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Essays on the economics of specialized skills

Tianze Liu

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* Public economics
* Macroeconomics
* Microeconometrics
* Environmental economics
* Housing and urban economics

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Abstract
Liu, T. 2025. Essays on the Economics of Specialized Skills. *Economic studies* 227. 125 pp. Uppsala: Department of Economics, Uppsala University. ISBN 978-91-506-3125-8.

Essay I: This paper studies how industry-specific shocks affect workers with specialized skills, focusing on the impact of the burst of the dotcom bubble on the careers of IT-specialized college graduates in Sweden. Graduates entering the labor market during the bust faced sharp initial earnings penalties and lower probabilities of IT sector employment compared to boom cohorts. However, they exhibited remarkable resilience, recovering earnings by leveraging their skills in high-paying, non-IT occupations. Incumbent IT workers, while remaining within the IT sector, experienced a decline in earnings as they moved to lower-premium firms.

Essay II: We study local labor market effects from massive boom-bust movements in the IT sector. We use Swedish register data, exploring regional variation in the exposure to the IT boom-bust cycle around year 2000. Our results show clear evidence of pro-cyclical spillovers, in particular affecting earnings in local construction, housing, and business services. The results suggest that regions that attract IT-firms also expose themselves to larger earnings variability in other sectors.

Essay III: This paper examines how university applicants in China respond to a government policy that designates specific university-discipline units as centers of excellence. Using a Difference-in-Differences approach, we analyze the policy's impact at the discipline level. We find that the excellence designation attracts higher-ranking applicants to designated units, significantly increasing competition within those disciplines. Furthermore, we observe spillover effects within universities: non-designated disciplines also benefit from increased competition, likely due to students perceiving an overall enhancement in quality. These findings underscore how discipline-specific designations can elevate not only the designated units but also other fields within the same institution, shaping student decisions and elevating the university's overall competitiveness.

Keywords: specialized human capital, IT industry, higher education policy

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To my family

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I could never have reached this point without the unwavering support of my family. 爸爸妈妈，感谢你们一直以来的支持和鼓励。也以此文献给我的奶奶，并以此追思在这期间离开我的爷爷。

Finally, to my wife Meng Meng—no words are enough. Your love, patience, and endless belief in me carried me through every setback. This thesis is as much yours as it is mine, and I dedicate it to you.

Uppsala, June 2025

Contents

Introduction

The information technology (IT) sector is widely recognized as a critical engine of economic growth, driving innovation and productivity across the global economy (Oliner and Sichel, 2000; Jorgenson, 2001). Its transformative power reshapes industries, creates new markets, and fundamentally alters the nature of work. As illustrated in Figure 1, the share of the IT sector in total gross value added has trended upwards in both Sweden and the United States since 1990s. As a result, policymakers at national, regional, and local levels invest considerable effort and resources in attracting IT firms and fostering high-tech clusters, viewing them as cornerstones of 21st-century prosperity. The promise of high-wage jobs, knowledge spillovers, and enhanced competitiveness makes the cultivation of a vibrant IT sector a central goal of modern industrial policy.

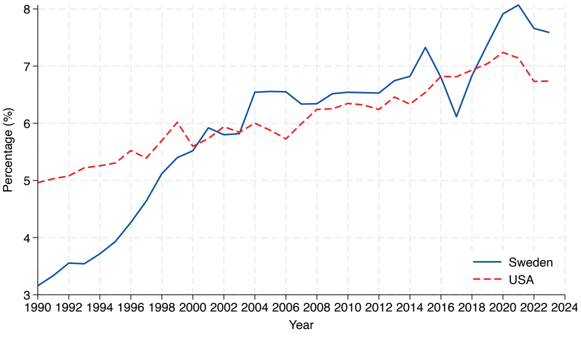

Figure 1. IT Sector Share of Gross Value Added for Sweden and USA

Notes: This figure plots the share of the IT sector in gross value added for both Sweden and the USA. The data is sourced from the OECD.

However, this powerful engine of growth is also characterized by significant volatility. The IT industry operates in a risky environment where rapid technological advances and speculative investment can fuel spectacular booms, followed by sharp and painful busts. The dot-com bubble of the late 1990s, the sector's contraction following the 2008 financial crisis, and the widespread tech layoffs of the 2020s are stark reminders of this inherent instability. These cycles have profound consequences that ripple far beyond the balance sheets of tech firms. They deeply affect the specialized workforce that powers the industry, the local economies where these firms cluster, and the educational systems tasked with producing the next generation of talent. Understanding the multifaceted economic impacts of this volatility is therefore not just an academic exercise; it is crucial for crafting resilient economic and social policy. This dissertation confronts this challenge by investigating the life cycle of specialized human capital in the context of the volatile high-tech economy.

The central theme of this thesis is the economics of specialized human capital, examined through the lens of the IT sector. The decision to invest in specialized skills—such as pursuing a degree in computer science—is a high-stakes gamble for individuals, promising high rewards but also exposing them to significant industry-specific risks. To fully grasp the implications of this gamble, we must analyze it from three interconnected perspectives, which form the structure of this thesis. First, we must understand the "supply side": how is this specialized talent pool formed? What role do government policies and information signals play in guiding students toward fields like IT? Second, we must examine the direct consequences for individuals: how do major industry cycles affect the careers and earnings of those who have invested in specialized skills? How do these effects differ for new graduates versus experienced workers? And third, we must assess the broader "demand-side" and equilibrium effects: what are the spillover consequences for the local economies that host these high-tech clusters? Does the rising tide of an IT boom lift all boats, and who is most vulnerable when the tide goes out?

This thesis investigates these questions through three distinct but complementary essays. The first essay forms the core of the analysis, examining how a major IT industry cycle—the dot-com boom and bust—affected the returns to specialized human capital, measured by college majors. The second essay broadens this perspective by investigating the spillover effects of the same IT cycle on the wider local economy, moving from the individual to the regional level. The third and final essay takes a step further back in the causal chain to explore the supply side of this equation: how government education policy and excellence designations influence the student selection process and competition for the very types of specialized programs that are central to the first two essays. Together, these essays provide a comprehensive analysis of the life cycle of IT-driven economic shocks—from the formation of specialized talent to the direct impacts on their careers and the indirect consequences for their local communities.

Situating the Research: A Review of the Literature

This dissertation is situated at the intersection of three major fields within economics: the economics of education, labor economics, and urban and regional economics. It builds upon and contributes to a rich body of literature in each area.

First, the thesis engages with the extensive literature on the returns to education, particularly the returns to college majors. It is well-established that the choice of major is one of the most important financial decisions an individual makes, with dramatic differences in lifetime earnings across fields (Kirkeboen et al., 2016; Andrews et al., 2024). STEM and economics majors, for instance, typically yield substantial earnings premiums. However, much of this research estimates average returns, often abstracting from the dimension of risk. My work adds to a growing literature that considers the volatility and uncertainty of these returns. The value of specialized skills is not static; it is tied to the fortunes of the industries that demand them. This connects my research to studies on graduating in a recession, which show that adverse initial labor market conditions can have persistent negative effects on careers (Oreopoulos et al., 2012; Schwandt and von Wachter, 2019). Essay I extends this logic to an *industry-specific* shock, showing that even high-return majors like IT can be highly vulnerable, creating a cyclical mismatch between skills and opportunities (Liu et al., 2016). Furthermore, it speaks to the literature on skill obsolescence, which finds that the value of applied skills can depreciate rapidly as technology evolves, forcing workers to adapt or be left behind (Deming and Noray, 2020; Horton and Tambe, 2025).

Second, the thesis contributes to the literature on local labor markets, agglomeration, and economic spillovers. A central question in urban economics is why firms and workers cluster geographically. The literature points to agglomeration economies, where density facilitates knowledge sharing, labor market pooling, and access to specialized inputs. High-tech industries are known to be particularly prone to clustering, leading to vibrant local economies like Silicon Valley. A key strand of this literature examines local multipliers, finding that the creation of a job in a high-skilled, tradable sector (like tech) can create multiple additional jobs in the local non-tradable sector (like restaurants and construction) (Moretti, 2010; Moretti and Thulin, 2013). This provides a powerful argument for policies aimed at attracting high-tech firms. However, this literature has paid less attention to the downside of such specialization. Essay II contributes by documenting the full boom-bust cycle of spillovers, showing that the multiplier effect is pro-cyclical. The forces that fuel prosperity during a boom can amplify the pain during a bust, creating significant volatility for the entire local economy. This finding aligns with research on the "resource curse" and the transitional costs of sectoral shocks, which show how dependence on a single volatile industry can be a double-edged sword (Walker, 2013; Lorentzen, 2024). It also explores the mechanisms of these spillovers, considering whether they operate through reinforcing demand channels or through mitigating competition for skilled labor (Bai et al., 2024).

Third, the thesis speaks to the literature on the economics of education, focusing on how human capital is formed. The supply of specialized workers is not fixed; it responds to market signals and policy interventions. A vast body of work has explored how students make decisions about higher education, emphasizing the role of information in shaping these choices. University rankings, for example, have been shown to significantly influence application patterns and student sorting (Sauder and Lancaster, 2006; Luca and Smith, 2013; Broecke, 2015). Essay III builds on this literature by examining a particularly powerful and official information signal: a national excellence initiative in China. While previous studies have looked at university-level designations (Fischer and Kampkötter, 2017), this is one of the first to analyze a policy that designates excellence at the granular *discipline level*. This allows for a cleaner identification of how such signals channel talent, not just to elite universities but to specific fields of study targeted by policymakers. It provides a unique window into the mechanisms by which a government can steer the development of its national human capital base, a process that ultimately feeds the pipeline of specialized workers whose careers are analyzed in the other two essays.

Methodology and Geographic Scope

Beyond the thematic connections, the essays in this dissertation are united by a common methodological approach and a distinct geographic scope that, together, form a core part of its contribution. Each essay moves beyond correlation to identify the causal effects of economic shocks and policy interventions by applying quasi-experimental research designs to large-scale, granular data.

The empirical strategy is powered by two different but equally powerful types of datasets. For the analyses of the Swedish labor market (Essays I and II), this thesis leverages the country's world-renowned and comprehensive administrative registers. This longitudinal data makes it possible to track the complete career and earnings histories of individuals and link them to firm and regional characteristics, providing a uniquely powerful lens for studying labor market adjustments. For the analysis of China's higher education system (Essay III), the thesis constructs a novel and extensive dataset compiled from a public web repository of university admission outcomes, supplemented with official information from provincial authorities. While not administrative microdata in the same vein as the Swedish registers, this dataset is similarly large in scale, offering an unprecedented and granular view of student choices across thousands of academic programs over multiple years.

The geographic scope of the thesis is another defining feature. By drawing evidence from two vastly different institutional contexts—Sweden and China—the dissertation implicitly engages in a comparative exercise. Sweden, a high-income social democracy with a highly developed IT sector, serves as an ideal laboratory for studying how individual careers and local markets adjust to shocks within a mature, open economy. In contrast, China's rapidly developing, state-influenced economy provides a unique setting to analyze the power of large-scale government policy in shaping human capital formation. While the findings are specific to their contexts, the juxtaposition of these two cases allows for a richer understanding of the underlying economic principles. The fundamental trade-offs of specialization, the power of information signals, and the reality of local economic linkages are universal phenomena, and examining them in these diverse settings enhances the generalizability and robustness of the conclusions drawn.

Policy Relevance and Contributions

By bridging these distinct bodies of literature, this dissertation offers a holistic perspective with significant policy implications. The findings speak directly to governments, educational institutions, and individuals navigating the complexities of the modern knowledge economy.

For local and national governments, the research provides a nuanced perspective on industrial policy. While attracting high-tech industries remains a laudable goal, policymakers must recognize and plan for the associated volatility. The pro-cyclical spillovers documented in Essay II suggest that a strategy focused solely on attracting tech firms without considering the downside risks is incomplete. It implies a need for complementary policies, such as building robust social safety nets, promoting economic diversification, and investing in workforce retraining programs that can help buffer local economies and vulnerable workers during industry downturns.

For education policymakers and university administrators, the thesis offers two key insights. First, Essay III demonstrates that well-designed excellence initiatives can be a powerful tool for channeling talent toward strategic fields. The finding of significant intra-university spillovers, where the prestige of a designated discipline lifts the entire institution, suggests that such policies can have a broad and positive impact on institutional quality. Second, the findings from Essay I serve as a crucial reminder that education should not only be about specialization but also about fostering adaptability. The fact that young IT graduates were able to recover from a massive industry shock by redeploying their skills in other sectors highlights the value of foundational, transferable skills that transcend any single industry. This suggests that curricula should balance deep technical expertise with broader analytical and problem-solving abilities.

Finally, for individuals—students making educational choices and workers managing their careers—this thesis underscores the fundamental trade-off between specialization and flexibility. The high potential returns of specializing in a field like IT are undeniable, but so are the risks. The findings illustrate that career resilience, especially for new entrants, depends on the ability to adapt and leverage one's human capital in new and unforeseen ways.

In summary, this dissertation provides new, credible evidence on the life cycle of specialized skills in the modern economy. Methodologically, the three essays are united by their reliance on large-scale administrative microdata and quasi-experimental research designs to identify causal effects. By examining the formation of human capital (Essay III), its direct risks and rewards (Essay I), and its aggregate impact on regional economies (Essay II), the thesis tells a comprehensive story about the opportunities and challenges of economic specialization in our increasingly volatile world.

The Essays

Essay I: How IT-Specialized Majors Pay Off: Evidence from an IT Industry Shock

This essay investigates how an industry-specific shock affects the careers of workers with specialized skills, focusing on the burst of the dot-com bubble in Sweden. Using comprehensive Swedish administrative data, I analyze the short- and long-term consequences for two distinct groups: new labor market entrants who graduated during the cycle and experienced incumbent workers who were already established in the labor market. The findings reveal a sharp contrast in their adjustment mechanisms.

Graduates who entered the labor market during the bust years faced a substantial initial earnings penalty of 27 log points compared to boom-era cohorts. Their probability of securing employment in the IT sector plummeted from approximately 50 percent for the 2000 cohort to just 20 percent for the 2003 cohort. However, these entrants demonstrated remarkable resilience, recovering most of the initial earnings gap within nine years. This recovery was not driven by re-entry into the IT sector—where their employment probability remained persistently 15 percentage points lower—but by leveraging their skills in other high-paying, non-IT occupations.

In contrast, incumbent IT workers largely remained within the IT sector despite a sharp 16-log-point decline in the returns to their major. Their primary adjustment margin was at the firm level; they absorbed the shock by moving to lower-premium firms within the IT industry, which explains the majority of their earnings decline. This chapter underscores that while specialized skills are highly vulnerable to industry cycles, the ability to weather such shocks depends critically on career experience, with younger workers showing greater adaptability by redeploying their human capital across sectors.

Essay II: Local Spillover Effects of IT-Sector Booms and Busts

This essay (co-authored with Oskar Nordström Skans) shifts the focus from the individual worker to the local economy, examining the spillover effects of the IT boom-bust cycle on non-IT sectors in Sweden. Exploiting regional variation in the pre-cycle concentration of the IT industry, we analyze how local labor markets with higher IT exposure fared compared to those with less. The results show significant and clear *pro-cyclical* spillover effects.

During the IT boom leading up to 2001, earnings in the local non-IT private sector grew systematically faster in municipalities with a larger initial IT share. This pattern sharply reversed during the bust, with these same municipalities experiencing a relative decline in non-IT earnings. These effects were primarily driven by changes in employment rather than wages, and they were most pronounced for younger workers. The spillovers were also highly heterogeneous across industries, with the largest cyclical swings observed in construction and finance.

Crucially, the cycle amplified local earnings inequality. During the boom, the positive spillovers primarily benefited high-educated workers, whereas during the bust, the negative shock was felt most acutely by the least educated. The essay concludes that attracting a vibrant, high-tech sector is a double-edged sword for local economies: it can fuel prosperity during good times but also introduces significant volatility that disproportionately harms more vulnerable workers during downturns.

Essay III: You Are the Elite Now: Admission Effects of an Excellence Initiative in the Chinese Higher Education System

This essay (co-authored with Meng Meng) investigates the *formation* of specialized human capital by analyzing how a major government policy in China, the "Double First-Class Initiative," influences student behavior and university competition. This policy designates specific university-discipline pairings as centers of excellence, providing a strong quality signal to over 10 million university applicants annually. Using a Difference-in-Differences approach on a novel dataset of university admission outcomes, we examine the impact of this excellence designation.

The findings show that the policy is highly effective at channeling talent. Disciplines designated as a "First-Class Discipline" (FCD) experienced a significant increase in admission competition, attracting higher-ranking students. The effect was an average increase of 1.5 percentiles in the admission threshold, meaning the last-admitted student had to outperform thousands of additional peers. The effect was largest in less traditionally popular fields like Agriculture, suggesting the policy successfully directed talent toward targeted areas.

Furthermore, the analysis reveals significant spillover effects *within* universities. Non-designated disciplines at universities hosting at least one FCD also saw their admission competition rise, suggesting students perceive an overall enhancement in institutional quality. There was no significant change in the competition gap between FCD and non-FCD programs within the same university after the policy. This essay demonstrates that granular, discipline-level quality signals are a powerful tool for shaping student choice, not only elevating the targeted programs but also lifting the competitive standing of the entire institution.

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Essay I. How IT-Specialized Majors Pay Off: Evidence from an IT Industry Shock

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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.

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.

[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

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.

When studying entrant workers, I track graduation cohorts in IT-specialized fields and compare their trajectories to graduates from other fields for both boom and bust cohorts. To estimate the returns to IT majors, I compare students with similar ninth-grade GPAs who graduated from the same high school, attended the same college, and belonged to the same cohort but chose IT majors versus other fields of study[4]. When comparing across graduation cohorts, 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. Conceptually, this aligns with a large body of literature on graduating during a recession (see references below), though I rely on a sectoral shock rather than regional unemployment rates. I use data on student grades to show that selection on personal abilities across majors is unrelated to the dotcom cycle.

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. The likelihood of working in the IT sector at labor market entry plummeted from about 50 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 9 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

[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] This approach is similar in spirit to Andrews et al. (2024), who use a nearly identical identification strategy to study the distributional and career effects of returns to fields of study.

lower a decade later. Instead, their earnings recovery occurs through transitioning into other higher-paying, non-IT occupations.

For incumbent workers who entered the labor market before the boom years, the effects were significant as well, but followed a very different pattern compared to entrants. Using models with individual fixed effects, I show that their overall returns to IT majors declined sharply by about 16 log points from the boom to the bust years. In contrast to entrants, incumbents resiliently remained *within* the IT sector, despite shifting toward lower-premium firms within the industry, which explains most of the earnings decline.

My analysis merges perspectives from three different literatures, describing the impact of graduating in a recession, the labor market consequences of major choice, and the impact of industrial shocks, respectively. To the best of my knowledge, 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. My focus on the IT bust around the year 2000 aligns with the arguments of Beaudry et al. (2016), who posit that this event marked a significant turning point, initiating a "great reversal" in the demand for skill where high-skilled workers began moving down the occupational ladder. 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). Recent work by Schmieder et al. (2023) provides a potential mechanism for these severe effects, showing that earnings losses from displacement are highly cyclical and that a key driver of these losses is the re-employment at lower-paying firms. 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. The high returns to IT majors in the period I study should be seen in the context of broader labor market trends, such as the job polarization documented by Autor and Dorn (2009), which saw simultaneous growth in high- and low-skilled jobs. 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 in their early 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. Complementing this view, Horton and Tambe (2025) study the decline of a specific technical skill (Adobe Flash) and find that the supply of developers adjusted rapidly, not necessarily due to wage declines, but because the expected future value of the skill collapsed, prompting younger workers with fallback options to exit. This provides a clear micro-foundation for how workers might respond to skill obsolescence. The finding on IT major returns within industries turning negative in the late stage of a career is consistent with these results.

Lastly, this paper provides new insights into the consequences of industry shocks. A central theme in technological transitions is the speed of labor market adjustment, which Adão et al. (2024) argue is slower when an innovation requires skills that are highly specific and different from those in the rest of the economy. In such cases, adjustment is driven more by the gradual entry of new cohorts than by the reallocation of incumbents, a framework that is particularly relevant for the ICT transition I study. 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.

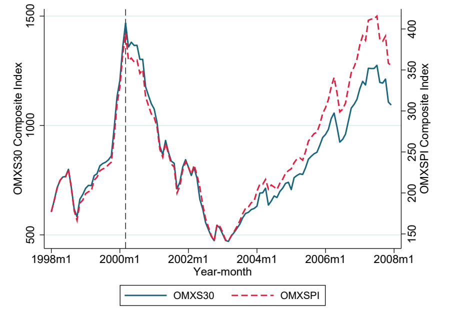
2 The Dotcom Bubble and Its Impact on Sweden's IT Labor Market

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 potential of the internet and digital technologies.

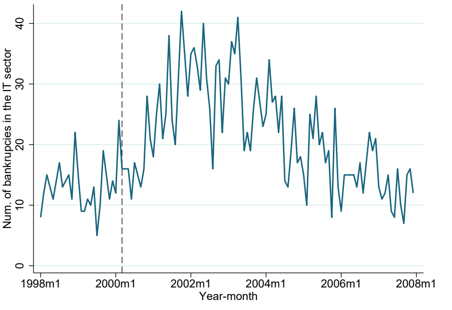
The crash that followed in 2000 led to a significant market correction, severely affecting IT firms worldwide, including those in Sweden. As shown in Panel (b) of Figure 1, the number of bankruptcies in Sweden's IT sector increased sharply in the aftermath of the stock market crash. Many firms that had 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



(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.

indices dropping by 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 Descriptive Analysis

3.1 Main Analysis Data and Sample Construction

The main data source for worker-level information comes from Swedish administrative registers and educational registers. These datasets offer detailed labor market information, including annual pre-tax 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. Further details on the variables and the treatment of earnings are provided in Section A.1.

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 Section A.2. 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.

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. Incumbent workers are defined as those who graduated prior to 1998. This choice encompasses 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.

To complement the main analysis, I incorporate supplementary data from Sweden's Wage Structure Statistics for the Private Sector. This dataset provides detailed wage, occupational, and employer information. This allows me to define IT occupations and estimate firm and occupational premia. Merging this with the primary analysis sample captures 30% of observations. The Section A.2 provides further details on this dataset and variable construction.

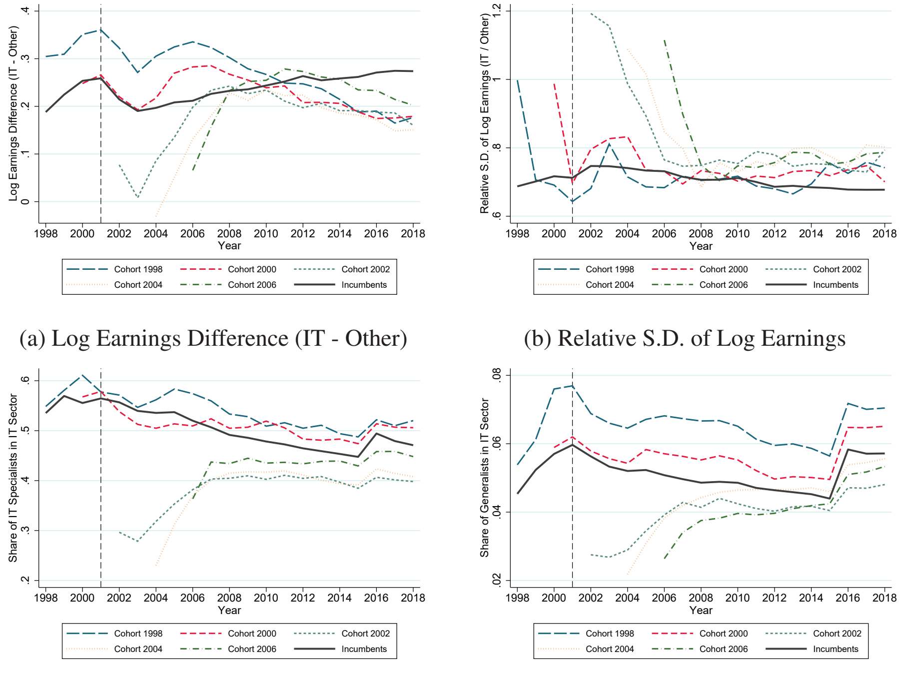
3.2 Descriptive Evidence

Figure 2 summarizes key labor market outcomes from 1998 to 2018 for selected graduation cohorts—including incumbents (graduating before 1997) and cohorts graduating around the dotcom cycle (1998–2006)—highlighting both career-stage and cohort differences.

Panel (a) shows the log earnings difference between IT majors and other graduates. Entrants from the boom cohorts (1998, 2000) started with substantial earnings premiums, peaking around graduation but gradually declining. In contrast, entrants from bust cohorts (2002, 2004) initially experienced negative or minimal earnings differentials, reflecting weakened demand post-bust. Incumbents maintained higher earnings differentials of 20–25 log points during the boom, but their advantage declined slightly after the crash, converging closer to entrant levels in subsequent years. Overall, early earnings differences diminished for all groups over time, although incumbents consistently held a relative advantage.

Panel (b) illustrates the relative earnings dispersion (standard deviation ratio) between IT and other majors. Post-bust entrants faced significantly greater earnings variability initially, indicating heightened uncertainty and heterogeneous early outcomes. This volatility declined with experience, aligning eventually with earlier cohorts. Incumbents experienced stable dispersion pre-bust, followed by a sharp increase immediately after the crash, suggesting diverse adaptability to industry changes.

Panel (c) tracks IT sector employment among IT graduates. Entrants' sectoral employment dramatically declined from nearly 55 percent for the 2000 cohort to around 20 percent for post-bust cohorts, reflecting diminished sectoral hiring capacity. Despite gradual recovery, the employment share never fully rebounded, suggesting structural labor market changes. Incumbents, in contrast, maintained relatively stable IT-sector employment throughout, with only a modest decline post-bust.



(a) Log Earnings Difference (IT - Other)

(b) Relative S.D. of Log Earnings

(c) IT Sector Employment Share (IT)

(d) IT Sector Employment Share (Other)

Figure 2. Descriptive Evidence for IT Graduates, 1998-2018

Notes: This figure shows the evolution of descriptive labor market outcomes from 1998 to 2018 across selected graduation cohorts. In addition to cohorts graduating between 1998 and 2006, the sample includes incumbents (those who graduated before 1997). Each line represents a distinct cohort group. Panel (a) displays the difference in mean log annual earnings between graduates from IT-related majors and those from other majors. Panel (b) shows the ratio of the standard deviation of log earnings for IT majors to that of other majors. Panels (c) and (d) present the share of graduates from IT majors and other majors, respectively, who are employed in the IT sector. The vertical dashed line at 2001 in each panel marks the burst of the dot-com bubble.

Panel (d) displays IT sector employment for other majors. Before the bust, about 6 – 9 percent of entrants with other majors worked in IT-related roles, but this share fell sharply post-crash to around 2 percent, indicating narrowed sectoral opportunities beyond IT graduates. Incumbents with other majors saw similar but milder declines, reflecting their comparatively limited exposure to the sector's contraction.

These descriptive patterns underscore how entrants experienced greater volatility and lasting disadvantage compared to incumbents, whose established careers buffered against the worst effects of the shock. These insights set the stage for a deeper analysis of causal effects in the subsequent sections.

4 Empirical Strategy

4.1 Specification for Entrants

I estimate the effects of IT majors on log earnings and IT sector employment for new labor market entrants. For each cohort graduating in a different phase of the dot-com cycle, I run the following econometric model separately:

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

where y_{it} denotes the outcome of interest for individual i in year t from a specific graduating cohort. $S_{m(i)}$ is an indicator variable equal to 1 for graduates from IT majors and 0 for graduates from other majors.[5] The vector Z_i includes time-invariant controls: gender, ninth-grade GPA, high school fixed effects, and college fixed effects. γ_t represents year fixed effects. The coefficient of interest, β_t, measures the change in the equilibrium return to an IT major relative to other college majors, conditional on the controls.

The causal interpretation of β_t hinges on the Conditional Independence Assumption (CIA). This assumption states that, conditional on the rich set of controls in Z_i and the fixed effects, the choice of an IT major is independent of unobserved factors that determine potential earnings and employment outcomes. While this is a strong assumption, the detailed nature of the administrative data strengthens its credibility. Specifically, ninth-grade GPA serves as a proxy for pre-college academic ability and motivation[6]. High school and college fixed effects control for variation in institutional quality, peer groups, and local labor market connections. The comparison is therefore between individuals of the same gender who graduated in the same cohort, attended the same

[5] The results are robust to an alternative specification that uses a continuous measure of IT exposure for all majors to account for potential spillovers to the control group. See Section B.4 for the full methodology and results.

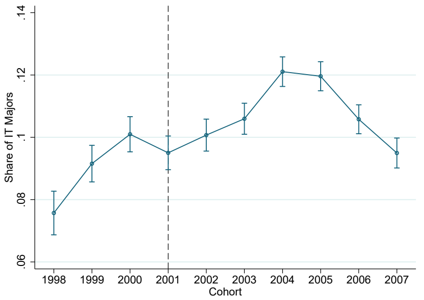
[6] To address potential concerns about the suitability of overall GPA as a measure of ability for sorting into IT-specialized majors, I conducted a robustness check using ninth-grade *math* scores as an alternative control. The results, presented in Table D6 and Table D7, demonstrate that the main findings remain highly consistent.

high school and college, and had similar academic abilities before entering college. This identification strategy, which leverages a rich set of observable characteristics to control for selection, is common in the literature on returns to education and is closely related to the methodology in Andrews et al. (2024).

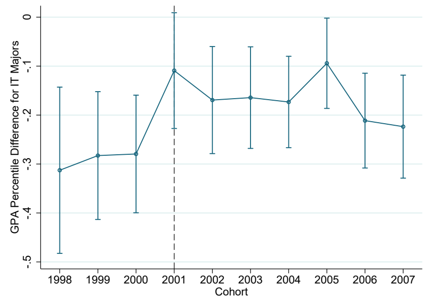
This specification relies on the Stable Unit Treatment Value Assumption (SUTVA), which consists of two components: no interference between units and treatment consistency. The no-interference assumption means that an individual's major choice does not directly alter the treatment or outcomes of another individual. While general equilibrium effects—such as increased supply of IT graduates influencing wages—can exist and may indeed be a mechanism behind the observed earnings differences, they do not necessarily violate SUTVA, provided they uniformly affect similarly defined treated individuals. In fact, panel (a) of Figure 3 shows only a moderate increase in the supply of IT graduates during this period. Hence, my estimates should be interpreted as capturing equilibrium effects specific to IT majors, under the assumption of no direct interference between individuals. The second component, treatment consistency, requires that the IT major designation represents a comparable set of skills and knowledge. I assume curriculum homogeneity, with college fixed effects capturing some variation in quality.

While the primary focus of this paper is on demand-side forces—how the labor market valuation of IT-specific skills evolved over the boom and bust—Figure 3 (a) shows that supply also responded to the cycle. The share of students selecting into IT majors increased for both boom and bust cohorts, who chose their fields of study during the pre-boom and boom years. This pattern suggests that students adjusted their choices in response to favorable market signals. Although this supply response is an important mechanism in its own right, my analysis focuses on estimating the return to IT specialization in equilibrium. I treat supply shifts as part of the forces shaping the equilibrium price of IT skills.

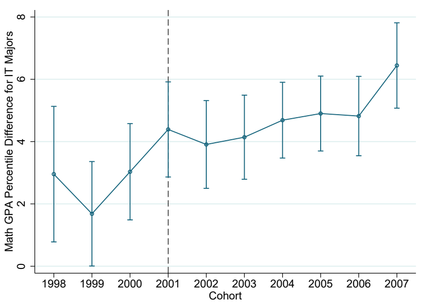
A crucial concern in studies spanning economic cycles is that the composition of students selecting into treatment may change relative to the control group. Figure 3 (b) shows that the gap in ninth-grade GPA between IT and non-IT majors changes little across cohorts, and Panel (c) reveals a similar stability for math grades. In contrast, Panel (d) indicates a shift in gender composition, with the share of females in IT majors declining relative to other fields for cohorts graduating after the dot-com bust. Since my main specification explicitly includes controls for gender, this observable shift in composition is accounted for in the analysis. Therefore, the stability of the academic selection metrics provides confidence in the validity of comparing cohorts to identify the returns to an IT major, conditional on the controls.



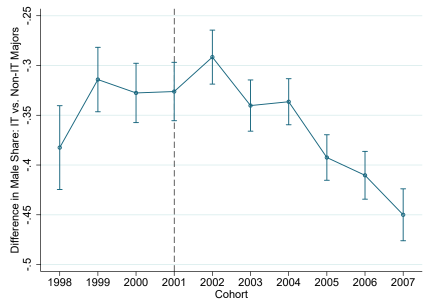
(a) Share of Students in IT Majors by Cohort



(b) Difference in Overall GPA (IT vs. Others)



(c) Difference in Math Grade (IT vs. Others)



(d) Difference in Share of Females (IT vs. Others)

Figure 3. Supply and Selection into IT Majors by Cohort

Notes: This figure illustrates selection patterns into IT majors across cohorts. Panel (a) plots the share of students majoring in IT by graduation cohort, based on regressions of an IT major indicator on cohort dummies. Panels (b), (c), and (d) present cohort-specific differences in characteristics between IT and non-IT majors. Each panel shows coefficients from regressions of the respective characteristic—ninth-grade GPA, ninth-grade math grade, and a female indicator—on cohort-by-IT-major interaction terms. No additional control variables are included. The vertical dashed line at 2001 marks the burst of the dot-com bubble.

4.2 Specification for Incumbents

For incumbent workers already active in the labor market, having access to pre-boom outcomes enables me to control for individual fixed effects. By tracking the same individuals over time, I employ a fixed effects model to account for unobserved, time-invariant heterogeneity. The specification is:

$$y_{it} = \alpha_i + \beta_t S_{m(i)} + \gamma_t + X_{it}\Gamma + \varepsilon_{it} \tag{2}$$

where y_{it} is the outcome for individual i in year t. The key term, α_i, is an individual-specific fixed effect that captures time-invariant characteristics, such as innate ability, motivation, or family background. The coefficient of interest, β_t, captures the premium for having an IT major in year t relative to the reference year of 1998. The model also includes year fixed effects (γ_t) to absorb common macroeconomic shocks and a vector of time-varying controls (X_{it}), which includes a quadratic in age interacted with gender.

The causal interpretation of β_t is derived from the fixed-effects framework. By including α_i, the model effectively controls for any selection into an IT major that is based on permanent individual traits. The estimate of β_t is therefore identified from *within-individual* changes in outcomes over time.

The primary advantage of this specification is that it allows for arbitrary correlation between the choice of major, $S_{m(i)}$, and the time-invariant unobservables captured in α_i. The crucial identifying assumption is that there are no time-varying unobserved characteristics that are correlated with both an individual's major and their outcomes over the business cycle. This comparison between the estimates from the incumbent model and the entrant model is instructive. While the entrant model relies on an assumption of selection on observables, the fixed-effects model for incumbents controls for selection on any time-invariant unobservable characteristic, providing a powerful point of comparison.

4.3 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 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[7].

[7] Specifically, I estimate $\ln(Wage_{it}) = \alpha_i + \psi_{j(i,t)} + X_{it}'\beta + \varepsilon_{it}$, where α_i captures time-invariant individual fixed effects, $\psi_{j(i,t)}$ denotes fixed effects for either the firm or occupation j that individual i is associated with at time t, and X_{it} includes time-varying controls such as a gender dummy interacted with a quadratic in age. This specification allows me to separate the contributions of worker and firm/occupation characteristics to wage determination.

The estimated firm (or occupation) effects are used as outcome variables in the main regressions to examine how IT majors sort into firms and occupations compared to other majors. 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.

5 Main Results: Earnings and Sorting into IT Sector

5.1 Results for Entrants

This subsection presents the regression results on earnings and IT sector sorting for IT *entrants* 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.

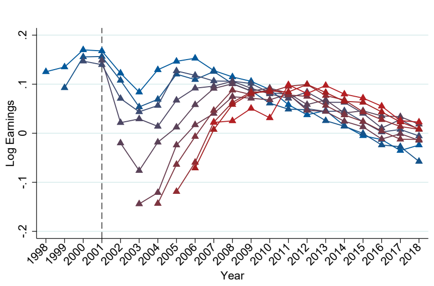
The effects on earnings

Figure 4 (a) shows the evolution of log earnings premiums to IT majors by graduation cohort over time. Blue lines represent earlier cohorts, and red lines indicate more recent ones. The timing of labor market entry plays a key role: cohorts entering before the dotcom crash enjoyed substantial initial premiums, while those entering after 2001 faced much lower or even negative returns. These differences reflect the sharp and immediate impact of the dotcom bust, particularly on new entrants. Panel (c) shows that the initial 27 log point gap in premiums between boom (1998–2001) and bust (2002–2004) cohorts.

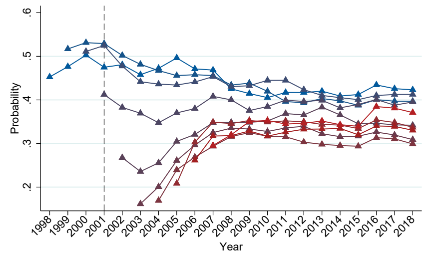
The figure highlights that the shock hit recent graduates hardest, while earlier cohorts saw only a modest decline in their premiums. This underscores how industry-specific shocks can have disproportionate effects on less experienced workers, shaping long-term returns depending on career timing (see Figure 5 for effects on incumbents).

Despite these initial gaps, returns tend to converge over time. Boom cohorts' high early premiums decline slightly, while bust cohorts recover steadily. By the tenth year post-graduation, earnings differences shrink to just around 6 percentage points (Panel (e)). This convergence suggests that early labor market shocks matter less as experience accumulates.

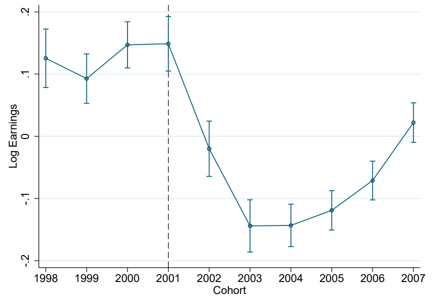
To unpack these dynamics, I decompose IT major returns into within-industry and industry-premium components (Section B.4). The analysis shows that early premiums for boom cohorts were driven by high within-industry returns. For bust cohorts, the eventual recovery stemmed from a similar channel—ris-



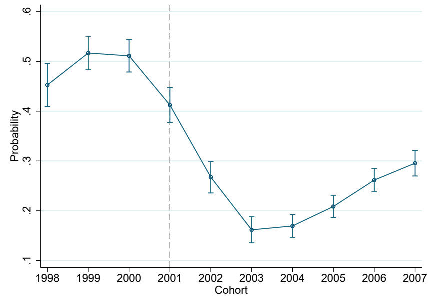
(a) Earnings



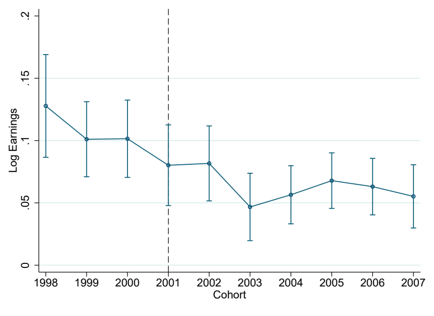
(b) IT sector employment



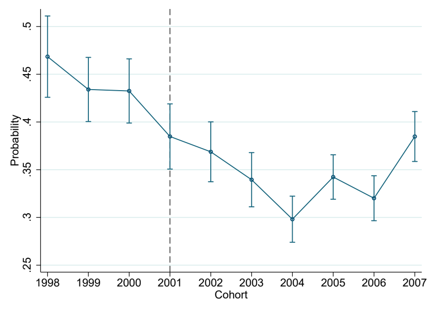
(c) Earnings (labor market entry)



(d) IT employment (labor market entry)



(e) Earnings (after 9 years)



(f) IT employment (after 9 years)

Figure 4. Effects of IT Majors on Earnings and IT Sector Sorting

Notes: This figure presents estimates of returns to IT majors for different graduation cohorts (1998–2007) over time. Panels (a), (c), and (e) show the log earnings differentials between IT and non-IT majors overall, at labor market entry, and nine years after graduation. Panels (b), (d), and (f) show the corresponding differentials in probabilities. The x-axis represents years in the first two panels and graduation cohorts in the other four. 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 that control for year, sex, 9th-grade GPA, high school fixed effects, and college fixed effects in equation (1). All estimates with standard errors are reported in Table D7.

ing returns to IT skills within non-IT sectors—highlighting how adaptation across industries shaped long-run outcomes.

The effects on IT sector employment

Figure 4 (b) shows cohort-specific probabilities of IT sector employment for IT-specialized graduates. Earlier cohorts exhibit consistently higher and more stable probabilities, while those graduating after the dotcom crash face a sharp decline in initial IT sector employment. This pattern closely mirrors the divergence in earnings outcomes across cohorts. Panel (d) shows that post-2001 graduates initially saw IT employment probabilities fall from nearly 50 to under 20 percentage points.

The gap between boom and bust cohorts persists over time. Although IT sector employment rises gradually for bust cohorts over their careers, they never fully catch up to earlier entrants. This suggests a lasting impact of early career shocks, which pushed many into non-IT industries. Even after 9 years, a 15-point gap remains between boom and bust cohorts (Panel (f)), emphasizing the strong path dependence in sectoral careers: favorable entry conditions anchor IT graduates within the industry, while adverse timing can redirect career paths permanently.

5.2 Results for Incumbents

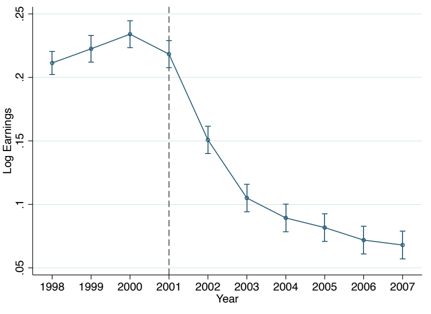
Figure 5 presents estimates of returns to IT majors among incumbent workers, with the reference-year mean level added using equation (2).[8] Panel (a) shows that log earnings premiums for incumbents rose modestly—about 2 log points above 1998 levels—during the boom, then declined sharply by 15 log points after the bust.[9] This drop suggests a substantial erosion of the earnings advantage for IT majors following the crash.

Decomposing these returns reveals that the decline was driven by both falling within-industry returns to IT skills (around 60%) and a shrinking IT sector premium (about 40%) (Figure D7).

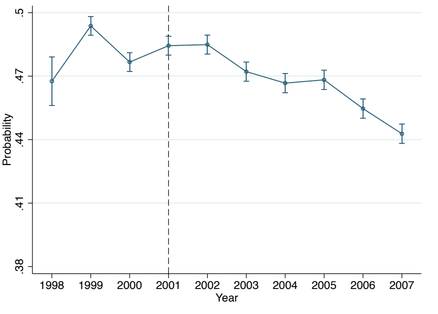
Panel (b) shows that IT majors were 47 percent more likely than other majors to work in the IT sector during the boom, with only a modest post-bust decline of under 3 percentage points. This persistence suggests that incumbents remained attached to the IT sector, likely due to industry-specific human

[8]These results are not sensitive to various specifications (shown in Figure D8 and Table D8). 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.

[9]Without individual fixed effects, the premium peaked at 20–23 log points and later fell below 10 (see Figure D6).



(a) Changes in IT major returns on earnings



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

Figure 5. Changes in Labor Market Outcomes of Incumbent IT Specialists by Year

Notes: This figure presents regression estimates of labor market outcomes for IT majors compared to other majors from 1998 to 2007. Panel (a) shows changes in the returns to IT-specialized majors in terms of log earnings, while Panel (b) displays changes in the probability differential of IT sector employment for IT majors relative to other majors. All regressions control for year fixed effects, individual fixed effects, and a quadratic term of age interacted with sex (see equation (2)). The year 1998 serves as the reference year in all panels. The coefficients in each year are shown as the sum of the estimated effect for that year and the baseline value from a similar regression without individual fixed effects in 1998. 95% confidence intervals are reported.

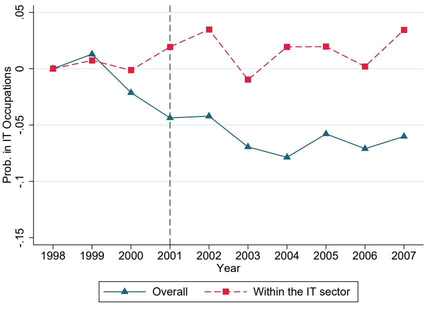
capital, search frictions, or employment protection policies for long-tenured workers in Sweden (Below and Thoursie, 2008).

6 Mechanisms: Occupations and Firm Dynamics

The previous results reveal distinct labor market outcomes for entrants and incumbents during the IT boom-bust cycle. Entrants initially faced lower earnings and limited IT sector opportunities but gradually caught up, despite relatively low re-entry into the IT sector. Incumbents, however, saw significant declines in IT premiums without substantial sectoral shifts. This raises key questions: How did entrants recover their earnings without returning to the IT sector, and why did incumbents lose their IT premiums without changing sectors? This section examines these mechanisms through occupational sorting and firm dynamics.

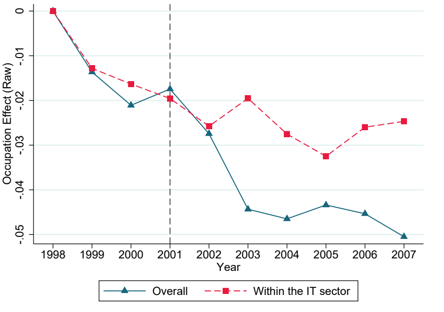
Figure 6 presents the channels of IT occupation sorting, occupation premiums, and firm premiums for both entrant and incumbent IT specialists. For entrants, I distinguish between immediate effects at labor market entry and longer-run outcomes after nine years, whereas for incumbents, I focus on career trajectories starting from 1998.

(a) Entrants: IT occ. prob. gap



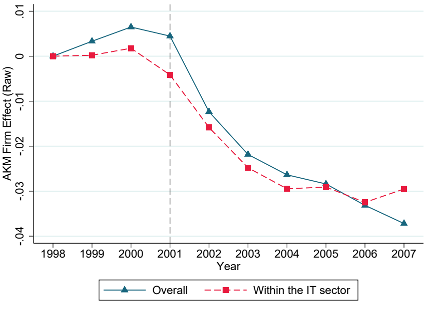
(b) Incumbents: IT occ. prob. gap

(c) Entrants: Occ. premium gap



(d) Incumbents: Occ. premium gap

(e) Entrants: Firm premium gap



(f) Incumbents: Firm premium gap

Figure 6. Effects of IT Majors on Occupational and Firm Outcomes: Entrants and Incumbents

Notes: This figure compares labor market outcomes of college graduates with IT and other majors for both entrants (left column) and incumbents (right column) across three outcomes: IT occupation probability gap (top row), occupation premium gap (middle row), and firm premium gap (bottom row). For entrants, outcomes are shown at labor market entry (solid blue line) and nine years after graduation (dashed red line), estimated using equation (1). Results for incumbents are estimated using equation (2), with 1998 as the reference year (standardized to 0). Firm and occupation premiums are estimated from the AKM model (see Section 4.3 for details).

Panels (a) and (c) show substantial initial disparities in occupational outcomes between boom and bust cohorts among entrants. Initially, boom cohorts had higher probabilities of entering IT occupations and secured occupations with higher wage premiums. In contrast, bust cohorts faced reduced opportunities in IT occupations at entry and started in occupations with lower premiums. Interestingly, while the bust cohorts largely did not return to IT occupations over nine years, they successfully transitioned into other occupations with high premiums, significantly closing the initial occupation premium gap. This highlights the resilience of bust cohorts through leveraging IT skills outside traditional IT occupations, consistent with productivity-enhancing adaptations observed in non-IT sectors (Bresnahan et al., 2002; Bartel et al., 2007).[10]

Panel (e) shows that at labor market entry, bust cohorts joined firms with lower wage premiums, reflecting the collapse of high-paying IT firms during the bust.[11] However, after nine years, this firm premium gap largely disappears, suggesting initial firm sorting did not leave persistent impacts on long-term outcomes. This initial sorting into lower-quality firms is mirrored by higher job mobility. Figure D5 (a) shows that IT graduates from bust cohorts were up to 15 percentage points more likely to switch firms one year after graduation compared to the other majors, suggesting a more turbulent entry into the labor market as they searched for better matches.

For incumbent workers, panels on the right illustrate that their significant earnings declines are driven by occupational shifts and firm transitions following the dotcom shock. Panel (b) indicates that incumbents experienced a moderate decline in the probability of remaining in IT occupations, particularly among those employed outside the IT sector. Panel (d) shows incumbents moving toward lower-premium occupations, again primarily outside the IT sector.

Panel (f) reveals that incumbents experienced substantial declines in firm premiums, particularly pronounced within the IT sector, underscoring that incumbents typically remained within the IT sector but shifted toward lower-premium firms. This move to lower-premium firms was an active process of

[10] A closer look at occupational sorting reveals how these transitions occurred. Figure D4 shows that, at labor market entry, bust cohorts were more likely to be employed in general clerical occupations compared to their boom counterparts. However, nine years later, they had shifted into other professional roles, such as sales, administration, and non-IT engineering occupations. This suggests a pathway where bust-cohort graduates initially took on lower-skilled jobs but eventually leveraged their underlying analytical skills to move into higher-paying, non-IT professional careers.

[11] Figure D3 illustrates how the distribution of firm premiums shifted downward following the bust. The bimodal shape of the distribution, which contrasts with the more continuous pattern for the general workforce in Card et al. (2013), likely reflects strong labor market sorting for our sample of college-educated workers, who cluster into distinct tiers of high-premium and low-premium firms.

job changing. Incumbent IT specialists were over 10 percentage points more likely to switch firms during the bust years, as shown in Panel (b) of Figure D5.

7 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 probability of working in the IT sector. In contrast, graduates entering during the bust faced significant initial earnings penalties, which narrowed after a decade. 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 in returns to their IT majors, incumbents largely remained within the IT sector. Nevertheless, incumbents were forced to move 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.

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Appendix A: Data

A.1 Data Sources and Variable Definitions

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 pre-tax 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.

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. Following Philippon and Reshef (2012), I drop the workers who work in public sector or farming sector. The final primary analysis sample consists of 9.8 million individual-year observations.

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.

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.

A.2 Data on Occupation and Firm

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[12].

[12] Figure D1 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.

Appendix B: Quantitive Measurements of IT Specialization

B.3 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 Table D1. 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.

B.4 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 D2.

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 D3 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 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.

Appendix C: Robustness to the potential spillover effects on other majors

A potential concern with the baseline analysis in Section 4 is that the IT industry shock may have generated spillovers onto majors not explicitly classified as IT, thereby biasing my estimates of the returns to IT majors by contaminating the control group. For instance, majors like business or industrial engineering might have become more IT-intensive during this period, which could attenuate the estimated β_t if they are part of the control group.

To address this, I implement a robustness check that exploits variation in the degree of IT specialization across all majors. I construct a continuous treatment variable measuring each major's pre-boom exposure to the IT industry, defined as the share of graduates from that major's 1995 cohort who were employed in the IT sector, as shown in section B.3. This measure captures the plausibility that majors with a higher pre-existing IT orientation were differentially affected by the subsequent IT boom and bust, effectively creating a continuous spectrum of treatment intensity. By leveraging this pre-determined variation in exposure, akin to a reduced-form shift-share approach, I can estimate the impact of the IT shock across the entire distribution of major-specific IT specialization.

The results obtained using this continuous measure of IT specialization are presented in Table D4 (for earnings) and Table D5 (for IT sector employment). The estimated coefficients are remarkably consistent with those from my baseline analysis using the binary IT major classification. The pattern of effects over the dot-com cycle is identical, and the magnitudes are comparable once scaled by the average IT-share of the treated group. This consistency reinforces the robustness of the primary findings to the specific definition of IT skill exposure and mitigates concerns about spillover effects biasing the main results.

Appendix D: Decomposition of returns to IT-specialized majors into between- and within-industry components

D.5 The methodology of decomposition

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:

$$y_{it} = \lambda_t S_{m(i)} + \phi_{j(i),t} + \gamma_t + Z_i \Phi + \varepsilon_{it} \tag{D1}$$

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 and other majors 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.

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 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.

D.6 Decomposition results 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 D2 (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).

As shown in Figure D2 (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 **??**(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 provide 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 D2), 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 D2) 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).

D.7 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 (D1). 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 D7.

Within-industry returns

Panel (a) in Figure D7 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 after four years and about 6 log points by 2007. Panel (c) of Figure D6 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 D7 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 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 D7). 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 D7 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 D6, although the magnitude of this premium was substantially diminished due to the shock.

After decomposing across multiple industries (Panel (c) of Figure D7), 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 [13]. In other industries, the industry-premium component did 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.

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

Appendix D Appendix Figures and Tables

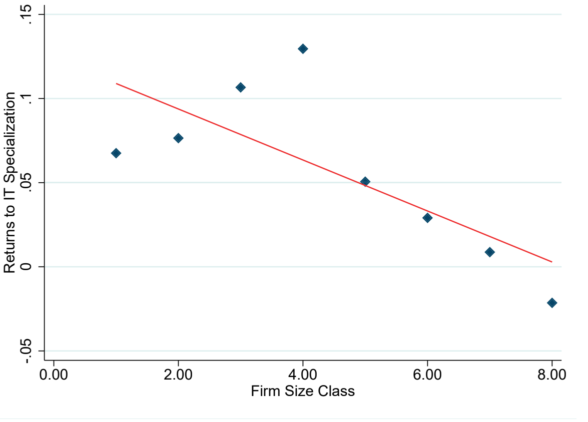
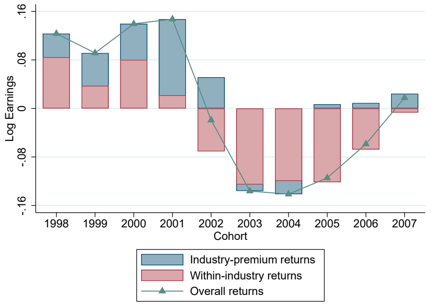
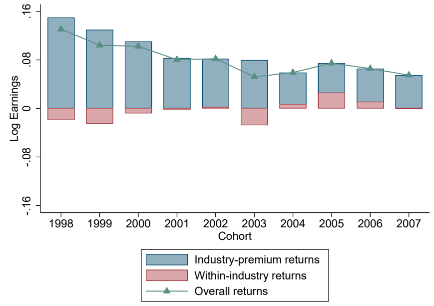


Figure D1. The Relationship between Firm Size and the Returns to IT Majors

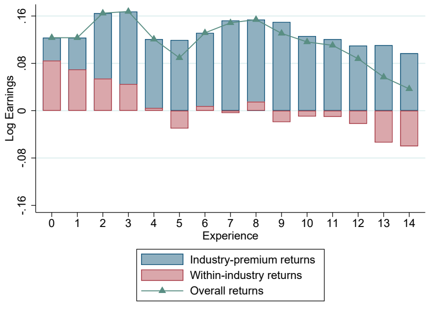
Notes: This figure plots the returns to IT specialization in log wage across different firm size classes. The returns are derived from a regression of log wage on IT specialization controlling for quadratic age interacted with sex, cohort, and year fixed effects. Each diamond represents the returns to 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.



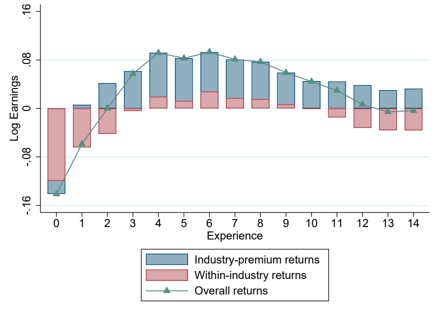
(a) Between cohorts (0 exp)



(b) Between cohorts (9 exp)



(c) A boom cohort by experience (1998)



(d) A bust cohort by experience (2004)

Figure D2. 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.

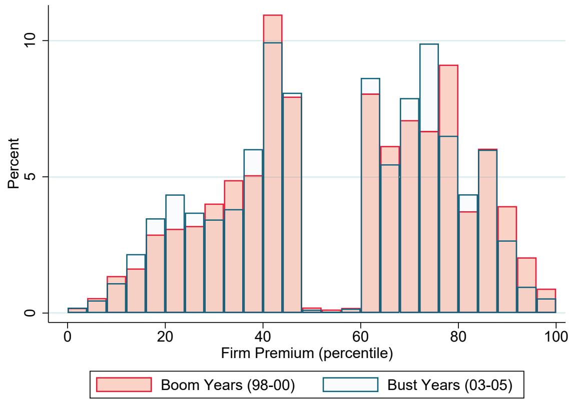
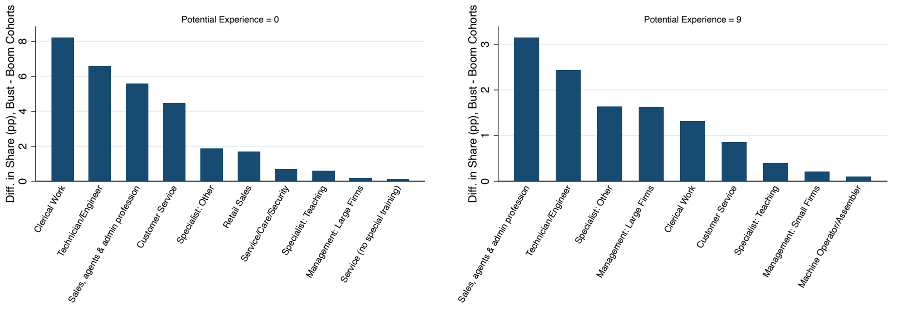


Figure D3. The Distribution of Firm Premiums in Boom and Bust Years

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.

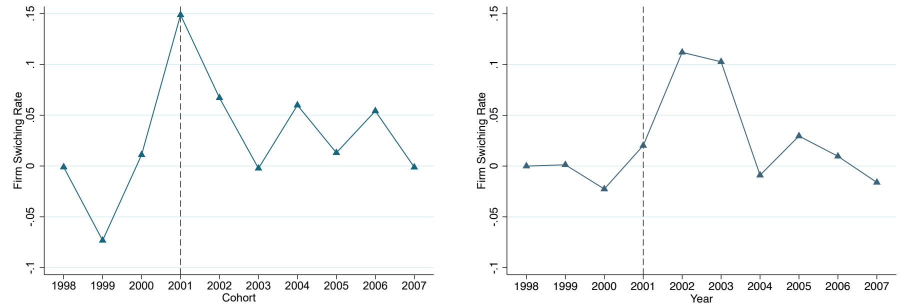


(a) Difference in Occupation Sorting (0 Exp)

(b) Difference in Occupation Sorting (9 Exp)

Figure D4. Difference in Occupation Sorting between Boom and Bust Cohorts

Notes: This figure shows the difference in occupation sorting between boom and bust cohorts at labor market entry (Panel a) and 9 years (Panel b) after graduation. The difference is calculated as the difference in the share of IT graduates in each occupation between boom and bust cohorts. The occupations are defined at the 2-digit level. Technician/Engineer occupation does *not* include IT occupations.

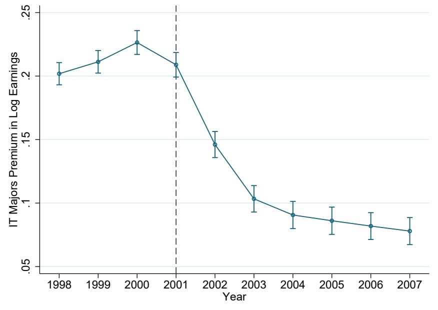


(a) Entrants at 1 year after graduation

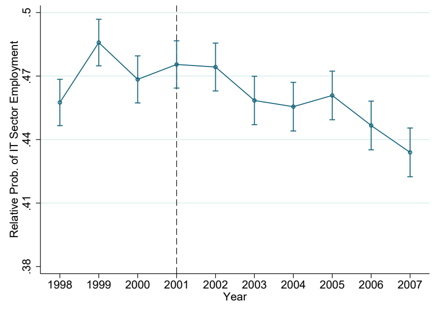
(b) Incumbents

Figure D5. Firm Switching for Entrants and Incumbents

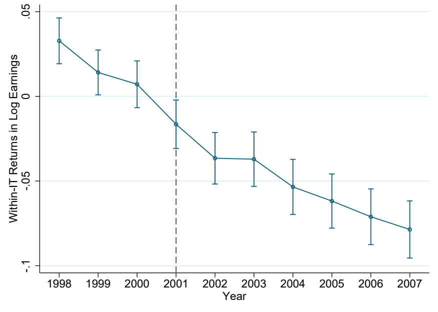
Notes: This figure shows the firm switching rate for entrants at 1 year after graduation (Panel a), and incumbents over the same period (Panel b). The switching is defined as changing firms within a year. The specifications for entrants and incumbents are consistent with those used in the main analysis. Please refer to the Section 4 for further details.



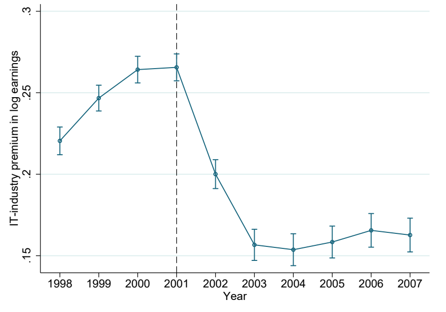
(a) Overall IT Major Returns



(b) Rel. Prob. of IT Sector Employment



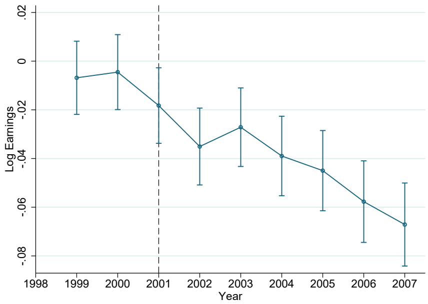
(c) IT Major Returns within IT Sector



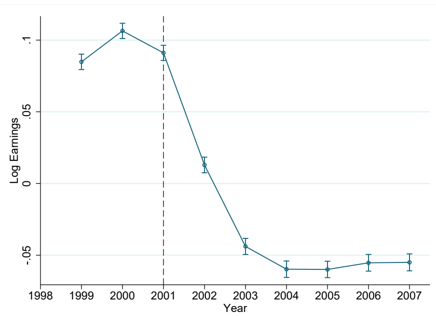
(d) IT industry Premium

Figure D6. Labor Market Outcomes of Incumbent IT Specialists by Year

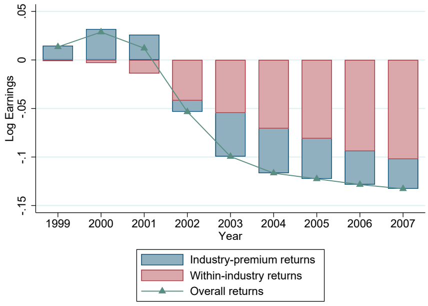
Notes: This figure presents regression estimates of labor market outcomes for IT majors compared to other majors from year 1998 to 2007. Panel (a) depicts the overall returns to IT-specialized majors in terms of log earnings. Panel (b) illustrates the probability differential of IT sector employment for IT relative to other majors. 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.



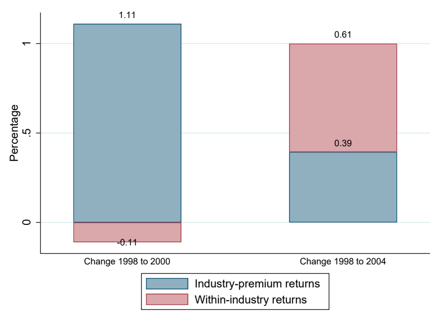
(a) Changes in IT Major returns within the IT sector



(b) Changes in IT industry premium



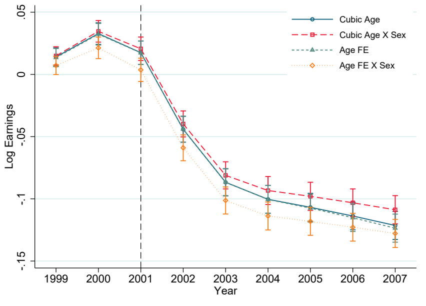
(c) Decomposition of changes in overall returns



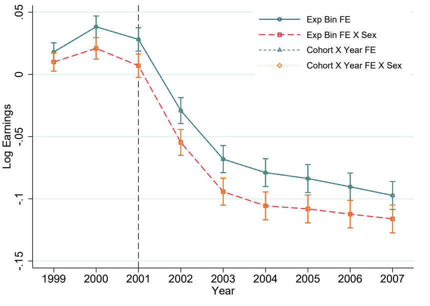
(d) Relative importance in percentage

Figure D7. 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.



(a)



(b)

Figure D8. 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%.

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

Table D1. Top 10 College Majors by Proportion of Graduates Employed in the IT Industry

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.

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

Table D2. IT Specialized Courses

Notes: 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.

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

Table D3. Top 10 Majors by Share of IT-Specialized Courses

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.

Cohort	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Panel A: Effect of a One Percentage Point Increase in IT Specialization										
Exp 0	0.00454*	0.00325*	0.00393*	0.00419*	-0.00153*	-0.00478*	-0.00438*	-0.00288*	-0.00166*	0.00171*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 1	0.00491*	0.00560*	0.00497*	0.000971*	-0.00332*	-0.00417*	-0.00142*	-0.000670*	0.00159*	0.00276*
	(0.000)	(0.000)	(0.000)	(0.015)	(0.000)	(0.000)	(0.000)	(0.044)	(0.000)	(0.000)
Exp 2	0.00730*	0.00635*	0.00351*	0.00131*	-0.000547	0.0000999	0.00117*	0.00238*	0.00355*	0.00356*
	(0.000)	(0.000)	(0.000)	(0.001)	(0.170)	(0.771)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 3	0.00802*	0.00502*	0.00295*	0.00178*	0.000999*	0.00191*	0.00310*	0.00392*	0.00436*	0.00355*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.008)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 4	0.00670*	0.00354*	0.00353*	0.00375*	0.00337*	0.00340*	0.00479*	0.00417*	0.00442*	0.00582*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 5	0.00577*	0.00456*	0.00566*	0.00478*	0.00471*	0.00468*	0.00437*	0.00424*	0.00505*	0.00542*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 6	0.00725*	0.00621*	0.00611*	0.00528*	0.00497*	0.00449*	0.00468*	0.00515*	0.00526*	0.00595*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 7	0.00817*	0.00596*	0.00605*	0.00560*	0.00450*	0.00430*	0.00421*	0.00483*	0.00477*	0.00527*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 8	0.00835*	0.00674*	0.00566*	0.00459*	0.00468*	0.00434*	0.00429*	0.00412*	0.00421*	0.00480*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 9	0.00823*	0.00613*	0.00519*	0.00451*	0.00369*	0.00375*	0.00379*	0.00372*	0.00388*	0.00419*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 10	0.00743*	0.00516*	0.00460*	0.00430*	0.00346*	0.00335*	0.00288*	0.00306*	0.00339*	0.00298*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Effect Scaled to Difference Between Average IT and Non-IT Major Specialization										
Exp 0	0.168	0.120	0.145	0.155	-0.057	-0.177	-0.161	-0.107	-0.061	0.063
Exp 1	0.182	0.207	0.184	0.036	-0.123	-0.154	-0.053	-0.025	0.059	0.102
Exp 2	0.270	0.235	0.130	0.048	-0.020	0.004	0.043	0.088	0.131	0.132
Exp 3	0.297	0.186	0.109	0.066	0.037	0.071	0.115	0.145	0.161	0.131
Exp 4	0.248	0.131	0.131	0.139	0.125	0.126	0.177	0.154	0.164	0.215
Exp 5	0.213	0.169	0.209	0.177	0.174	0.173	0.162	0.157	0.187	0.201
Exp 6	0.268	0.230	0.226	0.195	0.184	0.166	0.173	0.191	0.195	0.220
Exp 7	0.302	0.221	0.224	0.207	0.167	0.159	0.156	0.179	0.176	0.195
Exp 8	0.309	0.249	0.209	0.170	0.173	0.161	0.159	0.152	0.156	0.178
Exp 9	0.305	0.227	0.192	0.167	0.137	0.139	0.140	0.138	0.144	0.155
Exp 10	0.275	0.191	0.170	0.159	0.128	0.124	0.107	0.113	0.125	0.110
N	15.5	19.9	20.7	21.3	22.5	23.4	25.0	24.3	23.1	20.5

Table D4. Effect of Pre-Boom IT Specialization on Log Earnings by Cohort and Experience

Note: This table presents estimated effects of IT specialization on log earnings for different cohorts (graduating 1998-2007) and years of potential experience (0-10). IT specialization is a continuous variable measured as the share of each major's graduates employed in the IT industry during the pre-boom period. Panel A reports the estimated effect on log earnings of a one percentage point increase in IT specialization. Panel B reports effects scaled to reflect the estimated impact of moving from the average IT specialization of non-IT majors to the average of IT majors. In Panel A, each cell represents the coefficient on the interaction between IT specialization and a dummy variable for the corresponding experience year, from a separate regression for each cohort. All regressions control for 9th-grade GPA, sex, high school fixed effects, and college fixed effects. Standard errors, clustered at the individual level, are reported in parentheses. * indicates significance at the 5% level. N represents the number of observations in thousands (identical across panels).

Cohort	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Panel A: Effect of a One Percentage Point Increase in IT Specialization										
Exp 0	0.0139*	0.0151*	0.0147*	0.0122*	0.00749*	0.00507*	0.00572*	0.00722*	0.00905*	0.0109*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 1	0.0146*	0.0161*	0.0150*	0.0114*	0.00685*	0.00652*	0.00812*	0.0104*	0.0112*	0.0117*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 2	0.0154*	0.0162*	0.0140*	0.0110*	0.00781*	0.00828*	0.00955*	0.0119*	0.0112*	0.0124*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 3	0.0148*	0.0152*	0.0129*	0.0107*	0.00893*	0.00946*	0.0105*	0.0118*	0.0116*	0.0125*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 4	0.0149*	0.0146*	0.0130*	0.0114*	0.00952*	0.0104*	0.0109*	0.0120*	0.0113*	0.0123*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 5	0.0141*	0.0143*	0.0132*	0.0116*	0.0102*	0.0105*	0.0110*	0.0118*	0.0113*	0.0120*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 6	0.0144*	0.0141*	0.0133*	0.0123*	0.0103*	0.0105*	0.0110*	0.0119*	0.0113*	0.0121*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 7	0.0151*	0.0141*	0.0135*	0.0119*	0.0104*	0.0105*	0.0110*	0.0117*	0.0114*	0.0118*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 8	0.0143*	0.0141*	0.0127*	0.0114*	0.0103*	0.0105*	0.0108*	0.0115*	0.0112*	0.0117*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 9	0.0140*	0.0135*	0.0128*	0.0116*	0.0106*	0.0104*	0.0103*	0.0115*	0.0110*	0.0132*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp 10	0.0132*	0.0135*	0.0131*	0.0115*	0.0106*	0.0100*	0.0102*	0.0110*	0.0117*	0.0130*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Effect Scaled to Difference Between Average IT and Non-IT Major Specialization										
Exp 0	0.514	0.559	0.544	0.451	0.277	0.188	0.212	0.267	0.335	0.403
Exp 1	0.540	0.596	0.555	0.422	0.253	0.241	0.300	0.385	0.414	0.433
Exp 2	0.570	0.599	0.518	0.407	0.289	0.306	0.353	0.440	0.414	0.459
Exp 3	0.548	0.562	0.477	0.396	0.330	0.350	0.389	0.437	0.429	0.463
Exp 4	0.551	0.540	0.481	0.422	0.352	0.385	0.403	0.444	0.418	0.455
Exp 5	0.522	0.529	0.488	0.429	0.377	0.389	0.407	0.437	0.418	0.444
Exp 6	0.533	0.522	0.492	0.455	0.381	0.389	0.407	0.440	0.418	0.448
Exp 7	0.559	0.522	0.499	0.440	0.385	0.389	0.407	0.433	0.422	0.437
Exp 8	0.529	0.522	0.470	0.422	0.381	0.389	0.399	0.426	0.414	0.433
Exp 9	0.518	0.499	0.474	0.429	0.392	0.385	0.381	0.426	0.407	0.488
Exp 10	0.488	0.499	0.485	0.426	0.392	0.370	0.377	0.407	0.433	0.481
N	15.5	19.9	20.7	21.3	22.5	23.4	25.0	24.3	23.1	20.5

Table D5. Effect of Pre-Boom IT Specialization on the Probability of IT Industry Employment by Cohort and Experience

Note: This table presents estimated effects of IT specialization on the probability of IT industry employment for different cohorts (graduating 1998-2007) and years of potential experience (0-10). IT specialization is a continuous variable measured as the share of each major's graduates employed in the IT industry during the pre-boom period. Panel A reports the estimated effect on the probability of IT industry employment of a one percentage point increase in IT specialization. Panel B reports effects scaled to reflect the estimated impact of moving from the average IT specialization of non-IT majors to the average of IT majors. In Panel A, each cell represents the coefficient on the interaction between IT specialization and a dummy variable for the corresponding experience year, from a separate regression for each cohort. All regressions control for 9th-grade GPA, sex, high school fixed effects, and college fixed effects. Standard errors, clustered at the individual level, are reported in parentheses. * indicates significance at the 5% level. N represents the number of observations in thousands (identical across panels).

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 (k)	15.5	19.9	20.7	21.3	22.5	23.4	25.0	24.3	23.1	20.5

Table D6. Robustness by Using 9th Grade Math Grade: Earnings

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 nineth-grade GPA, while Panel B shows results controlling for math scores at Grade 9. 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.

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 (k)	15.5	19.9	20.7	21.3	22.5	23.4	25.0	24.3	23.1	20.5

Table D7. Robustness by Using 9th Grade Math Grade: IT Industry Employment Probability

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 nineth-grade GPA, while Panel B shows results controlling for math scores at Grade 9. 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.

	(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

Table D8. Robustness Checks: Returns to IT Specialization on Log Earnings Across Different Model Specifications

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.

Essay II. Local Spillover Effects of IT-Sector Booms and Busts

Co-authored with Oskar Nordström Skans

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1 Introduction

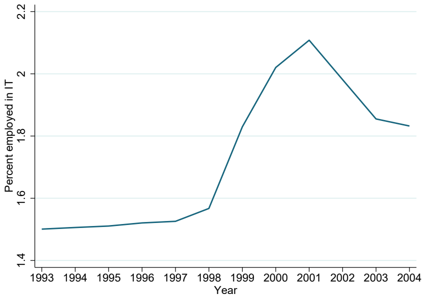
The IT sector is often considered as an engine of economic growth, generating positive economic spillovers to the rest of the economy (Draghi, 2024, as a recent example). As a consequence, policy makers both at the national and local level put considerable effort into attracting establishment of, and local investments in, IT sector firms. At the same time, IT firms tend to operate in a risky economic environment and the IT sector as a whole is subject to large variability and reoccurring boom-bust cycles. Considering the well-known spatial clustering of the IT-sector, these cycles may affect the economic activity in other sectors of the local economy. *A priori*, spillover effects can be *reinforcing* through demand spillovers and/or local production linkages, or *mitigating* through competition for local resources, such as IT-specialists, that will be relaxed when the IT sector enters into a bust phase. From a local public finance perspective, it is crucial to understand the nature of these potential spillovers across booms and bust stages.

In this paper, we study local market responses to the Y2K boom-bust cycle in Sweden. The context is highly suitable for our analysis. Sweden has a very active and regionally clustered IT-sector and the boom bust cycle around the year 2000 generated very large and rapid swings in economic activity within the IT sector. Using very detailed administrative micro-level register data, we analyze how the labor market activity in the non-IT private sector evolved in IT-exposed municipalities during the boom and bust phases of the cycle.

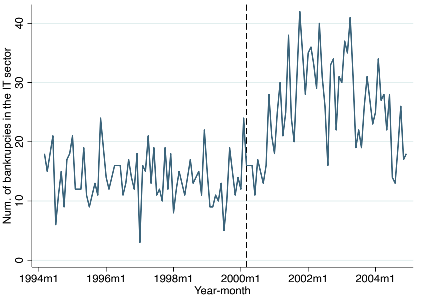
The research question is particularly interesting because previous studies have highlighted processes that point in opposite directions. On one side, the local agglomeration literature highlights the potential for local multipliers, see e.g. Moretti (2010) and Moretti and Thulin (2013) who show that local multipliers are particularly strong for high-human-capital workers and high-tech industries. This suggests that the activity in other sectors within IT-intensive municipalities should benefit from additional growth during an IT-boom, and instead suffer from a down-turn during an IT-bust period. On the other hand, the literature has emphasized the potentially productivity enhancing role that IT-workers can have in other sectors, see e.g. Tambe and Hitt (2014) and Bai et al. (2024). This process can generate counter-cyclical spill-overs through time-varying access to these key workers in other sectors. During a boom period, competition from IT firms may make it harder to attract IT workers to non-IT firms, but during a recession local non-IT firms may instead benefit if they are able to hire displaced IT workers.

Our empirical setting is the Swedish IT boom-bust cycle around year 2000. As illustrated in Figure 1a, the IT employment share of total employment grew by more than 30 percent in just three years leading up to the peak around 2001—a gain that was reduced by about half three years later. On the firm-side, the response was a bit more delayed but responses are equally visible—

the number of bankruptcies in the IT sector increased more than 3-fold between 1999 and 2002 as shown in Figure 1b.



(a) The employment share of the IT industry across years



(b) The number of bankruptcies in the IT industry

Figure 1. The consequences of the dotcom crash

Notes: This figure plots (a) the employment share of the IT industry across years and (b) the number of bankruptcies in the IT industry.

We perform a straightforward exposure analysis where we classify areas based on their exposure to the IT industry in 1996 and track the economic evolution across the cycle as a function of this initial IT-exposure. The classification is done at the municipality-level as this is the local administrative level where most sub-national political decisions are made. Our specification, although simple, is compelling because we study boom an bust periods that follow each other closely in time. Thus, our key identifying assumption is that any confounding trend differences between high-and low-exposed areas do not flip signs right at the peak of the IT-cycle.

Our primary outcome measure is individual earnings of workers employed in non-IT sectors in the different areas. Our results consistently indicate procyclical local spillover effects. Earnings grew systematically more in municipalities with larger (initial) IT-exposures leading up to the peak of the IT cycle. Right at the turn of the cycle, however, the earnings in IT-exposed areas instead saw a negative trend relative to other locations. These patterns change very little if we alter the empirical specification to account for other possibly relevant differences across the areas in 1996. In terms of point estimates, a bare-bones model with just region and year dummies produces estimates that are very similar to our most saturated model that also control for individual fixed effects, other aspects of the industry structure, the local educational structure, and average wages in 1996. Importantly, our most demanding specification, only exploiting the tilting trend at the peek, remains highly significant across all specifications.

We also find that much of the boom-to-bust variation is concentrated in the construction, real estate, and finance sectors. We further decompose the effects across educational groups and show that the positive boom-period spillovers appear to primarily benefit the highly educated, whereas the recession decline is more pronounced for the least educated. Thus, relative inequality across educational groups in non-IT jobs appears to grow in both phases of the cycle. In terms of other outcomes, we observe positive growth in monthly wages leading up to the peak, which flattens thereafter, while the bust-period decline is driven mainly by reductions in employment.

Our study contribute to a diverse literature on local spillovers. Moretti (2010) and Moretti and Thulin (2013) estimate local employment multipliers in the United States and Sweden, respectively, using panel fixed effects and instrumental variable (IV) methods to study the impact of local tradable employment (i.e. not the cyclical properties). They find that local employment multipliers are significantly higher for high-human-capital workers and high-technology industries. While the average multiplier is smaller in Sweden than in the U.S., the multiplier for high-skilled employment is sizable and broadly comparable across both countries. Similarly, Lee and Clarke (2019) examine the impact of high-technology industry growth on low- and mid-skilled workers across 182 British local labor markets from 2009 to 2015. They find a positive job multiplier, with each new high-tech job creating approximately 0.7 non-tradeable jobs. These new jobs primarily benefit low-skilled workers, though the growth is also associated with a reduction in average wages for less-skilled workers, suggesting that many of the new jobs are low-paying. Our main contribution relative to these studies, is that we highlight the cyclical properties of these spill-over effects, being positive during high growth periods, and abruptly turning negative thereafter. In this sense, our paper, has a close empirical counterpart in Lorentzen (2024) who analyze the local spillover effects of large and rapid movements in in labor demand in the Norwegian Oil industry. An interesting facet in Lorentzen (2024) is the detailed documentation of negative spillover effects arising through the labor market as displaced oil workers compete with other local workers after a decline in oil-industry labor demand. We add to her paper by documenting the (overall) spillover effects from a cyclical shock affecting a set of workers who may have a greater potential to generate *positive* firm-level effects, and thus potentially could help boost labor demand in other firms. As our results show, however, such positive spillovers are at least not strong enough to counteract the overall negative impact on the local economy.

The idea of positive spillover effects from displaced tech workers is related to a set of studies on labor mobility within high-tech clusters and the impact this may have on non-IT firms in these areas. Fallick et al. (2006) highlight that job-hopping among college-educated men in Silicon Valley's computer industry is a source of agglomeration economies. As part of our broader research program, Liu (2025) studies the same time period as us, using similar Swedish data, but focusing on short and long-run impact of IT graduates during the cycle. The paper shows that young IT graduates responded by significant and persistent sectoral shifts, that in principle could be beneficial for receiving firms[1]. Along these lines, a number of studies have analyzed the impact of cross-industry moves of IT specialists. Tambe and Hitt (2014) study how the movement of IT workers across firms contributes to productivity spillovers. In particular for the bust period, Ali-Yrkkö et al. (2024) is an interesting study using linked employer-employee data from Finland, using matching techniques, to compare firms that hired displaced Nokia employees to firms that did not. They find positive effects on a wide set of firm performance indicators in firms that hired displaced specialized workers from Nokia. Similarly, Bai et al. (2024) explore how large-scale tech layoffs affect non-tech firms in the same local labor markets using data from the US Census. They use data on non-tech firms from 1996 to 2013, comparing areas with mass layoffs to matched control areas using difference-in-differences methods. Their results indicate that small and young non-tech firms in affected areas tend to grow after tech layoffs. Finally, Harrigan et al. (2023) estimate the productivity impact of "techies" in France between 2011 and 2019. Using production function methods and administrative firm-level data, they show that techies contribute to long terms productivity growth and innovation rates in non-manufacturing firms.

A few studies have documented the firm- and worker-level impact of the dot-com cycle in various settings; for the US Mann and Nunes (2009) show that employment in 11 high-tech sectors declined by about 17 percent between 2001 and 2008, while average economy-wide wages grew by 36 percent over the same period. Kroll et al. (2010) analyze the effects of the dot-com boom and bust on firm survival, migration, and sectoral dynamics in San Francisco and the surrounding region between 1990 and 2005. Using establishment-level data, they document significant firm "churning" during the dot-com era. Their findings show that growth in the high-tech sector contributed to the displacement of older establishments, particularly in non-high-tech manufacturing and distribution. Although our results in general concur with these findings, our focus is different as we directly analyze the impact on the local labor market, which is an outcome likely to be of particular interest to local decision makers.

Overall, our paper provides what we believe to be the most compelling evidence yet on the local labor market effects of IT-exposure during an IT boom-bust cycle. Our results suggest that spillover effects should be a cause for concern at the local level. The large swings in the sector appears to be amplified at the local level as earnings in other industries grow and shrink in tandem with the IT sector. The results also indicate that the establishment of a large local IT sector may contribute to additional local earnings inequality as the educational earnings premia grow across the cycle, where educated workers gain during the boom, and less educated workers suffer during the bust.

[1] An indication that this may be beneficial to the receiving firms is that the earnings impact on the graduates was short-lived, despite the permanent shift of employing sector.

The paper is structured as follows: Section 2 explains data. Section 3 describes the methodology. Section 4 presents findings. The final section concludes.

2 Data

The empirical analysis relies on high-quality Swedish administrative register data provided by Statistics Sweden. These registers offer comprehensive, longitudinal information for the entire Swedish population, allowing us to track individuals over time and link them to their employers and geographic locations (municipalities). The core period for our analysis spans from 1997 to 2004, covering the key phases of the Y2K IT boom and subsequent bust. The data include detailed individual-level information on annual labor earnings, employment status, demographic characteristics (such as age and sex), and educational attainment.

Our primary sample consists of individuals employed in the private non-IT sector. We define the IT sector based on the Swedish Standard Industrial Classification (SNI) prevailing during the period. Specifically, we exclude individuals whose primary employment is in firms classified under SNI2002 code 72 ("Computer and related activities"). Furthermore, to isolate spillovers to the market-driven parts of the economy, we exclude all farming and public sector employees. To minimize biases arising from educational transitions or retirement decisions, the sample is restricted to prime-age individuals, defined as those between 18 and 65 years of age. We also trim observations with extreme values for wages to reduce the influence of outliers, though our results are robust to these minor adjustments. The longitudinal nature of the data is crucial, as it enables us to implement individual fixed effects in our main empirical specifications, thereby controlling for time-invariant unobserved individual heterogeneity.

A key variable for our identification strategy is the municipality-level IT exposure measure, S_r. This variable is designed to capture the baseline intensity of IT sector activity in a local labor market prior to the significant fluctuations of the boom-bust cycle. Following the approach in Lorentzen (2024), we define S_r for each municipality r as the employment share of the IT sector in that municipality in the year 1996. Formally:

$$S_r = \frac{\text{Employment in IT sector in municipality } r \text{ in 1996}}{\text{Total private sector employment in municipality } r \text{ in 1996}}$$

Employment figures for this calculation are derived from the establishment-level registers, aggregated to the municipality level. The IT sector for the numerator is defined using the same SNI code 72. By using this pre-determined measure of IT intensity, we aim to ensure that S_r is exogenous to individual-level earnings changes and other labor market outcomes during the 1997-2004 period, conditional on individual fixed effects and other controls. Figure 2 provides a geographical illustration of S_r across Swedish municipalities, highlighting the considerable spatial variation in IT sector concentration, with notable clusters in major urban areas such as Stockholm, Gothenburg, and Malmö, as well as in some university towns.

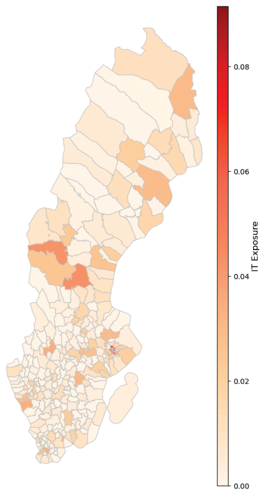


Figure 2. Municipality-level IT Exposure in Sweden

Notes: The map shows the municipality-level exposure to the IT sector in Sweden, measured by the share of IT workers working in each municipality in the year 1996. The exposure is calculated using the full population of employed individuals worked in the private sector. Darker colors represent municipalities with higher IT exposure.

To further assess the stability of our IT exposure measure, we examine how well the initial 1996 IT exposure predicts the evolution of IT employment in subsequent years. Figure 3 presents coefficients from year-by-year regressions of IT sector employment shares on the 1996 baseline exposure across municipalities. The results show a strong and persistent correlation: municipalities with high initial IT exposure in 1996 continued to exhibit elevated IT employment shares throughout the boom period, with coefficients peaking around 2001. Although the correlation declines during the bust years, the coefficients remain above one, suggesting a high degree of persistence in regional IT specialization. This supports the validity of using 1996 IT exposure as a pre-determined measure in our empirical design.

Our primary outcome variables are the natural logarithm of annual labor earnings and the natural logarithm of monthly wages for individuals in the non-IT private sector. We also examine employment status as an outcome. Annual earnings are sourced directly from tax records. Wages are sourced from Sweden's Wage Structure Statistics for the Private Sector, which are available for around 50 percent of workers in the private sector.

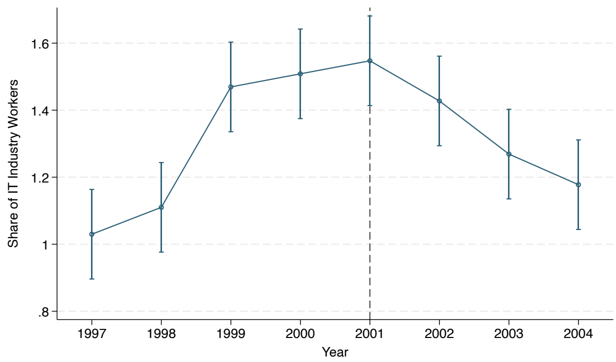


Figure 3. Persistence of Municipal IT Exposure Over Time

Notes: This figure plots the estimated coefficients from year-by-year dynamic regressions of the form $S_{r,t} = \gamma_t S_r + \mu_{r,t}$, where $S_{r,t}$ denotes the share of private-sector employment in the IT sector in municipality r in year t. The figure captures the correlation between the regional IT employment share in 1996 and those in subsequent years, indicating the persistence of regional IT sector specialization over time. A higher γ_t suggests stronger persistence. Ninety-five percent confidence intervals are reported.

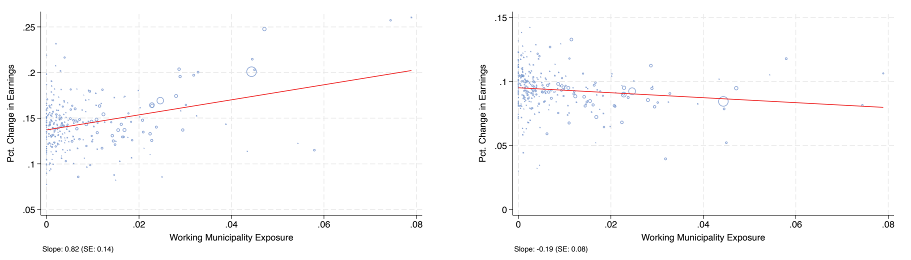
Table 1 presents descriptive statistics for our analytical sample, stratified by period (boom: 1997-2000; bust: 2001-2004) and by whether a municipality's IT exposure (S_r) is below or at/above the sample mean. The pre-determined IT exposure measure S_r averages 0.003 for below-mean municipalities and 0.0270 for at/above-mean municipalities. Across both boom and bust periods, individuals in municipalities with higher initial IT exposure tend to be slightly younger, have more years of schooling, and exhibit higher average annual earnings and monthly wages. For instance, during the boom period, average annual earnings were SEK 241,818 in high-exposure municipalities compared to SEK 213,492 in low-exposure areas. These differences persist into the bust period. The share of males is slightly lower in high-exposure areas. These initial differences suggest that it is crucial to ensure that our results are not confounded by these initial differences—in the end, however, our results are insensitive (at least in a qualitative sense) to adding a very rich set of parametric controls and fixed effects that address all of these differences.

Figure 4 offers a preliminary, unadjusted visualization of the relationship between our IT exposure measure and changes in earnings. Panel (a) plots the percent change in average earnings at the municipality level against S_r during the boom period (1997-2001), while Panel (b) does the same for the bust period (2001-2004). These scatter plots visually suggest a positive correlation between IT exposure and earnings growth during the boom, and a negative relationship during the bust. This pattern provides initial suggestive evidence consistent with the pro-cyclical spillover effects that we investigate more formally in the subsequent sections.

Variable	Boom Years (1997-2000) *Below mean* (1)	*Above mean* (2)	Bust Years (2001-2004) *Below mean* (3)	*Above mean* (4)
S_r	0.0030	0.0270		
	(0.0022)	(0.0141)		
Male	0.701	0.662	0.706	0.659
	(0.458)	(0.473)	(0.456)	(0.474)
Age	41.4	40.8	42.1	41.2
	(11.7)	(11.7)	(12.0)	(11.9)
Schooling Years	10.9	11.6	11.1	11.9
	(1.9)	(2.2)	(1.9)	(2.2)
Earnings (SEK)	213,492	241,818	243,636	279,392
	(88,265)	(125,977)	(102,082)	(150,444)
Wage (SEK)	19,124	21,293	21,882	25,106
	(5,913)	(8,649)	(7,129)	(11,018)
Obs.	2.88m	5.55m	2.89m	5.75m

Table 1. Summary Statistics: Boom vs. Bust Years

Notes: This table presents summary statistics. Columns (1) and (2) refer to the boom period (1997-2000), for individuals with S_r below mean and S_r at/above mean, respectively. Columns (3) and (4) similarly refer to the bust period (2001-2004) for the same S_r based groupings. Standard deviations are reported in parentheses below the means. Monetary values (Earnings, Wage) are rounded to the nearest whole number. The number of observations (in millions) is reported.



(a) Boom period (1997-2001) (b) Bust period (2001-2004)

Figure 4. Percent change in earnings vs. region IT exposure

Notes: This figure plots the relationship between the percent change in regional average earnings and region IT exposure by period.

3 Empirical Method

Our empirical strategy aims to identify the spillover effects of the dotcom boom and bust on the earnings of individuals working in non-IT sectors. We exploit the significant, and arguably exogenous, fluctuations in the IT sector during this period, which differentially impacted local labor markets based on their pre-existing reliance on the IT industry, S_r. The core idea is to compare changes in earnings and other outcomes for individuals in municipalities with varying degrees of IT sector exposure across the different phases of the cycle.

To estimate the spillover effects, we employ the following regression model:

$$y_{i(r),t} = \beta_t S_r + \alpha_r + \alpha_t + \alpha_i + X_{it}\Gamma + Z_r'\delta_t + \varepsilon_{i,t} \tag{2}$$

where $y_{i(r),t}$ denotes the outcome of interest (e.g., log annual earnings) for individual i working in a non-IT sector in municipality r at year t. The coefficients β_t capture the year-specific effect of a one percentage point increase in baseline municipal IT exposure (S_r) on the outcome, relative to the average exposure level and the omitted baseline year of 1997 (i.e., β_{1997} is normalized to zero).

The model incorporates municipality fixed effects (α_r) to control for time-invariant differences across regions, and year fixed effects (α_t) to absorb aggregate time trends and common shocks affecting all individuals and municipalities. Crucially, we also include individual fixed effects (α_i) to control for unobserved time-invariant individual characteristics, such as innate ability or motivation, that might be correlated with both earnings and location choices.

We include a vector of time-varying individual-level controls (X_{it}). This includes a quadratic in age to capture standard life-cycle earnings patterns. To allow for further heterogeneity, X_{it} also include interactions of time-invariant characteristics like gender and schooling years with age terms to allow their influence to vary flexibly over the life-cycle, beyond what is captured by individual fixed effects.

Critically, to account for potential pre-existing differential trends across municipalities that could be correlated with S_r and confound the estimation of β_t, the specification includes interactions ($Z_r'\delta_t$) between year dummies (δ_t) and a vector of baseline (year of 1996) municipality characteristics (Z_r). These characteristics are, for example, the pre-period average wage, average years of schooling, and the manufacturing employment share within the municipality. This allows the earnings trends to vary across municipalities based on these initial conditions. Standard errors ($\varepsilon_{i,t}$) are clustered at the municipality level to adjust for potential serial correlation within municipalities over time and arbitrary heteroskedasticity.

The key identifying assumption is a conditional parallel trends assumption. Specifically, it assumes that, in the absence of the dotcom bubble burst, the average earnings of individuals in non-IT sectors in municipalities with different levels of IT exposure would have followed parallel paths over time, once we control for individual, municipality, and year fixed effects, individual-level covariates, and importantly, the interaction of baseline municipality characteristics with year dummies ($Z_r'\delta_t$). The inclusion of $Z_r'\delta_t$ is particularly important as it relaxes the strict parallel trends assumption by allowing for different trends based on observable pre-existing municipal characteristics.

Another assumption is that the timing of the dotcom bubble burst and its differential impact based on S_r are exogenous with respect to idiosyncratic shocks to individual earnings in the non-IT sector, conditional on the full set of controls. We will present unconstrained estimates year by year. In more compact form, we also present linear trends for the two periods (boom vs. bust) *and* estimates for how these trends differ in fully interacted model for the two periods. This last estimate is insensitive to differences in secular trends across areas as it only exploits the kink at the burst of the bubble.

4 Results

4.1 Spillover Effects on Earnings

We begin by examining the estimated effects of pre-determined regional IT exposure (S_r) on individual earnings in the non-IT private sector. Figure 5 plots the year-specific coefficients from equation 2, capturing the differential earnings trend across municipalities with varying IT intensity.

The results show a clear pro-cyclical pattern. During the boom years (1997-2001), individuals in high-exposure municipalities experienced systematically faster earnings growth. The effect peaks in 2001, with an estimated impact of around 0.7 log points per percentage point of S_r. After the IT bust, this pattern reverses: the post-2001 years show a gradual decline in the earnings differential, with the effect becoming close to 0.4 log points by 2004[2].

Importantly, the figure also shows that there are no systematic differences in earnings trends across municipalities in the years before the boom (1993-1997), suggesting that concerns about differential pre-trends are limited.

Table 2 corroborates this dynamic using a more parsimonious representation where we instead estimate differences in time trends as a function of initial S_r for the two time periods. This allows us to present results from a battery of model variations. In Panel A, we focus on the boom period, and in Panel B, we show corresponding estimates for the bust period. Panel C, shows the differences, effectively isolating the change in trends at the peak. Panel D

[2]The IT exposure variable S_r is demeaned in all regressions, so the coefficients capture effects relative to the mean municipality. The highest-exposure municipality in the sample has a value of $S_r = 0.079$, which corresponds to approximately 7.1 percentage points above the mean after demeaning. To interpret the earnings gap between the most exposed municipality and an average one, multiply the estimated coefficients by 0.071. For example, a coefficient of 0.7 implies a difference of approximately 5 log points (i.e., $0.7 \times 7.1 \approx 5$) in earnings.

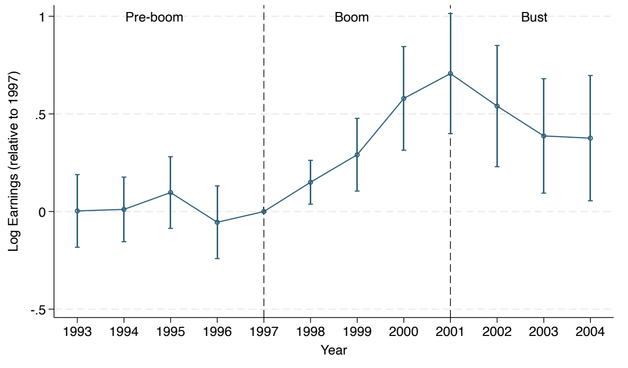


Figure 5. The effect of IT exposure on log earnings (working municipality)

Notes: Estimated effects of S_r on log earnings from equation 2, including municipality and year fixed effects, individual fixed effects, individual controls and pretrend controls. Year 1997 serves as the reference year. Ninety-five percent confidence intervals are reported. Standard errors clustered at the municipality level.

presents estimates for the pre-boom period, providing a test for the presence of differential pre-trends before the IT expansion.

Results in Panel A show that across a wide set of specifications, the earnings gains during the boom period are positive and statistically significant to the initial exposure, ranging from 0.71 to 1.01 log points per percentage point of IT exposure. Panel B shows that these gains are partially undone in the subsequent bust period, where the estimates are uniformly negative and in all but one case, statistically significant. Panel C reports the difference in earnings trends between the two periods, which remains highly significant across all specifications, confirming a sharp reversal in the earnings trajectory after the bust. Panel D provides additional support by showing results for the pre-boom period. There is no consistent or robust association between initial IT exposure and earnings changes during this earlier period in more saturated specifications, though some positive or negative associations appear in the simpler models. This further suggests that the boom-bust dynamics are not driven by underlying differential pre-trends.

4.2 Heterogeneous Spillover Effects

Industry heterogeneity

We next examine whether the effects of IT exposure vary across industries. Figure 6 shows results from regressions estimated separately for each industry, using the same specification as in the main analysis.

Panel (a) presents the estimated changes in log earnings related to IT exposure for each industry during the boom (1997–2001) and bust (2001–2004) periods. The results indicate that industries differ in how they respond to IT

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Boom period						
Change 97-01	0.87***	1.01***	0.90***	0.79***	0.82***	0.71***
	(0.11)	(0.11)	(0.13)	(0.21)	(0.21)	(0.20)
Panel B: Bust period						
Change 01-04	−0.21***	−0.38***	−0.33***	−0.28**	−0.22	−0.38**
	(0.06)	(0.07)	(0.10)	(0.13)	(0.13)	(0.17)
Panel C: Boom - Bust Difference						
Diff. in Change	1.09***	1.39***	1.24***	1.07***	1.04***	1.09***
	(0.13)	(0.13)	(0.17)	(0.25)	(0.26)	(0.28)
Panel D: Pre-Boom period						
Change 93-97	0.19***	0.15***	−0.30***	−0.14	−0.08	0.003
	(0.07)	(0.04)	(0.06)	(0.09)	(0.09)	(0.10)
Region & Year FE	✓	✓	✓	✓	✓	✓
Individual controls		✓	✓	✓	✓	✓
Manufac. share ’96			✓	✓	✓	✓
Avg schooling ’96				✓	✓	✓
Avg wage ’96					✓	✓
Individual FE						✓
Obs.	8.38m	8.35m	8.35m	8.35m	8.35m	7.46m
Rsquared	0.08	0.31	0.31	0.31	0.31	0.83

Table 2. The Effect of IT Exposure on Earnings

Notes: This table reports OLS estimates of the relative change of region-level IT exposure S_r between years on individual earnings, separately for the boom period (1997 to 2001, Panel A), the bust period (2001 to 2004, Panel B), and the pre-boom period (1993 to 1997, Panel D). Panel C reports results for the boom-bust change difference. Column (1) includes region and year fixed effects; Column (2) further adds individual time-varying controls including interactions between schooling years, gender, and quadratic age profile; Column (3) also controls for the 1996 region manufacturing share; Column (4) additionally controls for 1996 average years of schooling; Column (5) further controls for 1996 average regional wage; and Column (6) includes all previous controls plus individual fixed effects. Standard errors in parentheses are clustered at the region level. The number of observations (in millions) and R squared are reported. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

shocks. Pro-cyclical industries such as Construction and Real Estate experience significant earnings gains during the boom, but also significant declines during the bust. In contrast, more traditional sectors like Manufacturing and Utilities show much smaller changes in both periods.

Panel (b) summarizes these patterns by showing the difference in IT exposure effects between the boom and bust periods for each industry. This panel also plots the share of IT experts in each industry in 1996. The results reveal that industries with a higher initial share of IT experts tend to experience larger changes in earnings related to IT exposure across the cycle (e.g. Finance, Other Business). This pattern suggests that the extent of industry-level IT intensity is closely linked to the magnitude of spillover effects, with the most IT-intensive and pro-cyclical sectors both benefiting most from the boom and suffering most during the bust.

Education heterogeneity

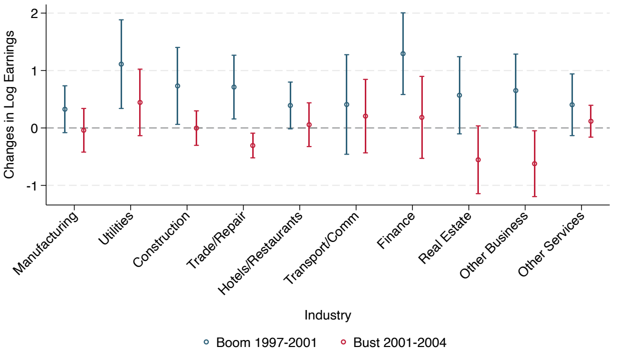
Figure 7 shows heterogeneous effects by worker education levels. During the boom, spillover gains are increasing in education. Workers with college or tertiary education experience significant earnings growth in IT-exposed municipalities, whereas those with only basic or high school education see much smaller effects. In the bust period, the pattern reverses for lower-educated workers, who face clear earnings losses, while the higher-educated are largely insulated from the downturn.

Taken together, these results suggest that IT-sector fluctuations amplify earnings inequality across both industries and skill groups. The boom disproportionately benefits higher-educated workers and knowledge-intensive service sectors, while the bust imposes the largest penalties on lower-skilled workers and sectors reliant on cyclical demand. These patterns highlight the uneven local labor market consequences of sectoral shocks and suggest that IT booms may widen spatial and socioeconomic disparities even outside the IT sector itself.

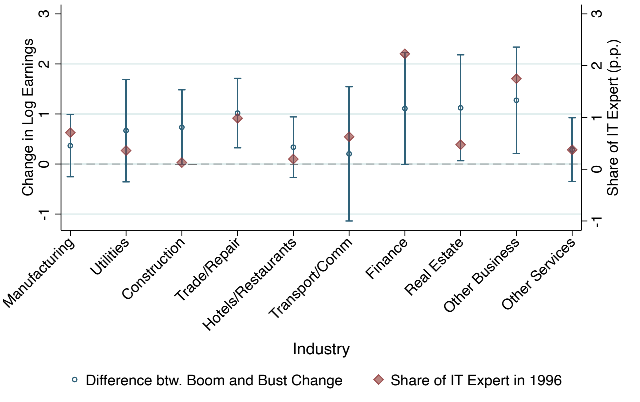
4.3 Resident Municipalities and the Roles of Wages and Employment

The preceding analysis focused on workplace-based IT exposure, capturing the economic influence of local production. However, a potential limitation of this measure is the significant commuting that characterizes modern labor markets. IT workers may live in municipalities different from where they work, generating residential spillovers through their roles as consumers, neighbors, and community members. These spillovers, driven by factors like local consumption demand and housing market pressures, can directly influence both the wages and employment opportunities available to other residents.

To investigate these channels, this section introduces an alternative exposure measure based on where IT workers reside. This residential approach is



(a) Boom and bust periods



(b) Boom-bust difference

Figure 6. Industry-level variation in the effects of IT exposure on log earnings

Notes: Each point shows the estimated change in log earnings related to IT exposure, based on separate regressions by industry using the same controls as in the main specification (including municipality and year fixed effects, individual fixed effects, individual controls, and pre-trend controls). Panel (a) shows the estimated effects for the boom (1997–2001) and bust (2001–2004) periods. Panel (b) shows the difference between boom and bust effects for each industry. In panel (b), the share of IT experts in 1996 is also displayed for each industry, where IT experts are defined as individuals who ever worked in the IT sector or hold an IT-related degree. Ninety-five percent confidence intervals are reported, with standard errors clustered at the municipality level.

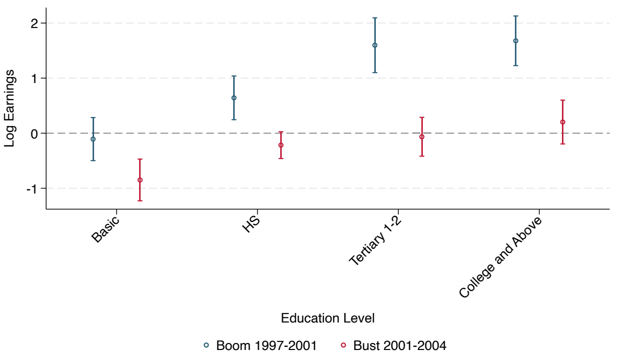


Figure 7. Heterogeneous effects of IT exposure on log earnings by education group

Notes: Coefficients from interaction of S_r with educationlevel dummies over boom and bust periods, controlling for municipality and year fixed effects, individual fixed effects, individual controls and pretrend controls. Standard errors clustered at the municipality level.

particularly well-suited for decomposing the overall earnings effect into wages and employment, since an individual's municipality of residence is consistently defined regardless of their employment status. Therefore, using a residential measure not only serves as a robustness check on our primary findings but, more critically, provides the appropriate analytical lens to distinguish between the wage and employment channels driving local spillovers.

We construct a residential IT exposure measure, $S_{r(res)}$, defined as the share of residents in municipality r who were employed in the IT sector in 1996:

$$S_{r(res)} = \frac{\text{Number of IT workers residing in municipality } r \text{ in 1996}}{\text{Total number of residents in municipality } r \text{ in 1996}}$$

We then re-estimate our main specification, replacing the workplace-based share with $S_{r(res)}$.

Figure 8 shows the estimated effects on log earnings using the baseline IT exposure measure based on residential measure ($S_{r(res)}$). Both series exhibit similar broad dynamics: rising spillover effects during the boom, peaking around 2001, followed by a reversal in the subsequent bust years. However, the magnitude of the effects is slightly larger when using the residential exposure measure, particularly during the bust. This suggests that IT workers' residential presence contributes additional local spillovers beyond what is captured by employment-side exposure alone. These effects may operate through local consumption demand, housing markets, or social network spillovers, as discussed in the context of industrial heterogeneity.

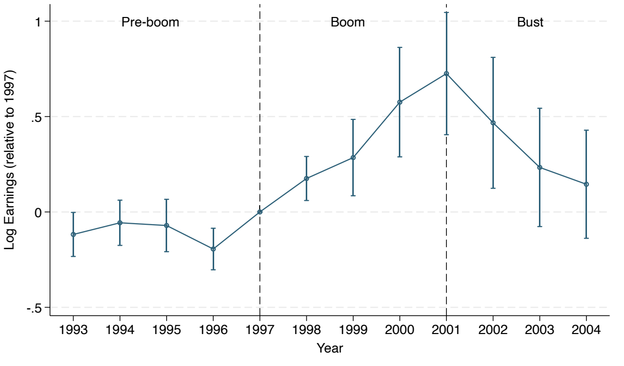


Figure 8. The effect of IT exposure on log earnings (resident municipality)

Notes: This figure shows estimated effects of $S_{r(res)}$ on log earnings from equation 2, including municipality and year fixed effects, individual fixed effects, individual controls and pretrend controls. Year 1997 serves as the reference year. Ninety-five percent confidence intervals are reported. Standard errors clustered at the municipality level.

To understand whether these earnings dynamics are driven by wage changes or employment adjustments, we analyze wages and employment separately[3]. Figure 9a plots the estimated effect of IT exposure on log monthly wages of workers employed in the private non-IT sectors and who were sampled into the wage structure statistics. The pattern broadly follows that of earnings pattern, but with smaller magnitudes and less precision. What is clear is that wages increase faster in exposed areas during the boom, and that the differences then flatten out. The results do not show as clear a decline in the bust period as with log earnings. This suggests that wage adjustments may play a mitigated role for earnings patterns during the downturn.

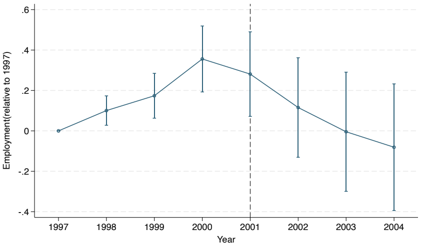
In contrast, Figure 9b shows a more pronounced boom-bust dynamic pattern in employment probabilities [4]. Employment in exposed areas rose steadily during the boom period, peaking around 2000-2001, and then declining over the bust years, mirroring the overall pattern in earnings. This indicates that the employment margin is the primary driver of the pro-cyclical spillover effects on earnings.

Further details on the employment adjustment is provided in Figure A1, which shows effects across the age distribution. The pro-cyclical pattern is most prominent among younger workers (below 30), who experience stronger private sector employment gains during the boom and sharper declines during the bust. Middle-aged workers (30-50) also show some cyclicality, while older

[3]Because of incomplete coverage in the wage data, and the fact that log earnings estimates already removed the full time unemployed, this is not a decomposition in a strict sense, but the intuition is similar.

[4]Here, all workers are included, regardless of earnings

(a) Log wage



(b) Employment

Figure 9. Estimated effects of IT exposure on (a) log wage and (b) the probability of employment, respectively.

Notes: Panel (a) shows the estimated effects of $S_{r(res)}$ on log wage. Panel (b) shows the estimated effects of $S_{r(res)}$ on the probability of employment. All estimates are based on equation 2, including municipality and year fixed effects, individual fixed effects, individual controls, and controls for pre-trends. Ninety-five percent confidence intervals are reported. Standard errors are clustered at the municipality level.

workers (50+) appear largely unaffected. These age-specific effects reinforce the interpretation that labor demand in IT-intensive regions fluctuated in a way that most affected younger, marginally attached workers.

Taken together, the evidence suggests that the local spillovers from IT sector dynamics primarily operate through employment rather than wages, at least during the bust period. The results indicate that the variability across the cycle may have meaningful distributional consequences, particularly for younger and more vulnerable workers in IT-exposed regions.

5 Conclusion

This paper has investigated the local spillover effects of the IT boom-bust cycle around the year 2000 on the non-IT private sector in Sweden. Our analysis, using detailed administrative micro-data and exploiting variation in initial municipal IT-sector employment, reveals significant *pro-cyclical* local spillover effects.

We found that earnings in the non-IT private sector systematically mirrored the IT sector's trajectory: growing faster in IT-exposed municipalities during the boom and experiencing a relative decline during the subsequent bust. These earnings spillovers were primarily driven by adjustments in *employment*, particularly affecting younger workers, rather than by wage changes. The impacts were also uneven. Industries that were pro-cyclical or had a high initial share of IT experts—such as Construction, Real Estate, and Finance—experienced the largest cyclical swings. Crucially, the spillovers exacerbated local earnings inequality: higher-educated workers in non-IT jobs disproportionately benefited during the boom, while less-educated workers bore a greater burden during the bust. Furthermore, analyzing IT workers' residential concentration confirmed these pro-cyclical effects, with notable spillovers into tradable sectors, suggesting mechanisms beyond local consumption.

These findings have important implications for local policymakers. While the presence of a vibrant IT sector can fuel local prosperity during expansionary periods, it also introduces a considerable source of economic volatility that transmits to other parts of the local economy. The cyclical nature of these spillovers, amplifying both booms and busts, poses challenges for stable local public finances and economic planning. Moreover, the tendency for IT cycles to widen the earnings gap between high- and low-educated workers within the non-IT sector is a significant concern. Policies aimed at attracting or fostering IT clusters should therefore be complemented by strategies to mitigate these risks, potentially through economic diversification efforts, support for affected non-IT sectors during downturns, and initiatives to enhance the resilience and adaptability of workers, particularly those with lower educational attainment.

Future research could further explore the persistence of these patterns across different economic cycles and investigate the effectiveness of various local policy responses. In essence, our study underscores that while the IT sector can be a powerful engine for local growth, its inherent volatility creates ripple effects that local economies must be prepared to navigate, particularly concerning economic stability and equitable outcomes.

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Appendix A: Appendix Figure

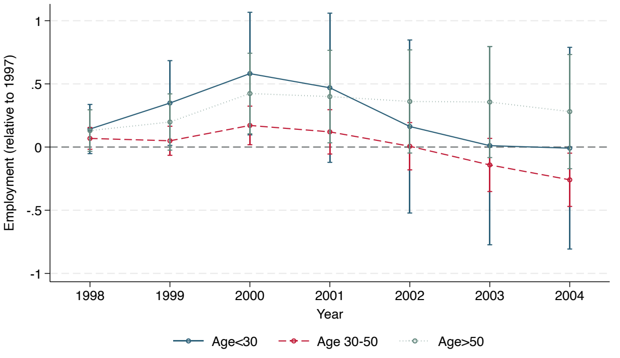

Figure A1. The effect of IT exposure on employment by age

Notes: Estimated effects of S_r on the probability of employment from equation 2 by age group, including municipality and year fixed effects, individual fixed effects, individual controls and pretrend controls. Standard errors clustered at the municipality level.

Essay III. 'You Are the Elite Now': Admission Effects of an Excellence Initiative in the Chinese Higher Education System

Co-authored with Meng Meng

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1 Introduction

In recent decades, numerous countries have launched national universities of excellence initiatives aimed at enhancing human capital and boosting global competitiveness.[1] Given the tremendous efforts and investments dedicated to these excellence initiatives (Guo et al., 2023), it is crucial to investigate their impacts on students and universities. However, few countries have implemented these initiatives at the disciplinary level, leaving a gap in understanding how such granular designations influence admission competition among university applicants. In this paper, we draw on China’s excellence initiative at the disciplinary level to answer this question.

China’s excellence initiative, the *Double First-Class Initiative*, introduces a dual-list system: (1) a list of universities designated as *First-Class University*, aligning with policies implemented in other countries; (2) a list of university-discipline units recognized as *First-Class Discipline* (FCD). Unlike the global practice of whole-university recognition, China’s approach to promoting excellence at the disciplinary level provides an opportunity to examine how excellence designation at a more granular level affects admission competition. We examine whether admission competition intensifies for university-discipline units designated as FCD compared to non-designated units within the same discipline. We also explore whether the designation’s effects spill over to non-designated units within the same university.

In this study, we use a novel dataset extracted from a website that serves as the repository for all college entrance exam admission information. For most university applicants, their exam score is the sole criterion for admission. This uniform standard allows us to quantify the admission competition for each program. Since exam scores may vary across years due to changes in content, difficulty, or cohort characteristics, we convert students’ scores into rankings within their academic tracks to measure and compare admission competition across years. The empirical analysis examines the impact of FCD on admission competition in two main parts: (1) at the disciplinary level, by comparing admission competition between FCD university-discipline units and non-FCD units within the same discipline; (2) within universities, by comparing admission competition between FCD and non-FCD units to assess the spillover effects. Additionally, we also analyze the effect on the university level, comparing admission competition between universities with FCD and those without FCD. The full results of this extended analysis can be found in Appendix B.

[1]Examples include: World-Class University Project in South Korea (1999); Universities with Potential for Excellence in India (2002); Universities of Excellence in Germany (2006); International Campus of Excellence program in Spain (2009); UNIK-Initiative in Denmark (2009, 2013); Initiatives d’Excellence in France (2010); Top Global University Project in Japan (2014); Excellence Initiative Research University in Poland (2019).

To investigate the effect of FCD at the disciplinary level, we first use the concept of regression discontinuity design to create treatment and control groups. We rely on authoritative evaluations and rankings of universities within each discipline, viewing these as university-discipline units that can correspond with the FCDs. The number of FCDs is then used as the cutoff for each discipline. FCDs and non-FCDs just above and below the cutoff form the treatment and control groups, allowing for comparability between them. Additionally, the authorities' oversight of the discipline evaluation and the selection of the FCD list prevents universities from manipulating outcomes and mitigates potential endogeneity concerns in our study.

We perform a Difference-in-Differences (DiD) analysis using 2017 as the baseline year when the FCD list was released late in the year. The results show a significant increase of 1.52 percentiles in admission competition for FCDs, meaning that the last admitted students need to improve their ranking by 1.52 percentiles. This increase represents an approximate 50% rise compared to the baseline difference. The dynamic DiD analysis supports the parallel trends assumption, revealing no significant changes in admission competition before the FCD implementation. Furthermore, the effects remain statistically significant and continue to grow over time following the initiative.

Next, we examine whether spillover effects exist from FCDs to their non-FCD counterparts within the same university. For this analysis, we restrict the sample to universities that host at least one FCD. If admission competition for FCDs increases significantly, it would suggest that FCDs outperform their non-recognized counterparts, attracting higher-ranking students who preferentially seek admission to them. However, the DiD results show no significant change in admission competition between the two groups. Additionally, the dynamic DiD results reveal no significant changes in admission competition before and after the policy implementation. One potential explanation for this finding is that students may perceive FCD and non-FCD programs within universities as equally prestigious, without distinguishing between them. Another explanation could be the application process, where students first select universities and then choose programs within them. To complete their preference forms, students may include non-FCD programs alongside FCDs at the same university. As a result, we observe spillover admission effects from FCD to non-FCD disciplines within universities.

Our study connects to two strands of literature. First, it relates to the availability of information about universities, which plays a critical role in students' decision-making processes when applying for higher education. Students actively search for and gather information to make informed choices about institutions (Hossler and Bontrager, 2014). Empirical research shows that specific information, such as student satisfaction scores, has a statistically significant, albeit small, effect on university applications (Gibbons et al., 2015). Additionally, studies have demonstrated that higher rankings lead to an influx of applications, and the reverse is also true (Sauder and Lancaster, 2006; Bowman and

Bastedo, 2009; Luca and Smith, 2013; Broecke, 2015; Biancardi and Bratti, 2019). A rise in rankings also intensifies the selectivity of the admissions process (Sauder and Lancaster, 2006; Griffith and Rask, 2007), attracting more academically accomplished students (Horstschräer, 2012), as seen in higher SAT/ACT scores and a greater likelihood of applicants being in the top 10% of their high school class (Bowman and Bastedo, 2009). While much of the existing literature has focused on private ranking entities, and rankings may vary across different lists, our research investigates the impact of government-led excellence initiatives at the disciplinary level. This offers new insights into how such information influences admission competition and reflects students' choices.

Second, we contribute to the literature on the role of official excellence designation in shaping student perceptions. Fischer and Kampkötter (2017) found that Germany's Excellence Initiative enhances the appeal of selected universities among top-tier students, influencing their perceptions of educational quality and employment prospects, though these effects diminish over time. Similarly, Biancardi and Bratti (2019) shows that Italy's Research Evaluation Exercise influences undergraduate enrollment, particularly among high-performing institutions and academically superior students. Our study extends this literature by being the first to examine disciplinary-level excellence designations, revealing how they not only increase competition for high-ranking students but also create spillover effects that elevate the admission competition for non-designated disciplines within the same university.

To the best of our knowledge, this is the first study to assess the impact of government-led excellence initiatives at the disciplinary level. Given the significant impact of college quality, reputation, and elite institutions on students' academic and employment prospects (Long, 2008; MacLeod et al., 2017; Zimmerman, 2019), official information regarding the quality of disciplines and universities plays a critical role in the decision-making of university applicants. Our findings show that excellence designations at the disciplinary level significantly heighten admission competition, attracting higher-ranking students. While the cause of the spillover effect remains unclear—whether due to students' perception of equal excellence, the application mechanism, or both—there is no significant change in admission competition between FCDs and non-FCDs, indirectly benefiting non-FCDs. University-level analysis supports this, showing a marked increase in competition for non-designated disciplines at universities with at least one FCD.

The rest of the paper is structured as follows: Section 2 describes the background of the NCEE and the *Double First-Class Initiative* in China. Section 3 details the data sources, sample selection, and outcome variables. Sections 4 and 5 present our empirical strategies and results across two main dimensions. In Section 6, we conduct a heterogeneity analysis and perform a placebo test. Finally, Section 7 concludes the paper.

2 Background

2.1 National College Entrance Examination (NCEE)

The NCEE is a formidable exam in China, marked by its rigorous competitiveness. Every year, nearly ten million students sit for the NCEE, competing for a spot in a university.

The NCEE takes place nationwide from June 6th to 9th, with students taking the exam in their home provinces. During our study period, students in most provinces had to opt between the social or natural science track at the end of the first high school year, determining their NCEE track. Consequently, the track chosen has implications for their university major applications. For instance, most STEM disciplines predominantly admit natural science track students. However, some disciplines, such as economics, are more versatile, as they consider students from both tracks but have separate admission quotas. Provincial educational authorities administer and grade the examinations, ensuring that students within the same province, track, and year are assessed based on identical exam content and compete against one another in a standardized context.[2].

Before the exam, the Ministry of Education sets the number of students each university will admit in social science and natural science programs separately for each province. This number, known as the *admission quota*, depends on factors such as the university's funding source, location, and cohort size in each province, and it remains binding. After the NCEE, students receive their scores and provincial rankings at the end of June. With this information, they apply to universities by filling out a preference form and selecting up to five different universities, each with five program choices.

Admission to universities primarily depends on NCEE scores. Applications are ranked based on students' NCEE scores, and university seats are allocated sequentially according to these rankings. The student with the highest score secures their first-choice option, followed by the second-highest scorer, and so on. As a result, students may be assigned to lower-ranked options on their preference list if higher-ranked students have already filled other slots. The score or ranking needed for admission varies depending on the program's competitiveness that year.

Students can receive at most one admission offer (one university-program pair). If they accept, they enroll; if they decline, they forfeit the chance to attend any university that year. To pursue a university education, they must retake the NCEE the following year and compete with the next cohort in the same track and province. This system makes university and program choice crucial, as retaking the exam is a significant commitment and introduces uncertainties. Meanwhile, potential employers adjust their hiring lists based on

[2]Teaching materials and examination content might vary by province, coupled with restrictions on household registration (*hukou*) and student registration. This combination hinders candidates from taking NECC in other provinces

widely recognized information about the perceived prestige and rigor of specific university-discipline pairs. Therefore, any information about the quality of universities and disciplines is valuable for students when filling out their preference forms, as it may significantly impact their future career prospects.

2.2 Double First-Class Initiative

The Double First-Class Initiative, officially titled *World First-Class University and First-Class Academic Discipline Construction*, is conceived by the central government of China to elevate elite universities and some academic disciplines to world-class status by 2050.

In September 2017, the government announced the inaugural lists of universities and disciplines targeted for enhancement under the plan, covering the first-round period from 2017 to 2021. The list of First-Class universities includes 42 of China's most comprehensive universities. The FCD list comprises 498 university-discipline units identified for development, distributed across 140 universities (e.g., Peking University−Physics is one of the FCDs).[3] These universities, each hosting at least one FCD unit, represent the top 5% of higher education institutions in mainland China, out of over 3,000 establishments. The *Double First-Class Initiative* employs a dynamic management approach, with First-Class universities and FCDs undergoing evaluations every five years. Universities and disciplines that fail to meet the established standards by the end of the period will be removed from the list, while those meeting the criteria will be added.

To bolster these institutions, the Chinese government emphasizes innovative support mechanisms, ensuring targeted assistance that takes into account the foundational strengths, discipline categories, and developmental levels of these institutions. Those universities are slated to receive additional funding from the central or local government, with infrastructure support, especially for discipline development. Governments and supervisory authorities will amplify their policy support, while universities are encouraged to diversify their funding sources. The government also seeks to deepen administrative reforms in the higher education sector, granting greater autonomy to the selected universities. Although these universities have received the designation of First-Class University or FCD and gained more autonomy, they can not expand their student admissions at will. First, admission plans need to be approved by the Ministry of Education. Second, higher education in China is primarily public and government-led rather than market-driven, resulting in relatively low tuition fees. Therefore, universities lack the motivation to increase student admission significantly.

The selection of FCDs is primarily based on the *China Discipline Evaluation (2012)* (CDE 2012). This evaluation, which categorizes academic disci-

[3] Disciplines are designated as an FCD based on a four-digit major code.

plines (four-digit major code), assesses the following aspects at each university: (1) quality of talent training, (2) teaching staff and resources, (3) scientific research, and (4) social service and disciplinary reputation. Universities are rated and ranked within the same discipline, enabling direct comparison across institutions. Our analysis shows that 85% of the selected FCDs align with the CDE 2012 rankings. For instance, the software engineering discipline at six universities is designated as an FCD, and these universities are precisely the top six in the CDE rankings. The discrepancy in the remaining 15% can be attributed to additional factors considered during the FCD selection process, such as regional development and the unique attributes of specific disciplines and universities. While there are some deviations, the CDE 2012 results remain the principal criterion for FCD selection.

The initiative has captured significant attention and exerted a broad impact throughout the country because attending elite universities indeed pays off (Li et al., 2012; Jia and Li, 2021) and can change one's fate to some extent (Jia et al., 2022) in China. The search trends for the *Double First-Class Initiative*, as illustrated in Figure A1a, reflect the search volume for this term on *Baidu*, China's largest search engine. The data reveals a pronounced peak in searches in September 2017, coinciding with the announcement of the policy, indicating substantial public interest. Subsequent peaks in search volume align with the university application season, underscoring the policy's enduring and widespread influence. The blue curve in Figure A1b delineates the search trends for universities included in the inaugural 2017 list of the *Double First-Class Initiative*. Notably, the search volume for these institutions surged during the university application season following the policy's introduction. Conversely, the green curve illustrates the search patterns for universities newly added in the second round of the list in 2022. There was a significant uptick in search volume for these universities post-inclusion in the policy. These trends underscore the initiative's prominence and influence on the preferences and decisions of university applicants and other key stakeholders.

2.3 Disciplines and Programs in China's Academic System

The academic classification system in China structures the field of study into a hierarchy of disciplines and programs, establishing a framework that mirrors the extensive scope and depth of scholarly exploration within universities. At the heart of this structure is the concept of disciplines, broad categories indicated by a four-digit major code, encompassing a wide spectrum of specialized knowledge. Within each discipline are more focused programs, identified by a six-digit major code, that delve into specific thematic areas and offer detailed exploration of particular subfields.

Achieving the status of FCD at the four-digit major code level carries implications beyond the discipline itself. This esteemed recognition extends to all six-digit major code programs within the discipline. Consequently, these programs, as integral components of the discipline, are automatically accorded the FCD distinction. This cascading recognition underscores not only the excellence of the discipline but also affirms the individual programs' contributions to the university's academic prestige.

The entity within the FCD roster is fundamentally a union of a specific university and its corresponding discipline[4]. This paper, therefore, designates such a combination as the 'university-discipline unit' or 'university-discipline pair', representing the core unit of analysis. It is pertinent to recognize that all programs encapsulated within a FCD are inherently included within this defined unit. This fact will not be reiterated in future discussions to avoid redundancy.

3 Data

3.1 Source of Data

The primary dataset employed in this study is sourced from the website *Zhang Shang Gaokao* (literally means NCEE in hands)[5], a comprehensive platform that stands as China's foremost repository for information about the NCEE. This exhaustive repository aggregates admission data across tiers of educational institutions since 2015. The specifics include university name, location, academic track, admission year, province of admission, program name, affiliated discipline, and the minimum NCEE score required for program admission. A representative entry sheds light on the minimum score required for a program at a particular university in a specified province, with details about the associated discipline. Hence, this allows us to link the university-discipline unit in the FCDs to our dataset.

Since the university admission process is centralized at the provincial level and exam content varies each year, scores may not be comparable across different years. Therefore, we use students' rankings within their academic track and province to measure admission competition. To ascertain the ranking associated with the minimum admission score in the corresponding natural science and social science tracks within a particular province, a secondary data source was consulted: the score-to-rank conversion tables published by the provincial admissions offices.[6] By leveraging these tables, one can accurately

[4]The complete FCD list is available at
http://www.moe.gov.cn/srcsite/A22/moe_843/201709/t20170921_314942.html

[5]https://www.gaokao.cn/

[6]Students can consult score-to-rank conversion tables to determine their provincial ranking among all examinees, allowing them to understand their relative position. Provincial admissions offices also provide the minimum rankings of students admitted to each program of different universities over the past few years. Therefore, students can use their ranking and historical minimum admission rankings for each program as crucial references when filling out their pref-

determine the exact ranking for any given score within these tracks for a specified year. Notably, the ranking of the student with the lowest score reflects the total number of examinees in the corresponding track for that year’s NCEE in the specified province.

3.2 Sample Selection

First, our sample selection focuses on the First-Class Disciplines (FCDs) included in the first round of the list, spanning from 2017 to 2021. Although the second round of the FCD list began in 2022, adding eight FCDs and increasing the total from 498 to 506, this round remains ongoing and has introduced only minor changes. We restrict our sample to FCDs from the first round to ensure consistency and robustness in our analysis. This approach allows us to assess the policy’s impact within a completed and clearly defined period, minimizing potential bias or uncertainty associated with the incomplete second round. Thus, focusing on the first-round FCD list provides a reliable foundation for evaluating the policy’s effects.

Second, our sample includes 20 provinces in China.[7] This selection is designed to ensure analytical consistency. Throughout our study period, there were notable shifts in the NCEE system in some provinces. While some maintained the traditional bifurcation into science and social science tracks, others introduced more flexible models.[8] In these adjusted systems, students are assessed collectively, regardless of their elective choices. Such structural variations pose challenges for making direct intra-provincial comparisons over time. To avoid these complexities, we keep provinces that maintained stable NCEE structures -two academic tracks -throughout the period in our sample.

Finally, as established earlier, student competition is confined to their respective academic tracks. Our primary analysis focuses on the natural science track for two key reasons. First, approximately 75% of university programs are oriented toward natural sciences, ensuring extensive coverage. Second, the FCD list shows a strong preference for natural science disciplines, with 80%

erence forms. More recent tables were digitally sourced from official admissions office websites, while older data was manually gathered from printed versions of the *College Entrance Examination Guide*.

[7] Full list: Qinghai, Gansu, Guizhou, Heilongjiang, Henan, Guangxi, Xinjiang, Jiangxi, Shanxi, Yunnan, Inner Mongolia, Jilin, Sichuan, Ningxia, Anhui, Hunan, Hubei, Guangdong, Jiangsu, and Fujian.

[8] In the traditional bifurcation, students in the natural science track take Physics, Chemistry, and Biology, while those in the social science track take History, Political Science, and Geography, in addition to the mandatory subjects of Chinese, Mathematics, and English. In more flexible models, students still take Chinese, Mathematics, and English but must choose either Physics or History, along with two additional subjects of their choice. Some provinces have shifted to a system where students can freely select three subjects beyond the mandatory ones, pooling them together to compete for university seats. Our sample excludes these provinces because the absence of distinct academic tracks prevents meaningful intra-provincial comparisons.

in STEM fields. To provide a comprehensive perspective, we also include an analysis of the social science track in our heterogeneity analysis, offering a holistic evaluation of the policy's impact.

3.3 Outcome Variable: Admission Competition

To investigate how FCD designation affects admission competition, we construct the outcome variable, *admission competition*, which reflects how competitive a program is. For a given program i nested in discipline d in science track and university u within student's home province p and year t, we quantify the *admission competition* as follows:

$$\text{Competition}_{idupt} = 1 - \frac{\text{Minimum admission ranking}_{idupt}}{\text{Examinee}_{pt}}$$

Here, *Minimum admission ranking*$_{idupt}$ represents the ranking of the student with the lowest score admitted into program i nested in discipline d in the natural science track and university u for student's home province p in year t, and Examinee$_{pt}$ is the total number of examinees in science track for student's home province p in year t. This computation yields a competition-level metric ranging from 0 to 1, where values closer to 1 indicate a higher relative ranking required for program admission, signifying increased competitiveness. For example, if the last admitted student for a specific program ranks 100th out of 1,000 students in the province, the admission competition is calculated as 1-(100/1000)=0.9. Thus an increase of 0.01 in the outcome variable indicates that students need to improve one percentile ranking to potentially gain admission, reflecting enhanced selectivity, and vice versa. The metric's design accounts for variations in the examinee pool over time, providing an intuitive and effective tool for measuring admission competition levels in academic programs across years.

4 Effect of FCD Policy on Admission Competition at Disciplinary Level

To assess the impact of the FCD policy on admission competition at the disciplinary level, we first use the concept of the RDD method to create treatment and control groups, then apply DiD to estimate the treatment effect. In this section, we will introduce the construction of treatment and control groups, describe the empirical model, and present the estimation results.

4.1 Treatment and Control Groups

The construction of the treatment and control groups is guided by the *China Discipline Evaluation(2012)* (CDE(2012)) and the FCD list [9]. From the list, we enumerate the number of universities designated as FCD for each discipline, defining this number as the FCD quota. For example, *Physics* is designated as FCD in six universities, and the FCD quota for *Physics* is six. This quota serves as the cutoff for each discipline's ranking within the CDE framework. We identify FCDs just above the cutoff as the treatment group and non-FCDs just below the cutoff as the control group. To enhance comparability between treatment and control units, we select only those within half the quota on both sides of the cutoff.

Table 1 illustrates the construction of the CDE treatment and control groups. As shown in Table 1a, *Software Engineering* is designated as FCD in five universities, giving it an FCD quota of five. In this case, FCD selection aligns with the evaluation rankings, meaning the top five universities are designated as FCDs. Consequently, three universities (half of the total quota, rounded to the nearest integer) just above and below the cutoff are classified into treatment and control groups. Therefore, the *Software Engineering* programs at universities C, D, and E are included in the treatment group, while those at universities F, G, and H are in the control group.

A more complex scenario is presented in Table 1b for the discipline of *Physics*, where the FCD selection does not fully align with the evaluation rankings. The FCD quota in this case is six, but not all top six universities receive the FCD title—universities D and E rank 3rd and 5th, but are non-FCD. However, we still select units within half the quota on both sides of the cutoff for the treatment and control groups. Accordingly, the programs nested in *Physics* discipline at universities F and G are included in the treatment group, while those at universities D, E, H, and I are in the control group.

The Ministry of Education and relevant authorities conducted the CDE (2012) before the FCD policy was implemented in 2017 and determined the FCD quota (the cutoff). As a result, individual universities could not manipulate these outcomes, helping to reduce potential endogeneity concerns in our research design.

4.2 Empirical Model

The NECC takes place in early June each year. Applicants typically complete their application forms by the end of June. Given that the FCD policy was unveiled in September 2017, the first group of examinees to be influenced by

[9] In the English version of the CDE(2012), outcomes are categorized into A, B, and C grades. However, the Chinese version delineates results through explicit numerical scores. This study employs the detailed scoring system provided by the Chinese version. https://www.cdgdc.edu.cn/cde/index.htm

(a) Example 1

Software Engineering					
University	Score	Rank	FCD	FCD Quota	T/C
A	88	1	Yes	5	-
B	88	1	Yes	5	-
C	**87**	**3**	**Yes**	**5**	**T**
D	**86**	**4**	**Yes**	**5**	**T**
E	**86**	**4**	**Yes**	**5**	**T**
F	**80**	**6**	**No**	**5**	**C**
G	**78**	**7**	**No**	**5**	**C**
H	**77**	**8**	**No**	**5**	**C**
I	76	9	No	5	-
J	76	9	No	5	-
K	75	11	No	5	-
L	75	11	No	5	-

(b) Example 2

Physics					
University	Score	Rank	FCD	FCD Quota	T/C
A	98	1	Yes	6	-
B	95	2	Yes	6	-
C	90	3	Yes	6	-
D	***90***	***3***	***No***	***6***	***C***
E	***88***	***5***	***No***	***6***	***C***
F	**86**	**6**	**Yes**	**6**	**T**
G	**85**	**7**	**Yes**	**6**	**T**
H	***85***	***7***	***No***	***6***	***C***
I	***83***	***9***	***No***	***6***	***C***
J	82	10	Yes	6	-
K	*81*	*11*	*No*	*6*	-
L	80	12	No	6	-

Table 1. Treatment and Control Group Construction

Notes: This table demonstrates the construction of the treatment and control groups based on the *CDE (2012)*. Within each discipline, universities are ordered according to their evaluation scores. The number of universities designated as FCD within the same discipline, FCD quota, serves as the cutoff, indicated by the red horizontal line. In Table 1 (a), the three FCD units (half the FCD quota and round to the nearest integer) just above the cutoff form the treatment group (blue), while the three non-FCD units just below form the control group (orange). Table 1 (b) illustrates the case where FCD designation does not fully align with the *CDE (2012)* outcome. In this case, we still choose university-discipline units within half the quota on both sides of the cutoff into the analysis sample. Therefore, universities F and G are included in the treatment group, while universities D, E, H and I are included in the control group.

this policy is those sitting for the NECC in 2018. Consequently, the year 2017 serves as the baseline year in the analysis.

To examine how the FCD designation affects admission competition that reflects students' choice, we use the DiD specification:

$$Y_{idupt} = \beta \text{Treated}_{du} \times Post_{2017} + X_{it}\Gamma + \phi_p + \alpha_d + \delta_t + \varepsilon_{idupt} \quad (1)$$

where Y_{idupt} represents the admission competition level of program i within discipline d, university u, student's home province p, and year t. Treated_{du} is the treatment variable, indicating whether a university-discipline pair is listed in the FCD list. Additionally, Treated_{du} equals 1 for all programs nested within the treated discipline-university pair. The binary variable $Post_{2017}$ takes 1 from years following the policy announcement and 0 otherwise. X_{it} refers to a vector of control variables, including the GDP of the student's home province, the unemployment rate, and the GDP of the province where the university is located.

ϕ_p accounts for the fixed effects of students' home provinces, eliminating inter-provincial variation as students compete for university seats only with peers from their own province. α_d, the discipline fixed effect, controls for unobservable characteristics intrinsic to each discipline that may influence the outcome. Additionally, δ_t, the year-fixed effect, is included to mitigate potential biases from year-specific trends or events. Finally, ε_{idupt} encapsulates the unique error term associated with each program, discipline, university, province, and year. Standard errors are clustered at the university level because applicants can select up to five universities, each with five program choices. This suggests that applicants are likely to prioritize universities first and then select programs within those universities, leading to a potential association between programs at the same institution.

The coefficient β is of primary interest, denoting the treatment effect that captures the differential change in the program's admission competition following the discipline's inclusion in the FCD list. A statistically significant β would imply a discernible impact on a program's admission competition attributable to its discipline's recognition under the FCD initiative.

Our identifying variation comes from cross-university differences within each discipline, just above and below the CDE-based cutoff that determines FCD status. Conditioning on discipline fixed effects already restricts comparisons to within-discipline units. Including university or university–discipline fixed effects would absorb this key cross-university variation, as each unit appears only once per discipline and changes treatment status only once (post-2017). In particular, university–discipline fixed effects would introduce near-collinearity with the treatment variable and existing fixed effects, leaving little identifying variation and reducing efficiency. For this reason, we omit these fixed effects in the baseline analysis but include university fixed effects where the comparison is explicitly within universities—namely, in the spillover analysis in Section 5.

4.3 Estimation Results

Given that the majority of FCD programs and university admissions are STEM-oriented (Section 3.2), our main analysis focuses on the natural science track. Results for the social science track are reported in as heterogeneity analysis (Section 6.2).

Table 2 presents the estimated coefficients from Equation (1) with different sets of fixed effects. Column (1), incorporating year and province fixed effects, shows that the minimum admission ranking of FCD increases by an average of 1.65 percentiles post-policy compared to the baseline competition level. When column (3) adds the discipline fixed effect, the magnitude slightly decreases. To control for the economic conditions of students' home provinces and university locations, we further include additional control variables in columns (2) and (4). The coefficients from these specifications are slightly reduced compared to those obtained from the model specification without control variables. Overall, the statistically significant and positive estimated coefficients in Table 2 indicate that admission competition for FCD increases by 49%, attracting and admitting higher-ranking students.

	(1)	(2)	(3)	(4)
FCD	0.0165***	0.0158***	0.0156***	0.0152***
	(0.0062)	(0.0058)	(0.0043)	(0.0043)
Sample Mean Outcome	0.9111	0.9111	0.9111	0.9111
	(0.1047)	(0.1047)	(0.1047)	(0.1047)
Year FE	✓	✓	✓	✓
Province FE	✓	✓	✓	✓
Discipline FE			✓	✓
Province GDP		0.0005***		0.0004***
		(0.0002)		(0.0013)
Unemployment		-0.0003		-0.0001
		(0.0017)		(0.0015)
Uni. Province GDP		0.0007***		0.0004***
		(0.0002)		(0.0001)
N	50,423	50,423	50,423	50,423
R^2	0.0771	0.1403	0.5307	0.5480

Table 2. The Effect of FCD on Admission Competition at Disciplinary Level

Notes: This table presents DiD estimates of the admission effect of FCD at the disciplinary level (Equation (1)) where, within the same discipline, we compare the FCDs to the non-FCDs. Robust standard errors are reported in parentheses (clustered at the university level). Significance: *$p < 0.10$, **$p<0.05$, ***$p<0.01$.

To better understand the practical implications of the effect, consider that approximately 120,000 students per province took the NCEE annually during the study period in our sample. The coefficients translate to an increase of 1,824 in the minimum admission ranking post-policy (120,000 * 1.52 percentiles). This suggests that the last admitted student must surpass at least 1,824 more peers compared to pre-policy conditions.

A potential concern is that universities with FCDs might expand their admission upon receiving FCD titles along with additional economic resources. This could result in a biased estimation. However, we should not be concerned about this issue. First, as discussed in Section 2.2, expanding admissions requires approval from the Ministry of Education, and universities lack the incentive to pursue this as they are government-led rather than market-driven. Second, the estimated coefficients can be considered underestimated if the admissions were expanded. This inference is based on the assumption that increasing admission quotas would reduce competition for admission. However, an increase in admission competition has been observed. Therefore, if admission quotas have indeed been raised while competition has intensified, it implies that the true estimate should be larger than the observed estimate. Thus, the estimated coefficients might be regarded as lower bounds. Third, while admission quotas for 2015 and 2016 are not provided, data on admission quotas have been available since 2017, one year before the implementation of the FCD. Therefore, as shown in Table A2, we present the DiD estimate of how the admission quota per examinee allocated to each province varies over time with 2017 as the baseline year as supplemental evidence to demonstrate that no significant change in admission quota per examinee occurred post-policy as the estimated coefficients are insignificant at 95% confidence interval.

4.4 Dynamic DiD Analysis

To test the parallel trend assumption and explore treatment effects over time, we introduce a dynamic DiD methodology:

$$Y_{idupt} = \sum_{s=2015}^{2021} \beta^s \cdot (\text{Treated}_{du} \times D^s_{dut}) + X_{it}\Gamma + \phi_p + \alpha_d + \varepsilon_{idupt} \tag{2}$$

where D^s_{dut} takes 1 if $t = s$ and other variables are defined in the same way as in Equation (1). This identification is based on the assumption that in the absence of the FCD policy, the treatment and control groups should have experienced parallel trends in the admission competition over time. We empirically test the parallel trend assumption, and show the outcome in columns (1) and (2) in Table A1 where the estimated coefficients are insignificant pre-policy in 2015 and 2016, implying that the parallel trend assumption holds.

Figure 1 plots the estimated coefficients of Equation (2), providing the evolution of the treatment effect after isolating discipline and province fixed effects. Starting in 2018, the treatment effects became statistically significant and continued to increase, indicating that the FCD policy has made FCDs increasingly competitive. By 2021, the minimum admission ranking improved by 2.76 percentiles, requiring students with the lowest scores admitted to FCDs to surpass at least 3,312 peers.

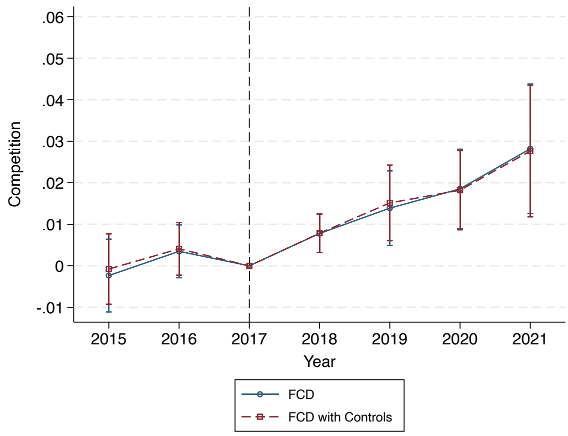

Figure 1. Dynamic Effect of FCD on Admission Competition at Disciplinary Level

Notes: The figure plots the estimated coefficients and 95% confidence intervals for the dynamic admission effects of the FCD policy (Equation (2)), both without control variables (solid blue line) and with control variables (dashed red line). The reference year is 2017 (indicated by the dashed vertical line), before the initiative's announcement.

5 Spillover Effect of FCD within the University

In this section, we examine the spillover effect of the FCD designation by comparing recognized disciplines with their non-recognized counterparts within the same university. Therefore, we restrict the sample to universities hosting at least one FCD.

5.1 Empirical Model

The empirical model for this spillover effect examination is:

$$Y_{idupt} = \beta \text{Treated}_{du} \times Post_{2017} + X_{it}\Gamma + \phi_p + \lambda_u + \alpha_d + \delta_t + \varepsilon_{idupt} \quad (3)$$

where the variables are defined in the same way as in Equation (1), with the addition of the university fixed effect (λ_u), which eliminates the variation between universities.

The parameter of interest is β. Within the same university, if certain disciplines are designated as FCDs, we would typically expect the admission competition for these FCDs to increase significantly post-policy compared to their non-FCD counterparts, indicating a statistically significant β. Conversely, if β is insignificant, it may indicate no significant change in admission competition between the two groups. This can be interpreted as a spillover effect.

5.2 Spillover Result

Table 3 presents the estimated coefficients from Equation (3). Column (1) includes fixed effects for year, province, and university, while column (2) incorporates additional control variables. Building on these specifications, columns (3) and (4) further introduce discipline fixed effects. Across all specifications, the estimated coefficients remain statistically insignificant, small, and negative. While the estimates are statistically insignificant, we interpret this null result as evidence of spillover effects. If the policy' s benefits were limited strictly to FCD disciplines, admission competition should increase for FCD programs *relative to* non-FCD programs within the same university following the policy. The fact that this gap does *not* widen—despite the strong positive shock to FCDs seen in the baseline regression—suggests that non-FCD disciplines also attracted stronger applicants. In other words, the lack of a divergence implies that admission competition rose for both groups, consistent with spillover effects.

There are two potential explanations for the spillover effect. First, the excellence associated with FCDs may have been perceived as diffusing across the entire university, leading students to view non-recognized disciplines as equally excellent, thus generating a spillover from treated to non-treated disciplines. Second, due to the application mechanism, where students must prioritize universities before selecting programs, and given the competitive nature of the NCEE, most students fill out the entire preference form. As a result, in addition to selecting FCD programs, students also choose non-FCD programs, potentially increasing admission competition in non-recognized disciplines.

5.3 Dynamic DiD Analysis

We re-analyze the dynamic DiD model (Equation (2)) by adding a university fixed effect and with the updated sample. Figure 2 illustrates the spillover effects from FCD to non-FCD within the same university over time, which is flat. Columns (2) and (3) of Table A1 show detailed estimated coefficients. All estimated coefficients, both pre-and post-policy, are insignificant at 95% confidence interval, indicating no significant change in admission competition between treatment and control groups. Moreover, the post-policy coefficients are substantially smaller than the pre-policy ones, suggesting that admission competition has shrunk between the two groups. This implies that higher-ranking students apply for both FCDs and non-FCDs within the same universities.

6 Heterogeneity Analysis and Robustness Check

In this section, we conduct a heterogeneity analysis to examine variations in the treatment effect across different disciplines and the impact of the FCD

	(1)	(2)	(3)	(4)
FCD	-0.0015	-0.0010	-0.0013	-0.0008
	(0.0012)	(0.0012)	(0.001)	(0.001)
Sample Mean Outcome	0.9049	0.9049	0.9049	0.9049
	(0.0866)	(0.0866)	(0.0866)	(0.0866)
Year FE	✓	✓	✓	✓
Prov FE	✓	✓	✓	✓
Uni. FE	✓	✓	✓	✓
Discipline FE			✓	✓
Province GDP		0.0005***		0.0005***
		(0.0001)		(0.0001)
Unemployment		-0.0016*		-0.0016*
		(0.0009)		(0.0009)
Uni. Province GDP		-0.0002***		-0.0002***
		(0.0001)		(0.0001)
N	340,668	340,668	340,667	340,667
R^2	0.672	0.672	0.682	0.683

Table 3. Spillover Effect of FCD on Admission Competition within the University

Notes: This table presents the estimated spillover effect of the FCD using the sample of universities with at least one FCD (Equation (1)), where we compare the FCDs to the non-FCD counterparts within the same university. Robust standard errors are reported in parentheses (clustered at the university level). Significance: *p < 0.10, **p<0.05, ***p<0.01.

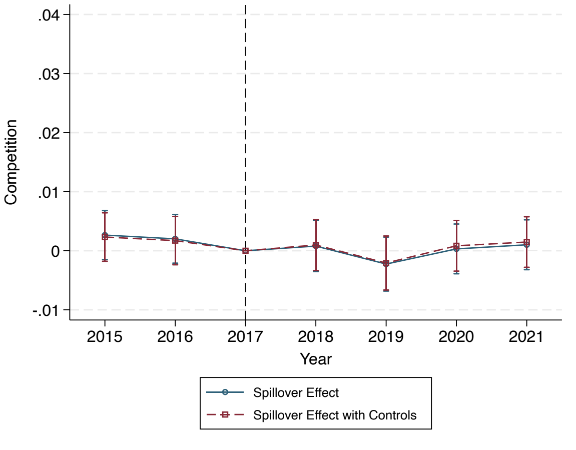

Figure 2. Dynamic Spillover Effect of FCD on Admission Competition

Notes: The figure plots the estimated coefficients and 95% confidence intervals for the dynamic spillover effects of the FCD policy within the FCD university, both without control variables (solid blue line) and with control variables (dashed red line). The reference year is 2017 (indicated by the dashed vertical line), before the initiative's announcement.

policy on admission competition in the social science track. Additionally, we perform a placebo test to validate the findings from the main analyses.

6.1 Heterogeneity by Disciplines

To assess the differential impact of the FCD policy across various academic disciplines, we employ an expansive classification including six primary categories for natural science track students: Social Science, Agriculture, Medicine, Engineering, Science, and Management.[10]

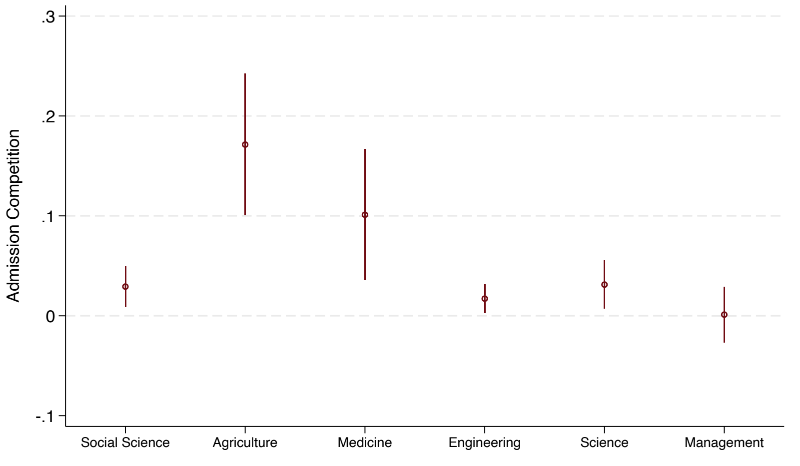

Figure 3. Heterogeneity Analysis for FCD by Discipline

Notes: The figure plots the estimated coefficients and 95% confidence intervals for the admission effects of the FCD policy by discipline at the disciplinary level. The reference year is 2017, before the initiative's announcement.

As shown in Figure 3, our results reveal varying degrees of response to FCD policies across different disciplines. Detailed estimated coefficients are presented in Table 4. Except for Management, the estimated coefficients for all other categories are statistically significant at the 95% confidence interval. Notably, the increase in admission competition for Agriculture and Medicine stands out, with both fields experiencing a rise of over 10 percentiles post-policy, compared to the more modest increases of 1.7 to 3.1 percentiles observed in Social Science, Engineering, and Science. This highlights the heterogeneous impact of the initiative, with Agriculture and Medicine seeing the most pronounced effects.

[10]Some programs within the Social Science category admit students from both the social science and natural science tracks, such as Economics, Management, etc, with separate admission quotas. The heterogeneity analysis in this section is an extension of the main analysis and therefore only includes Social Science programs that admit students from the natural science track.

	(1) Social Science	(2) Agriculture	(3) Medicine	(4) Engineering	(5) Science	(6) Management
Treated x Post	0.0292***	0.171***	0.101***	0.0172**	0.0312**	0.0012
	(0.010)	(0.034)	(0.031)	(0.007)	(0.012)	(0.013)
Sample Mean Outcome	0.9552	0.7789	0.8831	0.9239	0.9357	0.9472
	(0.0602)	(0.1504)	(0.1219)	(0.0883)	(0.0671)	(0.0701)
Year FE	✓	✓	✓	✓	✓	✓
Discipline FE	✓	✓	✓	✓	✓	✓
Province	✓	✓	✓	✓	✓	✓
N	3,572	4,619	5,081	28,880	7,569	694
R^2	0.52	0.36	0.45	0.53	0.26	0.49

Table 4. Heterogeneity Analysis for FCD by Discipline

Notes: This table presents the heterogeneous effects of FCD on admission competition by discipline. All standard errors are in parentheses (clustered at the university level). Significance: *p < 0.10, **p<0.05, ***p<0.01.

This differential impact may be attributed to the long-established emphasis and popularity of STEM and business-related disciplines. As noted in Table 4, Engineering and Science have over 28,000 and 7,500 programs, respectively and the average admission competition of STEM and business-related disciplines is over 0.92. In contrast, Agriculture and Medicine have the lowest average admission competition among all categories but have seen the largest increase in admission competition. Thus, the official recognition of these less sought-after disciplines likely plays a key role in informing prospective students about the quality of disciplines and attracting more high-caliber candidates.

6.2 Analysis in Social Science Track

In this section, we perform the same analysis on social science track programs, enabling a comparative evaluation to ascertain potential heterogeneous effects across the two academic tracks. Table 5 reveals the impact of the FCD policy on the admission competition level in the social science track.

Columns (1) and (2) present the estimated coefficients for FCD when compared to non-FCD within the same discipline. In column (1), the coefficient of FCD is statistically significant at the 90% confidence interval, suggesting that FCD designation may impact admission competition. However, when we add control variables such as students' province GDP, unemployment, and universities' province GDP in column (2), the coefficient of FCD becomes statistically insignificant. Instead, the coefficient of universities' provincial GDP becomes significant, indicating that the economic conditions in the province where the universities are located play a more critical role in determining admission competition.

This shift suggests that the economic development of a university's province is a more important factor than FCD designation for students on the social science track given the specific discipline. A possible explanation is that China's policies emphasize the development of natural sciences and technology, which skews resources and attention toward these fields, leading to fewer options and less competition in social science disciplines. As shown in the table, the sample for the disciplinary-level analysis in social science includes 7,653 programs, while the corresponding sample size for the natural science track exceeds 50,000. This imbalance suggests that students in social sciences have fewer choices, making them more likely to favor universities in economically developed areas where employment prospects are more promising.

	Disciplinary Level		**Within University**	
	(1)	(2)	(3)	(4)
FCD	0.0061*	0.0040	0.0003	0.0001
	(0.003)	(0.003)	(0.001)	(0.001)
Sample Mean Outcome	0.9726	0.9726	0.9527	
	(0.0542)	(0.0542)	(0.0653)	(0.0653)
Year FE	✓	✓	✓	✓
Province FE	✓	✓	✓	✓
Discipline FE				✓
Province GDP		-0.0002	0.0002	0.002
		(0.0002))	(0.0001)	(0.001)
Unemployment		-0.0022	0.0006	0.0018
		(0.0015)	(0.0015)	(0.0011)
Uni. Province GDP		0.0003**	-0.0001	-0.001
		(0.0001)	(0.0000)	(0.0001)
N	7,653	7,653	98,001	97,996
R^2	0.513	0.549	0.460	0.521

Table 5. The Effect of Social Science Track FCD on Admission Competition

Notes: The sample is restricted to programs that admit only social science track students. This table presents the effect of the FCD policy on admission competition. Columns (1) and (2) show the DiD estimates at the disciplinary level, while columns (3) and (4) display spillover effects within the same FCD university. Standard errors are shown in parentheses (clustered at the university level). Significance: *p < 0.10, **p<0.05, ***p<0.01.

We observe an insignificant effect of FCDs within universities. As shown in columns (3) and (4), there is no significant change in admission competition between FCDs and non-FCDs within the same university, although the estimated coefficients are positive, rather than negative as in the main analysis.

6.3 Placebo Test

We conduct a placebo test to validate our main findings by maintaining the original intervention timing while randomly reassigning treatment status across units, keeping the proportion of treated and control units constant. For discipline-level analyses, treatment is assigned randomly to university-discipline units within each discipline. To examine spillover effects, treatment status is reassigned to disciplines within universities. The underlying premise is that if our main findings accurately capture the treatment effect, random reassignment should not produce significant estimates.

	Discipline Level		Spillover	
	(1)	(2)	(3)	(4)
FCD	-0.0029	-0.0026	0.0004	0.0002
	(0.0021)	(0.0020)	(0.0005)	(0.0005)
Year FE	✓	✓	✓	✓
Discipline FE	✓	✓		✓
Univ. FE			✓	✓
Province FE	✓	✓	✓	✓
Province GDP		0.0004***		0.005***
		(0.0018)		(0.0001)
Unemployment		0.0003		-0.0016**
		(0.0018)		(0.0008)
Uni. Province GDP		0.0005***		-0.0002**
		(0.0001)		(0.0001)**
N	50,423	50,423		340,668
R^2	0.50	0.53	0.67	0.68

Table 6. Placebo Test: Random Reassignment of Treatment Status

Notes: This table presents the results of the placebo test wherein the treatment status was randomly reassigned across units. All standard errors are in parentheses (clustered at the university level). Significance: *p $<$ 0.10, **p<0.05, ***p<0.01.

The outcomes of the placebo test, detailed in Table 6, show no significant effects at both the disciplinary level (columns (1) and (2)). This result strengthens our confidence in the main findings, suggesting that the identified effects are indeed attributable to the treatment rather than artifacts of the modeling approach or other confounding factors. Regarding the test for spillover effects in columns (3) and (4), the estimated coefficients remain insignificant. This is consistent with the main analysis, which suggests that higher-ranking students apply to both FCD and non-FCD programs within the same university, either due to a perceived equivalence in excellence or the structure of the application mechanism. As a result, even with the random assignment of treatment status within universities, there is no significant change in admission competition between the treatment and control groups. This validates the main findings and further confirms the existence of spillover effects.

7 Conclusion

The FCD policy, which designates certain discipline-university units as centers of excellence, has attracted considerable attention and significantly influenced admission competition, reflecting the decisions of prospective students regarding their university applications. Previous studies have predominantly focused on the influence of university-level rankings or official evaluations on the quantity and caliber of applicants. However, little is known about how an excellence designation at the disciplinary level affects students' choices and admission competition and its potential transmission mechanism within the same university. Our study, by adopting this finer level of granularity, provides a more precise understanding of the mechanisms through which the policy exerts its effects.

Utilizing the DiD methodology, we find clear evidence that university-discipline units designated as FCD experience a significant increase in admission competition. Moreover, FCDs generate spillover effects on non-FCD counterparts within the same universities, as there is no significant change in admission competition between them post-policy. A possible explanation is that students perceive FCD and non-FCD programs as equally excellent within the same university, or that the application mechanism requires students to prioritize universities before selecting several programs within them. The treatment and spillover effects can increase overall admission competition of universities hosting at least one FCD, indicating that programs in these universities attract and admit higher-ranking students as shown in Appendix 7.

Our main analysis from two perspectives indicates that talent increasingly clusters in FCDs and their host universities over time. The results of the heterogeneity analysis suggest that official recognition of less sought-after disciplines, such as Agriculture, through the FCD policy is instrumental in showcasing their quality and attracting high-ranking students, thereby drawing more high-caliber candidates to traditionally underappreciated fields. Due to China's longstanding emphasis on the importance and prioritization of STEM disciplines, the FCD designation does not significantly increase admission competition within the same discipline in the social science track but does significantly enhance the overall admission competition at universities hosting these FCDs. Finally, the outcomes of the placebo test validate the findings of the main analysis.

To the best of our knowledge, this study is the first to investigate how discipline-level excellence designations influence admission competition and to evaluate the impact of China's FCD policy. Our findings indicate that the FCD policy has intensified admission competition in three key areas for students pursuing the natural sciences: within individual disciplines, among universities with FCD designations, and in less popular fields. However, the mechanisms underlying spillover effects within universities remain unclear, potentially due to the diffusion of excellence or the existing application process. To enhance the policy's effectiveness, policymakers might consider restructuring the application procedure by shifting from a university-centric prioritization to a system that allows students to rank university-discipline units based on their preferences. This adjustment could better align high-ranking applicants with FCD-designated programs. Additionally, information asymmetries between universities and students regarding the quality of specific academic disciplines can be reduced through excellence designations, thereby improving transparency and facilitating a more efficient match between top-performing students and strong academic programs. Nevertheless, such designations may also exacerbate inequalities among universities, particularly in terms of resource allocation and the future recruitment of high-caliber students and faculty. Policymakers need to carefully balance the trade-offs between efficiency and equity to ensure the fair and effective implementation of excellence designations.

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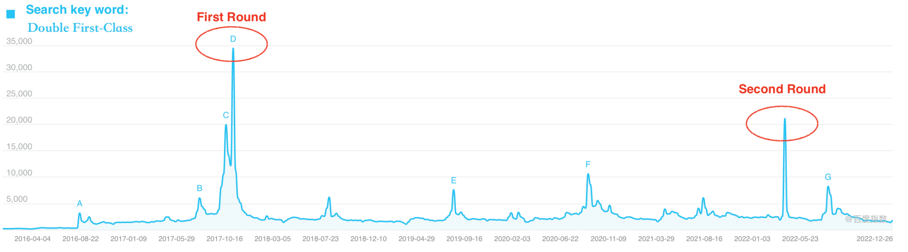
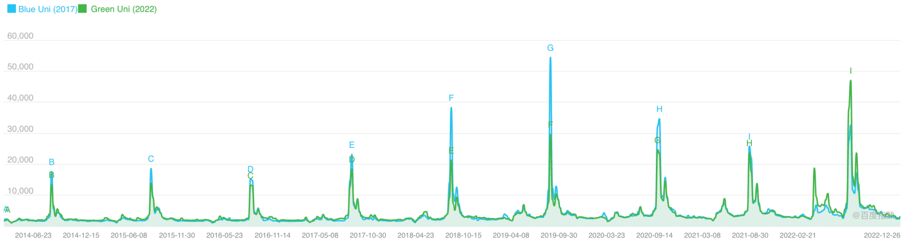
Appendix A: Figures and Tables



(a) Search Trend of *Double First-Class*



(b) Search Trend of Designated Universities

Figure A1. Search Trend

Note: Figure(a) shows the search index volume for the keyword *Double First-Class* on China's largest search engine, *Baidu*. The *First Round* in the graph refers to the announcement of the DFC initiative in September 2017, which spanned from 2017 to 2021. The *Second Round* indicates the announcement of the newly updated list of *First-Class Universities* and *First-Class Disciplines* following the re-evaluation of universities and disciplines in 2022. Figure(b) displays the search volume for a specific university's keyword, for example, *"Blue/Green Univ."*, as retrieved from *Baidu*. *Blue University* denotes the university included in the inaugural list of the *Double First-Class initiative* in September 2017, while *Green University* refers to one included in the second round in February 2022.

	Disciplinary Level		Spillover Effect		University Level			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated x 2015	-0.0024	-0.0008	0.0027	0.002	-0.0038	-0.0040	-0.0043	-0.0045
	(0.004)	(0.004)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)
Treated x 2016	0.0035	0.0041	0.0020	0.0017	0.0032	0.0031	0.0027	0.0025
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Treated x 2017	base	base	base	base	base	base	base	base
Treated x 2018	0.0078**	0.0079***	0.0008	0.0010	0.0086***	0.0085***	0.0086***	0.0084***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Treated x 2019	0.0139**	0.0151**	-0.0022	-0.0021	0.0064***	0.0064***	0.0066***	0.0064***
	(0.005)	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Treated x 2020	0.0185***	0.0182***	0.0003	0.0008	0.0139***	0.0137***	0.0138***	0.0136***
	(0.005)	(0.005)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Treated x 2021	0.0282***	0.0276***	0.0010	0.0015	0.0325***	0.0323***	0.0321***	0.0320***
	(0.008)	(0.008)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)
Discipline FE	✓	✓				✓	✓	
Province FE	✓	✓	✓	✓	✓	✓	✓	✓
Univ. FE			✓	✓	✓	✓	✓	✓
Province GDP		0.0004***		0.0005***	0.0013***	0.0013***	0.00014***	0.0014***
		(0.0001)		(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Unemployment		-0.0002		-0.0016*	-0.0044***	-0.0044***	-0.0044***	-0.0044***
		(0.0001)		(0.0009)	(0.0015)	(0.0015)	(0.0016)	(0.0015)
Uni.-Province GDP		0.0004***		-0.0002***	0.0002	0.0001	0.0001	0.0001
		(0.0001)		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
N	50,423	50,423	340,668	340,668	505,846	505,846	485,714	485,714
R^2	0.53	0.55	0.67	0.67	0.73	0.74	0.72	0.73

Table A1. Dynamic Effect of FCD Policy on Admission Competition

Notes: This table presents the dynamic effect of the FCD policy on admission competition. Columns (1) and (2) show the DiD estimates at the disciplinary level, while columns (3) and (4) display spillover effects within the same FCD university. Columns (5) through (8) present the admission effects at the university level, with columns (7) and (8) focusing on non-FCDs in the treatment group. Standard errors are shown in parentheses (clustered at the university level). Significance: *p < 0.10, **p<0.05, ***p<0.01.

	(1) Coefficient	(2) Standard Error	(3) t-Statistic	(4) p-Value
Panel A: Discipline				
Treated x 2017	base			
Treated x 2018	2.01×10^{-6}	2.76×10^{-6}	0.73	0.467
Treated x 2019	-7.14×10^{-7}	2.69×10^{-6}	-0.27	0.791
Treated x 2020	3.78×10^{-6}	4.45×10^{-6}	0.85	0.397
Treated x 2021	-4.19×10^{-6}	6.43×10^{-6}	-0.65	0.516
Province FE	✓			
Discipline FE	✓			
Uni. FE				
N	36,048			
R^2	0.121			
Panel B: Within University				
Treated x 2017	base			
Treated x 2018	4.95×10^{-6}*	2.57×10^{-6}	1.93	0.056
Treated x 2019	1.59×10^{-6}	2.4×10^{-6}	0.66	0.510
Treated x 2020	7.23×10^{-6}*	3.7×10^{-6}	1.95	0.053
Treated x 2021	-1.80×10^{-6}	4.08×10^{-6}	-0.44	0.660
Province FE	✓			
Discipline FE	✓			
Uni. FE	✓			
N	228,797			
R^2	0.154			
Panel C: University				
Treated x 2017	base			
Treated x 2018	-2.02×10^{-6}	2.46×10^{-6}	-0.82	0.414
Treated x 2019	-1.85×10^{-6}**	2.36×10^{-6}	-1.98	0.049
Treated x 2020	-1.85×10^{-6}	2.40×10^{-6}	-0.77	0.441
Treated x 2021	-5.20×10^{-6}	5.38×10^{-6}	-0.97	0.334
Province FE	✓			
Uni. FE	✓			
N	305,513			
R^2	0.092			

Table A2. Admission Quota at Provincial Level

Notes: The dependent variable is the admission quota per examinee for each program, in each province, and for each year. This table presents the DiD estimate of how the admission quota per examinee allocated to each province varies over time, with 2017 as the baseline year. Standard errors are in parentheses. Significance: *p $<$ 0.10, **p$<$0.05, ***p$<$0.01.

Appendix B: Effect of FCD Policy at the University Level

In this section, we examine the impact of receiving an FCD designation on overall university admission competition by comparing universities hosting FCDs with those without FCDs. We first describe the construction of the treatment and control groups. We then present the empirical model and estimation results.

Treatment and Control Groups

First, we exclude the universities designated as First-Class universities - China's 42 most comprehensive universities, as including these preeminent universities in the analysis could potentially skew the results given their distinguished status. Thus, the treatment group consists of universities hosting FCDs but not designated as First-Class universities.

Second, we use the related search keywords function of the search engine *Baidu* to form the control group, as we do not have access to students' preference forms when applying for university. *Baidu*, a leading search engine in China, offers valuable insights into user behavior through its related search keywords feature. These keywords, which reflect users' associated searches around a central search term, are ranked in the order of popularity[11]. Due to a lack of information about students' real preference sets, related search keywords provide information about which universities are frequently compared or considered together by students[12]. Students' decision-making process, particularly regarding their choice of universities, is often influenced not only by quantifiable factors such as academic rankings but also by perceptions, word-of-mouth, and other subjective elements. These search trends yield insights into how students categorize universities, revealing the universities they consider comparable during their decision-making process. Utilizing the available data, we identify 191 universities that are frequently contrasted by students to those in the treatment group, forming our control group.

Empirical Model

To examine how receiving an FCD designation affects overall university admission competition, we use the following specifications:

$$Y_{idupt} = \beta \text{Treated}_u \times Post_{2017} + X_{it}\Gamma + \phi_p + \lambda_u + \alpha_d + \delta_t + \varepsilon_{idupt} \qquad \text{(B1)}$$

where Treated_u is our university-level treatment variable, representing universities with any recognized discipline. The coefficient β captures the effect on

[11] See Figure B2 for a depiction of the *Baidu*-related keywords interface.

[12] Ideally, related keyword data at the program or discipline level would be most beneficial for our analysis. However, *Baidu* does not provide data with such specificity, which limits our data-driven methodology.

admission competition levels in these universities post-2017. Other variables are defined in the same way as in Equation (3).

Estimation Result

Columns (1)-(4) of Table B1 show the effect of FCD policy at the university level with distinct sets of fixed effects. Column (1) presents the estimate with fixed effects for year, province, and university, indicating that hosting at least one FCD increases a university's average admission competition by 1.5 percentiles. This estimate decreases after adding additional control variables in column (2). The statistically significant coefficients of the control variables suggest that the economic conditions of both the provinces where students originate and where universities are located influence students' application decisions. Building on the first two specifications, columns (3) and (4) include discipline fixed effects, yielding a slightly smaller result, which suggests that discipline characteristics might influence students' choice of university as well. Overall, receiving an FCD designation increases university admission competition by 9%.

	All Disciplines				**non-FCD**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FCD Uni.	0.0150***	0.0138***	0.0149***	0.0137***	0.0153***	0.0141***	0.0152***	0.0140***
	(0.0019)	(0.0020)	(0.0019)	(0.0020)	(0.0020)	(0.0021)	(0.0019)	(0.0021)
Sample Mean Outcome	0.7849	0.7849	0.7849	0.7849	0.7796	0.7796	0.7796	0.7796
	(0.1548)	(0.1548)	(0.1548)	(0.1548)	(0.1550)	(0.1550)	(0.1550)	(0.1550)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Uni. FE	✓	✓	✓	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓	✓	✓	✓
Discipline FE			✓	✓			✓	✓
Province GDP		0.0013***		0.0013***		0.0014***		0.0013***
		(0.0001)		(0.0002)		(0.0002)		(0.0002)
Unemployment		-0.0046***		-0.0046***		-0.0046***		-0.0045***
		(0.0015)		(0.0015)		(0.0016)		(0.0016)
Uni. Province GDP		0.0002**		0.0002**		0.0003**		0.0003**
		(0.0001)		(0.0001)		(0.0001)		(0.0001)
N	505,846	505,846	505,846	505,846	485,714	485,714	485,714	485,714
R^2	0.73	0.73	0.74	0.74	0.72	0.72	0.73	0.73

Table B1. Effect of FCD Policy on Admission Competition at University Level

Notes: This table presents DiD estimates of the admission effect of FCD at the university level (Equation (B2)), where we compare the FCD universities to the universities without any FCD. Robust standard errors are reported in parentheses (clustered at the university level). Significance: *p < 0.10, **p<0.05, ***p<0.01.

Moreover, we exclude FCDs and retain only non-FCDs from the universities with FCDs in the treatment group. Specifically, we compare non-FCDs at universities in the treatment group to those at universities in the control group to further assess whether spillover effects from FCDs to their non-FCD counterparts persist. This test assumes that if no spillover effect exists, the difference in admission competition for non-FCDs between the treatment and control groups would be statistically insignificant post-policy. Columns (5)-(8) of

Table B1 display the estimated coefficients with the corresponding fixed effects as in Columns (1)-(4). We observe a slight increase in the magnitude and statistically significant coefficients in columns (5)-(8) compared to columns (1)-(4), respectively. Therefore, the spillover effects persist, as the average admission competition of the non-FCDs in recognized universities increases by 1.4 percentiles compared to the disciplines in unrecognized universities.

Dynamic DiD Analysis

To explore how the treatment effect varies over time, we use the following specification:

$$Y_{idupt} = \sum_{s=2015}^{2021} \beta^s \cdot (\text{Treated}_u \times D_{ut}^s) + \phi_p + \lambda_u + \alpha_d + \varepsilon_{idupt} \tag{B2}$$

where D_{ut}^s takes 1 if $t = s$ and other variables are defined in the same way as in Equation (3). The estimates are shown in columns (5) and (6) of Table A1 with all discipline samples and columns (7) and (8) with only non-FCD in the treatment group. For both analyses, the pre-policy estimates are insignificant, which confirms the parallel trend assumptions.

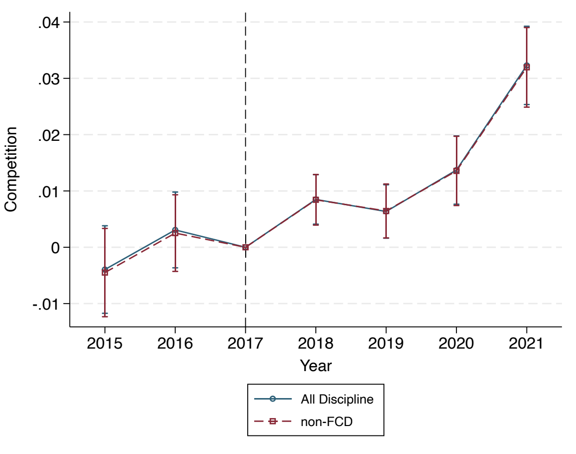


Figure B1. Effect of FCD Policy on Admission Competition at University Level

Notes: The figure displays the estimated coefficients and 95% confidence intervals for the dynamic admission effects of the FCD policy at the university level (Equation (B2)). The reference year is 2017 (marked by the dashed vertical line), before the initiative's announcement.

In Figure B1, the blue line represents the estimated effect of FCD policy on admission competition at the university level, using the full discipline sample. Post-policy, from 2018 onwards, the estimated impacts remain statistically significant and grow over time, rising by 3.2 percentiles, approximately 22%, by 2021. The red line shows the evolution of the treatment effect by isolating the influence of FCDs within these recognized universities. It closely aligns with the blue line, indicating that the overall increase in admission competition at universities with FCDs is not only attributed to the designated FCDs but also non-FCDs receive the spillover effect from FCDs and indirectly benefit from the FCD policy.

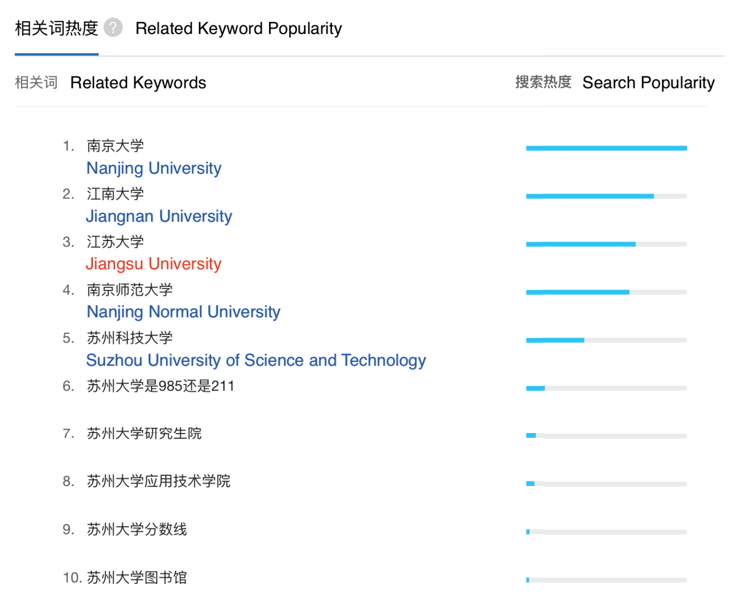


Figure B2. Construction of the Baidu Control Group

Notes: This figure illustrates the method employed to construct the control group, aiming to assess the impact of the *Double First-Class* initiative on the admission competition at the university level. Specifically, when a user conducts a search for Soochow University, identified as a FCD university, we can retrieve the related searches associated with Soochow University. These associated searches are listed in the figure in descending order according to their popularity. Jiangsu University, which was not selected as a FCD university, was identified through search-related popularity and subsequently included in the control group. However, Nanjing University, Jiangnan University, and Nanjing Normal University are either designated as FCUs or host FCD programs, making them ineligible for inclusion in the control group.

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