly addressed: (i) the changing supply of IT majors over time, and (ii) compositional shifts in the characteristics of IT majors. Figure A1 provides evidence on these two dimensions.

The first concern relates to potential fluctuations in the supply of IT majors over time. As shown in Panel (a) of Figure A1, the share of IT majors remains relatively stable between cohort 1998 and 2004. However, there are slight increases in the 2004 and 2005 cohorts. This variation in IT major supply could influence observed earnings gaps, as larger cohorts of IT-trained workers may face increased competition for a limited number of high-paying jobs, potentially reducing the returns to IT majors in those years. Despite these increases, the change in supply is relatively modest, and thus unlikely to dramatically alter the observed returns to IT majors. As such, while supply changes should be considered, they are unlikely to be the primary driver of any cohort-level differences in wage outcomes.

A second concern relates to potential compositional changes in IT majors across cohorts, which could reflect differences in the quality of students entering IT-related fields. Panel (b) of Figure A1 displays the GPA gaps between IT majors and non-IT majors, using GPA percentiles as a proxy for the relative academic ability of IT majors. The figure reveals that in most years, IT majors tend to have lower GPAs than their non-IT counterparts. Additionally, the magnitude of the GPA gaps is relatively small, as the unit is expressed in percentiles. There is no clear trend indicating significant shifts in the academic selectivity of students choosing IT majors across cohorts. This suggests that there is little evidence of stronger or weaker self-selection into IT majors based on academic performance over time. Thus, compositional changes in terms of academic ability are unlikely to be a major driver of wage differences across cohorts.

Other robustness checks

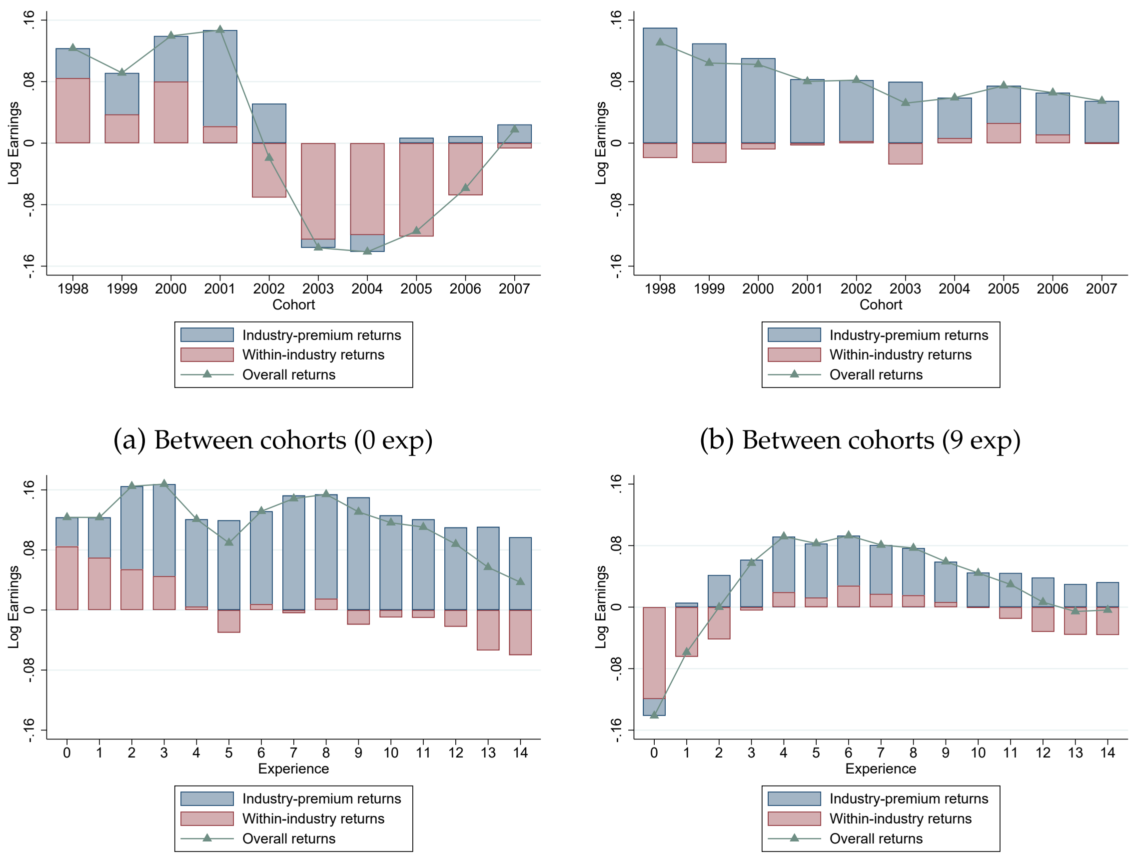
To address potential concerns about the suitability of ninth-grade GPA as a measure of ability for sorting into IT-specialized majors, I conducted a robustness check using ninth-grade *math* scores as an alternative control. The results, presented in Table A4 and Table A5, demonstrate that the main findings remain highly consistent when controlling for math scores instead of overall GPA. The patterns of earning returns and IT sector employment probabilities across cohorts and experience levels are remarkably similar to those observed in the primary specification.

4.4 Decomposition of IT Major Returns for Entrants

In this section, I perform a decomposition of the returns to IT majors for entrants to disentangle the sources of earnings differentials across different career stages. This approach is essential to understanding how industry-specific demand for IT skills, the ability of workers to transition across sectors, and overall industry conditions shape the career returns of IT-specialized graduates. By decomposing the returns into within-industry payoffs and industry-premium effects, I aim to clarify the mechanisms driving observed earnings differences between boom and bust cohorts, specifically addressing how initial sorting into high-paying industries and subsequent career mobility contribute to long-term outcomes. The analysis focuses on how initial sorting into high-paying industries and career mobility affect long-term outcomes, revealing distinct patterns of earnings adjustment tied to market conditions at entry.

Between-Cohort Decomposition

In Figure 5 (a), initial returns to IT majors are primarily driven by the within-industry channel, highlighting the value of IT human capital in specific sectors. For boom cohorts, IT major premiums are largely explained by the within-industry payoffs of IT skills, reflecting both industry demand for these skills and the quality of the match between industry needs and worker expertise. In contrast, bust cohorts experience negative returns due to two key factors: a decline in the value of IT skills within non-IT sectors (as indicated by their different sorting patterns into IT sectors) and potentially higher partial unemployment. Graduates with narrowly specialized skills are more vulnerable to industry cycles, as their human capital is less adaptable to the broader labor market, illustrating the cost of mismatch between industry and skills (Liu et al., 2016).



(a) Between cohorts (0 exp)

(b) Between cohorts (9 exp)

(c) A boom cohort by experience (1998)

(d) A bust cohort by experience (2004)

Figure 5. Decomposition of IT Major Returns for Entrants

Notes: This figure shows the decomposition of IT major returns both between and within cohorts. Panels (a) and (b) depict the absolute levels of IT returns for cohorts with 0 and 9 years of experience, respectively. Panels (c) and (d) illustrate the evolution of overall returns during the first 15 years of experience for the 1998 and 2004 cohorts, breaking down the returns into the industry-premium and within-industry components.

As shown in Figure 5 (b), the remaining earnings gap between bust and boom cohorts, after nine years, is primarily due to reduced access to high-paying industries. For instance, the persistent employment gap in the IT sector (as seen in Figure 3(b)) could explain this observed difference. The majority of the IT major premium is driven by the industry premium channel by the ninth year of experience, not within-industry returns. This suggests that as workers gain more experience, their earnings advantage from an IT major no longer comes from their IT skills within industries, but from working in high-premium industries.

These patterns also provides insights into potential brain drain in the IT industry. While some IT specialists who graduated during the bust years still entered the IT sector, a significant portion found employment in other industries. The increase in overall within-industry returns throughout their careers suggests that these IT specialists were able to leverage their specialized skills across various sectors, although they were less likely to access the high industry premiums.

Within-Cohort Decomposition

For the 1998 cohort (Panel (c) of Figure 5), it shows strong positive returns from both channels in early careers. Their earnigns advantage within industries decline with experience. This decline is partially offset by gains in the industry premium channel. As shown in Panel (b) in Figure 3, their probability of working in the IT industry is not significantly affected.

The 2004 cohort (Panel (d) of Figure 5) starts with negative returns in both components. They narrow the within-industry gap over time and also benefits from higher industry premiums. This indicates that bust graduates resorted into industries that offered better matches for their IT skills or higher wages. Not all of this shift was back into the IT industry, which suggests that they found ways to either utilize their IT human capital in other industries or accumulated new skills to succeed in those other sectors.

For both of the cohorts, the within-industry coponent dominates the overall returns in the early of their careers, but its importance gradually declins over time and turn negative in the long term. This might reflect IT-specific human capital depreciation as shown in (Deming and Noray, 2020). While initial conditions significantly impact early career outcomes, the specific vintage of IT skills becomes less relevant over time. Instead, the ability to adapt and acquire new skills becomes crucial for long-term success in rapidly evolving technological fields (Spitz-Oener, 2006).

4.5 Occupations and Firm Dynamics for Entrants

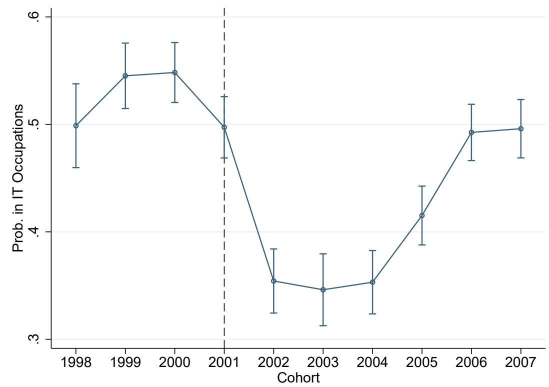
Beyond the sectoral shifts discussed earlier, occupational sorting and firm dynamics offer additional perspectives on how industry-specific shocks impact IT-specialized entrants. These mechanisms complement our findings on industry premiums and within-industry returns by illustrating how entrants adjust their labor market choices in response to economic fluctuations. For instance, during downturns, IT graduates may accept positions outside their field or at firms offering lower wage premiums.

Initial gaps *between* cohorts

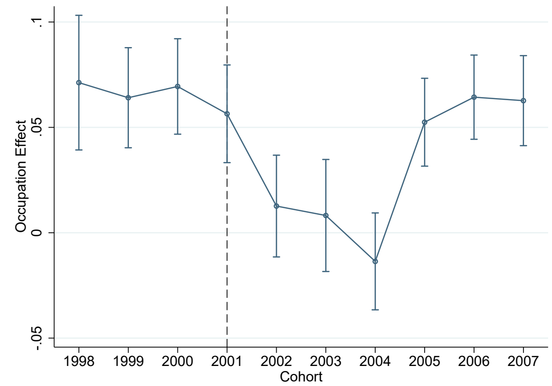
Panel (a) of Figure 6 depicts the differential probability of IT specialists versus generalists working in IT occupations across cohorts. For the boom cohorts, IT specialists are significantly more likely—by up to 55 percentage points—to work in IT occupations compared to generalists. However, this probability declines sharply for bust cohorts, reaching a low of approximately 35 percentage points. Although there is a gradual recovery for subsequent cohorts, the gap remains only partially closed. This pattern underscores the impact of the dotcom bust on occupational placement, indicating that entrants during downturns are less likely to secure positions within their specialized field, which is consistent with the previous findings on IT industry sorting.

Panel (b) presents the occupation premium gap, defined as the difference in esitmated wage premiums between the occupations held by IT specialists and generalists. Boom cohorts exhibit relatively stable and positive occupation premiums. In contrast, bust cohorts experience a sharp decline in occupation premiums, with the 2003 cohort even showing a slightly negative premium before a recovery commences. This suggests that IT specialists graduating during downturns not only are less likely to enter IT occupations but also tend to enter lower-paying occupations relative to their boom counterparts.

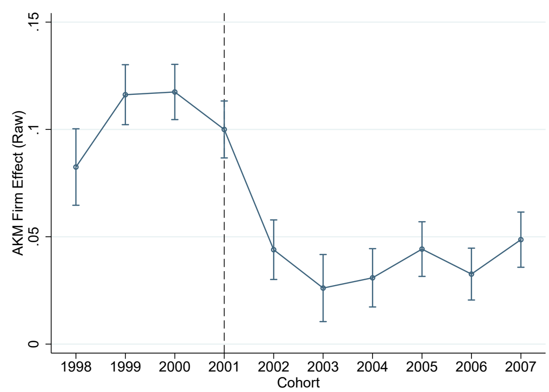
Panel (c) shows the AKM firm premium gap between IT specialists relative to generalists. Unlike the pattern observed for the occupation premium gap, firm premiums exhibit a sharp and persistent decline after 2001 and never recover. This indicates a structural shift in the composition of employers hiring IT specialists post-bust, with the firms that previously offered high wage premiums for IT skills not recruiting or disappearing from the market. As a result, IT specialists graduating during downturns are more likely to be employed by firms offering significantly



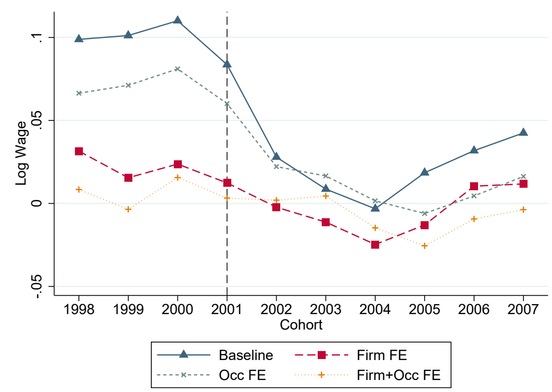
(a) Estimated IT occupation probability difference



(b) Estimated occupation premium gap



(c) Estimated firm premium gap



(d) Wage losses explained by firm and occupation

Figure 6. The Effects of IT Majors on IT Occupation Probability, Occupation Premiums, Firm Premiums, and Wage Components Across Cohorts in Initial Years

Notes: This figure shows the effects of IT majors for entrant workers during their first years, using equation (1) on various outcom variables. Firm and occupation premiums are estimated from the AKM model. Panel (a) depicts the estimated difference in IT occupation probability between IT specialists and generalists. Panel (b) presents the estimated difference in occupation premiums. Panel (c) illustrates the difference in firm premiums. Panel (d) displays the wage losses for IT specialists while consecutively adding controls on estimated firm and occupation premiums. All specifications control for 9th-grade GPA, year, sex, high school and college fixed effects. The analysis sample consists of college workers who graduated between 1998 and 2007. 95% confidence intervals are reported.

lower wage premiums, contributing to their wage gaps.

Finally, Panel (d) quantifies the contribution of firm and occupation premiums to the overall wage losses. For the cohorts between 1998 and 2004, firm premiums explain about 45 percent of their initial wage gap, while occupation premiums account for approximately 36 percent. Combined, these factors explain 77 percent of the total wage gap between boom and bust cohorts. These findings suggest that the initial wage penalties experienced by IT specialists graduating during downturns are primarily due to their sorting into lower-paying occupations and firms.

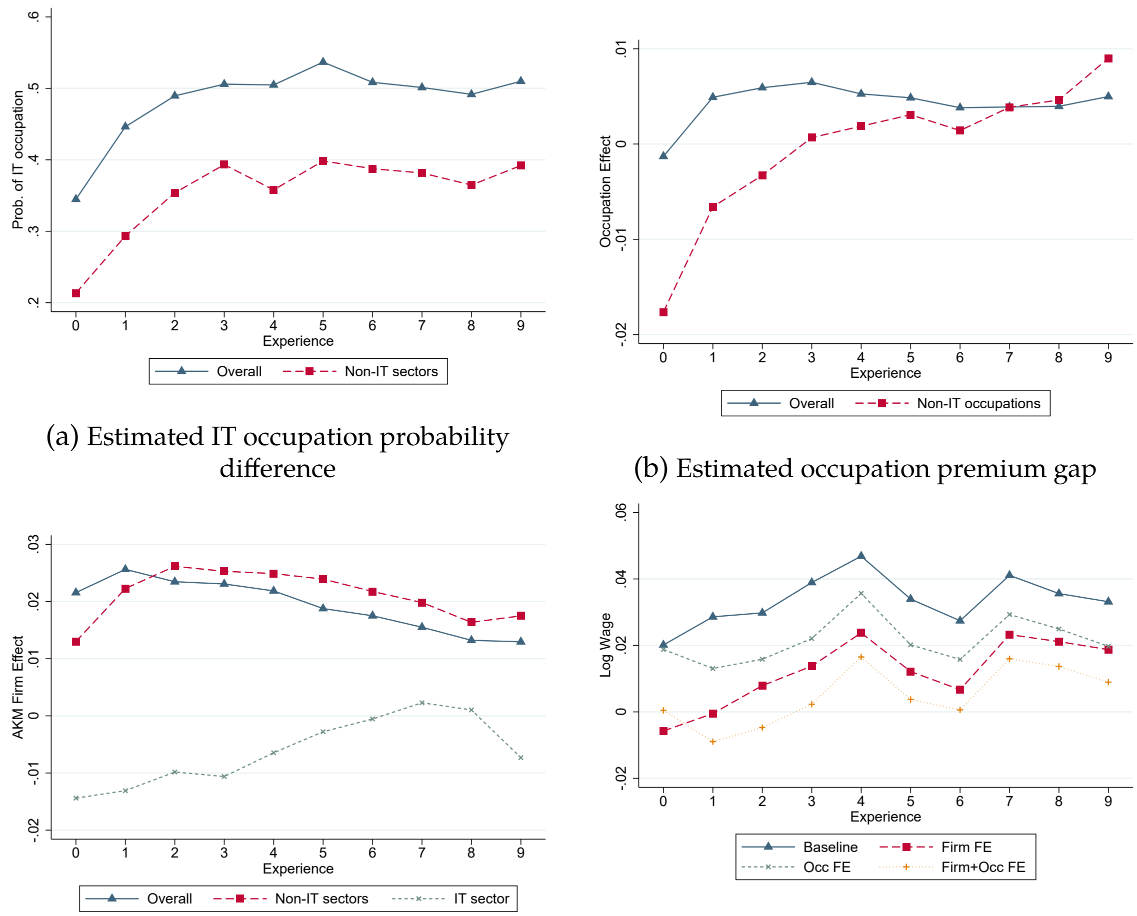
Recovery of bust cohorts

The figures presented in figure 7 depict the effects of IT majors on key labor market outcomes for the 2004 bust cohort over their first decade of experience. These panels allow us to understand how IT specialists' career trajectories evolved relative to generalists, with specific emphasis on differences across sectors and the contributions of occupation and firm sorting.

Panel (a) shows the estimated difference in the probability of working in IT occupations between IT specialists and generalists, with a focus on workers overall and those in non-IT sectors. At entry, IT specialists from the 2004 cohort are about 35 percentage points more likely to work in IT occupations compared to generalists. This probability increases rapidly in the first few years, reaching about 50 percentage points by year 3, indicating a strong recovery. The probability of working in IT occupations within non-IT sectors follows a similar pattern but at a lower level, starting at about 20 percentage points and rising to about 40 percentage points. This suggests the majority of IT specialists did not sort into IT occupations outside of the IT sector.

Panel (b) illustrates the estimated occupation premium gap between IT specialists and generalists. The 2004 cohort starts with a minor negative occupation premium, but turns positive within the first year and relatively stable over time. Notebly, IT specialists in non-IT occupations show a more pronounced recovery in occupation premiums, starting lower but catching up to and even surpassing the overall trend by year 9. This implies that IT specialists in non-IT roles are able to recover some of their lost wage potential by transitioning into better-paying non-IT occupations.

Panel (c) presents the firm premium gap between IT specialists and generalists through their career. The overall gap remains relatively stable over time, with a slight decline in later years. IT specialists in non-IT sectors consistently have higher



(a) Estimated IT occupation probability difference

(b) Estimated occupation premium gap

(c) Estimated firm premium gap

(d) Wage losses explained by firm and occupation

Figure 7. The Effects of IT Majors on IT Occupation Probability, Occupation Premiums, Firm Premiums, and Wage Components for a Bust Cohort over Experience

Notes: This figure shows the effects of IT majors for the bust cohort of 2004, using equation (1) on various outcome variables. Panel (a) depicts the estimated difference in IT occupation probability between IT specialists and generalists over experience, for both workers overall and those employed in non-IT sectors. Panel (b) presents the estimated difference in occupation premiums over experience for workers overall and for those in non-IT occupations. Panel (c) illustrates the difference in firm premiums over experience for workers overall and for those in non-IT occupations. Panel (d) displays the wage returns for IT specialists over experience, sequentially adding controls for estimated firm and occupation premiums (from the AKM model). All specifications control for 9th-grade GPA, year, sex, and include high school and college fixed effects.

firm premiums compared to the overall average after a few years, while those in the IT sector have lower (and initially negative) firm premiums. Thus, IT specialists in IT sectors find wage recovery through firm sorting, which contributes to the narrowing within-industry wage gap observed in early career stages.

Finally, Panel (d) reveals the wage recovery explained by firm and occupation sorting. The baseline wage returns for IT specialists increase over time. Controlling for firm fixed effects reduces the wage returns, especially in the early years, indicating that part of the initial wage recovery is due to sorting into higher-paying firms. Adding occupation fixed effects further reduces the wage returns, suggesting that a significant portion of the wage recovery is attributable to moving into higher-paying occupations. When both firm and occupation effects are controlled for, the residual wage returns are close to zero and relatively stable over time.

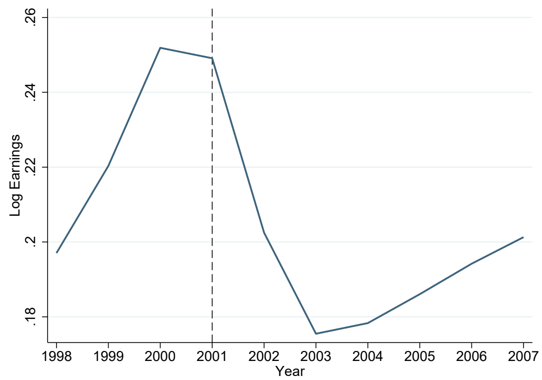
In summary, the results show that although IT specialists who graduated in the bust cohort of 2004 experienced initial disadvantages, their career trajectories partly recovered over time through a combination of firm and occupation mobility. While their likelihood of working in IT occupations and receiving IT-specific firm premiums diminishes, those who transition into non-IT sectors manage to recover through higher-paying non-IT occupations and firms. This reinforces the broader narrative that the recovery of bust cohorts occurs not within the IT sector, but through adaptation and mobility into better opportunities in non-IT industries.

5 The Effects on Incumbent Workers

In this section, I examine the effects of the dotcom cycle on incumbent IT specialists, who entered the labor market before the boom years and had accumulated experience prior to the shock. Their outcomes may differ from labor market entrants for two key reasons. First, search theories suggest that the cost of job search increases with age due to higher reservation wages and reduced mobility (**?**). Second, older workers typically have more specialized skills tied to previous industries or employers, making it harder for them to find jobs that match their qualifications. The results for these pre-boom cohorts also serve as a benchmark for evaluating the impact of the dotcom shock.

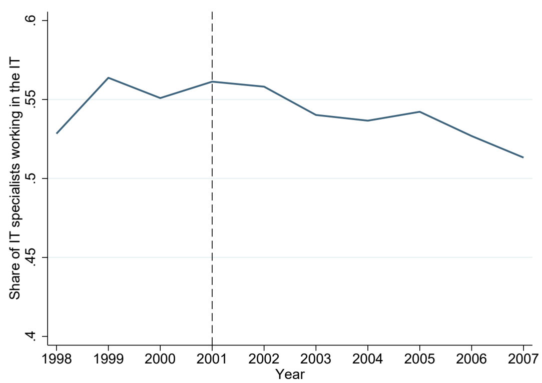
5.1 Average labor market outcomes of incumbent IT specialists

Figure 8 presents descriptive evidence on the labor market outcomes of incumbent IT specialists and generalists over the period 1998-2007, encompassing the dotcom boom and subsequent bust. This analysis provides initial insights into how the IT industry shock affected workers with specialized IT skills relative to those with more general skills.

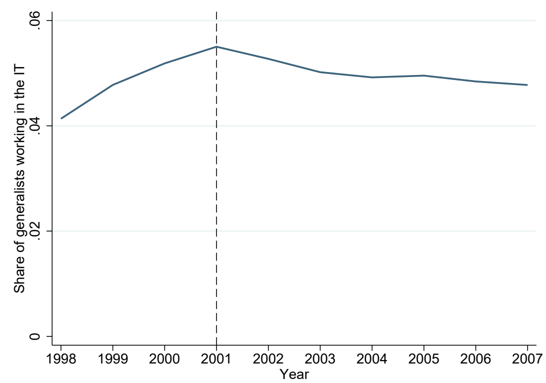


(a) Log annual earnings - raw difference

(b) Relative S.D. of raw earnings



(c) Share of IT majors employed in IT sector



(d) Share of other majors employed in IT sector

Figure 8. Average Labor Market Outcomes of Incumbent IT Specialists and Generalists by Years

Notes: This figure shows average labor market outcomes for IT specialists and generalists from year 1998 to 2007. Panel (a) shows the average difference in log earnings between IT specialists and generalists by year. Panel (b) depicts the relative standard deviation of log earnings for IT specialists compared to generalists by year. Panel (c) and (d) show the share of IT specialists and generalists working in the IT sector by year. The vertical dashed line at 2001 in each panel marks the burst of the dotcom bubble. The analysis sample consists of college workers who graduated before 1998.

Panel (a) illustrates the evolution of the raw earnings gap between IT specialists and generalists. Prior to 2001, IT specialists earned 20 to 25 log points more averagely, which peaked around the height of the dotcom boom. However, following the burst of the bubble in 2001, this gap rapidly diminished by around 7 log points, suggesting that IT specialists were disproportionately affected by the industry downturn. By 2003, the earnings gap had narrowed considerably, though it began to recover slightly in subsequent years.

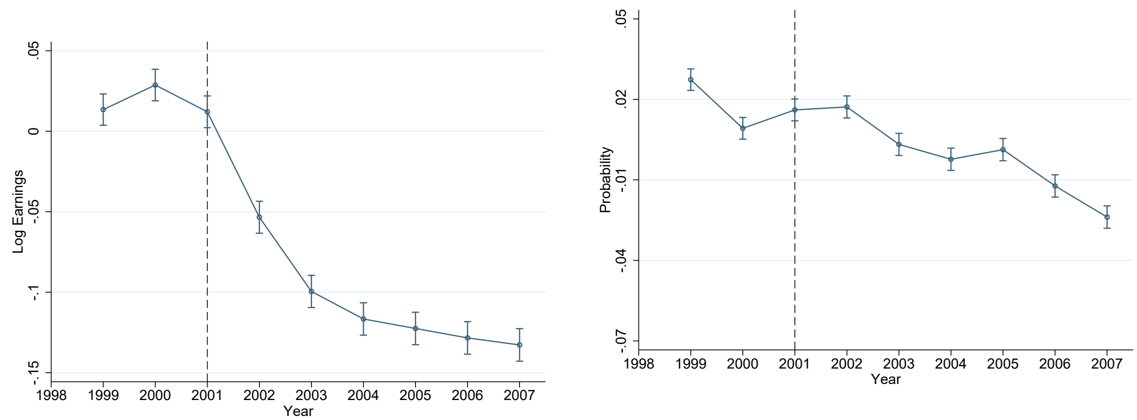
The relative variability in earnings between the two groups is captured in Panel (b). The standard deviation of log earnings for IT specialists relative to generalists remained stable before the shock, followed by a sharp rise immediately after the dotcom bubble burst. This suggests that while the earnings gap between IT specialists and generalists narrowed (as seen in Panel a), the dispersion of earnings among IT specialists relative to generalists actually increased post-bubble. The relative variability remained elevated throughout the post-bust period, indicating persistent heterogeneity in how IT specialists were affected by or adapted to the industry shock. This pattern might reflect divergent career paths among IT specialists, with some potentially remaining in the IT sector or finding success in new roles while others faced more significant challenges in the altered labor market landscape.

Panels (c) and (d) provide insights into sectoral employment patterns. Panel (c) shows that the share of IT specialists employed in the IT sector remained stable. There was a slight decrease post the shock showing that some IT specialists moved out of the IT sector, possibly due to reduced employment opportunities or seeking better prospects outside the IT sector. Panel (d) reveals that the share of generalists in the IT sector followed a similar pattern, albeit at a relatively lower level. This suggests that while both groups experienced sectoral shifts, the magnitude of these shifts was relatively larger for IT specialists.

These descriptive patterns highlight the volatility experienced by incumbent IT specialists during this period. The boom years were characterized by rising earnings difference and relatively low earnings dispersion. However, the subsequent bust led to a sharp reversal of these trends, with IT specialists experiencing a more pronounced decline in relative earnings and sector-specific employment compared to their generalist counterparts. These findings motivate a more rigorous analysis of the causal effects of the IT industry shock on the careers of IT specialized workers, which I pursue in the following sections.

5.2 Regression Analysis of Returns to IT Majors for Incumbents

Figure 9 shows the results of regressing labor market outcomes for IT specialists relative to generalists by year, controlling for individual fixed effects, graduation



(a) Changes in overall IT major returns

(b) Changes in rel. prob. of IT sector employment

Figure 9. Changes in Labor Market Outcomes of Incumbent IT Specialists by Year

Notes: This figure presents regression estimates of labor market outcomes for IT specialists compared to generalists from year 1998 to 2007. Panel (a) depicts the chanegs in overall returns to IT-specialized majors in terms of log earnings. Panel (b) illustrates the chanegs in probability differential of IT sector employment for IT specialists relative to generalists. All regressions control for a quadratic term of age interacted with sex, and graduation cohort fixed effects. 95% confidence intervals are reported. The year 1998 serves as the reference year in all panels.

cohort fixed effects, and the interaction between gender and quadratic age. By controlling for individual fixed effects, the estimated coefficients reflect changes in labor market outcomes for IT specialists compared to generalists, using 1998 as the reference year [8] [9].

Panel (a) of Figure 9 illustrates the changes in returns to IT-specialized majors in log earnings relative to the returns in 1998. After accounting for individual characteristics and fixed effects, the increase in returns during the boom years was modest, peaking at around 2 log points above the 1998 level, but experienced a sharp decline after the collapse, ultimately reduced by approximately 15 log points. Without controlling for individual fixed effects, IT specialists commanded an earnings premium of approximately 20-23 log points over generalists during the boom, which contracted to below 10 log points afterwards (Panel (a) of Figure A4). This trajec-

[8] Figure A4 presents similar results without individual fixed effects, suggesting that the findings are not driven by unobserved, time-invariant worker characteristics.

[9] These results are not sensitive to various specifications (shown in Figure A5 and Table A6). Across various specifications, including different controls for age, sex, experience, and cohort effects, the overall pattern of returns to IT specialization remains consistent. All models show an initial positive return that declines sharply after the dotcom bubble burst. While there are minor variations in the magnitude of effects across specifications, the consistency of the pattern reinforces the conclusion that the observed decline in returns to IT specialization is a robust phenomenon and not an artifact of any particular modeling choice.

tory indicates that while IT specialists maintained some advantage after the bust, their earnings premium was significantly reduced due to the shock compared to the boom period.

This pattern aligns with career effects in Deming and Noray (2020), who find a gradual decline of about 12 percent (11 log points) in returns to computer science and engineering majors over 25 years. However, I found that returns decreased by 16 log points within ten years, indicating that the industry shock exacerbated this decline beyond career dimension effects. Andrews et al. (2024) find that returns to IT majors are 29 percent (25 log points) higher than the mean using US data, which resembles my estimates in boom years[10].

Panel (b) shows the probability differential of IT sector employment for IT specialists relative to generalists. The likelihood of IT specialists being employed in the IT sector increased by 2 percentage points in 1999, indicating that IT specialists were more responsive in reallocating to the IT sector during the boom. After the bust, this probability declined slightly, by less than 3 percentage points. This pattern suggests the resilience of incumbent IT specialists in IT sector employment, which can be attributed to search theory, human capital theory described previously, or employment protection policies that favor long-tenured workers in Sweden (von Below and Thoursie, 2008).

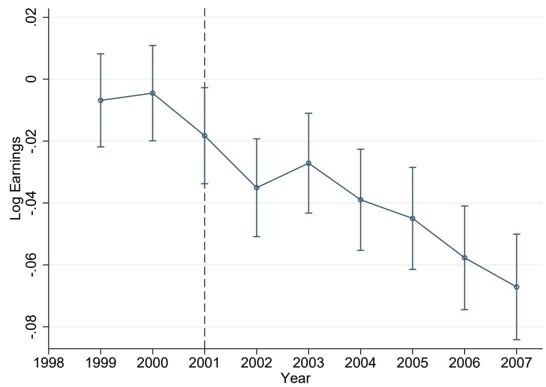
5.3 Decomposing IT specialization losses for incumbents

In this section, I decompose the changes in overall returns to IT majors into within-industry and industry-premium components by estimating Equation (2). The within-industry component reflects the returns to specific IT skills relative to other majors within industries, while the industry-premium component captures the industry premium and sorting. To investigate the role of the IT sector, I estimate a two-sector model to comparing the IT to other sectors. The results are shown in Figure 10.

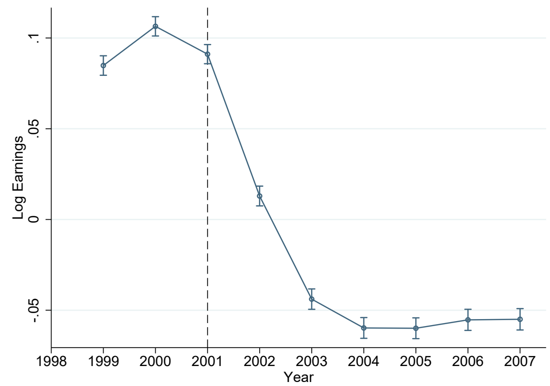
Within-industry returns

Panel (a) in Figure 10 shows a gradual decline in the returns to IT majors within the IT sector relative to 1998 after the collapse. The returns decreased by 4 log points

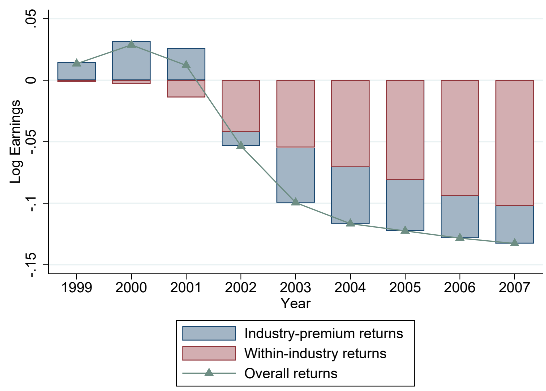
[10]The estimated returns may be affected by both the industrial cycle and sample composition, as IT specialists might face a gradual decline over their careers. Pooling entrant and incumbent workers together might yield a larger effect, which is not the case for my analysis on incumbents.



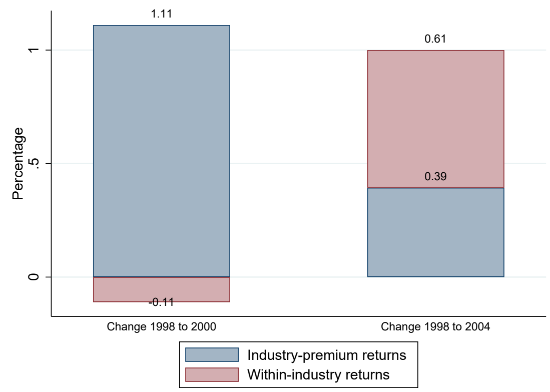
(a) Changes in IT Major returns within the IT sector



(b) Changes in IT industry premium



(c) Decomposition of changes in overall returns



(d) Relative importance in percentage

Figure 10. Decomposition of Returns to IT Majors for Incumbent Workers

Notes: Panel (a) shows the changes in returns to IT-specialized majors within the IT sector. Panel (b) presents the changes in the estimated IT sector earnings premium. Panel (c) illustrates the overall returns from 1999 to 2007, decomposed into the industry premium and within-industry channels across all industries. Panel (d) highlights the relative contributions of each channel to the overall returns, focusing on changes between 1998-2000 and 1998-2004. The sample includes college graduates who entered the workforce before 1998.

after four years and about 6 log points by 2007. Panel (c) of Figure A4 presents the results without individual fixed effects, showing a small positive return to IT majors in the IT sector during the boom, which turned negative during the bust. Given that over half of IT specialists work in the IT sector, this decline likely drove the changes in within-industry returns.

Panel (c) of Figure 10 also decomposes returns across all industries, confirming and amplifying this pattern. Within-industry returns remained stable during the boom but declined sharply from 2002 onward, suggesting that IT specialists' skills became less valuable relative to generalists across industries. The magnitude of the decline is larger than the IT sector, indicating a more significant drop in returns to IT majors in other non-IT sectors. A possible explanation is that the demand for IT skills outside the IT sector was also affected by the shock, or IT specialists faced worse outside options.

Within-industry returns accounted for -11 percent of the total change between 1998 and 2000, as overall returns increased while within-industry returns declined. This change represented 61 percent of the overall decline in IT specialization returns between 1998 and 2004 (Panel (d) of Figure 10). Given the short time frame, this reflects a change in the price of their human capital rather than a depreciation of their IT skills.

Industry-premium returns

Panel (b) of Figure 10 illustrates a significant upward trend in the estimated premium for working in the IT sector leading up to the year 2000, with an increase of approximately 10 log points. This rise reflects the booming demand and high valuations in the IT industry during the dotcom bubble. However, following the bust, the IT sector premium experienced a sharp decline of over 15 log points. Despite this reduction, workers who remained in the IT sector continued to earn more than those in other sectors, as shown in Panel (d) of Figure A4, although the magnitude of this premium was substantially diminished due to the shock.

After decomposing across multiple industries (Panel (c) of Figure 10), the industry-premium returns reduced by about 8 log points. This decline closely mirrors the reduction in the IT sector premium, indicating that the decrease in industry-premium returns for IT majors was primarily driven by changes within the IT sector itself [11]. In other industries, the industry-premium component did

[11] Approximately half of the change in industry-premium component can be attributed to changes in the IT sector premiums due to the weighting.

not significantly impact the returns to IT majors.

Between 1998 and 2004, the industry-premium component accounted for 39 percent of the overall decline in returns to IT majors. This substantial contribution suggests that shifts in industry-specific premiums, particularly in the IT sector, played a crucial role in shaping the labor market outcomes for IT majors during this period.

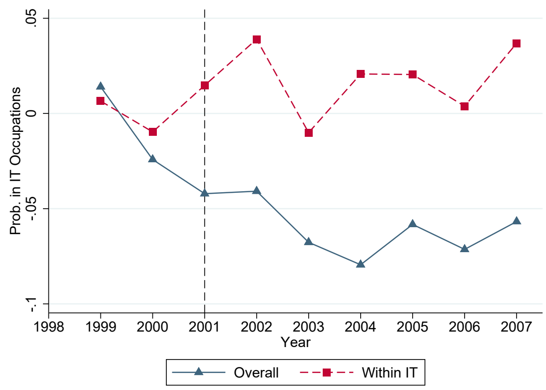
5.4 Occupations and Firm Dynamics for Incumbents

The preceding results on the significant earnings declines observed among incumbent IT specialists within industries can be partially attributed to shifts in firm-level and occupation-specific effects. In this subsection, I explore these underlying mechanisms by examining how incumbent IT specialists transition between occupations and firms over time.

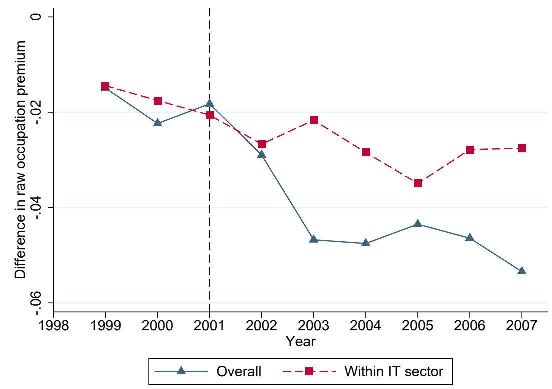
Panel (a) of Figure 11 illustrates the employment trends of IT specialists in IT occupations both overall and specifically within the IT industry. Generally, IT specialists are increasingly less likely to remain in IT occupations both before and after the economic shock. However, for those employed within the IT sector, the likelihood of staying in IT occupations remains relatively stable. This divergence suggests that IT specialists in non-IT sectors are more prone to switching away from IT-related jobs.

Panel (b) further investigates the transition of IT specialists across occupations with varying premiums. Over time, IT specialists lose their advantage of occupying high-paying positions. Nonetheless, those within the IT sector experience a considerably smaller decline in high-paying occupations. Taken together, Panels (a) and (b) suggest that IT specialists outside the IT sector tend to move into lower-premium and non-IT occupations. This occupational reallocation likely contributes to the pronounced decline in returns to IT majors outside the IT sector.

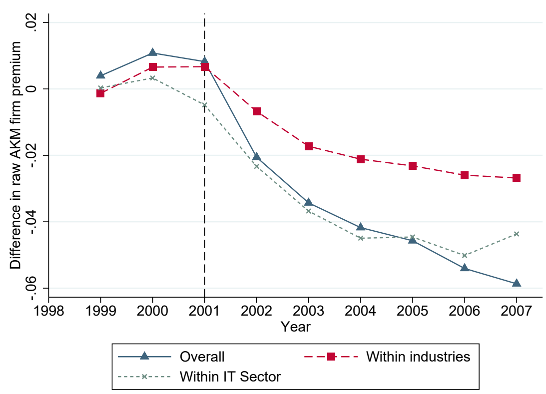
Given the background of the dramatic changes in firms during the dotcom cycle, I examine how IT specialists move across firms with different premiums, shown in Panel (c) Figure 11. They experienced a dramatic deline in working in high-premium firms, especially for those who work in the IT sector. This reveals an important pattern, even though incumbent IT specialists are not likely to switch the sector, they do switch from high to low-premium firms. After isolating the changes in firm premiums within industries from between industry, it shows a similar pattern but with a smaller magnititude. These results suggest that IT specialists moved to lower premium firms, especially true for those who remain in the IT sec-



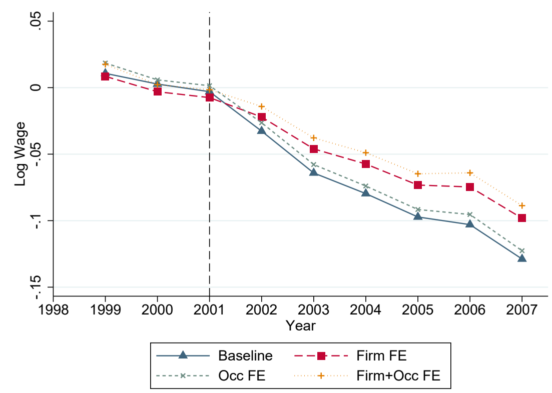
(a) Estimated IT occupation probability difference



(b) Estimated occupation premium gap



(c) Estimated firm premium gap



(d) Wage losses explained by firm and occupation

Figure 11. The Effects of IT Majors on Firm Premiums, Occupation Premiums, and Wage Components for Incumbent Workers

Notes: This figure shows the effects of IT majors for incumbent workers, using the same specification specified in section 3.2. Panel (a) depicts the estimated difference in IT occupation probability between IT specialists and generalists. Panel (b) presents the estimated difference in occupation premiums. Panel (c) illustrates the difference in firm premiums. Panel (d) displays the wage losses for IT specialists while consecutively adding controls on estimated firm and occupation premiums (estimated from the AKM model). All specifications control for individual fixed effects and a quadratic age term interacted with gender. The reference year is 1998.

tor. Lossing firms which would like to pay high price of IT skills plays a crucial role in explaining the large decline in within-industry returns.

Considering the significant firm-level changes during the dotcom cycle, Panel (c) of Figure 11 examines the movement of IT specialists across different paying firms. There is a marked decline in employment within high-premium firms, particularly among those remaining in the IT sector. This pattern indicates that, although incumbent IT specialists are less likely to switch sectors, they do transition from high-premium to low-premium firms. When isolating within-industry changes in firm premiums from between-industry variations, a similar pattern emerges, albeit with a smaller magnitude. These findings suggest that IT specialists are increasingly employed by lower-premium firms, especially those who remain within the IT sector. The loss of employment opportunities in high-premium firms that are willing to pay a premium for IT skills plays a crucial role in explaining the substantial decline in within-industry returns.

Finally, to quantify the contribution of occupational and firm dynamics to the wage losses experienced by IT specialists, I sequentially include estimated firm and occupation premiums in the baseline wage regression model. In the baseline specification, returns to IT majors, measured in log wages, decline by approximately 8 log points following the bust period (1998–2004). Of this decline, changes in firm premiums account for 28 percent, while occupational shifts explain about 7 percent.

6 Conclusion

This paper investigates how the dotcom bust of 2000 affected the earnings and career trajectories of workers with IT-specialized college majors in Sweden. By leveraging comprehensive administrative data, I examined both labor market entrants and incumbent workers to understand how career experience influences the ability to weather industry-specific shocks.

My findings reveal a stark contrast between entrants and incumbents. For labor market entrants, the timing of graduation relative to the dotcom cycle had profound effects. Those who graduated during the boom enjoyed substantial initial earnings premiums and high employment rates within the IT sector. In contrast, graduates entering during the bust faced significant initial earnings penalties—an earnings gap of 27 log points compared to their boom-year counterparts—which narrowed after a decade. These initial losses were primarily driven by negative returns within non-IT industries, reflecting both a decrease in the value of IT skills outside the

IT sector and potential skill mismatches. Over time, bust cohorts mitigated their disadvantages by transitioning into higher-paying, non-IT occupations, but they remained significantly less likely to work in the IT sector.

Incumbent workers experienced a different set of challenges. Despite a sharp decline of about 16 log points in returns to their IT majors, incumbents largely remained within the IT sector. The earnings decline was driven by both a devaluation of IT skills within industries and a reduction in industry premiums. Rather than switching industries, incumbents adjusted by moving to lower-premium firms within the IT sector. Their accumulated industry-specific human capital and higher switching costs may have made them less responsive to the shock in terms of sectoral mobility, leading them to absorb the impact through diminished earnings within their existing career paths.

These contrasting experiences highlight the critical role of career timing and adaptability in the face of industry volatility. For workers and students choosing between industries or college majors, my results underscore the trade-off between specialization and flexibility. While IT-specialized majors can offer high returns during periods of strong industry demand, they also expose individuals to greater risk from industry-specific downturns. Entrants must navigate a more uncertain landscape but demonstrate adaptability by leveraging their skills across different industries and occupations. Incumbents, on the other hand, may find it challenging to pivot away from declining sectors due to their specialized human capital.

From a policy perspective, my findings suggest the importance of supporting skill adaptability and mobility across industries. Educational institutions might consider incorporating broader skill sets within specialized programs to enhance graduates' flexibility. For workers, continuous skill development and openness to cross-sector opportunities can mitigate the risks associated with industry-specific shocks.

In conclusion, the interplay between specialized human capital and industry cycles has profound implications for both individual workers and the broader economy. Understanding these dynamics is essential for making informed decisions about education and career paths, as well as for developing policies that support a resilient and adaptable workforce.

References

Abowd, John M., Francis Kramarz, and David N. Margolis, "High Wage Workers and High Wage Firms," *Econometrica*, 1999, *67* (2), 251–333.

Altonji, Joseph G. and Ling Zhong, "The Labor Market Returns to Advanced Degrees," *Journal of Labor Economics*, April 2021, *39* (2), 303–360.

_, Erica Blom, and Costas Meghir, "Heterogeneity in Human Capital Investments: High School Curriculum, College Major, and Careers," *Annual Review of Economics*, 2012, *4*, 185–223.

_, Lisa B. Kahn, and Jamin D. Speer, "Cashier or Consultant? Entry Labor Market Conditions, Field of Study, and Career Success," *Journal of Labor Economics*, January 2016, *34* (S1), S361–S401.

Andrews, Rodney J., Scott A. Imberman, Michael F. Lovenheim, and Kevin M. Stange, "The Returns to College Major Choice: Average and Distributional Effects, Career Trajectories, and Earnings Variability," March 2024.

Berge, Wiljan Van Den, "Bad Start, Bad Match? The Early Career Effects of Graduating in a Recession for Vocational and Academic Graduates," *Labour Economics*, August 2018, *53*, 75–96.

Bleemer, Zachary and Aashish Mehta, "Will Studying Economics Make You Rich? A Regression Discontinuity Analysis of the Returns to College Major," *American Economic Journal: Applied Economics*, April 2022, *14* (2), 1–22.

Bloemen, Hans G., "Job Search, Search Intensity, and Labor Market Transitions: An Empirical Analysis," *Journal of Human Resources*, January 2005, *XL* (1), 232–269.

Böhm, Michael J, Daniel Metzger, and Per Strömberg, ""Since You're So Rich, You Must Be Really Smart": Talent, Rent Sharing, and the Finance Wage Premium," *The Review of Economic Studies*, October 2023, *90* (5), 2215–2260.

Brown, James R., Steven M. Fazzari, and Bruce C. Petersen, "Financing Innovation and Growth: Cash Flow, External Equity, and the 1990s R&D Boom," *The Journal of Finance*, 2009, *64* (1), 151–185.

Brynjolfsson, Erik and Lorin M. Hitt, "Computing Productivity: Firm-Level Evidence," *The Review of Economics and Statistics*, November 2003, *85* (4), 793–808.

Card, David, Jesse Rothstein, and Moises Yi, "Industry Wage Differentials: A Firm-Based Approach," August 2023.

_, Jörg Heining, and Patrick Kline, "Workplace Heterogeneity and the Rise of West German Wage Inequality," *The Quarterly Journal of Economics*, August 2013, *128* (3), 967–1015.

Chen, Pengyu and SangKyum Kim, "The Impact of Digital Transformation on Innovation Performance - The Mediating Role of Innovation Factors," *Heliyon*, March 2023, *9* (3), e13916.

Dale W. Jorgenson, Dale W. Jorgenson, Mun S. Ho, Mun S. Ho, Kevin J. Stiroh, Kevin J. Stiroh, Kevin J. Stiroh, Kevin J. Stiroh, and Kevin J. Stiroh, "A Retrospective Look at the U.S. Productivity Growth Resurgence," *Journal of Economic Perspectives*, February 2008, *22* (1), 3–24.

Deming, David J and Kadeem Noray, "Earnings Dynamics, Changing Job Skills, and STEM Careers," *The Quarterly Journal of Economics*, November 2020, *135* (4), 1965–2005.

Edin, Per-Anders and Peter Fredrikson, *LINDA : Longitudinal Individual Data for Sweden*, Nationalekonomiska institutionen, 2000.

Ellingsen, Jon and Caroline Espegren, "Lost in Transition? Earnings Losses of Displaced Petroleum Workers," Working Paper December 2022.

Engdahl, Mattias, Mathilde Godard, and Oskar Nordström Skans, "Early Labor Market Prospects and Family Formation," *Journal of Human Resources*, May 2022.

Eriksson, Göran, "Human Capital Investments and Labor Mobility," *Journal of Labor Economics*, July 1991, *9* (3), 236–254.

Hombert, Johan and Adrien Matray, "Innovation Booms, Easy Financing, and Human Capital Accumulation," December 2023.

Jorgenson, Dale W, "Information Technology and the U.S. Economy," *American Economic Review*, March 2001, *91* (1), 1–32.

Kirkeboen, Lars J., Edwin Leuven, and Magne Mogstad, "Field of Study, Earnings, and Self-Selection," *The Quarterly Journal of Economics*, August 2016, *131* (3), 1057–1111.

Kline, Patrick, "Understanding Sectoral Labor Market Dynamics: An Equilibrium Analysis of the Oil and Gas Field Services Industry," 2008.

Kogut, Bruce Mitchel, *The Global Internet Economy*, MIT Press, 2003.

Leighton, Margaret and Jamin D. Speer, "Labor Market Returns to College Major Specificity," *European Economic Review*, September 2020, *128*, 103489.

Liu, Kai, Kjell G. Salvanes, and Erik Ø. Sørensen, "Good Skills in Bad Times: Cyclical Skill Mismatch and the Long-Term Effects of Graduating in a Recession," *European Economic Review*, May 2016, *84*, 3–17.

Lorentzen, Linnea, "Domino Effects: Understanding Sectoral Reallocation and Its Wage Implications," 2024.

Maican, Florin, "From Boom to Bust and Back Again: A Dynamic Analysis of IT Services," *SSRN Electronic Journal*, 2012.

Martin, Shawn M, "College Major Specificity, Earnings Growth and Job Changing," 2022.

Müller, Sune, E.B. Møller, and T.J. Nygaard, "IT-enabled Process Innovation: A Literature Review," in "18th Americas Conference on Information Systems 2012, AMCIS 2012," Vol. 4 January 2012, p. Paper 4.

Oliner, Stephen D. and Daniel E. Sichel, "The Resurgence of Growth in the Late 1990s: Is Information Technology the Story?," *Journal of Economic Perspectives*, December 2000, *14* (4), 3–22.

Oreopoulos, Philip, Till von Wachter, and Andrew Heisz, "The Short-and Long-Term Career Effects of Graduating in a Recession," *American Economic Journal: Applied Economics*, 2012, *4* (1), 1–29.

Philippon, Thomas and Ariell Reshef, "Wages and Human Capital in the U.S. Finance Industry: 1909–2006," *The Quarterly Journal of Economics*, November 2012, *127* (4), 1551–1609.

Sandra E. Black, Sandra E. Black, Lisa M. Lynch, and Lisa M. Lynch, "How to Compete: The Impact of Workplace Practices and Information Technology on Productivity," *The Review of Economics and Statistics*, 2001, *83* (3), 434–445.

Schwandt, Hannes and Till von Wachter, "Unlucky Cohorts: Estimating the Long-Term Effects of Entering the Labor Market in a Recession in Large Cross-Sectional Data Sets," *Journal of Labor Economics*, January 2019, *37* (S1), S161–S198.

Spitz-Oener, Alexandra, "Technical Change, Job Tasks, and Rising Educational Demands: Looking Outside the Wage Structure," *Journal of Labor Economics*, 2006, *24* (2), 235–270.

von Below, David and Peter Skogman Thoursie, "Last in, First out? Estimating the Effect of Seniority Rules in Sweden," 2008.

Walker, W. Reed, "The Transitional Costs of Sectoral Reallocation: Evidence From the Clean Air Act and the Workforce," *The Quarterly Journal of Economics*, November 2013, *128* (4), 1787–1835.

A Appendix

A.1 Quantitive Measurements of IT Specialization

The share of a major employed in the IT industry

The specialization of a college major for the IT sector is quantified by the proportion of workers with a major m employed in the IT industry before the boom years. This is calculated using the following formula:

$$s_m \equiv \frac{N_{m,IT}}{N_m}$$

where, $N_{m,IT}$ denotes the number of workers with a 3-digit major m in the IT sector, and N_m signifies the total number of workers with major m. The majors with fewer than a hundred observations during the period are excluded for this calculation. The data used to calculate s_m span from 1990-1997, which predates the primary analysis sample. This mitigates the concern of potential collinearity in the subsequent analysis, ensuring that the measure of IT specialization is not too closely related to other variables from the same period in the primary analysis. I normalize IT specialization to have a mean of zero and a standard deviation of one.

This metric is designed to measure the degree of IT specialization of a 3-digit major m. A higher value of s_m implies that major m is more specific to the IT industry. There are 102 three-digit level majors in total, with standardized specialization from -0.41 to 5.54 (0 to 0.48 in raw share). Majors related to computer science are the most specialized, followed by technical engineering and some of the natural sciences. The majors in business and materials manufacturing fall around the average. Most other majors fall below the mean.

The standardized specialization and raw share of the 10 largest majors at the 3-digit level are presented in **??**. In the main specification, I define the first four majors with the highest IT specialization as IT-specialized majors. These majors exhibit significantly higher levels of IT specialization compared to other, more general majors.

IT-specialized courses

To further validate the robustness of my definition of IT-specialized majors, I conducted an additional analysis based on the share of IT-specialized courses within each major. This approach provides an alternative perspective on the degree of IT specialization, complementing my primary method based on industry employment rates.

To quantify the IT specialization of each major, I calculated the proportion of IT-specialized courses within the curriculum. Using administrative data on course registrations from 1993 to 2007, I identified IT-specialized courses based on their subject codes, which correspond to various aspects of computer science, informatics, and related fields. The list of these courses and their corresponding codes is provided in Table A2.

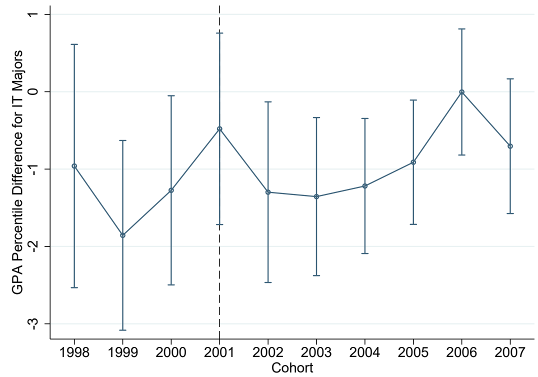
This measure provides an indication of the IT content in each major's curriculum, offering a complementary perspective to the industry-based specialization metric.

Table A3 presents the top 10 majors ranked by their share of IT-specialized courses. Notably, the majors identified as IT-specialized in our main analysis (Computer science, general (480), Computer and systems sciences (481), Computer, other/unspecified education (489), and Electronics, computer engineering and automation (523)) consistently rank at the top of this alternative measure. This alignment between the industry-based and curriculum-based measures of IT specialization provides strong support for the robustness of the main specification.

These findings reinforce the validity of the classification of IT-specialized majors, demonstrating that these programs not only lead to high rates of employment in the IT sector but also feature a curriculum heavily focused on IT-related courses.

B Appendix Figures and Tables

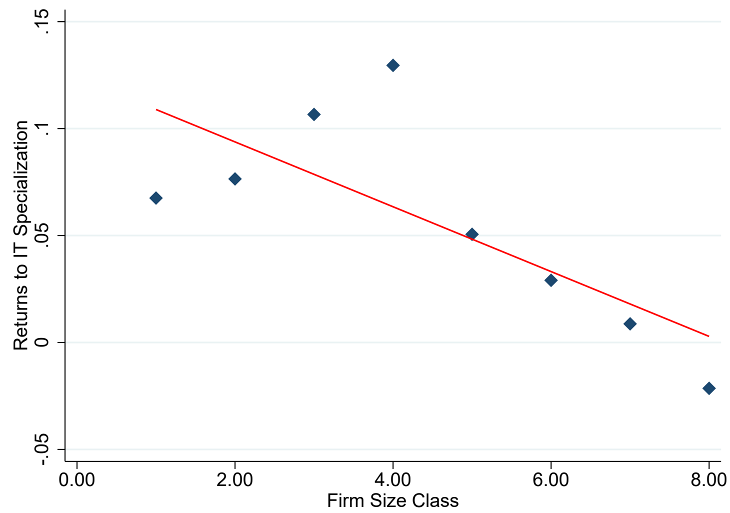
(a) Share of IT majors by cohort



(b) GPA gaps of IT majors by cohort

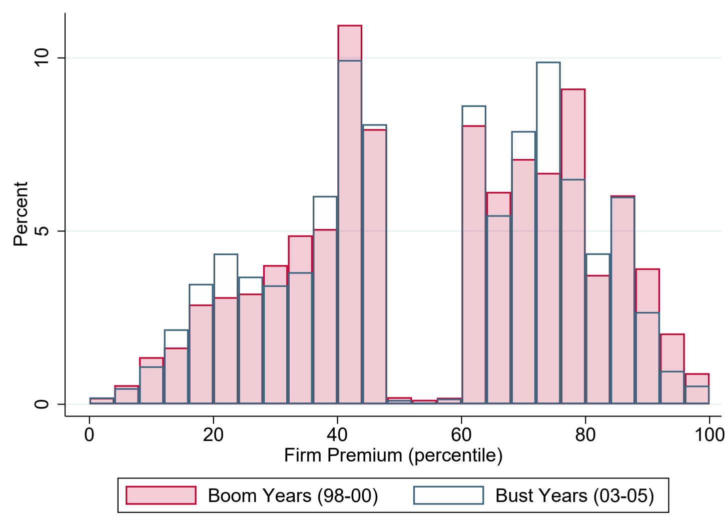
Appendix Figure A1. IT Major Supply and GPA Gap Across Cohorts

Notes: This figure presents the share of IT majors and the GPA gaps of IT majors across cohorts. The share of IT majors is calculated as the number of IT majors divided by the total number of students in the cohort. The GPA gap is calculated as the difference between the average GPA of IT majors and the average GPA of non-IT majors.



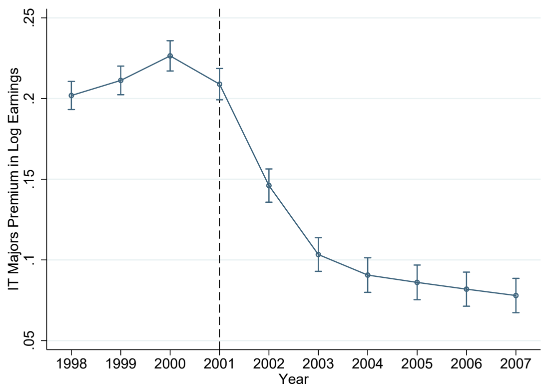
Appendix Figure A2

Notes: This figure plots the returns to IT specialization in log wage across different firm size classes. The returns are derived from a regression of log wage on IT specialization controlling for quadratic age interacted with sex, cohort, and year fixed effects. Each diamond represents the returns to IT-specialized majors for a specific firm size class. The red line shows the linear fit of the relationship between firm size and returns to IT specialization.

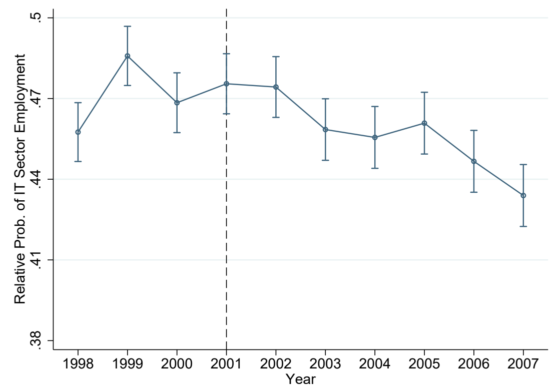


Appendix Figure A3

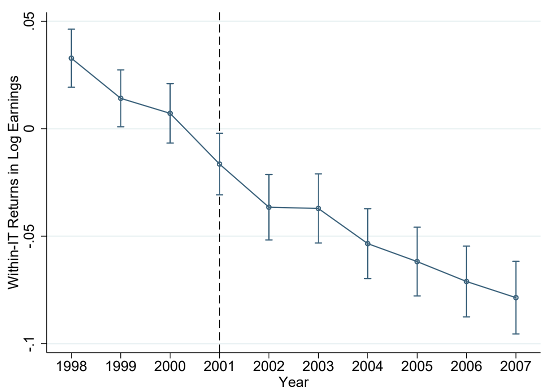
Notes: This figure compares the distribution of firm premiums during boom years (1998-2000) and bust years (2003-2005). Firm premiums are expressed in percentiles. All specifications align with the main analysis.



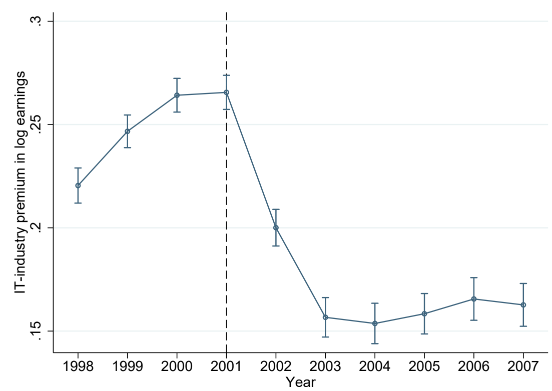
(a) Overall IT Major Returns



(b) Rel. Prob. of IT Sector Employment



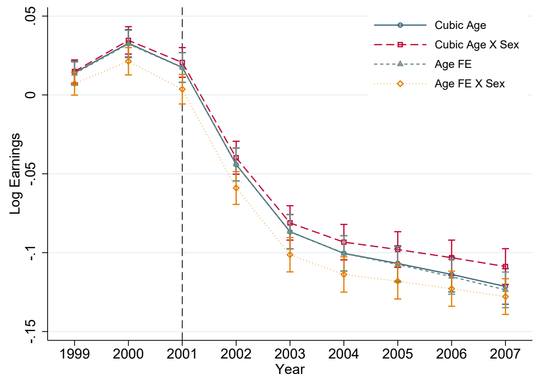
(c) IT Major Returns within IT Sector



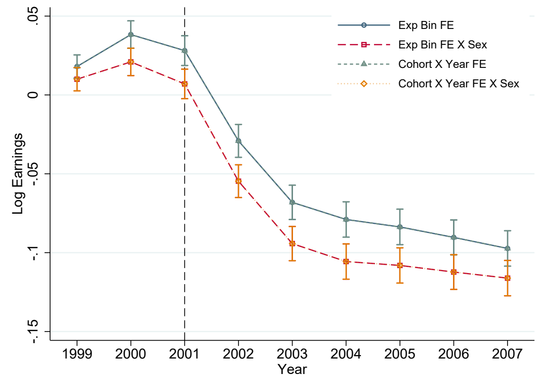
(d) IT industry Premium

Appendix Figure A4. Labor Market Outcomes of Incumbent IT Specialists by Year

Notes: This figure presents regression estimates of labor market outcomes for IT specialists compared to generalists from year 1998 to 2007. Panel (a) depicts the overall returns to IT-specialized majors in terms of log earnings. Panel (b) illustrates the probability differential of IT sector employment for IT specialists relative to generalists. Panel (c) shows the returns to IT-specialized majors within the IT sector. Panel (d) displays the estimated IT sector earnings premium. The analysis sample consists of college workers who graduated before 1998. All regressions control for a quadratic term of age interacted with sex, and graduation cohort fixed effects. 95% confidence intervals are reported. The year 1998 serves as the reference year in all panels.



(a)



(b)

Appendix Figure A5. Robustness checks of returns to IT specialization

Notes: This figure presents robustness checks of the returns to IT majors for incumbents. Panel (a) displays the estimated coefficients of IT specialization on log earnings using different age specifications: cubic age, cubic age interacted with sex, age fixed effects, and age fixed effects interacted with sex. Panel (b) shows the estimated coefficients using experience bin fixed effects, experience bin fixed effects interacted with sex, cohort-by-year fixed effects, and cohort-by-year-by-sex fixed effects. All regressions include cohort and sex fixed effects, unless these are interacted with other variables. Standard errors are clustered at the individual level. The omitted year is 1998. Confidence intervals are set at 95%.

Appendix Table A1. Top 10 College Majors by Proportion of Graduates Employed in the IT Industry

Major Name	**Share**
Computer, other/unspecified education	0.48
Computer and systems sciences	0.42
Computer science, general	0.35
Electronics, computer engineering and automation	0.31
Mathematics	0.20
Engineering & technology, general	0.14
Industrial econ & org	0.13
Math & science, other	0.13
Energy & electrical tech	0.11
Biology & environment, other	0.09

Notes: This table presents the 10 largest college majors by share of graduates in the IT industry. The share is calculated as the number of graduates with a given major working in the IT industry divided by the total number of graduates from that major, using data prior to 1997.

Appendix Table A2. IT Specialized Courses

Course Name	Course Code
Administrative Data Processing	ADA
Computer Engineering	DTA
Computer Science	DVA
Data and Information Science	DIO
Data and Systems Science	DSA
Computational Linguistics	DLA
Computer Science/Informatics	DAO
Computer Education	DPE
Computer Graphics	DGI
Computer Communication	DKA
Computer-Aided Machine Design	DMA
Computer Systems Engineering	DBA
Computer Science/Numerical Analysis	DNA
Computer Technology	DOA
Information Processing/Computer Science	IIA
Information Systems	IFY
Information Technology	IFO, IXA
Informatics	IKA
Informatics with focus on Business Technology	IBE
Informatics and Systems Science	ISY
Information and Communication Technology	IFI
Systems Science	SYA
IT Economics	ITO
Software Engineering	PAA
Information Systems Development	ISU
Interaction Design	IDI
Internet Technology	INE
Applied Information Technology	TIE
Economics with IT	EAA
Electronics	ELA
Electrical Engineering	ETA
Electronics System Design	ESO

Note: This table lists the IT-specialized courses and their corresponding course codes used to calculate the share of IT content in each major's curriculum. These courses cover various aspects of computer science, informatics, and related fields. The data is based on course registrations from 1993 to 2007 for workers with college degrees. Some courses (e.g., Information Technology) have multiple codes due to variations in coding across institutions or over time.

Appendix Table A3. Top 10 Majors by Share of IT-Specialized Courses

Major	**Share of IT Courses**
Computer, other/unspecified education	0.43
Electronics, computer engineering and automation	0.43
Computer and systems sciences	0.42
Computer science, general	0.34
Electrical engineering	0.27
Engineering physics	0.24
Mechanical engineering	0.14
Materials engineering	0.14
Interdisciplinary engineering	0.13
Chemical engineering	0.13

Note: This table shows the top 10 majors ranked by their share of IT-specialized courses. The share is calculated as the ratio of IT-specialized courses to the total number of courses in each major, based on course registration data from 1993 to 2007.

Appendix Table A4. Returns to IT-Specialized Majors: Log Earnings

Cohort	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Panel A: Controlling for Grade 9 GPA										
Exp 0	0.126*	0.0938*	0.145*	0.150*	-0.0162	-0.135*	-0.140*	-0.118*	-0.0564*	0.0163
	(0.000)	(0.000)	(0.000)	(0.000)	(0.477)	(0.000)	(0.000)	(0.000)	(0.000)	(0.290)
Exp 1	0.135*	0.155*	0.139*	0.0194	-0.0758*	-0.110*	-0.0568*	-0.0473*	0.0130	0.0386*
	(0.000)	(0.000)	(0.000)	(0.263)	(0.000)	(0.000)	(0.000)	(0.000)	(0.208)	(0.001)
Exp 2	0.170*	0.156*	0.0736*	0.0268	-0.0218	-0.0214	0.00127	0.0374*	0.0650*	0.0566*
	(0.000)	(0.000)	(0.000)	(0.103)	(0.195)	(0.129)	(0.911)	(0.000)	(0.000)	(0.000)
Exp 3	0.168*	0.110*	0.0432*	0.0107	0.0122	0.0169	0.0605*	0.0725*	0.0876*	0.0429*
	(0.000)	(0.000)	(0.008)	(0.550)	(0.431)	(0.198)	(0.000)	(0.000)	(0.000)	(0.001)
Exp 4	0.124*	0.0562*	0.0573*	0.0633*	0.0558*	0.0459*	0.0902*	0.0919*	0.0903*	0.107*
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 5	0.0841*	0.0700*	0.128*	0.0898*	0.0905*	0.0777*	0.0824*	0.0976*	0.0840*	0.0870*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 6	0.130*	0.123*	0.123*	0.0965*	0.0996*	0.0693*	0.0937*	0.0990*	0.0921*	0.0987*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 7	0.147*	0.109*	0.106*	0.107*	0.0849*	0.0703*	0.0775*	0.0982*	0.0745*	0.0792*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 8	0.154*	0.125*	0.106*	0.0911*	0.0902*	0.0821*	0.0758*	0.0804*	0.0695*	0.0685*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 9	0.129*	0.0993*	0.0978*	0.0801*	0.0794*	0.0489*	0.0593*	0.0708*	0.0626*	0.0561*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 10	0.117*	0.0872*	0.0793*	0.0729*	0.0575*	0.0472*	0.0406*	0.0466*	0.0492*	0.0325*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.009)
Panel B: Controlling for Grade 9 Math Score										
Exp 0	0.119*	0.0867*	0.141*	0.147*	-0.0199	-0.138*	-0.143*	-0.121*	-0.0619*	0.0115
	(0.000)	(0.000)	(0.000)	(0.000)	(0.385)	(0.000)	(0.000)	(0.000)	(0.000)	(0.459)
Exp 1	0.127*	0.149*	0.135*	0.0169	-0.0780*	-0.114*	-0.0597*	-0.0509*	0.00680	0.0328*
	(0.000)	(0.000)	(0.000)	(0.331)	(0.000)	(0.000)	(0.000)	(0.000)	(0.513)	(0.003)
Exp 2	0.162*	0.150*	0.0699*	0.0244	-0.0250	-0.0253	-0.00169	0.0331*	0.0588*	0.0513*
	(0.000)	(0.000)	(0.000)	(0.138)	(0.139)	(0.073)	(0.883)	(0.001)	(0.000)	(0.000)
Exp 3	0.160*	0.104*	0.0395*	0.00806	0.00840	0.0128	0.0569*	0.0687*	0.0812*	0.0373*
	(0.000)	(0.000)	(0.015)	(0.655)	(0.591)	(0.335)	(0.000)	(0.000)	(0.000)	(0.003)
Exp 4	0.117*	0.0495*	0.0530*	0.0595*	0.0521*	0.0425*	0.0868*	0.0877*	0.0837*	0.102*
	(0.000)	(0.002)	(0.002)	(0.000)	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 5	0.0763*	0.0630*	0.124*	0.0868*	0.0865*	0.0738*	0.0794*	0.0935*	0.0772*	0.0820*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 6	0.122*	0.116*	0.119*	0.0935*	0.0959*	0.0657*	0.0905*	0.0956*	0.0854*	0.0941*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 7	0.139*	0.102*	0.101*	0.104*	0.0812*	0.0669*	0.0743*	0.0944*	0.0673*	0.0749*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 8	0.146*	0.118*	0.100*	0.0889*	0.0859*	0.0788*	0.0730*	0.0767*	0.0621*	0.0634*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 9	0.122*	0.0919*	0.0929*	0.0780*	0.0758*	0.0453*	0.0567*	0.0667*	0.0557*	0.0511*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 10	0.109*	0.0796*	0.0745*	0.0702*	0.0537*	0.0432*	0.0378*	0.0431*	0.0426*	0.0277*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.026)
N	15.5	19.9	20.7	21.3	22.5	23.4	25.0	24.3	23.1	20.5

Notes: This table presents the returns to IT-specialized majors in terms of log earnings for different cohorts (1998-2007) and years of potential experience (0-10). Panel A shows results controlling for Grade 9 GPA, while Panel B shows results controlling for Grade 9 Math scores. Each cell represents the coefficient on the interaction between the IT-specialized major indicator and the corresponding experience year, estimated separately for each cohort. Standard errors are reported in parentheses. All regressions include controls for sex, high school fixed effects, and college fixed effects. Standard errors are clustered at the individual level. * indicates significance at the 5% level. N represents the number of observations in thousands, which is the same for both panels.

Appendix Table A5. Returns to IT-Specialized Majors: IT Employment Probability

Cohort	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Panel A: Controlling for Grade 9 GPA										
Exp 0	0.451*	0.519*	0.510*	0.415*	0.269*	0.164*	0.167*	0.212*	0.248*	0.288*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 1	0.477*	0.529*	0.526*	0.384*	0.234*	0.203*	0.233*	0.299*	0.301*	0.312*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 2	0.504*	0.526*	0.482*	0.369*	0.255*	0.262*	0.264*	0.349*	0.309*	0.341*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 3	0.477*	0.499*	0.443*	0.346*	0.304*	0.299*	0.294*	0.345*	0.318*	0.340*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 4	0.479*	0.481*	0.437*	0.370*	0.321*	0.329*	0.311*	0.352*	0.309*	0.337*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 5	0.460*	0.466*	0.438*	0.380*	0.346*	0.338*	0.319*	0.345*	0.320*	0.339*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 6	0.474*	0.455*	0.446*	0.407*	0.347*	0.335*	0.308*	0.342*	0.325*	0.346*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 7	0.496*	0.458*	0.458*	0.399*	0.346*	0.328*	0.309*	0.339*	0.324*	0.333*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 8	0.470*	0.456*	0.434*	0.372*	0.348*	0.334*	0.298*	0.337*	0.324*	0.327*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 9	0.468*	0.434*	0.436*	0.381*	0.367*	0.337*	0.293*	0.335*	0.313*	0.369*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 10	0.425*	0.438*	0.448*	0.397*	0.362*	0.317*	0.287*	0.328*	0.337*	0.371*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Controlling for Grade 9 Math Score										
Exp 0	0.450*	0.517*	0.508*	0.413*	0.267*	0.163*	0.166*	0.210*	0.247*	0.287*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 1	0.475*	0.528*	0.525*	0.382*	0.232*	0.201*	0.231*	0.297*	0.300*	0.310*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 2	0.502*	0.524*	0.480*	0.368*	0.254*	0.260*	0.262*	0.347*	0.307*	0.340*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 3	0.475*	0.497*	0.441*	0.345*	0.303*	0.297*	0.292*	0.343*	0.316*	0.338*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 4	0.477*	0.479*	0.435*	0.368*	0.319*	0.328*	0.309*	0.350*	0.308*	0.336*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 5	0.458*	0.464*	0.437*	0.379*	0.344*	0.337*	0.318*	0.343*	0.318*	0.338*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 6	0.471*	0.453*	0.445*	0.405*	0.346*	0.333*	0.307*	0.341*	0.324*	0.345*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 7	0.493*	0.456*	0.456*	0.397*	0.345*	0.326*	0.307*	0.338*	0.323*	0.331*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 8	0.468*	0.454*	0.432*	0.371*	0.346*	0.333*	0.297*	0.335*	0.322*	0.325*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 9	0.466*	0.432*	0.434*	0.379*	0.365*	0.336*	0.292*	0.333*	0.312*	0.368*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 10	0.423*	0.436*	0.446*	0.396*	0.360*	0.316*	0.285*	0.326*	0.336*	0.369*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	15.5	19.9	20.7	21.3	22.5	23.4	25.0	24.3	23.1	20.5

Notes: This table presents the returns to IT-specialized majors in terms of IT employment probability for different cohorts (1998-2007) and years of potential experience (0-10). Panel A shows results controlling for Grade 9 GPA, while Panel B shows results controlling for Grade 9 Math scores. Each cell represents the coefficient on the interaction between the IT-specialized major indicator and the corresponding experience year, estimated separately for each cohort. Standard errors are reported in parentheses. All regressions include controls for sex, high school fixed effects, and college fixed effects. Standard errors are clustered at the individual level. * indicates significance at the 5% level. N represents the number of observations in thousands, which is the same for both panels.

Appendix Table A6. Robustness Checks: Returns to IT Specialization on Log Earnings Across Different Model Specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Baseline (1998)	21.43*	20.85*	20.87*	21.82*	19.60*	20.19*	18.71*	20.22*	22.69*	20.29*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Diff in 1999	0.980*	1.403*	1.353*	-0.574	1.804*	0.935*	1.491*	0.723	-1.093*	0.999*
	(0.009)	(0.000)	(0.000)	(0.134)	(0.000)	(0.012)	(0.000)	(0.053)	(0.005)	(0.008)
Diff in 2000	2.537*	3.281*	3.230*	0.775	3.829*	2.456*	3.462*	2.136*	-1.290*	2.096*
	(0.000)	(0.000)	(0.000)	(0.086)	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.000)
Diff in 2001	0.781	1.748*	1.732*	-0.818	2.813*	0.703	2.062*	0.366	-3.579*	0.701
	(0.103)	(0.000)	(0.000)	(0.094)	(0.000)	(0.141)	(0.000)	(0.444)	(0.000)	(0.143)
Diff in 2002	-5.499*	-4.414*	-4.395*	-5.893*	-2.911*	-5.580*	-3.979*	-5.899*	-8.714*	-5.466*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Diff in 2003	-9.788*	-8.675*	-8.656*	-9.156*	-6.809*	-9.853*	-8.112*	-10.13*	-11.88*	-9.425*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Diff in 2004	-11.10*	-10.04*	-10.05*	-9.774*	-7.895*	-11.13*	-9.333*	-11.38*	-12.48*	-10.56*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Diff in 2005	-11.62*	-10.68*	-10.75*	-10.29*	-8.367*	-11.58*	-9.799*	-11.81*	-13.04*	-10.81*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Diff in 2006	-12.11*	-11.38*	-11.52*	-10.97*	-9.031*	-12.00*	-10.32*	-12.29*	-13.43*	-11.23*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Diff in 2007	-12.61*	-12.14*	-12.36*	-11.91*	-9.731*	-12.39*	-10.88*	-12.78*	-14.14*	-11.61*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Change 01-05	-12.40	-12.43	-12.48	-9.470	-11.18	-12.28	-11.86	-12.17	-9.463	-11.51
N (millions)	2.59m	2.59m	2.59m	2.59m	2.59m	2.59m	2.59m	2.59m	2.59m	2.59m
Spec	Quad Age	Cubic Age	Age FE	Year-Cohort	Exp Bin FE	Quad Age X Sex	Cubic Age X Sex	Age FE X Sex	Year-Cohort X Sex	Exp Bin FE X Sex

Note: This table presents robustness checks for the returns to IT specialization on log earnings. Each column represents a different specification as indicated in the bottom rows. The baseline row shows the initial difference between IT specialists and generalists in 1998. Subsequent rows show changes from this baseline for each year. The Change0105 row represents the relative change between 2001 and 2005. Coefficients and differences are expressed in log points. P-values are in parentheses. * indicates significance at the 5% level. N represents the number of observations in millions.