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Education Choices and Family Outcomes

Effects of Economic and Policy Shocks

Meng Meng

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Education Choices and Family Outcomes
Effects of Economic and Policy Shocks

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Academic dissertation for the Degree of Doctor of Philosophy in Economics at Stockholm University to be publicly defended on Monday 25 May 2026 at 13.00 in Hörsal 4, Södra huset B, Universitetsvägen 10B.

Abstract

Sectoral Shocks and Gender Differences in Field-of-Study Choice: Evidence from the Dot-Com Collapse

This paper studies how sector-specific shocks shape gender differences in field-of-study choice. I examine the collapse of the dot-com bubble as an exogenous shock that increased uncertainty in the Information Technology (IT) sector. I develop a theoretical model of field choice under uncertainty in which students differ in risk aversion by gender. When sectoral risk rises, more risk-averse individuals are disproportionately deterred from entering that field, leading to lower female participation, stronger positive selection among those who remain, and reallocation toward close substitute fields. Using Swedish administrative data and a difference-in-differences design, I find that the gender gap in IT graduation widens by about 4.2 percentage points following the bust, a relative increase of roughly 50 percent. At the labor market entry margin, a negative and statistically significant gender gap emerges for later cohorts, with women less likely than men to enter IT employment, conditional on holding an IT degree. Women who select into IT become more positively selected, with their average GPA rank rising by about three percentile points relative to men. Cross-field evidence shows that women shift toward engineering, a close substitute but with lower exposure to the shock. These findings provide evidence consistent with a mechanism in which sector-specific shocks amplify gender segregation by altering both participation and the allocation of talent across fields. More broadly, the results suggest that gender differences in field-of-study choice evolve with economic conditions: sectoral downturns may reinforce existing disparities by diverting relatively high-ability women away from more volatile but promising fields.

Property Rights, the Intra-Couple Wealth Gap, and Family Outcomes: Evidence from China

This paper documents intra-couple housing wealth gaps in China and examines their consequences for household decisions. I exploit the 2011 Marriage Law reform, which replaced equal division at divorce with a registered-owner rule, as a natural experiment. Using spouse-level panel data and a difference-in-differences design, I find that the reform increased the husband–wife legal share gap by 28.3 percentage points and generated an average housing wealth gap of CNY 63,667, approximately ten times the wives' annual income. The wealth gap persisted and widened as housing prices rose, even as legal share gaps narrowed over time. In the second stage, 2SLS estimates show that a one-unit increase in the husband's relative ownership share reduces divorce probability by 6.75 percentage points, raises the wife's probability of employment by 6.8 percentage points, and increases her weekday housework by approximately one hour. Heterogeneity analysis reveals that the reform lowers divorce probability regardless of which spouse holds the title; female employment rises when the husband's relative ownership increases but no significant change when the wife's does; and wives' housework burden rises in both cases. Standardized comparisons show that wealth gap effects exceed share gap effects across all outcomes, indicating that the economic magnitude of housing inequality, not just formal ownership status, amplifies bargaining consequences. The findings show how a formally gender-neutral legal reform can reinforce intra-household inequality when layered onto pre-existing gendered ownership norms.

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

with Tianze Liu

This paper examines how university applicants respond to government policies that label specific programs as centers of excellence. Such policies, increasingly common worldwide, aim to enhance human capital and global competitiveness by directing students toward high-priority fields. We study this question in the context of China's excellence initiative, which designates selected university-discipline units as First-Class Disciplines (FCDs). Using a difference-in-differences design, we show that designation attracts higher-ranking applicants, raising admission competition by about 1.5 percentiles in exam rankings, equivalent to surpassing roughly 1,800 additional peers per province. Importantly, we also find strong spillover effects: non-designated disciplines within the same universities become more competitive, suggesting that quality signals extend beyond the targeted programs. By increasing competition in designated fields, this policy not only reallocates top students toward strategic areas but also improves the supply of skilled students in priority fields. Our findings provide the first evidence that university-discipline-level excellence initiatives can shape talent allocation, amplify institutional reputation, and ultimately influence the future composition of a country's human capital

Keywords: *Human capital, talent allocation, gender gap, risk preferences, household bargaining, higher education policy.*

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To a better world

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孟梦 Meng Meng
Stockholm, April 2026

Contents

Introduction

This thesis consists of three self-contained essays examining how economic and policy shocks shape education choices and family outcomes. Essay I studies how a sector-specific economic shock, the dot-com collapse, shaped gender differences in field-of-study choice. Essay II examines how a 2011 reform of China's Marriage Law altered the distribution of housing wealth within couples and its consequences for divorce, female labor supply, and domestic work. Essay III, joint with Tianze Liu, investigates how government-led excellence designations at the university-discipline level reshape student application choices and admission competition in China. This introduction provides non-technical summaries of each essay.

Essay I: How do sector-specific shocks shape gender differences in field-of-study choice?

Women remain underrepresented in Information Technology (IT) and related STEM fields (Goldin, 2014). A growing literature attributes this gender gap, in part, to several mechanisms, including differences in comparative advantage and preferences (Altonji, 1993; Zafar, 2013), gendered beliefs about ability and social identity (Bénabou and Tirole, 2002; Carrell et al., 2010; Murphy et al., 2007), and differential exposure to role models and stereotypes (Beaman et al., 2009; Porter and Serra, 2020). While prior work shows that women and men respond differently to broad economic downturns (Blanton et al., 2019; Daskalaki et al., 2021; Kondo, 2015), what is less understood, however, is whether sector-specific shocks, sudden increases in the uncertainty of one field that leave other fields relatively unaffected, can widen gender gaps in high-return industries.

The first essay, *Sectoral Shocks and Gender Differences in Field-of-Study Choice: Evidence from the Dot-Com Collapse*, examines how a large, sector-specific shock can reshape gender differences in educational specialization. I study the collapse of the dot-com bubble in 2000–2001 as a natural experiment. The late-1990s IT boom attracted a growing share of students into computing and related fields. When the bubble burst, employment prospects in IT deteriorated sharply, increasing the uncertainty of IT careers while leaving most other fields relatively unaffected. This concentrated shock provides a clean setting to examine whether women and men respond differently to changes in sector-specific risk.

To guide the empirical analysis, I develop a model of field-of-study choice under uncertainty in which students differ in their risk preferences by gender. When uncertainty about returns in a field increases, individuals who are more risk-sensitive are disproportionately deterred from entering that field. This framework yields three testable implications: a widening gender gap in participation in the affected field; stronger positive selection among more risk-sensitive individuals who remain in that field; and reallocation away from the affected field toward nearby alternatives that offer similar skills but lower exposure to the shock.

The empirical analysis uses Swedish administrative data on graduation cohorts from 1997 to 2007, covering both the IT boom and the subsequent bust. The data track students' field-of-study choices and, for degree completers, their entry into the labor market. The Swedish institutional setting is particularly well-suited for this analysis: students apply directly to specific programs, admissions are centralized and merit-based, and tuition is publicly financed. As a result, differences in field choices largely reflect preferences and expectations rather than financial constraints.

The results show that the IT bust widened the female-male graduation gap in IT by about 4.2 percentage points, corresponding to a relative increase of roughly 50 percent. Among those who pursue IT degrees, women are more positively selected, with higher average GPA ranks relative to men. At the labor market entry stage, a negative and statistically significant gender gap emerges for later cohorts, with women less likely than men to enter IT employment, conditional on holding an IT degree. This gap, however, does not reflect differences in ability: among those who enter IT employment, there is no significant gender difference in GPA, indicating convergence at the employment margin. At the same time, women did not withdraw from higher education. Instead, many appear to have shifted toward engineering, a closely related field. The timing and concentration of this shift are consistent with reallocation away from IT toward nearby fields rather than a general decline in participation.

Overall, the findings highlight the role of economic shocks in shaping educational specialization and early career outcomes. While much of the existing literature emphasizes average returns as a driver of field choice, the evidence here shows that changes in sector-specific uncertainty can substantially alter gendered patterns of specialization. Gender gaps in STEM are therefore not fixed but respond to economic conditions, widening when increases in sectoral risk interact with differences in how individuals respond to uncertainty.

Essay II: How do property rights affect intra-couple wealth inequality and household behavior?

A central prediction of the collective model of household decision-making is that the allocation of resources within a couple—that is, who controls income and assets—shapes individual behavior on labor supply, consumption, and household specialization (Browning et al., 2014; Chiappori, 1988). Most empirical work on this question focuses on income flows, but wealth, especially housing wealth, may be an equally important determinant of bargaining power. In China, residential property has risen to dominate household balance sheets, accounting for around three-quarters of total household net worth, making it a natural candidate through which legal ownership rules affect intra-couple bargaining (Chen et al., 2022). At the same time, because housing deeds in China are typically registered in the husband's name due to prevailing social norms, formally gender-neutral changes in property law can have sharply gendered effects.

The second essay, *Property Rights, the Intra-Couple Wealth Gap, and Family Outcomes: Evidence from China*, studies the effects of China's 2011

Marriage Law reform, a judicial interpretation by the Supreme People's Court, which replaced the prior default rule of equal division of marital property at divorce with a registered-owner rule. Because deeds were disproportionately in husbands' names, this single legal change generated a large and sudden shift in the intra-couple distribution of legal ownership rights.

The empirical analysis uses spouse-level panel data from the China Family Panel Studies (CFPS), which tracks both spouses within the same household across survey waves. I implement a difference-in-differences design comparing changes in intra-couple housing ownership gaps for couples whose housing was registered solely to one spouse prior to the reform to those with equal ownership within the couple, before and after the reform. Single-spouse registration is not a marginal phenomenon. In the baseline data, the majority of homeowner couples hold housing in the name of only one spouse, most often the husband, reflecting prevailing social norms and parental financing patterns. As a result, the reform directly altered legal ownership shares for a substantial fraction of married homeowners, making the empirical setting broadly representative rather than confined to a narrow subgroup. To estimate the causal effect of intra-couple inequality on household behavior, I use the reform-induced shift in legal ownership as an instrument for intra-couple inequality, which serves as a proxy for bargaining power, in a two-stage least squares framework.

The first-stage results show that the reform substantially altered the distribution of housing ownership within marriage. Before 2011, the law treated marital housing as jointly owned regardless of whose name appeared on the deed. After the reform, ownership followed formal registration. As a result, the reform increased the average husband-wife legal share gap by 28.3 percentage points, while event-study estimates show that registered husbands held on average 43 percentage points more property than their wives immediately after the reform. Using self-reported housing values, this shift translated into an average wealth gap of CNY 63,667, approximately ten times the wife's annual income in the sample. Dynamic estimates show that while some couples later adjusted registration and narrowed formal ownership differences, the associated wealth gap continued to widen as housing prices rose.

In the second stage, I examine how these reform-induced shifts in ownership affected family behavior. A reallocation of 10 percentage points of ownership toward the husband reduces divorce probability by about 0.7 percentage points, increases the wife's probability of employment by nearly 0.7 percentage points, and raises her weekday housework by roughly one hour per day when scaled to a full reform-sized shift. Heterogeneity analysis shows that strengthening the bargaining position of the registered spouse reduces divorce regardless of whether the husband or the wife holds the property. Female employment responds asymmetrically: wives increase labor supply when the husband's bargaining position strengthens but show no significant change when the wife's position strengthens, consistent with women compensating for weakened property claims by increasing market work. Wives' housework, however, increases regardless of which spouse holds greater ownership, suggesting that traditional gender norms in the division of unpaid labor are highly persistent. Standardized comparisons indicate that differences in housing wealth, rather than formal ownership shares alone, account for the largest behavioral responses, suggesting that the economic value of assets plays a central role in shaping bargaining outcomes.

These results show how a formally gender-neutral legal reform can reinforce intra-household inequality when layered onto pre-existing gendered ownership norms, and document that asset stocks, not income flows alone, are an important channel for intra-household bargaining.

Essay III: How do excellence designations affect student sorting and admission competition?

Many governments have sought to enhance national human capital by designating selected universities or disciplines as centers of excellence. Evidence on university-level initiatives shows that such labels affect perceived prestige and can shift application patterns toward higher-ranked institutions (Luca and Smith, 2013). What is less understood is whether more granular designations, at the level of university-discipline units rather than whole universities, can shape how students sort across fields, and whether their effects extend beyond the targeted programs.

The third essay, *You Are the Elite Now: Admission Effects of an Excellence Initiative in the Chinese Higher Education System*, joint work with Tianze Liu, studies China's Double First-Class Initiative (DFC), announced in 2017. The policy designates specific university-discipline units as First-Class Disciplines (FCDs) based on prior evaluation scores. China's National College Entrance Examination (NCEE) provides an unusually clean setting for this study: admission to all university programs is determined by a single standardized exam score, and students submit their program preferences after learning their exam scores and their relative ranking among all test-takers. This means that program-level admission cutoffs, the minimum exam score/rank required for admission, directly reflect how strongly applicants prefer a program, making them a transparent measure of how quality signals shift demand.

Our analysis draws on a novel dataset compiled from official provincial records, covering more than 50,000 university-discipline-province-year observations. We compare changes in admission cutoffs between designated and non-designated disciplines within the same field before and after the 2017 designation using a difference-in-differences design. To address concerns about endogenous selection into the FCD program, we exploit the fact that designation was based on prior discipline evaluation scores, which gives the policy variation an approximately continuous and pre-determined character.

We find that the FCD designation significantly raises the minimum exam ranking required for admission by approximately 1.5 percentiles on average, equivalent to surpassing roughly 1,800 additional peers per province. The effect is especially pronounced in agriculture and medicine, fields that were historically less competitive and where the excellence label substantially elevates prestige. Effects in STEM fields, already highly sought after by applicants before the policy, are more modest. Beyond the targeted programs, we document strong spillover effects: non-designated disciplines within universities hosting FCD also attract stronger applicants after designation, indicating that excellence labels raise the perceived quality of the institution as a whole, not only the targeted programs.

These findings show that discipline-level quality signals can reshape the allocation of high-ability students across fields and institutions, and that the reputation effects of excellence designations extend well beyond the programs directly targeted by the policy. More broadly, they suggest that governments can use selective excellence designations to alter the supply of skilled students in strategic priority fields and ultimately influence the future composition of a country's human capital.

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1. Sectoral Shocks and Gender Differences in Field-of-Study Choice: Evidence from the Dot-Com Collapse*

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1.1 Introduction

Women remain underrepresented in some of the most promising and dynamic fields, especially in IT and related STEM disciplines (Goldin, 2014; Goldin et al., 2006). Prior research attributes the gender gap in STEM to several mechanisms, including differences in comparative advantage and preferences (Altonji, 1993; Zafar, 2013), gendered beliefs about ability and social identity (Bénabou and Tirole, 2002; Carrell et al., 2010; Murphy et al., 2007), and differential exposure to role models and stereotypes (Beaman et al., 2009; Porter and Serra, 2020). This paper studies how sector-specific shocks affect gender differences in field-of-study choice. In particular, I ask whether women and men adjust their study choices differently when a sector experiences a sharp downturn.

While prior work shows that women and men respond differently to broad economic downturns (Blanton et al., 2019; Daskalaki et al., 2021; Kondo, 2015), much less is known about how sector-specific shocks reshape field-of-study choices. Such shocks alter the relative distribution of risk across fields: fields tied to the distressed sector become more uncertain, while alternative fields remain comparatively stable. If gender differences in risk aversion are economically meaningful in high-stakes educational decisions, these changes should generate differential re-sorting across fields of study.

I study this question in the context of the dot-com bubble burst, a large and salient shock to the IT sector globally. The late 1990s IT boom and its abrupt collapse in 2000–2001 generated sharp swings in employment demand and increased uncertainty about returns in IT. The dot-com collapse was widely covered in the media and reflected in stock market crashes and layoffs, making it a highly visible signal about the instability of IT careers. This setting provides a natural experiment to examine whether women responded more strongly than men by reallocating away from the IT field.

To guide the empirical analysis, I develop a model of field-of-study choice under uncertainty in which students differ in risk aversion by gender. When return variance increases, more risk-averse individuals require higher expected returns to enter the risky field. Because women are, on average, more risk-averse, the model predicts a decline in female participation, stronger positive selection among those who remain, and reallocation toward close substitute fields.[1] Accordingly, the model yields three testable implications: (i) higher sectoral risk disproportionately reduces women's propensity to choose the affected field, widening the gender gap in participation; (ii) among those who still select into the field, the ability threshold rises more sharply for women, generating positive selection on ability; (iii) when the affected field and nearby fields are close substitutes, increases in sector-specific risk induce reallocation toward technically similar but less risky fields. In the empirical analysis, I examine these predictions in the context of the IT sector during the dot-com collapse.

I test these predictions using Swedish administrative data covering the 1997-2007 graduation cohorts, spanning both the IT boom and the bust. The institutional context—early program-specific applications, limited scope for switching fields of study, centralized merit-based admissions, and publicly financed tuition—provides a clean environment in which sector-specific shocks map directly into field-of-study choices. The empirical strategy adopts a difference-in-differences (DID) framework that compares women and men within cohorts and evaluates how the gender gap changes relative to the reference cohort before and after the IT bust. While the analysis does not directly estimate the causal effect of return volatility, it uses the dot-com collapse as a source of exogenous variation in sectoral conditions and evaluates whether the resulting patterns are consistent with changes in uncertainty.

The findings reveal several notable patterns. Before the bust, the estimated gender gap in IT graduation is generally smaller relative to the reference co-

[1] Gender differences in risk preferences are used here in a reduced-form sense to capture differential responses to uncertainty about labor market returns, including volatility in earnings and employment prospects. The dot-com collapse plausibly affected both the level and dispersion of returns in the IT sector, increasing uncertainty about future outcomes. Several underlying channels may contribute to differential responses. For example, women may possess more transferable skill sets that lower their cost of reallocating across fields (Cortés et al., 2024; Ngai and Petrongolo, 2017), or may face higher perceived layoff risk if firms disproportionately dismissed female employees during downturns (Doepke, 2013; Schmieder et al., 2023). The key maintained assumption is that these channels generate greater sensitivity to increases in return uncertainty among women. The empirical analysis tests this implication by examining whether changes in sectoral conditions that increase uncertainty lead to differential sorting, selection, and reallocation patterns across genders.

hort, although differences are not statistically significant. Following the bust, however, the pattern reverses sharply. The gender gap in IT graduation widens by about 4.2 percentage points, representing a relative increase of roughly 50 percent. In addition to testing the model's predictions on field-of-study choice, I also examine early labor market outcomes to assess how these patterns translate into employment decisions. A negative and statistically significant gender gap emerges for later cohorts, with women less likely than men to enter IT employment, conditional on holding an IT degree.

Among IT graduates, women become more positively selected after the shock, as reflected in a higher GPA relative to men. However, conditional on entering IT employment, there is no significant gender difference in GPA, indicating convergence in ability at the employment margin.

Importantly, the decline in women's participation in IT is not accompanied by a withdrawal from higher education. Instead, many women appear to have reallocated toward engineering, a close substitute that is less directly exposed to the IT sector downturn. The increase in women's representation in engineering fields closely coincides with the timing of the IT collapse and is consistent with a substitution mechanism rather than a broad retrenchment. Overall, the effects associated with the shock are concentrated in the IT field and absent in less-exposed disciplines, supporting a risk-based interpretation in which heightened sectoral uncertainty shifts women's specialization choices without reducing their overall investment in higher education.

This paper contributes to three strands of research. First, it builds on the literature examining gender differences in educational specialization. Prior work emphasizes the role of gendered beliefs about ability, stereotypes, and exposure to role models in shaping field selection (Avilova and Goldin, 2018; Buser et al., 2014; Bénabou and Tirole, 2002; Carrell et al., 2010; Ceci and Williams, 2010; Murphy et al., 2007; Porter and Serra, 2020; Reuben et al., 2014). A complementary line of work documents gender differences in risk preferences and competitiveness (Charness and Gneezy, 2012; Niederle and Vesterlund, 2007) and links these differences to educational track selection (Buser et al., 2014). While many studies document gender differences in risk preferences, their magnitude and interpretation remain debated (Croson and Gneezy, 2009; Nelson, 2017; Boschini et al., 2019). This paper takes no stand on the origins of these differences but examines their implications for educational sorting under sectoral uncertainty.

Second, this study complements research on expectations and major choice. A well-established literature shows that students' career and earnings expectations strongly shape educational decisions (Arcidiacono et al., 2012; Beffy et al., 2012; Montmarquette et al., 2002; Patnaik et al., 2022; Wiswall and Zafar, 2015; Zafar, 2013). While much of this work focuses on expected earnings levels, less attention has been paid to the role of return risk. By focusing on the dot-com collapse, this paper demonstrates that increases in sector-specific uncertainty can drive substantial reallocation across fields.

Third, this paper contributes to the literature on how labor market conditions shape educational investment. Prior studies show that students adjust field choices in response to business cycles and shifts in labor demand (Aalto et al., 2023; Blom et al., 2021; Ersoy, 2020; Giacomo and Lerch, 2023). During aggregate downturns such as the Great Recession, some evidence suggests that women shift toward male-dominated or more challenging fields as relative opportunities change (Blom et al., 2021). This paper shows that sector-specific contractions generate different dynamics: in the dot-com collapse, heightened risk in IT discouraged women from entering the IT field disproportionately, leading many to reallocate toward related fields rather than withdraw from higher education.

Building on this literature, this paper makes three contributions. First, it identifies the causal effect of a sector-specific shock on gender differences in field-of-study choice, showing that the dot-com collapse led to a widening of the gender gap in IT graduation. Second, it provides evidence consistent with a risk-based mechanism: the observed patterns of sorting, selection, and reallocation align with an increase in sectoral uncertainty affecting educational choices. Third, it documents how sector-specific shocks affect both the quantity and composition of entrants into a field, showing that women who select into affected fields are more positively selected.

The remainder of the paper is structured as follows. Section 1.2 provides institutional background and context. Section 1.3 develops the theoretical framework and derives its predictions. Section 1.4 introduces the data sources and outlines the sample construction. Section 1.5 details the empirical strategy.

Section 1.6 presents the main results. Finally, Section 1.7 concludes.

1.2 Background

1.2.1 Swedish Tertiary Education

The Swedish tertiary education system is program-based and front-loaded in key decisions. Unlike in the United States, Sweden does not have a distinct college stage preceding university; instead, students apply directly to named degree programs e.g., Computer Science, Business, Nursing) at universities or university colleges (högskolor), rather than seeking general admission. This structure implies that the major choice is made early and deliberately. Curricula are highly structured, with sequenced prerequisites and limited room for lateral moves once enrolled. In principle, a change of major might be possible.[2] However, a change of field of study might not be possible unless students reapply through the centralized admissions system. As a result, the initial admission decision largely determines the subsequent course bundle and eventual graduation field of study.

Admissions are centralized and merit-based, administered by the national application portal. Seats are allocated at the program level based on upper-secondary grades or the Swedish Scholastic Aptitude Test (högskoleprovet). Program capacities are fixed, and admission thresholds are publicly reported ex post, producing sharp variation in entry conditions across cohorts and programs. These institutional features make application timing and program choice salient margins through which prospective students respond to information about sector-specific prospects.

Financing rules further limit confounding from liquidity constraints. Tuition is fully publicly financed, and students have access to generous living-cost support through the national study aid system (CSN), which combines grants with income-contingent loans. As a result, marginal shocks to family resources are unlikely to drive field choice, sharpening the link between perceived labor-market risk and program selection.

[2] Under narrow allowances, students might transfer into closely related programs that share much of the coursework.

Taken together, the Swedish setting provides a clean environment to study how students reallocate across fields when relative risks shift across sectors.

1.2.2 The Dot-Com Bubble Burst and Sweden's IT Sector

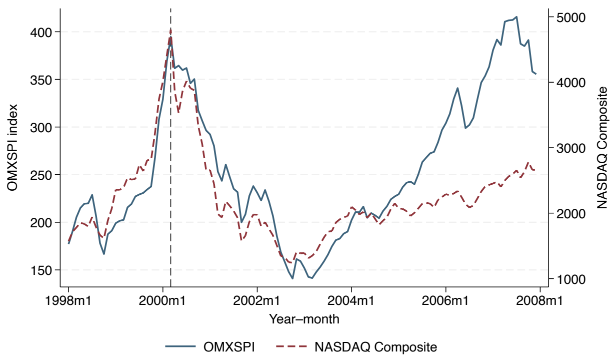
The dot-com boom, fueled by intensive speculation in internet-related businesses, built through the late 1990s and peaked in early 2000. As shown in Figure 1.1a, Sweden's equity market closely mirrored the U.S. experience: the Swedish OMXSPI index more than tripled between 1995 and March 2000, while the NASDAQ Composite rose nearly fourfold over the same period. Both then fell precipitously, losing roughly two-thirds of their value from peak to trough.[3] Sweden's substantial concentration of IT-intensive firms, including Ericsson and a group of telecom and software companies, exposed its economy to global collapse and magnified the domestic impact.

Labor market conditions adjusted with a lag as the capital-market correction filtered into hiring. The IT sector's employment share rose steadily through the late 1990s but contracted by about 11 percent in the early 2000s (see Figure 1.1b). This cooling of IT labor demand, visible in real time, sent a salient signal of weaker near-term prospects and uncertainty in IT-related careers. Consistent with this sectoral retrenchment, the fraction of women employed in IT also declined following the bust, suggesting that the shock not only reduced overall employment but also disproportionately affected female participation in the industry. Meanwhile, aggregate higher-education enrollment and graduation rates continued to rise, underscoring that the shock was sector-specific rather than system-wide.

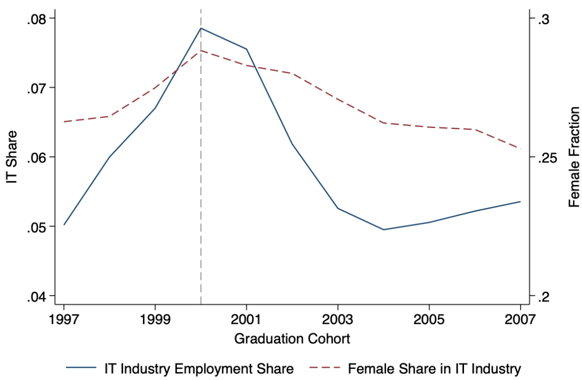
For prospective students, the dot-com collapse therefore represented a clear and exogenous negative shock to the perceived risk of returns in the IT field. Because Sweden's tertiary system requires early, program-specific applications and makes switching costly, these shifts in sectoral expectations translated into field-of-study reallocation, providing a natural setting to study gender differences in responses to risk.

[3]Compared to other countries, the UK and Germany experienced a smaller market contraction, their indices declined by approximately half (Liu, 2025).

Figure 1.1: The Dot-Com Bubble and Sweden's IT Sector



(a) Stock Market Indices: OMXSPI & NASDAQ



(b) IT Sector Employment Share

Notes: Panel (a) presents stock market indices for Sweden (OMXSPI) and the United States (NASDAQ). The OMXSPI is a broad index covering all shares listed on Nasdaq Stockholm. Panel (b) shows the share of employment in the IT sector and the female share within it. The labor force includes individuals employed or actively seeking work. The IT sector is defined based on the Swedish industry classification codes (SNI 2002 code 72, Computer and related activities). The vertical line marks March 2000, the peak of the dot-com bubble. Data on stock indices are from Nasdaq, Inc.; employment data are from Swedish administrative registers.

1.3 Theoretical Model

1.3.1 Setup

I develop a model of field-of-study choice under uncertainty to understand how economic shocks differentially affect men's and women's educational decisions. Consider a continuum of students indexed by i who must choose a field of study f from a finite set $\mathcal{M}$ at time $t = 0$. Each student is characterized by gender $g_i \in \{\text{female}, \text{male}\}$ and ability $a_i \sim F_g(a)$, where the ability distribution may differ by gender.

Students derive utility from their lifetime income stream and non-pecuniary job characteristics. The utility function for student i choosing the field f is:

$$U_i(f) = \mathbb{E}_0 \left[\sum_{t=1}^{T} \delta^{t-1} u(c_{it}, l_{it}, s_{it} \mid f, g_i, a_i) \right]$$

where δ is the discount factor, c_{it} is consumption, l_{it} is leisure, and s_{it} represents job characteristics including status, work environment, and flexibility. The expectation is based on the information available at the time of a field-of-study choice.

1.3.2 Labor Market Returns and Uncertainty

The log earnings for individual i with field f at time t is given by:

$$\ln \text{Earnings}_{it}(f) = \alpha_f + \beta a_i + \gamma_{fg} + \eta_{ft} + \varepsilon_{it}$$

where α_f is the field-specific baseline return, β captures returns to ability, γ_{fg} represents gender-specific returns (capturing potential discrimination or differential sorting), η_{ft} is a field-specific shock, and $\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2)$ is an idiosyncratic shock.

The key innovation is that students face uncertainty about field-specific shocks. Before the dotcom bust, students believe that $\eta_{ft} \sim N(\mu_f, \sigma_f^2)$. The bust constitutes an information shock that causes students to update their beliefs about both the mean and variance of returns to the IT field. In particular, I assume the shock increases the variance of returns (σ_f^2) in the IT field, reflecting greater uncertainty about future outcomes.

1.3.3 Gender-Specific Preferences

I assume the period utility function takes the form:

$$u(c_{it}, l_{it}, s_{it} \mid f, g_i, a_i) = \frac{c_{it}^{1-\rho_{g_i}}}{1-\rho_{g_i}} + \theta_{g_i} v(l_{it}) + \mathcal{K}_i$$

This specification captures preferences over consumption and leisure, allowing for gender-specific differences in risk aversion and the valuation of non-pecuniary components. Consumption c_{it} is financed by labor market earnings, which depend on the chosen field of study and are subject to uncertainty. The concave utility over consumption implies that individuals are averse to fluctuations in income, with the degree of risk aversion governed by ρ_{g_i}. A higher value of ρ_{g_i} increases the disutility from income volatility, making individuals less willing to enter fields with uncertain returns. The parameter θ_{g_i} captures the weight placed on leisure, while $\mathcal{K}_i$ summarizes other components of utility that may vary across individuals.[4] Gender differences in ρ_{g_i} play a central role in the model. If women are, on average, more risk-averse than men, then an increase in return volatility in a given field reduces their expected utility from entering that field by more. As a result, increases in sectoral uncertainty lead to differential sorting across fields of study by gender.

Key assumption: Women face a higher effective cost of earnings volatility. Formally, this is captured by allowing the coefficient of relative risk aversion to differ by gender, with

$$\rho_{\text{female}} > \rho_{\text{male}}$$

This assumption should be interpreted in reduced form. Gender differences in risk preferences may arise from various sources, including differences in beliefs about return uncertainty and exposure to labor market risk, rather than reflecting intrinsic preferences alone. The model abstracts from these dis-

[4] $\mathcal{K}_i$ may capture non-pecuniary job attributes and psychic costs associated with the choice of field f. However, this component is constant, and when differentiating the value function with respect to the variance of earnings, this component therefore drops out. Further details are provided in Section 1.7.

tinctions and focuses on their common implication: heightened sensitivity to sector-specific uncertainty. Throughout, risk aversion should be understood as a reduced-form representation of how individuals respond to uncertainty, rather than as a claim about the origins of gender differences. In the model and empiricals, risk should be interpreted as perceived return uncertainty, which may be proxied ex post by observed earnings volatility.

1.3.4 Information Updating and Field-of-Study Choice

At $t = 0$, students observe a signal about labor market conditions. For the IT field, the dotcom bust provides a negative signal about both the expected level and stability of returns. Students update their beliefs about IT earnings according to Bayes' rule.[5] which yields a posterior expectation $\mu_{IT,\text{post}}$ reflecting a precision-weighted combination of prior beliefs and new information.

After updating their beliefs, students choose the field of study that maximizes expected lifetime utility. The resulting decision rule implies that student i chooses field f if and only if:

$$V_i(f) \geq V_i(f') \quad \forall f' \in \mathcal{M}$$

where the value function $V_i(f)$ denotes the value associated with choosing field f and incorporates risk-adjusted expected returns:

$$V_i(f) = \sum_{t=1}^{T} \delta^{t-1} \left[\mathbb{E}[\text{Earnings}_{it}(f)] - \frac{\rho_{g_i}}{2} \text{Var}[\text{Earnings}_{it}(f)] + \theta_{g_i} \bar{l}_f + \bar{\mathcal{K}}_f \right]$$

The variance term captures the disutility from earnings volatility, which is weighted by the individual's degree of risk aversion. As a result, increases in uncertainty reduce the attractiveness of fields with volatile returns, particularly for more risk-averse individuals. If women are, on average, more risk-averse than men, then an increase in return volatility in the IT field leads to a larger

[5] Formally, posterior beliefs are given by $\mu_{IT,\text{post}} = \frac{\tau_0 \mu_{IT,\text{prior}} + \tau_s \mu_{\text{signal}}}{\tau_0 + \tau_s}$ and $\tau_{IT,\text{post}}^{-1} = \tau_0^{-1} + \tau_s^{-1}$, where $\mu_{IT,\text{prior}}$ is the prior expectation of IT earnings and μ_{signal} represents the information conveyed by the market shock. The dot-com bust implies $\mu_{\text{signal}} < \mu_{IT,\text{prior}}$ and a low signal precision τ_s, leading to a decline in expected IT returns and an increase in uncertainty.

decline in their expected utility from entering that field. This generates differential reallocation across fields of study by gender. Students therefore allocate across fields according to updated beliefs.

1.3.5 Equilibrium Gender Gap

A negative labor market shock to the IT field reduces the demand for IT-skilled workers and lowers expected returns, while also increasing the volatility of earnings. In the model, I focus on the increase in return uncertainty as the key channel through which the shock affects field-of-study choices. Consistent with the literature that women are on average more risk-averse than men, this increase in uncertainty discourages female enrollment disproportionately, widening the gender gap in IT graduation.

I define the female-male gap in field f as the difference in graduation shares:

$$\Delta_f = \Pr(f \mid g = \text{female}) - \Pr(f \mid g = \text{male})$$

Prediction 1: Gender gap response to increased risk A rise in the variance of IT returns (σ_{IT}^2) lowers the expected utility from choosing IT more strongly for women who have higher relative risk aversion ($\rho_{\text{female}} > \rho_{\text{male}}$) As a result, female enrollment in IT declines more than male enrollment, implying

$$\frac{\partial \Delta_{IT}}{\partial \sigma_{IT}^2} < 0 \tag{P1}$$

That is, the gender gap in IT graduation widens following an increase in IT return volatility. In the empirical analysis, I do not directly estimate the effect of return variance; instead, I examine how a sector-specific shock that increases uncertainty in the IT field affects gender differences in field-of-study choice.

Prediction 2: Differential threshold ability shifts by gender Let $a_g^*(IT)$ denote the ability level at which a student of gender g is indifferent between IT and an alternative field. The model implies

$$\frac{\partial a_g^*(IT)}{\partial \sigma_{IT}^2} = \frac{\rho_g}{2B_g} > 0, \tag{P2}$$

where $B_g > 0$ is the net return to ability in IT relative to the alternative. Because $\rho_{\text{female}} > \rho_{\text{male}}$, the threshold ability rises more for women, leading to a larger reduction in female participation at the margin.

Prediction 3: Substitutability When IT and other fields are close substitutes, the relative return to ability across fields (B_g) is smaller. Intuitively, a lower B_g means that the payoff difference between IT and nearby fields is small, making it easier for students to switch across fields in response to uncertainty. From the comparative static

$$\frac{\partial \Delta_{IT}}{\partial \sigma_{IT}^2} = \frac{1}{2B_g} \cdot \underbrace{\left(f_{female}(a^*_{female})\rho_{female} - f_{male}(a^*_{male})\rho_{male}\right)}_{\textit{gender-specific sensitivity to uncertainty}} \tag{P3}$$

the response of the gender gap to changes in return volatility is inversely proportional to B_g. That is, for a given increase in uncertainty, a smaller difference in returns across fields amplifies the change in field choice.

Hence, when IT and nearby fields are close substitutes, increases in IT-sector uncertainty lead to stronger reallocation away from IT, particularly among more risk-averse individuals. This implies a larger widening of the gender gap in IT participation and a corresponding shift toward nearby fields.

1.4 Data and Descriptive Evidence

This section describes the data and presents descriptive evidence on field-of-study choices around the dot-com collapse. I first introduce the administrative data sources and outline the sample construction. I then document cohort patterns in IT enrollment and related fields, highlighting how gender differences evolve before and after the shock. These descriptive patterns provide initial evidence consistent with differential responses to changes in sectoral conditions and motivate the empirical analysis that follows.

1.4.1 Data and Sample Construction

This study draws on Swedish administrative data, primarily the Longitudinal Integration Database for Health Insurance and Labor Market Studies (LISA).

The registers provide individual-level information on education, including the upper-secondary GPA, the three-digit tertiary program code, and the highest degree attained; demographics, including municipality of residence, birth year, and gender; and labor market outcomes, including annual employment status, pre-tax earnings, and industry.

The analysis sample comprises individuals whose highest degree attained is a post-secondary degree of at least three years during the study period.[6] Graduation cohorts are assigned by the calendar year in which the highest degree is awarded. Upper-secondary GPA is mapped to within-cohort percentile rank to ensure comparability across cohorts. Because the registers do not identify the specific upper-secondary school or university attended, I proxy institutional affiliation with the municipality of residence during upper-secondary schooling and during university.[7]

I classify IT-specialized fields as those with the two-digit field-of-study code 48 (Information and Communication Technologies) and the three-digit code 523 (Computer Engineering). Code 48 covers programs such as Computer Science, General; Computer and Systems Sciences; and Computer, Other/Unspecified. For labor-market outcomes, I define the IT sector using the Swedish Standard Industrial Classification (SNI 2002), mapping to the two-digit industry 72 (Computer and related activities).

To study how the IT cycle shaped program choice and early labor market outcomes, I focus on cohorts graduating from 1997 through 2007. This window spans the late-1990s IT boom and subsequent bust in the early 2000s while avoiding confounding from the Swedish recession of the early 1990s and the post-2008 financial crisis.

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[6] The degree classification is based on the Swedish education register (`Sun2000niva`). I include codes 53, 54, and 55, which correspond to post-secondary programs of three years or more.

[7] Specifically, I use the recorded year in which the upper-secondary GPA is obtained as the upper-secondary graduation year and the year of tertiary graduation as the university completion year. For each individual, I extract the municipality of residence in the three years preceding each graduation year and assign the modal municipality over this window as the proxy for the location of the upper-secondary school and university, respectively. If the municipality of residence does not have a unique mode within the three-year window, I assign the municipality of residence in the year immediately preceding graduation as the proxy.

Figure 1.2: Correspondence between Graduation and Approximate Application Years

Graduation year	2000	2001	2002	2003	2004	2005	2006
Approximate Application year	1997	1998	1999	2000	2001	2002	2003
	Graduation cohorts exposed to the bust			Application cohorts exposed to the bust			

Notes: The figure illustrates the correspondence between graduation year and inferred application year, assuming typical program durations of three to four years. The dashed-orange box marks cohorts graduating during the IT bust (applications made before 2000), while the solid-purple box marks cohorts whose application decisions occurred after the onset of the bust. Because graduation data do not record application timing, this mapping clarifies the lag between the timing of field choice and observed graduation.

Because the registers record the year of graduation but not the year of program application, I infer application timing based on the typical duration of Swedish tertiary programs. Most post-secondary degrees last three to four years, implying that students graduating in year t applied around $t-3$ or $t-4$. While some programs may take longer, they represent a relatively small share of the sample and do not materially affect the cohort classification. As the IT stock market began to collapse in March 2000, this correspondence implies that cohorts graduating in 2000-2002 applied before the downturn and thus made field-of-study choices largely unaffected by it. For these cohorts, the shock primarily affected early labor-market outcomes rather than educational choice. In contrast, students graduating in 2003 were the first whose field decisions may have reflected the deteriorating IT prospects, while cohorts graduating in 2004-2006 entered tertiary education fully after the crash, with the latter cohorts also facing weaker IT-sector conditions upon graduation. Section 1.7 provides corroborating evidence using application data, which display parallel timing and gender patterns.[8]

Table 1.1 reports summary statistics for the main analysis sample at the individual level, separately for men and women. Several patterns are noteworthy.

[8] Application statistics come from the Swedish Higher Education Authority and are available only in aggregate form, which prevents linking them to the individual-level administrative registers used in the main analysis

Table 1.1: Summary Statistics by Gender

	Men	Women	Mean
Upper-secondary GPA Rank	65.10	69.72	67.88
	(25.02)	(23.29)	(24.10)
IT Field (=1)	0.148	0.028	0.076
	(0.355)	(0.165)	(0.265)
Enter IT Industry (=1)	0.056	0.013	0.030
	(0.230)	(0.115)	(0.171)
Age at Graduation	26.72	26.49	26.58
	(2.85)	(3.19)	(3.06)
Observations	93,22	134,183	227,412

Notes: This table reports summary statistics at the individual level. Upper-secondary GPA rank is measured as within-cohort percentiles. IT Field is an indicator equal to one if the individual graduates in an IT field. Enter IT Industry is an indicator equal to one if the individual is employed in the IT sector one year after graduation, conditional on holding an IT degree. Age at graduation is measured in years. Standard deviations are reported in parentheses.

First, women have higher upper-secondary GPA ranks than men on average (69.72 versus 65.10), consistent with well-documented gender differences in academic performance. Despite this advantage, women are substantially less likely to specialize in IT fields: only 2.8 percent of women graduate with an IT degree compared to 14.8 percent of men, implying that women account for around 30 percent of IT graduates in the sample. A similar gap appears in early labor market outcomes, where 1.3 percent of women versus 5.6 percent of men enter the IT sector within one year of graduation. In contrast, age at graduation is similar across genders, suggesting comparable timing of educational completion.[9] Overall, the summary statistics highlight a pronounced gender gap in both IT specialization and IT-sector entry despite women's stronger academic performance, a pattern that motivates the analysis of differential responses to sector-specific shocks.

[9]The median age at graduation is 26 years, and 72.4% of students graduate between ages 23 and 28, indicating a relatively concentrated distribution. In Sweden, students often delay entry into higher education, for example, by taking gap years to work or travel. Consistent with this pattern, the median gap between upper-secondary graduation and university enrollment in the sample is approximately three years, contributing to the relatively higher age at graduation.

1.4.2 Cohort Patterns in Higher Education

This section documents cohort-level patterns in tertiary graduation to motivate the analysis of gendered responses to the IT cycle.

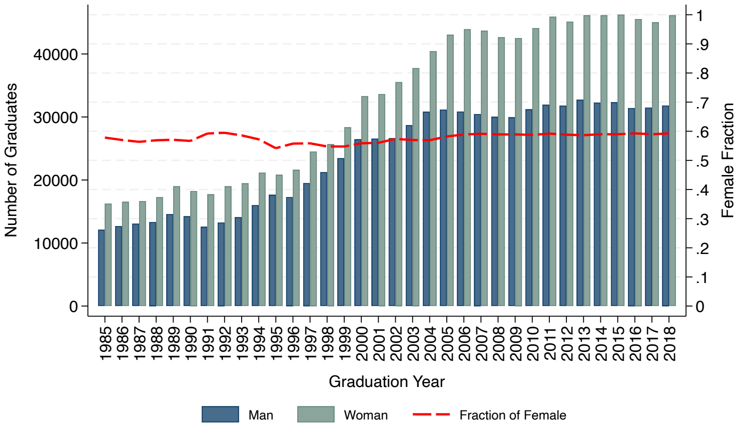
Aggregate graduation trends. Figure 1.3a plots the number of male and female graduates by cohort together with the female share. Two features stand out. First, there is no indication of a system-wide contraction around the dot-com burst episode: graduation counts rise steadily for both men and women throughout the early 2000s, consistent with continued expansion of higher education. Second, the female share remains broadly stable at 60 percent. These patterns imply that the dot-com shock did not operate through a general decline in tertiary completion but, if present, through reallocation across fields.

IT-specific dynamics. Figure 1.3b focuses on the IT field. Both the number and share of IT graduates increase through the late 1990s, peak in the mid-2000s, and then decline. Because cohorts are indexed by graduation year, this downturn appears with a natural lag relative to the 2000–2001 crash: students adjusted their field choices at application and enrollment, while effects are observed only upon graduation. The boom-bust pattern in IT, set against aggregate stability in overall graduations in the tertiary education, suggests a sectoral rather than system-wide response, consistent with rising perceived risk in IT following the crash.

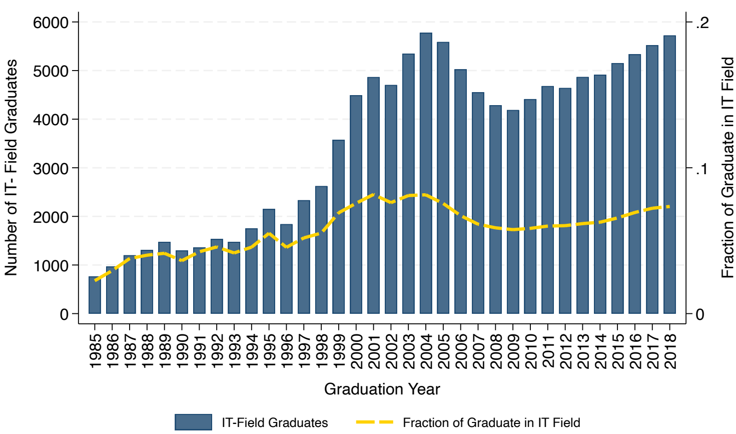
Gender composition within IT. Figure 1.4 decomposes IT graduations by gender (bars) and plots the female share among IT graduates (solid line). When IT programs emerged in the 1980s, the field was relatively gender-balanced, with women comprising around 40 percent of graduates.[10] Although the early-1990s Swedish recession temporarily reduced the female share, it recovered to nearly 40 percent by the late 1990s as the IT boom gained momentum. Following the dot-com bust, however, the female fraction fell sharply and never re-

[10]Following standard definitions in the literature (e.g., England et al., 2002; Hegewisch and Hartmann, 2014), I classify a field as gender-balanced if women constitute 40-60 percent of graduates, female-dominated if the share exceeds 60 percent, and male-dominated if it falls below 40 percent.

Figure 1.3: Aggregate stability and IT-specific adjustment



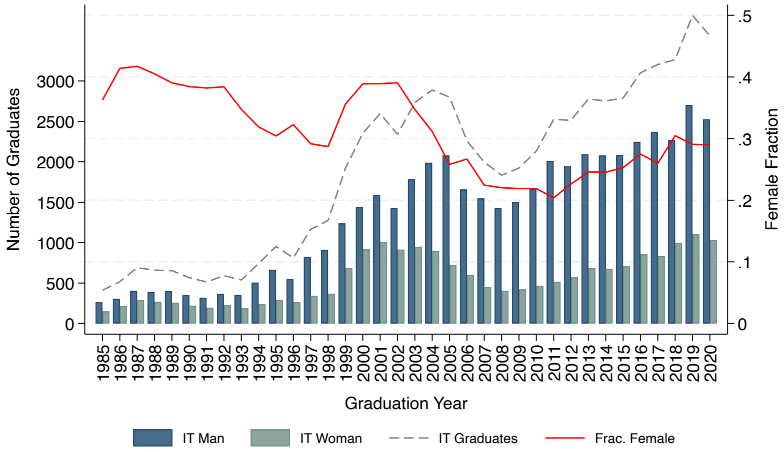
(a) Graduates by Gender (Cohorts 1985–2018)



(b) IT-field Graduates (Cohorts 1985–2018)

Notes: Panel (a) represents the aggregate trends of graduation. Bars show the number of male and female graduates by graduation year; the line shows the female share (right axis). Overall graduations rise steadily, and the female share remains roughly constant. Panel (b) shows the IT field dynamics. Bars show the number of IT-field graduates by graduation year; the line shows the IT share of all graduates (right axis). IT graduations and shares rise through the late 1990s, peak in the mid-2000s, and subsequently decline, consistent with a lagged adjustment to the dot-com bust.

Figure 1.4: IT-Field Graduates by Gender and Female Share (Graduation Cohorts 1985-2020)



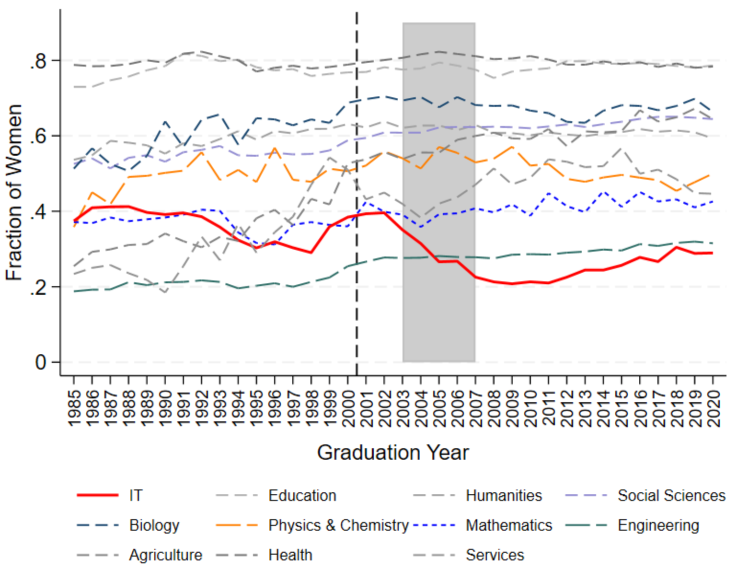
Notes: Bars show the number of IT graduates by gender (left axis); the dashed line is the total number of IT graduates (left axis). The solid red line is the female share among IT graduates (right axis).

turned to its pre-crash level, remaining near 30 percent through 2020.[11] Thus, what began as a relatively mixed-gender field evolved into a male-dominated one. While total IT graduations contracted for both genders after the bust, the steeper decline among women produced a persistent drop in their share, consistent with stronger sensitivity among women to increased risk and volatility in IT-related career prospects.

Cross-field comparison. Figure 1.5 compares the female share of graduates across broad fields of study, with IT in a red solid line. Most non-IT fields, such as education, health, and humanities, exhibit stable or rising female representation over the same period, whereas IT shows a pronounced decline following the dot-com bust (gray band). The divergence underscores that the contraction in female participation was concentrated in IT rather than reflecting a general withdrawal of women from tertiary education.

[11] Consistent with this interpretation, aggregate application data in Section 1.7 show the same boom-bust cycle and gender dynamics during the period of study, confirming that graduation-year cohorts accurately reflect application patterns.

Figure 1.5: Female Share of Graduates by Field (Graduation Cohorts 1980–2020)



Notes: Each series plots the fraction of women among graduates within fields across cohorts. The gray band marks cohorts graduating 2003–2007, who would have applied/enrolled around the 2000–2001 dot-com crash. Most non-IT fields (e.g., humanities, education, mathematics) are flat or rising over this window, while IT exhibits a sharp decline, consistent with a sector-specific response.

Taken together, the aggregate stability of overall graduations and the pronounced boom-bust cycle within IT motivate the empirical analysis that follows. If heightened uncertainty in IT disproportionately deterred more risk-averse students, we should observe a widening gender gap in IT program completion relative to other fields, with timing consistent with the lag between enrollment and graduation. In addition, the persistent underrepresentation of women in IT after the dot-com bust may reflect a role-model and feedback effect: as the female share declined, subsequent cohorts faced fewer same-gender peers and mentors, reinforcing perceptions of IT as a male-dominated domain. Consistent with evidence from studies on role-model scarcity and field identity (e.g., Breda et al., 2020; Cheryan et al., 2017), this dynamic can sustain gender imbalance even after labor-market conditions recover.

1.5 Empirical Strategy

I adopt a DID framework that compares changes in women's probability of graduating in IT relative to men across graduation cohorts surrounding the dot-com collapse. The specification uses the 2002 cohort as the reference group, which is the last cohort whose field-of-study decisions were largely made before the IT bust.

I control for upper-secondary GPA rank and include fixed effects for the municipality of residence during upper-secondary schooling, which proxies for school affiliation. Because field-of-study choice is determined before university enrollment, these fixed effects capture differences in the educational environment at the time the decision is made.

I estimate the following DID specification using a linear probability model:

$$\begin{aligned} \text{IT\_Field}_{ic} = & \sum_{c \neq 2002} \beta_c \left(\text{Woman}_i \times \mathbf{1}\{\text{Cohort}_i = c\} \right) + \lambda \, \text{Woman}_i + \pi \, \text{GPA Rank}_i \\ & + \gamma_c + \delta_s + \varepsilon_{ic}. \end{aligned} \tag{1.1}$$

where IT_Field_{ic} is an indicator equal to one if individual i in cohort c graduates in an IT field, and zero otherwise. GPA Rank_i is the within-cohort percentile rank in upper-secondary GPA, included to control for academic ability so that estimated differences in field-of-study outcomes reflect behavioral responses to the IT shock rather than gender differences in ability within cohorts. γ_c denotes graduation-year fixed effects, which absorb common time trends and year-specific shocks affecting all students. δ_s denotes fixed effects for the municipality of residence during upper-secondary schooling. In the Swedish context, where schooling and residence are geographically concentrated, particularly around 2000, these fixed effects absorb persistent differences in local educational environments and socioeconomic background, such as access to schools of similar quality, exposure to IT-oriented curricula, and proximity to labor markets. They effectively compare men and women with similar family backgrounds and educational opportunities, helping isolate differential responses to the IT shock from variation in local context. Standard errors are clustered at the upper-secondary school level to account for within-school correlation in residuals.

The coefficients of interest, β_c, measure the cohort-specific female–male difference in the probability of graduating in IT relative to the 2002 reference cohort, conditional on ability and location-specific factors. Each coefficient therefore captures how the gender gap in IT graduation for cohort c differs from that of the baseline cohort. A negative value of β_c indicates that, relative to men, women in cohort c are less likely to complete an IT degree compared with the baseline gender gap. The identifying assumption is that, in the absence of the sector-specific increase in uncertainty in the IT sector following the dot-com collapse, the gender gap in IT graduation would have followed a stable path across cohorts.[12]

The empirical analysis is structured to test the key predictions of the model. First, I examine how the gender gap in IT graduation evolves across cohorts to assess whether increases in sectoral uncertainty lead to a widening gender gap (Prediction 1). In addition, I examine early labor market outcomes to assess how changes in field-of-study choice translate into differences in entry into IT employment, although this analysis is not directly derived from the model's predictions. Second, I analyze changes in the ability composition of IT

[12] If instead the counterfactual trend followed that observed in other fields, such as mathematics and health, where the female share continued to increase over the same period, then the estimated coefficients would represent a lower bound on the true effect of the IT shock.

graduates to test whether the threshold for entry rises more for women, leading to stronger positive selection (Prediction 2). Third, I study reallocation patterns across fields to evaluate whether declines in IT enrollment are accompanied by increased enrollment in related fields, consistent with substitution across fields of study (Prediction 3). Because return uncertainty is not directly observed, the dot-com collapse serves as a source of variation in sectoral conditions affecting the IT field.

1.6 Results

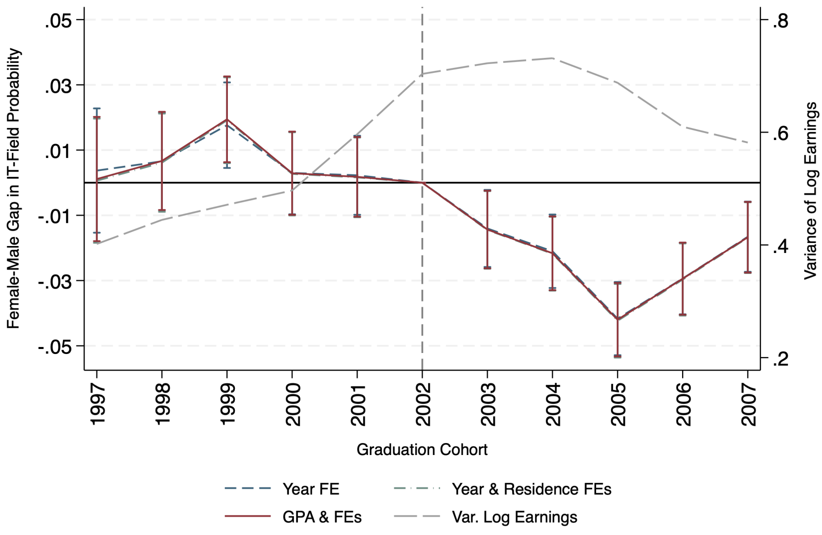
1.6.1 Gender Gap in Graduation in the IT Field

Figure 1.6 plots the estimated coefficients $\hat{\beta}_c$ from Equation (1.1). The dashed blue line shows estimates including cohort fixed effects only. The dash-dotted green line adds upper-secondary school fixed effects, while the solid red line further includes GPA rank and represents the preferred specification. The long-dash gray line plots the variance of log earnings among individuals with an IT degree. Detailed coefficient estimates are reported in Table A1.

Three patterns emerge. First, for cohorts graduating before the bust, the event-study coefficients are generally positive, although only the 1999 estimate is statistically significant. These estimates suggest that the gender gap in IT graduation was smaller during the late boom period than for the 2002 cohort. Notably, earnings volatility in the IT sector remains relatively stable during this period, consistent with the model's prediction that stable return uncertainty leads to little change in gender differences in field choice. Importantly, the pre-bust coefficients show no systematic downward trend relative to the reference cohort, providing supportive evidence for the identifying assumption that the gender gap would have followed a stable path across cohorts in the absence of the sector-specific shock.

Second, this pattern reverses sharply after the bust. Beginning with the 2003 cohort, the coefficients become negative and statistically significant, indicating that the gender gap widened relative to the 2002 reference cohort. The effect reaches its largest magnitude for the 2005 cohort, where women are about four percentage points less likely than men to graduate in IT compared

Figure 1.6: Female-Male Gap in Probability of Graduating in IT by Graduation Cohort



Notes: The figure plots the event-study estimates of the cohort-specific female-male differences in the probability of graduating in IT from equation (1). The blue dashed, green dash-dotted, and red solid lines plot estimates of the female–male gap in IT graduation from three regression specifications: (i) cohort fixed effects only (Year FE), (ii) cohort and municipality-of-residence fixed effects (Year & Residence FEs), and (iii) the full specification including GPA rank and fixed effects (GPA & FEs). The grey long-dashed line (right axis) plots the variance of log earnings among IT graduates, measured one year after graduation, and serves as a proxy for return volatility in the IT sector. The vertical dashed line indicates the reference cohort of 2002.

with the baseline gender gap. The estimates are stable across specifications: adding upper-secondary school fixed effects and controlling for GPA rank does not materially change the results, suggesting that the widening gap reflects differential responses to the sectoral shock rather than differences in observable ability or educational background.

Third, the figure also reports, on the right axis, the variance of log earnings among IT graduates, which serves as a proxy for return volatility in the IT sector. The increase in earnings volatility coincides with the cohorts experiencing the largest widening of the gender gap, and the subsequent decline in the gender gap coincides with a decline in earnings volatility. While this overlay is not used for identification, the timing is suggestive and consistent with the risk-based mechanism proposed in the model (Section 1.3.5).

1.6.2 Early Labor Market Outcomes

This section extends the analysis to early labor market outcomes. While the theoretical framework focuses on field-of-study choice, examining labor market entry provides additional insight into how selection and sorting across fields translate into realized employment outcomes. These results should therefore be interpreted as complementary evidence rather than a direct test of the model's predictions.

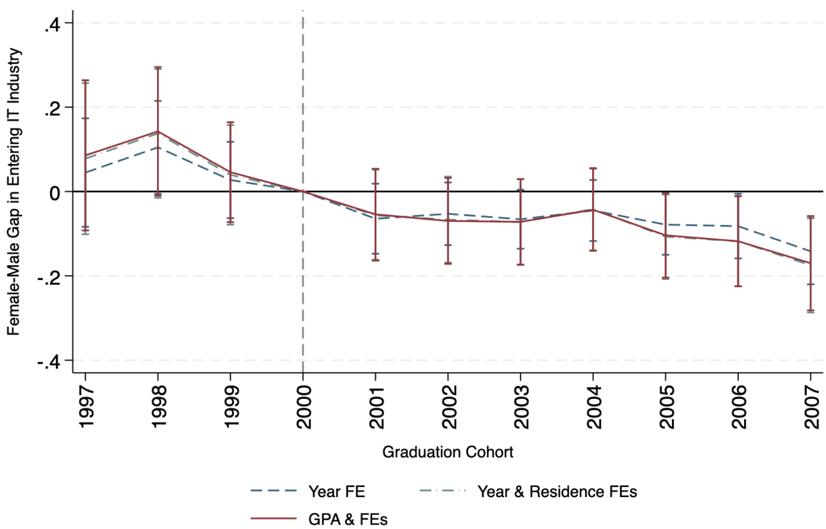
The sample is restricted to graduates from IT fields. I estimate event-study coefficients from Equation (1.1), replacing the outcome variable with an indicator equal to one if the graduate is employed in the IT sector one year after graduation, and zero otherwise.[13] All specifications include the baseline controls described above, along with fixed effects for the municipality of the university attended. Detailed coefficient estimates are reported in Table A2, which also presents robustness checks with alternative clustering; the results are unchanged.

Figure 1.7 plots the estimated female–male gap in IT industry entry by

[13] Employment status is measured one year after graduation to ensure consistent observation across individuals. Because the administrative registers record employment at any point during the calendar year, measuring outcomes in the graduation year could misclassify individuals who finish their studies late or are still searching for a job. Using the following year mitigates timing variation in the administrative data and provides a more accurate measure of post-graduation employment.

graduation cohort. During the boom period, estimates are generally positive but statistically insignificant, with the exception of the 1998 cohort, which is significant at the 10% level. For cohorts shortly after the bust, the estimates turn negative but remain statistically insignificant. For later cohorts, however, the estimates remain negative and become statistically significant. The gender gap reaches approximately 10 percentage points for the 2005 cohort and about 17 percentage points for the 2007 cohort, indicating that women with IT degrees are less likely than men to enter IT employment in these cohorts relative to the 2000 reference cohort.

Figure 1.7: Female-Male Gap in IT Industry Entry by Graduation Cohort



Notes: The figure plots the event-study estimates of the female-male gap in the probability of entering the IT industry, conditional on holding an IT degree. The dashed line shows estimates from a specification including graduation cohort fixed effects. The dash-dotted line adds upper-secondary school fixed effects, and the solid line further includes within-cohort GPA rank. Vertical bars represent 95% confidence intervals. The reference cohort is 2000, indicated by the vertical dashed line.

Compared with the degree-choice margin, the evolution of the gender gap in IT employment follows a different post-shock pattern. Prior to the bust, gender differences in both IT graduation and IT employment are small and statistically insignificant. Following the shock, the gender gap widens sharply in IT degree completion, while differences in IT employment among IT graduates remain limited in the early post-bust cohorts. The emergence of a negative and statistically significant gap in later cohorts suggests that selection alone may not fully offset gender differences in early career outcomes.

These findings remain consistent with a selection mechanism in the sense that the composition of women entering IT programs becomes more positively selected following the shock. At the same time, the persistence of gender differences in IT employment for later cohorts indicates that additional factors—such as differential job matching, preferences, or labor market conditions—may also contribute. The next section provides more direct evidence on selection by examining ability measures among IT graduates.

1.6.3 Selection on Ability within IT

The model implies that an increase in sector-specific uncertainty raises the ability threshold for entering IT, particularly for more risk-averse individuals. As a result, women who select into IT following the shock should be more positively selected in terms of academic ability.

To evaluate this prediction, I estimate a pre-post specification with a gender interaction using within-cohort GPA percentile ranks among IT graduates as a measure of academic ability. The estimating equation is

$$\text{GPA Rank}_i = \delta_1 \text{Woman}_i + \delta_2(\text{Woman}_i \times \text{Post}_i) + \gamma_c + \delta_s + \varepsilon_{ic}, \tag{1.2}$$

where Post_i equals one for graduation cohorts 2003-2007 (post-bust) and zero for 1997–2002. The coefficient δ_2 captures the change in women's GPA rank relative to men following the IT bust. The same specification is also estimated for the subsample of IT graduates employed in the IT industry one year after graduation. In this case, Post_i is defined as equal to one for graduation cohorts 2001–2007.

Table 1.2 reports the results. Column (1) includes all IT graduates, while Column (2) restricts the sample to those who enter IT employment. The estimates provide evidence consistent with the selection mechanism. Column (1) shows that among all IT graduates, women's within-cohort GPA rank increases relative to men's by about 3.4 percentile points following the bust. This pos-

Table 1.2: Selection on Ability within IT

	IT Field	IT Field & IT Sector
	(1)	(2)
Woman × Post	3.392***	2.69
	(0.921)	(2.62)
Woman	3.359***	3.39
	(0.764)	(2.17)
Constant	65.91***	69.80***
	(0.097)	(0.226)
Graduation Year FE	✓	✓
Upper-Secondary School FE	✓	✓
Observations	18,704	3,790
R-squared	0.263	0.701

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table reports estimates from the pre-post specification examining selection on ability among IT graduates. The dependent variable is the within-cohort percentile rank in upper-secondary GPA. Column (1) includes all IT graduates, while Column (2) restricts the sample to IT graduates employed in the IT sector one year after graduation. The coefficient on Woman × Post measures the change in women's GPA rank relative to men following the IT bust. The coefficient on Woman captures the pre-bust gender difference in GPA rank. All specifications include graduation cohort and upper-secondary school fixed effects. Robust standard errors are clustered at the upper-secondary school level.

itive, statistically significant effect indicates that women's relative position in the ability distribution improves following the shock. Consistent with this interpretation, women's GPA rank increases from 69.3 in the pre-period to 72.7 in the post-period (conditional on fixed effects), indicating positive selection among women entering IT. In contrast, Column (2) shows that among IT graduates who enter the IT industry, the interaction effect is no longer statistically significant, suggesting that the gender gap in ability does not change significantly following the shock. At the same time, women's GPA rank in this group increases from 73.2 in the pre-period to 75.89 in the post-period (conditional on fixed effects), consistent with positive selection among women entering IT employment.

Taken together, these results are consistent with the model's selection mechanism. The increase in sectoral risk raises the ability threshold for entering IT, leading to stronger positive selection among women who select into the field. As a result, the gender gap in ability among those who choose to pursue an IT degree widens significantly, while among those who enter the IT industry it does not change significantly following the shock, even though women consistently have higher GPA ranks than men.

1.6.4 Gender Reallocation Across Fields

To assess whether the observed gender response reflects an IT-specific shock rather than a broader shift in women's program choices, I conduct a cross-field test. If the dot-com bust primarily altered perceived returns in the IT sector, the widening gender gap should be concentrated in IT and possibly accompanied by offsetting changes in closely related fields, rather than appearing uniformly across disciplines.

For each broad field f, I estimate a DID specification in which the dependent variable equals one if individual i graduates in field f. The specification compares the 2002 cohort, the last cohort whose field-of-study decisions were largely made before the IT bust, with the 2005 cohort, which was fully exposed to the post-bust environment. Controls and fixed effects are identical to those used in the baseline specification.

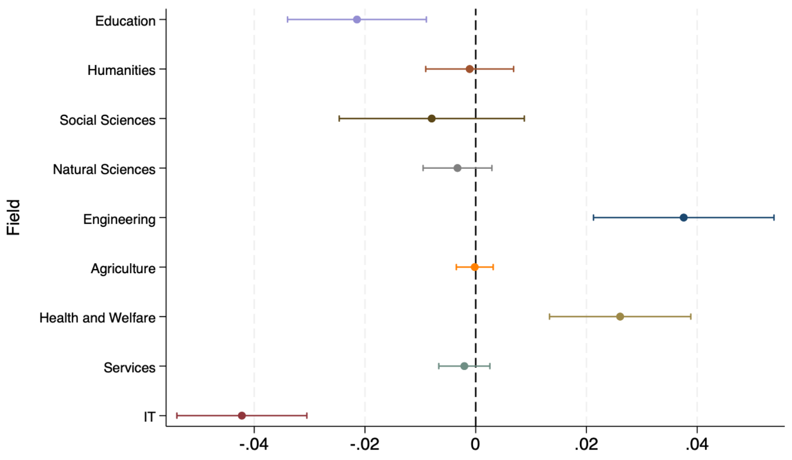
$$\text{Field}_{if} = \sigma_1 \text{Woman}_i + \sigma_2(\text{Woman}_i \times \text{Post}_i) + \pi\,\text{GPA Rank}_i + \gamma_c + \delta_s + \varepsilon_{ig}\,, \quad (1.3)$$

The interaction coefficient σ_2 captures the change in the female-male graduation gap in field f between the 2002 and 2005 cohorts.

Figure 1.8 plots the estimated interaction coefficients with 95% confidence intervals, with corresponding estimates reported in Table A3. The results show a sharp and statistically significant decline in women's representation in IT of about 4.2 percentage points between the 2002 and 2005 cohorts. In contrast, most other fields display coefficients close to zero, indicating little change in gender composition.

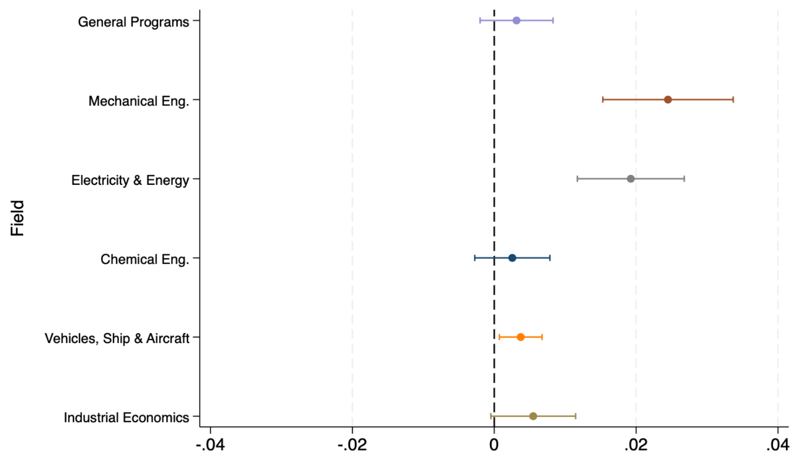
A notable exception is engineering, where the female share increases by about 3.7 percentage points. This pattern is consistent with substitution toward nearby fields. If IT and engineering are close substitutes in terms of skills and expected career opportunities, an increase in uncertainty in the IT sector may induce some students, particularly women, to shift toward engineering.

Figure 1.8: Change in Female-Male Graduation Gap by Field (2005 Relative to 2002)



Notes: The figure plots estimates of the coefficient on Woman × Post from Equation (1.3) for each broad field of study. The dependent variable equals one if an individual graduates in the corresponding field. Post equals one for the 2005 cohort and zero for the 2002 cohort. Each coefficient therefore measures the change in the female-male graduation gap between the 2002 and 2005 cohorts. All specifications include controls for within-cohort GPA rank and fixed effects for graduation year and upper-secondary school. Vertical bars indicate 95% confidence intervals. Robust standard errors are clustered at the upper-secondary school.

Figure 1.9: Change in Female-Male Graduation Gap in Engineering Field (2005 vs. 2002)



Notes: The figure plots estimates of the coefficient on Woman × Post from Equation (1.3) for engineering subfields. The dependent variable equals one if an individual graduates in the corresponding engineering major. Post equals one for the 2005 cohort and zero for the 2002 cohort. Each coefficient measures the change in the female-male graduation gap between the 2002 and 2005 cohorts. Vertical bars indicate 95% confidence intervals. Robust standard errors are clustered at the upper-secondary school.

To examine this reallocation in greater detail, Figure 1.9 decomposes the engineering result by subfield with corresponding estimates reported in Table A4. Positive coefficients indicate engineering programs in which the female share increased between the 2002 and 2005 cohorts. The increases are concentrated in Mechanical Engineering, Electricity and Energy, Vehicles, Ship and Aircraft, and Industrial Economics. Other subfields, such as General Programs, and Chemical Engineering, show little change in gender composition.

Most remaining fields exhibit little change in the gender gap. Two exceptions, Education and Health & Welfare, likely reflect contemporaneous sector-specific developments rather than responses to the IT shock. In Education, the reform of teacher-training (*lärarutbildning*) in the early 2000s altered the structure and timing of the programs, generating composition changes in the graduation cohorts. In Health & Welfare, expansions in nursing and related programs during the same period increased training capacity in care-sector occupations, mechanically raising the female share in those programs.

Taken together, these results point to a field-specific adjustment rather than a broad shift away from higher education. The large decline in IT, the offsetting increase in engineering, and the absence of comparable changes in most other disciplines suggest that the IT bust mainly induced substitution toward closely related fields. This pattern supports a mechanism in which heightened perceived risk in the IT sector leads women to reallocate toward technically related fields rather than withdraw from higher education.

1.7 Conclusion

This paper examines how sector-specific shocks to labor market prospects shape women's and men's choices of tertiary programs and subsequent labor market entry. Building on a model of field-of-study choice under uncertainty with heterogeneous risk preferences, the analysis provides evidence consistent with a mechanism in which increases in sectoral uncertainty disproportionately deter more risk-averse individuals, raise the ability threshold for entry, and induce reallocation toward close substitute fields. Using the Swedish experience around the dot-com boom and bust, the empirical results document patterns of gender sorting across fields and ability selection that align with these predictions.

At the degree-choice margin, the gender gap in IT graduation appears smaller during the IT boom but reversed sharply after the bust, widening by about four percentage points. This widening reflects a decline in women's entry into IT programs following the collapse of the technology sector, consistent with heightened sensitivity to sector-specific risk. Importantly, the decline in women's IT participation did not coincide with a withdrawal from higher education. Instead, women who might otherwise have entered IT appear to have shifted toward nearby STEM fields, particularly engineering.

Among those who pursue IT degrees, the composition of entrants changed markedly. Women who remained in IT after the bust were drawn from a higher part of the ability distribution, as reflected in an increase in their average GPA rank. However, this advantage disappears among graduates who entered the IT industry, indicating that men and women at the employment margin are drawn from comparable ability distributions.

Cross-field evidence reinforces the interpretation that the shock operated through specialization choices rather than through a broad change in educational participation. The widening gender gap is concentrated in IT, while closely related engineering programs experienced an increase in the female share, and most other fields show little change.

Overall, the findings highlight the role of perceived return risk in shaping educational specialization. While much of the literature emphasizes expected earnings, the evidence here shows that changes in sectoral uncertainty can meaningfully alter gendered patterns of field choice and early career outcomes. In this sense, sector-specific downturns may exacerbate existing disparities by diverting high-ability women from volatile yet promising sectors, thereby distorting the talent pipeline. Notably, the IT field was relatively gender-balanced prior to the bust, with women accounting for around 40 percent of entrants; however, their share declined sharply afterward and did not recover. This suggests that large, negative shocks can durably disrupt gender balance in affected fields. More broadly, the results suggest that gender gaps in fields of study are sensitive to labor market signals and that fluctuations in sector-specific risk can reallocate talent across fields in ways that reshape patterns of specialization.

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Appendix A: Tables

Table A1: Female-Male Gap in IT Graduation

	(1)	(2)	(3)
Pre-bust cohorts			
1997 × women	0.0037	0.0006	0.0011
	(0.0097)	(0.0097)	(0.0097)
1998 × women	0.0066	0.0061	0.0067
	(0.0076)	(0.0077)	(0.0077)
1999 × women	0.0176***	0.0191***	0.0194***
	(0.0067)	(0.0067)	(0.0067)
2000 × women	0.0030	0.0027	0.0029
	(0.0065)	(0.0065)	(0.0065)
2001 × women	0.0023	0.0016	0.0018
	(0.0062)	(0.0062)	(0.0062)
Post-bust cohorts			
2003 × women	-0.0140**	-0.0145**	-0.0144**
	(0.0060)	(0.0061)	(0.0061)
2004 × women	-0.0210***	-0.0218***	-0.0216***
	(0.0057)	(0.0058)	(0.0058)
2005 × women	-0.0417***	-0.0423***	-0.0420***
	(0.0057)	(0.0058)	(0.0058)
2006 × women	-0.0294***	-0.0297***	-0.0294***
	(0.0056)	(0.0056)	(0.0056)
2007 × women	-0.0166***	-0.0169***	-0.0167***
	(0.0055)	(0.0055)	(0.0055)
GPA (Rank)			0.0002***
			(0.0000)
Woman	✓	✓	✓
Graduation Year FE	✓	✓	✓
Upper-Secondary School FE		✓	✓
Observations	227,412	227,412	227,412
R-squared	0.055	0.083	0.083

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table reports event-study estimates of the female-male gap in IT graduation from Equation (1.1). The reference year is 2002. Cohorts 2003–2007 are defined as post-bust cohorts. All specifications include a main effect for women. Columns (1)–(3) include graduation year fixed effects, upper-secondary school fixed effects, and GPA rank as additional controls, respectively. Robust standard errors are clustered at the upper-secondary school level.

Table A2: Female-Male Gap in IT Industry Entry

	(1)	(2)	(3)	(4)	(5)	(6)
Pre-bust cohorts						
1997 × Woman	0.0450	0.0779	0.0857	0.0450	0.0779	0.0857
	(0.0656)	(0.0914)	(0.0908)	(0.0644)	(0.0888)	(0.0881)
1998 × Woman	0.105*	0.138*	0.142*	0.105*	0.138*	0.142*
	(0.0561)	(0.0779)	(0.0777)	(0.0571)	(0.0766)	(0.0764)
1999 × Woman	0.0273	0.0394	0.0458	0.0273	0.0394	0.0458
	(0.0461)	(0.0602)	(0.0604)	(0.0469)	(0.0597)	(0.0598)
Post-bust cohorts						
2001 × Woman	-0.0645	-0.0564	-0.0542	-0.0645	-0.0564	-0.0542
	(0.0424)	(0.0552)	(0.0551)	(0.0427)	(0.0535)	(0.0534)
2002 × Woman	-0.0529	-0.0666	-0.0698	-0.0529	-0.0666	-0.0698
	(0.0379)	(0.0520)	(0.0519)	(0.0381)	(0.0503)	(0.0502)
2003 × Woman	-0.0658*	-0.0726	-0.0719	-0.0658*	-0.0726	-0.0719
	(0.0356)	(0.0519)	(0.0517)	(0.0358)	(0.0501)	(0.0499)
2004 × Woman	-0.0450	-0.0418	-0.0432	-0.0450	-0.0418	-0.0432
	(0.0369)	(0.0498)	(0.0497)	(0.0373)	(0.0484)	(0.0483)
2005 × Woman	-0.0785**	-0.107**	-0.104**	-0.0785**	-0.107**	-0.104**
	(0.0365)	(0.0514)	(0.0512)	(0.0369)	(0.0504)	(0.0502)
2006 × Woman	-0.0821**	-0.118**	-0.118**	-0.0821**	-0.118**	-0.118**
	(0.0391)	(0.0545)	(0.0544)	(0.0397)	(0.0528)	(0.0528)
2007 × Woman	-0.142***	-0.175***	-0.170***	-0.142***	-0.175***	-0.170***
	(0.0400)	(0.0571)	(0.0570)	(0.0404)	(0.0552)	(0.0551)
GPA (Rank)			0.00139***			0.00139***
			(0.000232)			(0.000219)
Woman	✓	✓	✓	✓	✓	✓
Graduation Year FE	✓	✓	✓	✓	✓	✓
Upper-Secondary School FE		✓	✓		✓	✓
College FE		✓	✓		✓	✓
Observations	19,799	17,038	17,038	19,799	17,038	17,038
R-squared	0.051	0.430	0.432	0.051	0.430	0.432

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table reports event-study estimates of the female-male gap in entry into the IT industry, conditional on holding an IT degree. The reference cohort is 2000. Cohorts 2001–2007 are defined as post-bust cohorts. All specifications include a main effect for women. Columns (1)–(3) cluster standard errors at the upper-secondary school level. Columns (4)–(6) allow for clustering at both the upper-secondary school and university levels.

Table A3: Gender Reallocation Across Fields After the Dot-Com Bust

	(1) Education	(2) Humanities	(3) Social Sciences	(4) Natural Sciences	(5) Engineering	(6) Agriculture	(7) Health & Welfare	(8) Services	(9) IT
Female-Male Gap	-0.0214***	-0.0011	-0.0079	-0.0033	0.0376***	-0.0002	0.0261***	-0.0021	-0.0422***
	(0.0064)	(0.0041)	(0.0085)	(0.0032)	(0.0083)	(0.0017)	(0.0065)	(0.0024)	(0.0060)
Graduation Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Upper-Secondary School FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	50,513	50,513	50,513	50,513	50,513	50,513	50,513	50,513	50,513
R-squared	0.173	0.124	0.129	0.113	0.235	0.111	0.158	0.115	0.162

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: This table reports estimates of Equation (1.3). Each coefficient represents the estimated change in the female-male gap in the probability of graduating in the corresponding field after the dot-com bust. A negative value indicates a relative decline in women's representation, while a positive value indicates a relative increase. The model specification includes controls for within-cohort GPA rank and fixed effects for graduation year and upper-secondary school. Robust standard errors are clustered at the upper-secondary school level.

Table A4: Gender Reallocation within Engineering Subfields After the Dot-Com Bust

	(1) General Programs	(2) Mechanical Eng.	(3) Electricity & Energy	(4) Chemical Eng.	(5) Vehicles, Ship & Aircraft	(6) Industrial Economics
2005 × Women	0.0032	0.0245***	0.0193***	0.0026	0.0037**	0.0055*
	(0.0026)	(0.0047)	(0.0039)	(0.0027)	(0.0015)	(0.0031)
Graduation Year FE	✓	✓	✓	✓	✓	✓
Upper-Secondary School FE	✓	✓	✓	✓	✓	✓
Observations	50,513	50,513	50,513	50,513	50,513	50,513
R^2	0.125	0.139	0.142	0.109	0.125	0.115

Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Note: This table reports estimates of Equation (1.3). Each coefficient measures the change in the female-male gap in the probability of graduating in the corresponding engineering subfield after the dot-com bust. Negative coefficients indicate a decline in women's representation, while positive coefficients indicate an increase. All specifications control for within-cohort GPA rank and include fixed effects for graduation year and upper-secondary school. Standard errors are clustered at the upper-secondary school level.

Appendix B: Application Stage Responses

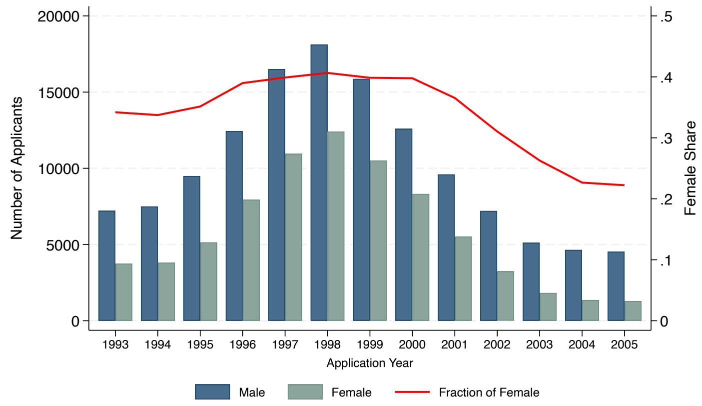
A natural concern is whether graduation patterns accurately capture students' field-of-study choices. Because the administrative registers record only graduation years, one might worry that the observed gender gap in IT completions does not fully reflect differences in field-of-study decisions made at the application stage. To address this concern, the section presents application statistics from the Swedish Higher Education Authority, which publishes aggregate counts of applicants by program and gender. Because these data are available only as aggregate statistics rather than individual-level records, they cannot be linked to the administrative registers used in the main analysis. They therefore serve as descriptive evidence rather than inputs to the regression analysis. Using these application data as shown in Figure A1, total applications to IT programs rise sharply through the late 1990s but contract abruptly after the 2000 dot-com bust. Both genders cut back, yet the decline is disproportionately female: the female share falls from about 40% at the peak to roughly 20% within a few cohorts, yielding a pronounced compositional shift toward male applicants. This entry-stage response aligns with a risk-based mechanism in which heightened volatility in the return on IT field deters marginal female applicants more than their male counterparts.

Figure A2 plots the female share among applicants by STEM field over application years. The four panels report (a) physics, chemistry and earth sciences; (b) mathematics; (c) economics and finance and (d) IT (including ICTs and computer engineering). Two patterns emerge. First, the IT panel mirrors the industry cycle. The female share among IT applicants rises through the late 1990s, then falls markedly after the dot-com crash, tracking the boom–bust timing. Second, natural sciences, mathematics and economics fields do not show an analogous change: female shares remain broadly flat or trend gently upward over the same window [14].

Because these series are by application year, the IT decline precedes the drop in women among graduates documented in Section 1.4.2 by the expected

[14] According to the Swedish Education Nomenclature (SUN) classification, one-digit major code 4 encompasses Natural Sciences, Mathematics, and Information and Communication Technologies (ICT).

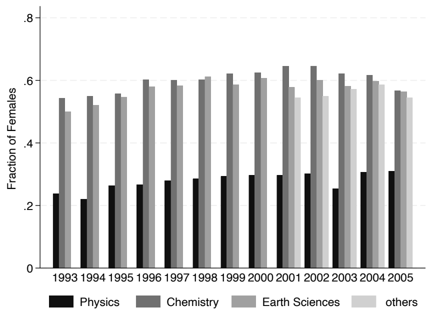
Figure A1: Applicants to the IT Field by Gender and Female Share



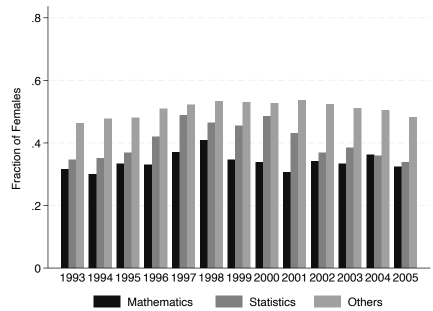
Notes: This figure shows the number of IT-field applicants and the fraction of female applicants between 1993 and 2005. Bars display annual counts of male and female applicants. The red line shows the female share among applicants.

lag from application/enrolment to completion. Together, these facts indicate that the gendered decline in IT graduation is driven primarily by program choice at entry, not by a general withdrawal from higher education or by differential attrition within programs.

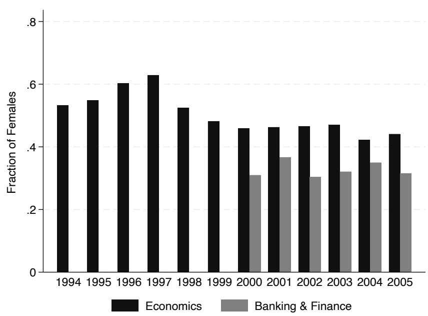
Figure A2: Female Share of Applicants by Field of Study



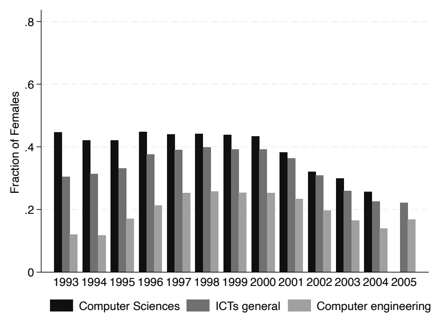
(a) Physics, Chemistry & Earth Sciences



(b) Mathematics & Statistics



(c) Economics and Finance



(d) Information Technology

Notes: The figure plots the fraction of women among applicants to programs within each indicated field, aggregated by application year. Panels (a)–(d) correspond to natural sciences, engineering, economics and finance, and computer-related fields, respectively. The data cover the period from 1993 to 2005, and the fraction is defined as the share of female applicants among all applicants within each field and year.

Appendix C: Theoretical Model

This appendix provides the formal derivation of the model of field-of-study choice under uncertainty discussed in Section 1.3. It details how gender differences in risk aversion interact with sectoral shocks to produce the three main comparative static results. In the model, when return variance increases, more risk-averse individuals require a higher expected return to enter the risky field. Because women are, on average, more risk-averse, this mechanism predicts three outcomes: (i) higher sectoral risk reduces women's relative entry into the affected field, widening the gender gap in IT graduation; (ii) among those who still choose IT, the ability threshold rises more sharply for women, implying positive selection on ability; and (iii) when IT and other fields are close substitutes, the gender-gap response to volatility shocks is amplified through reallocation toward nearby, less risky fields.

Let $\Omega = \sum_{t=1}^{T} \delta^{t-1}$ be the discounted sum of periods. I interpret the value function for the student i of the gender $g \in \{female, male\}$ choosing the field f and having the ability a_i based on the expected utility of the logarithmic earnings, consistent with the utility of CRRA on the income where the income is distributed in logarithmic normal and the variance term refers to the variance of the logarithmic earnings:

$$V_g(f,a_i) = \Omega\left(\mathbb{E}[\ln \text{Earnings}_{it}(f)] - \frac{\rho_g}{2}\text{Var}[\ln \text{Earnings}_{it}(f)] + \theta_g \bar{l}_i + \lambda_g \bar{s}_i - \kappa_g(f,a_i)\right) \tag{1.4}$$

Substituting the expression for $\ln \text{Earnings}$, $\ln \text{Earnings}_{it}(f) = \alpha_f + \beta a_i + \gamma_{fg} + \eta_{ft} + \varepsilon_{it}$, where $\mathbb{E}[\eta_{ft}] = \mu_f$ and $\text{Var}[\eta_{ft}] = \sigma_f^2$ (this is the field-specific variance component relevant to the proposition, so σ_{IT}^2 for IT field). We ignore ε_{it} for field choice decisions as it is idiosyncratic and averages out or affects all fields similarly.

$$V_g(f,a_i) = \Omega\left((\alpha_f + \beta a_i + \gamma_{fg} + \mu_f) - \frac{\rho_g}{2}\sigma_f^2 + \theta_g \bar{l}_f + \lambda_g \bar{s}_f - \kappa_g(f,a_i)\right) \tag{1.5}$$

We assume psychic costs $\kappa_g(f,a_i)$ are linear in ability: $\kappa_g(f,a_i) = \kappa_{g0}(f) - \kappa_{g1,g}(f)a_i$, where $\kappa_{g1,g}(f) \geq 0$ implies psychic costs decrease with ability.

Consider a two-field choice: IT versus an alternative field A. A student of gender g with ability a is indifferent between IT and A if $V_g(IT,a) = V_g(A,a)$.

This defines the threshold ability a_g^*:

$$(\alpha_{IT} + \beta_{IT} a_g^* + \gamma_{IT,g} + \mu_{IT}) - \frac{\rho_g}{2}\sigma_{IT}^2 + \theta_g \bar{l}_{IT} + \lambda_g \bar{s}_{IT} - (\kappa_{g0}(IT) - \kappa_{g1,g}(IT)a_g^*)$$
$$= (\alpha_A + \beta_A a_g^* + \gamma_{A,g} + \mu_A) - \frac{\rho_g}{2}\sigma_A^2 + \theta_g \bar{l}_A + \lambda_g \bar{s}_A - (\kappa_{g0}(A) - \kappa_{g1,g}(A)a_g^*)$$

Rearranging terms to solve for a_g^*:

$$\begin{aligned} a_g^*((\beta_{IT} - \beta_A) + (\kappa_{g1,g}(IT) - \kappa_{g1,g}(A))) = \\ &(\alpha_A - \alpha_{IT}) + (\gamma_{A,g} - \gamma_{IT,g}) + (\mu_A - \mu_{IT}) \\ &+ \frac{\rho_g}{2}(\sigma_{IT}^2 - \sigma_A^2) \\ &+ \theta_g(\bar{l}_A - \bar{l}_{IT}) + \lambda_g(\bar{s}_A - \bar{s}_{IT}) \\ &+ (\kappa_{g0}(A) - \kappa_{g0}(IT)) \end{aligned}$$

Let $B_g = (\beta_{IT} - \beta_A) + (\kappa_{g1,g}(IT) - \kappa_{g1,g}(A))$ be the net return to ability in IT versus field A. We assume $B_g > 0$, implying that individuals with higher ability are relatively more inclined to choose IT (i.e., $V_g(IT,a) - V_g(A,a)$ is increasing in a). Let $K_g = (\alpha_A - \alpha_{IT}) + (\gamma_{A,g} - \gamma_{IT,g}) + (\mu_A - \mu_{IT}) + \theta_g(\bar{l}_A - \bar{l}_{IT}) + \lambda_g(\bar{s}_A - \bar{s}_{IT}) + (\kappa_{g0}(A) - \kappa_{g0}(IT))$. Then, the threshold ability is:

$$a_g^* = \frac{K_g + \frac{\rho_g}{2}(\sigma_{IT}^2 - \sigma_A^2)}{B_g} \tag{1.6}$$

The derivative of a_g^* with respect to σ_{IT}^2 (the variance of returns in IT) is:

$$\frac{\partial a_g^*}{\partial \sigma_{IT}^2} = \frac{\rho_g/2}{B_g} \tag{1.7}$$

Since $\rho_g > 0$ (students are risk-averse) and we assumed $B_g > 0$, it follows that $\frac{\partial a_g^*}{\partial \sigma_{IT}^2} > 0$. An increase in IT return variance raises the ability threshold for choosing IT.

The gender gap in IT enrollment is $\Delta_{IT} = \Pr(IT \mid g = m) - \Pr(IT \mid g = f)$. Assuming students with ability $a > a_g^*$ choose IT, then $\Pr(IT \mid g) = 1 - F_g(a_g^*)$, where $F_g(\cdot)$ is the cumulative distribution function (CDF) of ability for gender g. So, $\Delta_{IT} = (1 - F_m(a_m^*)) - (1 - F_f(a_f^*)) = F_f(a_f^*) - F_m(a_m^*)$. The derivative of the gender gap with respect to σ_{IT}^2 is:

$$\frac{\partial \Delta_{IT}}{\partial \sigma_{IT}^2} = f_f(a_f^*) \frac{\partial a_f^*}{\partial \sigma_{IT}^2} - f_m(a_m^*) \frac{\partial a_m^*}{\partial \sigma_{IT}^2} \tag{1.8}$$

where $f_g(\cdot)$ is the probability density function (PDF) of ability for gender g. Substituting $\frac{\partial a_g^*}{\partial \sigma_{IT}^2}$:

$$\frac{\partial \Delta_{IT}}{\partial \sigma_{IT}^2} = f_f(a_f^*) \frac{\rho_f/2}{B_f} - f_m(a_m^*) \frac{\rho_m/2}{B_m} \tag{1.9}$$

The proposition states that $\frac{\partial \Delta_{IT}}{\partial \sigma_{IT}^2} > 0$. This requires $f_f(a_f^*) \frac{\rho_f}{B_f} > f_m(a_m^*) \frac{\rho_m}{B_m}$. We are given the key assumption that women are more risk-averse: $\rho_f > \rho_m$.

To simplify, we make an assumption that the net ability gradient is not gender-specific: **Assumption (A1):** $B_f = B_m = B > 0$. This implies that the term $(\kappa_{g1,g}(IT) - \kappa_{g1,g}(A))$ is the same for men and women. Under Assumption (A1), Equation (1.9) becomes:

$$\frac{\partial \Delta_{IT}}{\partial \sigma_{IT}^2} = \frac{1}{2B} \left(f_f(a_f^*)\rho_f - f_m(a_m^*)\rho_m \right) \tag{1.10}$$

For $\frac{\partial \Delta_{IT}}{\partial \sigma_{IT}^2} > 0$, we need $f_f(a_f^*)\rho_f > f_m(a_m^*)\rho_m$. Given $\rho_f > \rho_m$, this condition holds if $f_f(a_f^*)$ is not substantially smaller than $f_m(a_m^*)$ such that it would offset the difference in risk aversion. The "proof sketch" argument that "$a_g^*(IT)$ increases more for women than men, reducing female enrollment disproportionately" implies that the net effect $f_f(a_f^*) \frac{\partial a_f^*}{\partial \sigma_{IT}^2}$ (which contributes positively to Δ_{IT}'s change) dominates $f_m(a_m^*) \frac{\partial a_m^*}{\partial \sigma_{IT}^2}$. This requires precisely that $f_f(a_f^*)(\rho_f/(2B)) > f_m(a_m^*)(\rho_m/(2B))$, which is $f_f(a_f^*)\rho_f > f_m(a_m^*)\rho_m$. This inequality is thus taken to hold based on the model's premises and the stated mechanism.

Part (i): Effect is larger when $(\rho_f - \rho_m)$ is greater. To make this transparent, let's make a further simplifying assumption often employed: **Assumption (A2):** The densities at the respective thresholds are approximately equal, $f_f(a_f^*) \approx f_m(a_m^*) = f^* > 0$. Under Assumptions (A1) and (A2), Equation

(1.10) becomes:

$$\frac{\partial \Delta_{IT}}{\partial \sigma_{IT}^2} \approx \frac{f^*}{2B}(\rho_f - \rho_m) \tag{1.11}$$

Since $f^* > 0$, $B > 0$, and $\rho_f > \rho_m$ (given), it follows that $\frac{\partial \Delta_{IT}}{\partial \sigma_{IT}^2} > 0$. From this expression, it is clear that if the difference $(\rho_f - \rho_m)$ is greater, the magnitude of $\frac{\partial \Delta_{IT}}{\partial \sigma_{IT}^2}$ is larger, ceteris paribus.

Part (ii): Effect is larger when substitutability between IT and other high-return fields is higher. Higher substitutability between IT and field A can be interpreted as a smaller net return to ability specific to IT over A. In our model, this means $B = (\beta_{IT} - \beta_A) + (\kappa_{g1}(IT) - \kappa_{g1}(A))$ is smaller (though still positive). A smaller B implies that individuals are more sensitive to other characteristics of the fields, as ability differentiates them less strongly. Looking at the expression $\frac{f^*}{2B}(\rho_f - \rho_m)$ (under A1 and A2) or $\frac{1}{2B}(f_f(a_f^*)\rho_f - f_m(a_m^*)\rho_m)$ (under A1), if B is smaller (but positive), the term $1/(2B)$ is larger. Therefore, a smaller B (higher substitutability) leads to a larger $\frac{\partial \Delta_{IT}}{\partial \sigma_{IT}^2}$, meaning the gender gap in IT enrollment is more sensitive to changes in IT return variance.

This completes the proof under the stated assumptions.

2. Property Rights, the Intra-Couple Wealth Gap, and Family Outcomes: Evidence from China*

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2.1 Introduction

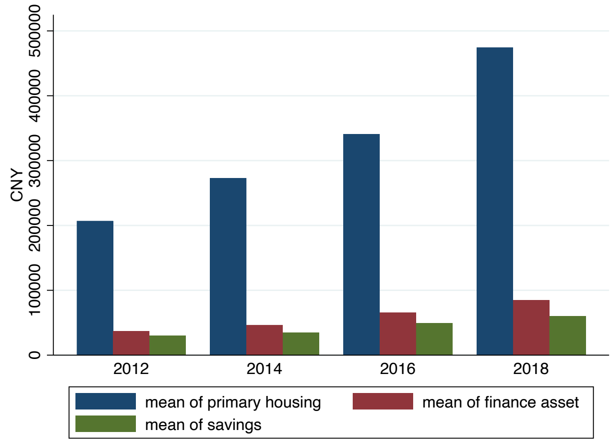
While the gender wage gap has narrowed and plateaued in many settings, the gender wealth gap, particularly within households, remains a critical and underexplored dimension of economic inequality. Intra-couple disparities in asset ownership may exceed income differences in both magnitude and long-term impact, shaping individual well-being and bargaining power within marriage (Deere and Doss, 2006; Piketty, 2014). Yet we have little evidence on how property and housing wealth are distributed between spouses, largely due to data limitations and the difficulty of identifying causal effects.

This paper addresses that gap by asking two related questions: how large are husband-wife housing wealth gaps, and what are their consequences for family decisions? To answer these questions, I use the 2011 Marriage Law reform, which replaced equal division of marital property upon divorce with a rule that assigns housing to the registered owner. This change provides a natural experiment that shifted relative ownership shares between husbands and wives without altering household fundamentals. By combining this legal shock with spouse-level panel data, I can trace both the emergence of within-couple property and wealth gaps and their downstream effects on household behavior.

The first step of the analysis quantifies the magnitude and persistence of intra-couple wealth disparities, a dimension absent from prior work. Earlier studies of the same reform focus on whether the wife lost property rights, using a binary indicator and restricting attention to households where only the husband is on the deed. By contrast, I construct a continuous measure of intra-couple ownership shares for all married couples, which allows me to document both the size and direction of wealth gaps across the population. Building on this measurement, I then link ownership disparities to family outcomes: divorce, female labor force participation, and housework.

China provides an ideal setting for studying intra-couple wealth inequality and the power dynamics of asset ownership. Housing is by far the dominant component of household balance sheets, accounting for over 70% of wealth in the China Family Panel Studies (CFPS), while financial market participation remains limited, as shown in Figure 2.1. A home is also a prerequisite for

Figure 2.1: Household Wealth Composition



Data source: China Family Panel Studies

Note: This figure presents the composition of household wealth from 2012 to 2018. Primary housing accounts for the dominant share, constituting about 76% in 2012 and rising further over time. In contrast, the mean values of savings and financial assets remain relatively stable throughout the period.

marriage: prevailing norms dictate that the groom's family provides the marital dwelling, and deeds are consequently registered in the husband's name in roughly four out of five first-marriage households (Painter et al., 2003; Yang et al., 2021). Parents reinforce this pattern by providing financial support disproportionately to sons (Chai and Feng, 2021; Deng et al., 2019; Gao et al., 2022; Hardin et al., 2022; Li and Wu, 2017). These customs create a substantial stock-wealth asymmetry at the very start of married life.

The 2011 Marriage Law reform provides a clean natural experiment. A judicial interpretation shifted the rule at divorce from equal division of marital property to awarding the home to the registered owner. Although formally gender-neutral, the reform applied retroactively and effectively converted implicit joint claims into individual property rights, disproportionately reducing wives' legal claims. The combination of a dominant asset, patriarchal ownership norms, and a nationwide legal shock creates sharp, plausibly exogenous variation in within-couple wealth gaps.

The analysis draws on the 2010–2018 CFPS, a nationally representative panel that records both deed registration and self-reported market values. I focus on couples already married in 2010, the last survey before the reform. Using a difference-in-differences (DID) design, I estimate the effect of the reform on the intra-couple property share gaps and translate these into wealth gaps. In the second stage, I estimate two-stage least squares (2SLS) regressions, using the reform-induced shifts in intra-couple gaps as instruments, to identify their causal effects on divorce, female labor force participation, and housework.

The results show that the reform increased the husband-wife legal share gap by 28.3 percentage points, generating an average housing wealth gap of CNY 63,667, approximately ten times wives' annual income. While joint registration became more prevalent in later years, gradually narrowing the legal share gap, the wealth gap persisted as housing prices continued to rise. In the second stage, 2SLS estimates show that exogenous increases in the husband's relative ownership share reduce divorce probability, raise female employment, and increase wives' housework. Standardized comparisons reveal that wealth gap effects exceed legal share gap effects across all outcomes, indicating that the economic magnitude of housing inequality, not just formal ownership status, amplifies bargaining consequences. Heterogeneity analysis shows that the reform lowers divorce probability regardless of which spouse holds the title. Female employment increases when the husband's bargaining position strengthens, but shows no significant change when the wife's does. Taken together, these findings highlight how legal reforms that appear gender-neutral can entrench inequality when layered onto existing social norms.

This paper relates to three strands of literature: gender wealth inequality, marital property regimes, and gender-neutral reforms and inequality. Recent work documents large cross-country gender wealth gaps (Diana Deere et al., 2012; Grabka et al., 2015; Meriküll et al., 2021; Schneebaum et al., 2018; Vo et al., 2019; Warren, 2006), but evidence on intra-couple housing wealth inequality remains scarce, particularly in emerging economies where real estate dominates balance sheets. This study contributes new evidence from China, where housing dominates household balance sheets.

A second strand studies how marital property regimes shape household behavior. Influential U.S. studies exploit variation in divorce and property laws to show effects on labor supply, marriage stability, and bargaining outcomes (Gray, 1998; Stevenson, 2007; Voena, 2015). Building on this tradition, I use China's 2011 Marriage Law reform as a natural experiment. Unlike most prior studies that rely on discrete legal categories, I measure a continuous intra-couple ownership share and the implied wealth gap, which makes it possible to link bargaining outcomes directly to the magnitude of ownership disparities.

Related work shows that formally gender-neutral reforms often reinforce existing inequalities. Land titling in Ghana and Rwanda, joint titling in Peru, and pensions in South Africa all produced asymmetric benefits for men when norms or institutions favored them ex ante (Ali et al., 2014; Duflo, 2003; Goldstein and Udry, 2008; Wiig, 2013). The Chinese reform fits this pattern: although the rule change was gender-neutral in form, it disproportionately weakened wives' claims, widened intra-couple asset gaps, and shifted household behavior.

Finally, two recent studies are closest to mine. Dong (2022) and Huang et al. (2023) exploit the same reform but define treatment using a binary indicator equal to one if the husband is the registered owner. This binary approach classifies a household as treated if the husband alone is on the deed, and as control if both spouses or neither spouse is listed. While this captures the direction of ownership, it assigns the same treatment intensity to all treated households regardless of how many family members share the deed. In practice, many households have extended family members (typically parents) co-registered on the deed, so the wife's actual loss of property rights varies continuously with the number of co-owners. The economic implications of a household where the husband is the sole owner differ substantially from those of a household where the husband shares the deed with other family members. Notably, these two studies reach contrasting conclusions regarding women's labor supply when the husband holds the title: Dong (2022) finds a negative effect on employment, while Huang et al. (2023) finds no significant effect. Their analysis also focuses primarily on households in which the husband is the registered owner, leaving less explored the cases in which wives hold the title.

This paper departs from the binary approach by constructing a continuous measure of intra-couple ownership shares that accounts for all individuals listed on the deed, directly quantifying the magnitude of each spouse's property claim. Because the CFPS records the names of all registered owners, I can compute the fraction of the property legally attributed to each spouse, producing a share that ranges continuously between zero and one rather than collapsing to a binary indicator. I also translate these shares into a husband-wife wealth gap by multiplying the share gap by the property's market value. This continuous measurement has three advantages. First, it allows estimation of the marginal effects of ownership shifts on household behavior. Second, it enables symmetric heterogeneity analysis across households in which husbands gain ownership and those in which wives do. Third, by separately estimating the effects, this paper helps reconcile the contrasting findings in Dong (2022) and Huang et al. (2023). Earlier binary studies, which primarily focused on husband-registered households, may yield different conclusions due to differences in sample composition and the limitations of a binary treatment in capturing heterogeneous responses. In particular, female employment responds asymmetrically: it rises when the husband's bargaining position strengthens (husband-registered households) but shows no significant change when the wife's does (wife-registered households). In contrast, divorce probability declines and wives' housework increases regardless of which spouse holds the title, indicating that these outcomes respond in the same direction irrespective of ownership.

The remainder of the paper is organized as follows. Section 2.2 reviews the Chinese housing market and the 2011 Marriage Law interpretation. Section 2.3 describes the data. Section 2.4 presents the empirical strategy. Section 2.5 shows the main results, with heterogeneity analyses. Section 2.6 reports robustness checks, including propensity-score matching and semiparametric DID. Section 2.7 concludes.

2.2 Background

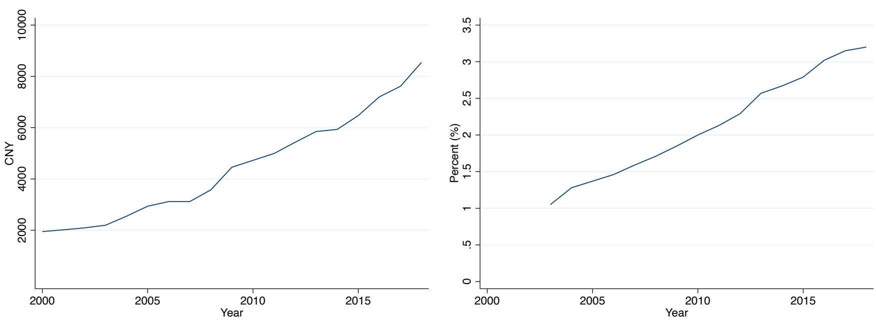
2.2.1 Housing Market in China

Until 1998, China lacked a formal housing market. Urban residents typically lived in employer-provided units, mostly from state-owned institutions. Households held use rights rather than ownership, and housing transactions were prohibited.

In 1998, the government initiated a major privatization reform, allowing urban residents to purchase their existing apartments at subsidized prices. This policy created private property rights in housing, enabling households to own, transfer, and sell their dwellings. It marked a decisive shift from state allocation to market-based ownership.

The reform triggered a surge in housing demand. Households sought to improve living conditions and treat real estate as an investment, leading to rapid growth in commercial apartment construction. The housing market expanded alongside urbanization, and property ownership became closely tied to family formation, as owning a home is widely viewed as a prerequisite for marriage. Parents often provide financial assistance to sons to facilitate these purchases, reinforcing gendered patterns of ownership. Between 2000 and 2018, average national housing prices quadrupled, rising from about 2,000 CNY/m^2 to over 8,000 CNY/m^2 (Figure 2.2a).

Figure 2.2: Average National Housing Prices and Divorce Rate



(a) Average National Housing Prices (m^2)

(b) Divorce Rate

Data source: National Bureau of Statistics of China

Note: This figure presents the average national housing price and divorce rate from 2000 to 2018. Panel (a) shows housing prices, measured in CNY per square meter, and Panel (b) presents the divorce rate.

2.2.2 2011 Marriage Law Reform

Before 2011, marital homes were generally considered joint property, regardless of how they were registered. In divorce, courts often awarded equal shares even if only one spouse was on the deed. This arrangement generated disputes, coinciding with a gradual increase in divorce rates (Figure 2.2b): husbands and their families argued that equal division was unfair given their larger financial contributions to home purchase, while wives emphasized their household contributions and the law's joint-property principle. The absence of clear rules led to contentious and inconsistent divorce outcomes.

In 2011, the Supreme People's Court (SPC) issued a judicial interpretation of the Marriage Law[1], clarifying property division at divorce. The new rule awarded the home to the registered owner(s), replacing the default of equal division. The clarification applied retroactively, covering all marriages and purchases, and thus represented a nationwide, uniform shift in property rights.[2]

The policy process unfolded in two stages. In November 2010, the SPC released a draft for public comment through its official website. The finalized interpretation was promulgated in September 2011 and took effect immediately. Although a consultation draft was formally posted online, attention to such notices is largely confined to legal professionals and specialized audiences. For households to adjust property registration in response to a draft, it would have required legal awareness, coordinated spousal agreement, and completion of formal administrative procedures, which are unlikely to occur rapidly in response to a draft document. The reform therefore represents a largely unanticipated shift in the legal allocation of divorce property.

Following formal issuance in September 2011, the interpretation received widespread media coverage and generated substantial public debate concerning women's property rights and marital bargaining power because social

[1] Formally titled *Interpretation III of the Supreme People's Court on Several Issues Concerning the Application of the Marriage Law of the People's Republic of China*.

[2] Although Chinese law permits prenuptial agreements, their use is uncommon in practice. Social norms and the reluctance to formalize marital contingencies prior to marriage limit their prevalence. As a result, most couples rely on the statutory property regime in place at the time of marriage and divorce. The 2011 judicial interpretation therefore applied to the vast majority of marriages and did not simply codify pre-existing private arrangements.

norms dictate that men (or their parents) typically provide the marital dwelling, and deeds are registered in the husband's name in most households. The combination of immediate legal enforcement and broad dissemination through mainstream media suggests that households became aware of the new regime after its implementation.

2.3 Data

2.3.1 Source of Data

CFPS is a nationally representative longitudinal survey conducted biennially since 2010 by Peking University. It covers 25 provinces, municipalities, and autonomous regions.[3] The survey collects rich information on household demographics, socioeconomic characteristics, housing assets, market values, and deed registration. Its panel structure allows tracking of the same households over time.

The analysis sample is constructed from the 2010-2018 waves. I restrict attention to couples married in 2010, prior to the reform.[4] The resulting panel includes 10,021 couples observed over time.

2.3.2 Key Variables

Housing constitutes the dominant component of household wealth in China and plays a central role in marriage formation. Property ownership is often regarded as a prerequisite for marriage and is heavily shaped by intergenerational transfers. I therefore focus on the value of the primary residence as the main measure of household wealth.[5]

[3]CFPS excludes Hong Kong, Macao, Xinjiang, Xizang, Qinghai, Inner Mongolia, Ningxia, and Hainan (Xie and Lu, 2015).

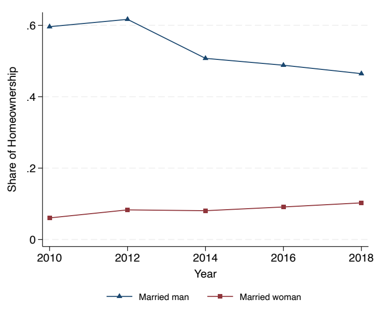
[4]The 2020 survey was conducted by telephone during the pandemic and exhibits lower response rates; it is therefore excluded.

[5]The CFPS does not provide comprehensive information on additional properties. As shown in Table A1, 84% of households own only one dwelling; 14% own a second property, typically reserved for a child's future marriage (usually a son). The analysis therefore captures the principal dimension of spousal wealth inequality.

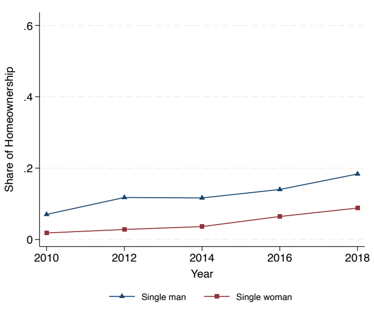
Ownership Measures. The empirical design requires measures of individual ownership shares and housing wealth. I construct two ownership concepts.

Deed share. This is the ownership share implied by names listed on the housing deed. Registered owners divide property equally; unregistered household members receive no formal share.[6] Figure 2.3 documents deed shares by gender from 2010 to 2018. Among married couples (Figure 2.3a), husbands hold the majority of titles, approximately 60% in 2010 and 2012, while wives hold about 8%. Shares for husbands decline modestly over time as wives gain registration. Among singles (Figure 2.3b), men also dominate ownership, though at lower rates than married individuals, consistent with norms linking housing to marriage. The reform may also have incentivized singles to secure property before marriage to protect individual claims.

Figure 2.3: Deed Share by Gender for Married and Single People



(a) Deed Share for Married People



(b) Deed Share for Single People

Note: This figure plots deed shares of homeownership based on the name listed on the housing deed, distinguishing it from the legal share. Subfigure (a) shows deed shares for married men and women from 2010 to 2018. Subfigure (b) presents deed shares for single men and women.

Legal share. This is the ownership share implied by marital property law. Before 2011, both spouses had equal legal claims to marital housing regardless of deed registration. After the reform, legal shares are determined by deed

[6]More details on registration patterns by generation and number of owners appear in Table A2 and Table A3. Individuals without deed shares typically live in rental or family-owned housing.

registration, making legal and deed shares identical from 2011 onward.

In many households, housing is jointly registered with extended family members, most commonly parents. When multiple individuals are listed on the deed, legal ownership is divided equally among registered owners.[7] The reform altered only the allocation of the registered spouse's share between husband and wife and did not affect the shares of other co-owners.

Legal Share Gap. The husband-wife legal share gap is defined as the husband's legal share minus the wife's legal share

$$\Delta_{ct} = s_{m,ct} - s_{f,ct},$$

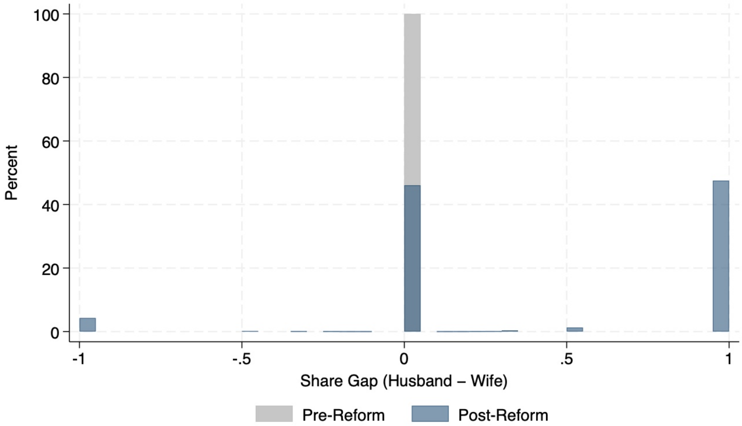
where c indexes couples and t survey years; $s_{m,ct}$ and $s_{f,ct}$ denote the legal shares of the husband and wife, respectively. Positive values indicate that the husband holds a larger ownership claim; negative values indicate that the wife does. Before the reform, the gap equals zero for all couples under the equal-division regime. After the reform, the gap becomes positive in husband-registered households and negative in wife-registered households. Fractional values arise in cases with extended-family co-owners. Figure 2.4 displays the distribution of the legal share gap before and after the reform. The pre-reform distribution is tightly concentrated at zero. Post-reform, the distribution spreads to positive and negative values, reflecting the reassignment of legal ownership to the registered spouse. This dispersion provides the key source of identifying variation.

Wealth Gaps. The intra-couple wealth gap is defined as the intra-couple legal share gap times the housing value, which is

$$\Delta W_{ct} = \Delta_{ct} \times \text{Housing Value}_{ct}$$

[7] For example, if the husband and his father are both listed on the deed, each holds one-half of the property. Under the pre-reform equal-division regime, the wife had a legal claim to half of the husband's share, giving each spouse one quarter of the total property value. After the reform, the husband retains his one-half share, and the wife receives nothing upon divorce. The resulting ownership gap thus varies continuously with the number of co-registered family members.

Figure 2.4: Distribution of the Intra-Couple Share Gap Before and After the 2011 Reform



Note: This figure plots the distribution of the intra-couple property share gap defined as the husband's legal ownership share minus the wife's share. Gray bars indicate the distribution before the reform, while green bars indicate the distribution after the reform.

2.3.3 Treatment Definition and Sample

The 2011 judicial interpretation replaced equal division at divorce with a registered-owner rule: only the spouse(s) listed on the deed retain ownership. Applied retroactively, the reform created a plausibly exogenous shock to spouses' legal shares.

Couples are classified using 2010 deed registration into four groups (Dong, 2022; Zang, 2020): (1) husband-only; (2) wife-only; (3) joint ownership; (4) neither spouse listed.[8] Before 2011, all couples—regardless of deed registration—expected equal division of marital housing at divorce. The reform changed this rule only for couples where one spouse is registered and the other is not: in these households, the registered spouse's legal share increased, while the unregistered spouse's share fell to zero. By contrast, jointly registered couples (group 3) were unaffected: both spouses remained on the deed before the reform, so each retained an equal legal claim. Couples where nei-

[8]In group (4), couples typically reside in property owned by parents or in rental housing.

ther spouse is listed (group 4) were likewise unaffected.[9] Accordingly, groups (1) and (2) constitute the treatment group—couples whose legal shares were altered by the reform—while groups (3) and (4) serve as controls.[10] The treatment group includes both husband-registered and wife-registered couples because both experienced a shift away from equal division; the reform increased the husband's legal share in group (1) and the wife's legal share in group (2). The baseline analysis estimates the average effect across both groups, while Section 2.5.4 examines heterogeneous responses by initial title holder. The 2010 wave was fielded prior to the public consultation draft released in mid-November 2010. Treatment status is therefore determined using pre-reform deed registration, substantially mitigating concerns about anticipatory sorting.

Table 2.1 reports pre-reform means and standard deviations for treatment and control groups. Panel A reports demographic characteristics. Treated couples are older, less educated, lower income, and have fewer children, motivating the propensity-score matching in Section 2.6. Panel B reports pre-reform means of the outcome variables.

2.3.4 Outcome Variables

I construct three sets of outcomes to examine marital stability, women's labor supply, and intra-household labor allocation.

Divorce. The divorce indicator is a binary variable that equals one when a divorce occurs, and remains one for the year of the divorce and all subsequent years.

Female labor force participation (FLFP). For couples observed in intact marriages in a given wave, an indicator equal to one if the wife reports employment. Restricting to intact marriages isolates bargaining responses from compositional changes due to divorce.

Housework hours. Using time-use data, I construct two measures: average weekday hours and average weekend hours. Weekday tasks (e.g., cooking,

[9]These couples typically reside in rental housing or property owned by other family members. As neither spouse had a deed-based claim before or after the reform, their legal shares were unchanged.

[10]Zang (2020) and Dong (2022) exclude wife-only households. I retain this group to examine overall gender asymmetries and heterogeneity by title holder.

Table 2.1: Descriptive Statistics Before Reform

	(1) Control Group	(2) Treatment Group	(3) Difference
Panel A: Characteristics			
Wife's Age	41.14	48.68	-7.54***
	(14.65)	(10.87)	
Husband's Age	43.18	50.69	-7.51***
	(14.92)	(11.16)	
Number of Children	0.98	0.84	0.14***
	(0.79)	(0.85)	
Income	7.55	5.89	1.67***
	(19.03)	(11.14)	
Wife's Education	6.96	5.36	1.61***
	(4.64)	(4.68)	
Husband's Education	8.25	7.34	0.91***
	(4.15)	(4.22)	
Panel B: Outcomes			
Divorce post-reform	0.093	0.065	0.029***
	(0.29)	(0.247)	
Wife's employment rate	0.476	0.535	-0.06***
	(0.50)	(0.50)	
Wife's Weekday housework	2.26	2.67	-0.409***
	(1.64)	(1.70)	
Wife's Weekend housework	2.48	2.83	-0.361***
	(1.62)	(1.73)	
Husband's Weekday housework	0.943	1.14	-0.208***
	(1.35)	(1.46)	
Husband's Weekend housework	1.164	1.35	-0.188***
	(1.45)	(1.53)	
Observations	3,534	6,487	

Note: This table presents pre-reform means and standard deviations (in parentheses) for treatment and control groups. Panel A shows characteristics variables; Panel B reports key outcomes. Column (3) reports mean differences.Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

cleaning, caregiving) are time-sensitive; weekend tasks are more discretionary. Comparing weekday and weekend responses sheds light on how bargaining power shifts affect routine versus flexible unpaid labor.

2.3.5 Panel Structure and Attrition

Because divorce is one of the outcomes, differential attrition may be a concern. The CFPS follows individuals rather than households, mitigating mechanical attrition from household splits. Even when marriages dissolve, at least one spouse, typically the husband, remains in the panel. Marital status and unique spouse identifiers allow divorce and remarriage to be observed directly.

For employment and housework outcomes, the sample is restricted to intact marriages in each wave. This design isolates within-marriage bargaining responses and avoids conflating behavioral adjustments with compositional changes induced by divorce.

Overall panel attrition in the CFPS is moderate and does not exhibit systematic pre-reform differences between treated and control couples. These features suggest that selective survey exit is unlikely to drive the main results.

2.4 Empirical Identification Strategy

This section outlines the empirical strategy for estimating the causal impact of the 2011 Marriage Law Reform on intra-household legal share and wealth gaps and the downstream effects on household decisions such as divorce, FLFP, and the allocation of housework. Conceptually, I interpret the husband-wife legal share gap (or wealth gap) as a proxy for spousal bargaining power. Because these gaps are endogenous to unobserved preferences and wealth accumulation processes, I exploit reform-induced changes in property registration, shifting from equal division at divorce to a registered-owner rule, as a source of exogenous variation. The analysis proceeds in two steps. First, using a DID framework, I estimate the emergence and persistence of legal share and wealth gaps between spouses following the reform (first stage). Second, I employ these predicted gaps as instruments for spousal bargaining power in a 2SLS design to identify their causal effects on family outcomes. The first stage tests whether the reform altered intra-couple property ownership, the reduced form estimates the total effect of the reform on outcomes, and the 2SLS specification isolates the causal impact of bargaining power on household behavior.

2.4.1 First Stage: Effect of the Marriage Law Reform on Intra-Couple Gaps

The 2011 Marriage Law reform created an exogenous shock to property division at divorce. By reallocating property rights to the registered owner, it immediately altered spousal ownership shares and induced legal share and wealth gaps within couples as defined in Section 2.3.2.

I estimate the causal effect of the reform using the DID model:

$$G_{ct} = \beta(\underbrace{Treated_c \times Post_t}_{\text{IV}}) + \theta X_{ct} + \gamma_t + \delta_c + \eta_p + \varepsilon_{ct} \tag{2.1}$$

where G_{ct} is the husband-wife legal share gap (Δ_{ct}) or the wealth gap (ΔW_{ct}), $Treated_c$ indicates couples whose 2010 deed listed only one spouse (husband-only or wife-only), and $Post_t$ is a post-reform dummy equal to one for survey waves after 2011 (2012–2018). $Treated_c \times Post_t$ captures the reform-induced change in property registration (the instrument). Control X_{ct} consists of income and the number of children. The specification includes survey-year fixed effects (γ_t), couple fixed effects (δ_c), and province fixed effects (η_p) to absorb macro shocks, time-invariant couple characteristics, and regional differences. Standard errors are clustered at the couple level. The coefficient β captures the average reform-induced shift in intra-couple gaps, providing the first-stage relevance condition for the instrumental variable strategy.

I then estimate the reduced-form relationship between the Marriage Law Reform and household outcomes:

$$Y_{ct} = \rho_0 + \rho_1(\underbrace{Treated_c \times Post_t}_{\text{IV}}) + \theta X_{ct} + \gamma_t + \delta_c + \eta_p + \varepsilon_{ct} \tag{2.2}$$

where Y_{ct} is one of the household outcomes. The controls are the same as in the first stage, including both the control variables and the fixed effects. The coefficient ρ_1 captures the total impact of the reform on family behavior, combining all mechanisms through which the policy may operate.

To examine dynamic effects, I estimate an event-study (dynamic DID) specification:

$$G_{ct} = \sum_{s=2012}^{2018} \alpha_s \left(Treated_c \times 1\{t = s\} \right) + \theta X_{ct} + \gamma_t + \delta_c + \eta_p + \varepsilon_{ct}, \tag{2.3}$$

where $1\{t = s\}$ is an indicator for survey year s, and 2010 is the omitted baseline year. The coefficients α_s trace out the evolution of the reform's effect over time relative to the pre-reform period. Although only one pre-treatment wave is available, the institutional setting, where equal ownership was the prevailing rule, supports the plausibility of parallel trends. To assess robustness, I also apply the semiparametric DID estimator of Abadie (2005), which reweights observations on rich covariates in Section 2.6.1.

2.4.2 Second Stage: Household Responses to Intra-Couple Inequality

Having established the reform's effect on intra-couple inequality, I next examine how shifts in bargaining power affect household decisions. Guided by the bargaining framework in Section 2.7, I focus on three outcomes: (i) divorce, (ii) FLFP, and (iii) spouses' unpaid housework hours.

I use the fitted gaps, $\widehat{G}_{ct}$ (husband-wife legal share gap $\widehat{\Delta}_{ct}$ or wealth gap $\widehat{W}_{ct}$), from Equation (2.1) as an instrument for shifts in spousal bargaining power in the following 2SLS specification:

$$Y_{ct} = \alpha \Delta \widehat{G}_{ct} + \lambda X_{ct} + \gamma_t + \delta_c + \eta_p + u_{ct}, \tag{2.4}$$

where the other terms are defined as in Equation (2.2). The 2SLS coefficient α identifies the local average treatment effect of an increase in the husband-wife legal share gap, driven by the reform, on the outcome, isolating exogenous variation in bargaining power.

2.4.3 Instrumental Variable Assumptions

The 2SLS specification relies on standard instrumental variable assumptions. First, the exclusion restriction requires that the 2011 judicial interpretation affect household outcomes only through its impact on intra-couple ownership shares. The reform altered the allocation of legal claims to the marital home conditional on divorce but did not modify divorce procedures, filing costs, custody rules, or other aspects of family law. Its primary institutional content was the reassignment of property rights. To the extent that households updated expectations about divorce settlements following the reform, such updates operate through changes in spouses' outside options and bargaining positions, the mechanism captured by the ownership gap. Behavioral responses to the reform are therefore interpreted as mediated by shifts in bargaining power rather than by independent policy channels.

Second, the monotonicity assumption requires that the instrument moves the endogenous variable in a consistent direction for all compliers. In this setting, the condition is satisfied by construction: before 2011, all married couples held equal legal claims to marital housing regardless of deed registration. After the reform, legal ownership upon divorce was reassigned to the person named on the deed. For every treated couple, the registered spouse's legal share increased, and the unregistered spouse's share fell to zero. The registered spouse always gains, and the unregistered spouse always loses. There is no household for which the reform transferred legal ownership away from the registered spouse toward the unregistered one. Defiers are thus ruled out by the institutional design of the reform.

Some households subsequently adjusted registration, for example, by adding a spouse to the deed, thereby attenuating the ownership gap over time. Because treatment status is defined using pre-reform registration and remains fixed, such adjustments constitute post-reform behavioral responses rather than violations of monotonicity. These changes reduce the magnitude of the first stage but do not reverse the initial direction of the reform-induced legal reallocation. The strong and consistently signed first-stage estimates provide empirical support for monotonicity in this setting.

2.5 Results

This section presents the main empirical findings. Section 2.5.1 reports the first-stage estimates of the reform's effect on intra-couple legal share and wealth gaps. Section 2.5.2 and Section 2.5.3 present the 2SLS results for divorce, employment, and housework. Section 2.5.4 examines heterogeneity by initial title holder.

2.5.1 Effect of the Marriage Law Reform on Intra-Couple Gaps

Static Estimates. Column (1) of Table 2.2 reports the first-stage DID estimates. The reform increased the average husband-wife legal share gap by 28.3 percentage points. This shift reflects the move from the pre-reform equal division rule to the post-reform registered-owner rule, which substantially strengthened the bargaining position of the titled spouse. The corresponding first-stage F-statistic is 852.19, exceeding conventional weak-instrument thresholds and confirming strong instrument relevance.

Panel B translates this ownership shift into pecuniary terms. The reform increased the husband-wife housing wealth gap by CNY 63,667 on average. The magnitude is economically large relative to typical household income levels in the baseline period. The first-stage F-statistic is similarly strong. Together, these results confirm that the 2011 judicial interpretation generated a sizable and empirically powerful source of variation in intra-couple inequality. Although the reform was formally gender neutral, prevailing ownership norms imply that the resulting increase in bargaining power disproportionately favored husbands in practice.

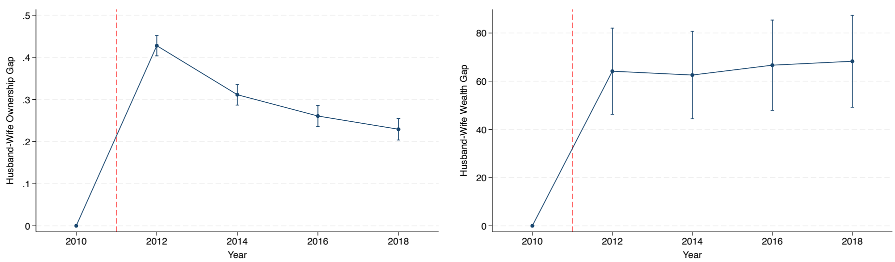
Dynamic Estimates. Table A4 and Figure 2.5 present the event-study estimates. Figure 2.5a shows the trajectory of the legal share gap. Before the reform, the gap was zero: by law, spouses held equal ownership regardless of whose name was on the deed. After the reform, registered husbands held on average 43 percentage points more property than their wives in 2012. The gap then narrowed steadily but remained 23 percentage points in 2018, the last wave in the study period. This decline might be consistent with non-registered spouses, typically wives, negotiating to add their names to deeds after the reform.[11]

[11] It is important to emphasize that Figure 2.3 reports deed shares, which reflect names listed on the housing deed and do not change mechanically with the reform. By contrast, Figure 2.5a reports legal shares, which shifted discontinuously in 2011 when the law began aligning legal ownership with deed registration.

Figure 2.5b shows the corresponding impact on wealth gaps. The reform raised the average husband-wife housing wealth gap to CNY 64,150 in 2012. Unlike the share gap, the wealth gap remained persistently large throughout the period, as rising housing prices amplified even modest differences in legal shares.

Taken together, the event-study estimates reveal a divergence: while legal share gaps narrowed over time, wealth gaps persisted. This pattern underscores that asset appreciation magnified the consequences of the reform and entrenched intra-household inequality.

Figure 2.5: The Dynamic Effects of Marriage Law on Intra-couple Gaps



(a) Share Gap **(b)** Wealth Gap

Note: This figure plots the estimates from Equation (2.3). Subfigure (a) shows the trajectory of the intra-couple legal share gap, while Subfigure (b) shows the corresponding housing wealth gap, measured in thousands of CNY.

2.5.2 Divorce

Column (2) of Table 2.2 reports the reduced-form effect of the reform on marital dissolution. Treated couples were 1.9 percentage points less likely to divorce relative to a baseline divorce rate of approximately 8 percent, implying a reduction of nearly one quarter of the baseline hazard.

Column (3) presents the corresponding 2SLS estimates. Using the legal share gap as the endogenous regressor (Panel A), a one-unit increase in the husband-wife legal share gap (from 0 to 1) reduces the probability of divorce by 6.75 percentage points. Interpreted more intuitively, a 10-percentage-point

Table 2.2: IV Estimates of Divorce Probability

	(1) First Stage	(2) Reduced Form	(3) 2SLS (Raw)	(4) 2SLS (Std.)
Panel A: Legal Share Gap				
Dependent Variable:	**Property Share Gap**	**Divorce**	**Divorce**	**Divorce**
IV (Treated × Post)	0.2834***	-0.0191***		
	(0.0086)	(0.0056)		
Property Share Gap			-0.0675***	-0.0387***
			(0.0196)	(0.0112)
Controls	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Couple FE	✓	✓	✓	✓
Province FE	✓	✓	✓	✓
Observations	36,677	36,677	36,677	36,677
R-squared	0.2085	0.0133	0.0180	0.0180
First-stage F-stat			852.19	852.19
Panel B: Wealth Gap				
Dependent Variable:	**Wealth Gap**	**Divorce**	**Divorce**	**Divorce**
IV (Treated × Post)	63,667***	-0.0191***		
	(7,214)	(0.0056)		
Wealth Gap			-0.0003***	-0.1039***
			(0.0001)	(0.0317)
Controls	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Couple FE	✓	✓	✓	✓
Province FE	✓	✓	✓	✓
Observations	36,677	36,677	36,677	36,677
R-squared	0.0372	0.0133	0.0205	0.0205
First-stage F-stat			852.19	852.19

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Notes: This table reports 2SLS estimates of the effect of intra-couple inequality on divorce probability. Panel A uses the intra-couple *legal share gap* as the endogenous regressor. Panel B uses the corresponding *wealth gap*. Column (1) reports the first-stage regression of the endogenous variable on the reform instrument. Column (2) reports the reduced-form effect of the reform on divorce. Column (3) reports the 2SLS estimates using the endogenous variable in levels (raw units). Column (4) reports standardized 2SLS estimates, where the endogenous variable is rescaled by its post-reform standard deviation to facilitate comparison between the legal share gap and the wealth gap. Standard errors are reported in parentheses and are clustered at the couple level.

reallocation of ownership toward the husband lowers divorce probability by roughly 0.7 percentage points.

When the wealth gap is used instead (Panel B), the raw-unit estimate indicates that each additional CNY 10,000 shifted toward the husband reduces divorce probability by approximately 0.3 percentage points. The smaller coefficient in raw terms largely reflects differences in measurement units.

To facilitate comparison across specifications, Column (4) reports standardized 2SLS estimates in which the endogenous variable is scaled by its post-reform standard deviation. A one standard deviation increase in the legal share gap reduces divorce probability by 3.9 percentage points, while a one standard deviation increase in the wealth gap reduces divorce probability by 10.4 percentage points.

The larger standardized effect associated with the wealth gap suggests that the economic value of the asset plays a quantitatively more important role in shaping marital stability than formal ownership shares alone. While reallocating legal control over property affects spouses' outside options, the financial stakes embedded in housing wealth appear to amplify the bargaining consequences of the reform.

2.5.3 Employment and Housework

For outcomes related to women's labor market participation and housework, the sample is restricted to couples who remain married after the reform; divorced couples are excluded by definition.

Table 2.3 reports the 2SLS estimates of how changes in the husband-wife legal gap and wealth gap affect women's labor market participation and both spouses' unpaid housework. Panel A uses the husband-wife legal share gap as the endogenous regressor, instrumented by the 2011 reform, while Panel B uses the husband-wife wealth gap. For each outcome (employment, weekday housework, weekend housework), the table reports the first-stage F-statistic and the corresponding 2SLS estimates. Using both the legal share gap and the wealth gap, the first-stage F-statistics are well above conventional weak-instrument thresholds.

For female employment (Column (1)), the 2SLS estimates reveal a contrast between marginal shifts in title and intensive changes in asset value. When I use the legal share gap (Panel A), a one-unit increase in the husband's share relative to the wife's raises the wife's probability of holding paid employment by 6.8 percentage points. By contrast, the wealth gap (Panel B) implies that a one-unit increase in relative housing wealth leads to only a 0.03 percentage point rise in employment.

For weekday housework (Column (2)), shifting the title from wife to husband increases the wife's burden by 1.04 hours per day, a large and statistically significant effect. The corresponding effect on husbands (Column (4)) is small and statistically insignificant at 0.21 hours. Using the wealth gap, the estimates are negligible for both spouses, 0.004 hours for wives and 0.0007 hours for husbands.

For weekend chores (Columns (3) and (5)), the pattern persists but at smaller magnitudes. A one-unit shift in title raises wives' housework by 0.62 hours and husbands' by 0.45 hours, with both estimates statistically significant. In contrast, the wealth gap again produces only modest effects, 0.0022 hours for wives and 0.0015 hours for husbands.

To facilitate comparison between the legal share gap and the wealth gap, the standardized coefficient estimates reported in Table 2.3 are based on standardized measures of intra-couple inequality. The coefficients therefore represent the effect of a one standard deviation increase in bargaining inequality induced by the reform.

For female employment (Column (1)), a one standard deviation increase in the legal share gap raises the wife's probability of employment by 3.9 percentage points (Panel A), whereas the corresponding wealth-gap effect is 10.5 percentage points (Panel B). The larger magnitude associated with the wealth gap suggests that the economic stakes embedded in housing wealth play an important role in shaping women's labor supply responses. When inequality increases through changes in asset value rather than solely through formal ownership shares, women appear more likely to adjust labor market participation.

For weekday housework (Column (2)), a one standard deviation increase in the legal share gap increases wives' housework by 0.59 hours per day, while the wealth gap produces a larger increase of 1.36 hours. The corresponding

Table 2.3: 2SLS Estimates: Employment, and Housework Hours

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	Employment	Weekday HW	Weekend HW	Husband WD	Husband WE
Panel A: Legal Share Gap					
Raw coefficients					
IV (Treated$\times$Post)	0.068**	1.035***	0.622***	0.213	0.450**
	(0.030)	(0.221)	(0.227)	(0.200)	(0.203)
Standardized coefficients					
IV (Treated$\times$Post)	0.039**	0.593***	0.356***	0.122	0.258**
	(0.017)	(0.126)	(0.130)	(0.114)	(0.116)
Observations	23,295	13,828	13,806	14,070	14,058
First-stage F-stat	1272	337	335	249	249
Panel B: Wealth Gap					
Raw coefficients					
IV (Treated$\times$Post)	0.0003**	0.0037***	0.0022***	0.0007	0.0015**
	(0.0001)	(0.001)	(0.001)	(0.0007)	(0.001)
Standardized coefficients					
IV (Treated$\times$Post)	0.105**	1.359***	0.816**	0.258	0.546**
	(0.047)	(0.358)	(0.323)	(0.245)	(0.258)
Observations	23,295	13,828	13,806	14,070	14,058
First-stage F-stat	167	45	44	41	41
Controls	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Couple FE	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: This table reports 2SLS estimates of the effects of intra-couple inequality on the wife's employment status, spouses' weekday and weekend housework hours. Panel A uses the legal share gap as the endogenous variable, while Panel B uses the wealth gap. In each panel, I report both raw and standardized coefficients. Standardized coefficients scale the endogenous variable by its post-reform standard deviation, so they represent the effect of a one-standard-deviation increase in husband-wife gap induced by the reform. All regressions include year, couple, province fixed effects, and controls. Standard errors are clustered at the couple level.

effects for husbands (Column (4)) are smaller and statistically insignificant for both measures. A similar pattern emerges for weekend housework (Columns (3) and (5)): the wealth gap generates stronger responses than the legal share gap, particularly for wives.

Taken together, these results indicate that although changes in legal control over property influence intra-household allocation decisions, the magnitude of economic inequality, captured by the wealth gap, is associated with larger behavioral adjustments.

2.5.4 Heterogeneous Effects by Initial Title Holder

To examine whether the impact of bargaining inequality differs depending on which spouse initially held the property title, I estimate a unified specification interacting the legal share gap with an indicator for wife dominance before the reform. Specifically,

$$Y_{ct} = \beta_1 \Delta_{ct} + \beta_2 (\Delta_{ct} \times \mathit{WifeDom}_c) + \eta X_{ct} + \gamma_t + \delta_c + \eta_p + u_{ct}, \tag{2.5}$$

where Δ_{ct} denotes the husband-wife ownership gap and $\mathit{WifeDom}_c$ equals one if the wife was the pre-reform title holder. Both Δ_{ct} and its interaction are instrumented by the reform and its interaction with the dominance indicator.[12]

Before 2011, the legal regime provided for equal division of assets in divorce regardless of deed registration. The reform replaced this with a registered-owner rule, thereby strengthening the bargaining position of the spousße whose name appears on the deed. In husband-registered households, the reform increases the husband's relative share; in wife-registered households, it increases the wife's relative share.

Divorce Hazard. Table 2.4 reports heterogeneous effects by initial title

[12]Both Δ_{ct} and its interaction with $\mathit{WifeDom}_c$ are treated as endogenous. They are instrumented by the reform indicator $IV_{ct} = \mathit{Treated}_c \times \mathit{Post}_t$ and its interaction $IV_{ct} \times \mathit{WifeDom}_c$. The corresponding first-stage equations are:

$$\Delta_{ct} = \pi_1 IV_{ct} + \pi_2 (IV_{ct} \times \mathit{WifeDom}_c) + \gamma X_{ct} + \gamma_t + \delta_c + \eta_p + \nu_{ct},$$

$$\Delta_{ct} \times \mathit{WifeDom}_c = \theta_1 IV_{ct} + \theta_2 (IV_{ct} \times \mathit{WifeDom}_c) + \kappa X_{ct} + \gamma_t + \delta_c + \eta_p + \omega_{ct}.$$

Standard errors are clustered at the couple level.

holder. The coefficient on the ownership gap (Δ) is -0.051, implying that in husband-registered households, an increase in the husband's relative ownership reduces the probability of divorce. The interaction term is positive (0.151), so the marginal effect in wife-registered households is -0.051 + 0.151 = 0.100.[13]

To interpret these coefficients, it is crucial to account for how the reform shifts Δ across groups. The reform increases Δ in husband-registered households (strengthening the husband's bargaining position) but decreases Δ in wife-registered households (strengthening the wife's position). Combining these directional changes with the estimated slopes implies that the reform reduces divorce in both cases: in husband-registered households because Δ rises and the slope is negative, and in wife-registered households because Δ falls and the slope is positive. Thus, strengthening the bargaining position of the registered owner—whether husband or wife—reduces the likelihood of marital dissolution.

Female Labor Supply. For female employment, the coefficient on Δ is positive (0.063) and statistically significant, indicating that in husband-registered households, an increase in the husband's relative ownership raises the wife's probability of employment. The interaction term is small and statistically insignificant, suggesting no significant difference in the effect across household types.

Given that the reform increases Δ in husband-registered households and decreases it in wife-registered households, these estimates imply that female employment rises when the husband's bargaining position strengthens. However, the lack of statistical significance for the interaction term suggests that there is no significant change in female employment when the wife's bargaining position strengthens.

[13] To interpret the reform effects by the initial title holder, note that the coefficients on Δ_{ct} and its interaction capture marginal effects (slopes) with respect to changes in the ownership gap. The overall effect of the reform for each group is given by the product of the relevant slope and the reform-induced change in Δ_{ct}. Specifically, in husband-registered households the effect equals $\beta_1 \times \Delta^{\text{reform}}$, while in wife-registered households it equals $(\beta_1 + \beta_2) \times \Delta^{\text{reform}}$. Because the reform increases Δ_{ct} in husband-registered households but decreases it in wife-registered households, the sign of the total effect depends on both the estimated slope and the direction of the change in Δ_{ct}.

Table 2.4: Heterogeneity by Initial Title Holder

	(1) Divorce	(2) Employment	(3) Wife WD	(4) Wife WE	(5) Husband WD	(6) Husband WE
Share Gap (Δ)	-0.0512***	0.0632***	0.879***	0.554***	0.142	0.335**
	(0.0155)	(0.0240)	(0.182)	(0.189)	(0.168)	(0.169)
Δ× Wife Dominant	0.1506***	0.0437	-2.790***	-1.330*	-0.296	-1.322**
	(0.0463)	(0.0848)	(0.781)	(0.731)	(0.485)	(0.537)
Controls	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓	✓
Observations	36,677	22,198	13,205	13,184	13,562	13,550

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Note: This table reports 2SLS estimates of the effect of intra-couple inequality on divorce, female employment, and spouses' housework hours, allowing for heterogeneity by initial title holder. The endogenous variable is the intra-couple legal share gap (Δ) and its interaction with the wife-dominance indicator. Both are instrumented by the reform indicator (Treated × Post) and its interaction with Wife Dominant. Wife Dominant equals one if the wife was the registered owner in 2010 (pre-reform). The coefficient on Δ captures the effect in husband-registered households, while the interaction term captures the differential effect in wife-registered households. Standard errors are clustered at the couple level.

Unlike the divorce outcome—which declines regardless of initial title-holder status—the labor supply response does not exhibit statistically significant asymmetry by initial title-holder status. Female employment increases when the husband's bargaining position strengthens, but shows no significant change when the wife's does.

Housework Allocation. For wives' housework, the coefficient on Δ is positive and large for both weekdays (0.879) and weekends (0.554), while the interaction terms are negative (-2.790 and -1.330, respectively). This implies that the slope is positive in husband-registered households and negative in wife-registered households.

Because the reform increases Δ in husband-registered households and decreases it in wife-registered households, the implied effect is positive in both cases: regardless of gender, wives' housework increases. The magnitude is substantial for weekday tasks, approaching one additional hour per day. This suggests that, irrespective of title holder, the reallocation of property rights places a heavier burden on wives' unpaid labor.

For husbands, there is no significant change in weekday housework regardless of title holder. However, the positive coefficient on Δ (0.335) and negative interaction term (-1.322) for weekend housework imply modest increases in husbands' housework in both household types, although these changes are considerably smaller than for wives.

Taken together, the housework results indicate that reallocation of property rights toward the registered owner primarily increases the unpaid labor demands on wives, especially for routine weekday tasks. This pattern suggests that shifts in legal control over housing reinforce traditional divisions of household labor.

2.6 Robustness

2.6.1 First-Stage Robustness: Abadie's Semiparametric DID

To test the robustness of the first-stage estimates, I implement Abadie's semiparametric DID estimator (Abadie, 2005). This approach re-weights controls by their estimated propensity scores, identifying the ATT under conditional parallel trends while relaxing parametric outcome restrictions and mitigating covariate imbalance. The covariates include both spouses' education, income, number of children, parents' education, as well as couple, year, and province fixed effects.

Table 2.5 compares the standard DID to the semiparametric estimates. In the baseline DID, the reform raises the property share gap by 28.3 pp and the wealth gap by CNY 63,667. The semiparametric ATT is somewhat smaller: 22 pp and CNY 51,980, but nearly identical in sign, magnitude, and precision.

Overall, the semiparametric results closely mirror the baseline, confirming that the 2011 reform substantially increased intra-couple gaps in both property shares and housing wealth. The slight attenuation is consistent with reweighting to account for baseline differences, underscoring that the main results are not an artifact of functional form assumptions.

Table 2.5: Robustness Check: Semiparametric DID Result

	Standard DID		**Semiparametric DID**	
	(1)	(2)	(3)	(4)
	Share Gap	Wealth Gap	Share Gap	Wealth Gap
Treated×2010	base	base	base	base
Treated×Post	0.283***	63,667***	0.22***	51,980***
	(0.01)	(7,214)	(0.01)	(3,520)
Couple FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Province FE	✓	✓	✓	✓
Observation	36,677	36,677	36,677	36,677

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Columns (1) and (2) represent the estimate of the standard DID model, corresponding to Columns (1) in Table 2.2. Columns (3) and (4) show estimates of the SDID following Abadie (2005).

2.6.2 Second-Stage Robustness: Propensity Score Matched 2SLS

To ensure the 2SLS estimates are not driven by systematic baseline differences between treated and control couples, I implement one-to-one propensity score matching on pre-reform characteristics. Using the 2010 CFPS wave, I estimate each couple's treatment probability (husband-only or wife-only deed) as a function of six observables: wife's age, husband's age, number of children, household income, wife's schooling, and husband's schooling.

Each treated couple is matched to its nearest control without replacement. Balance tests confirm that post-match, treated and control groups are statistically similar across most observables (Table A5). The matched subsample then forms the basis for re-estimating the main 2SLS specifications.

Table A6 contrasts results from the full sample and the matched sample. For divorce (Columns 1-2), the effect attenuates from -6.75 percentage points to -4.93 percentage points, retaining sign and significance. For female employment, the effect rises modestly from 5.9 percentage points to 6.94 percentage points. For weekday housework, the effect falls slightly from 1.06 to 0.87 hours but remains precise, while the weekend effect shrinks and becomes imprecise. First-stage F-statistics remain well above weak-instrument thresholds.

Panel B repeats the exercise with the wealth gap as the endogenous regressor. The post-match estimates closely track their pre-match counterparts in both sign and magnitude-except for weekend housework, which again becomes imprecise.

Taken together, the matching results show that the main conclusions are not sensitive to observable baseline differences: the reform-induced legal share gap remains a strong and valid instrument for shifts in intra-household bargaining power.

2.7 Conclusion

This paper documents a previously underrecognized dimension of gender inequality in China's housing market: large and persistent intra-couple gaps in property ownership and housing wealth. Using nationally representative CFPS panel data and exploiting the 2011 Marriage Law reform, which changed the legal rule for dividing housing property upon divorce from equal division to a registered-owner rule, I show that a formally gender-neutral legal change systematically widened spousal disparities. The reform converted equal legal claims into registered-owner rights, disproportionately strengthening the bargaining position of deed holders, typically husbands, and reinforcing existing gendered patterns of asset control.

In the first stage, a DID design shows that the reform increased the husband-wife legal share gap by 28.3 percentage points and generated an average housing wealth gap of CNY 63,667. While dynamic estimates reveal the legal share gap has gradually narrowed, the wealth gap persisted and widened as property prices rose. In the second stage, 2SLS estimates show that marginal reallocation of legal ownership carries large behavioral consequences. A one-unit increase in the husband's share relative to the wife's reduces divorce probability by 6.75 percentage points, raises the wife's employment probability by 6.8 percentage points, and shifts approximately one additional hour of weekday housework onto her. Standardized comparisons reveal that wealth gap effects exceed legal share gap effects across all outcomes, indicating that the economic magnitude of housing wealth inequality, not just formal ownership status, amplifies the bargaining consequences of property rights.

Heterogeneity analysis reveals that the reform lowers divorce probability in both husband-registered and wife-registered households: strengthening the registered spouse's bargaining position reduces the unregistered spouse's incentive to exit, regardless of which spouse holds the title. Female employment responds asymmetrically: wives increase labor supply when their bargaining position weakens (husband-registered households) but have no significant change when their position strengthens (wife-registered households). Wives' housework burden rises in both cases. These findings confirm that household dynamics respond to shifts in formal property claims, with the direction of labor supply adjustment depending critically on which spouse holds the title. Robustness checks, including semi-parametric DID and propensity-score matched 2SLS, confirm the stability of these findings.

Three broader insights follow. First, formally neutral legal reforms can generate substantial intra-household inequality when applied in settings with pre-existing gendered norms—in this case, the prevailing custom of registering the marital home in the husband's name. Second, both formal control over property and the economic magnitude of wealth inequality shape spousal bargaining power and, in turn, marital stability, labor supply, and the allocation of unpaid work. Third, while the 2011 reform widened wealth gaps within existing marriages, it may also create conditions for gradual norm change: by removing the presumption that only the groom's family provides housing, it opens space for women to acquire property independently, potentially fostering more balanced bargaining and a fairer division of paid and unpaid labor over time.

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Appendix A: Tables

Table A1: Distribution of Number of Other Houses (%)

Number	2010	2012	2014	2016	2018
0	84.4	84.7	83.3	80.2	79.0
1	13.9	13.5	14.5	17.1	17.6
2	1.4	1.5	1.8	2.3	2.8
3 above	0.3	0.3	0.4	0.4	0.6
Total	100	100	100	100	100

Note: The table shows the distribution of the number of additional houses owned by a household in addition to primary housing. The majority of families have no extra houses. Around 14% of families have one additional house, and 1.5% families have two extra houses. Less than 0.4 % of families have more than three additional houses.

Table A2: Distribution by Generation Living in the Same Household

Generation	2010
1	14.07
2	44.28
3	38.41
4	3.01
5	0.20
Total	100

Note: The table shows how many generations live in the same household. Most households have two or three generations living under one roof, which accounts for 82.69%. 14% of households have only one generation living together. Only 3.21% of households have more than four generations living under the same roof.

Table A3: Distribution of the Number of Homeowners Registered on Housing Deed

Number of owners	2010	2012	2014	2016	2018
0	16.95	13.77	26.5	27.9	30.5
1	80.95	77.92	61.95	59.3	53.28
2	1.51	5.65	7.62	8.5	10.69
3	0.59	1.58	2.07	2.2	2.59
4	-	0.62	0.84	1	1.28
above 5	-	0.46	1.02	1.1	1.66

Note: The table represents the distribution of the number of homeowners registered on property certificates from 2010 to 2018. In most households, only one person is registered on the property deed. In 2010, before the introduction of the new Marriage Law, at most three family members were registered on the deed. Yet, more family members are listed on the deed after 2011, so changes in registers on the deed can be observed.

Table A4: Dynamic Effects of Marriage Law on Intra-couple Gaps

	(1) Share Gap	(2) Wealth Gap
Treated×2010	base	base
Treated×2012	0.42***	63,790***
	(0.01)	(9,560)
Treated×2014	0.32***	62,843***
	(0.01)	(9,922)
Treated×2016	0.26***	69,264***
	(0.01)	(10,223)
Treated×2018	0.22***	66,47***
	(0.01)	(10,435)
Year FE	✓	✓
Couple FE	✓	✓
Province FE	✓	✓
R-square	0.56	0.49
Observation	36,677	36,677

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table reports estimates of Equation (2.2) on the dynamic effects of the Marriage Law Reform on intra-couple legal share gaps (column 1) and wealth gaps (column 2). Standard errors, clustered at the couple level, are reported in parentheses. All regressions include year, couple, and provincial fixed effects.

Table A5: Descriptive Statistics for Matching

Women's characteristics	(1) Control Group	(2) Treatment Group	(3) Difference
Panel A: Divorce Sample			
Age	43.81	43.99	-0.055
	(13.38)	(12.10)	
Husband's Age	45.78	46.10	-0.131
	(13.77)	(12.30)	
Number of Children	1.05***	0.98	0.064
	(0.83)	(0.82)	
Income	7.03	7.33	0.259
	(20.09)	(12.78)	
Education	6.49	6.66	0.007
	(4.57)	(4.87)	
Husband's Education	7.13	7.29	0.078
	(4.58)	(4.62)	
Observations	2,277	2,277	
Panel B: Employment			
Age	48.47	48.46	0.01
	(10.58)	(10.22)	
Husband's Age	50.40	50.37	0.03
	(11.05)	(10.55)	
Number of Children	0.93***	0.85	0.08
	(0.84)	(0.85)	
Income	5.67	5.44	0.23
	(10.00)	(10.03)	
Education	5.58**	5.36	0.22
	(4.48)	(4.54)	
Husband's Education	6.63*	6.45	0.18
	(4.50)	(4.46)	
Observations	1,518	1,518	
Panel C: Weekday Housework			
Age	48.58	48.47	0.11
	(10.60)	(10.24)	
Husband's Age	50.49	50.38	0.11
	(11.14)	(10.56)	
Number of Children	0.93***	0.86	0.07
	(0.86)	(0.85)	
Income	5.47	5.38	0.09
	(9.09)	(9.93)	
Education	5.65***	5.31	0.34
	(4.56)	(4.53)	
Husband's Education	6.77***	6.42	0.35
	(4.52)	(4.47)	
Observations	1,290	1,290	
Panel D: Weekend Housework			
Age	48.54	48.46	0.08
	(10.58)	(10.24)	
Husband's Age	50.46	50.38	0.08
	(11.09)	(10.56)	
Number of Children	0.91***	0.86	0.05
	(0.84)	(0.85)	
Income	5.68	5.36	0.32
	(9.57)	(9.90)	
Education	5.58***	5.31	0.27
	(4.53)	(4.53)	
Husband's Education	6.63**	6.42	0.21
	(4.52)	(4.47)	
Observations	1,310	1,310	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table reports pre-reform summary statistics for the treatment and control groups used in the matched-sample analysis. Panel A presents covariates for the divorce sample, while Panels B–D present covariates for the employment and housework samples. Column (3) reports mean differences between treatment and control groups. Standard errors are reported in parentheses.

Table A6: IV Estimates Before and After Matching

Dependent Variable:	**Divorce**		**Employment**		**Weekday Housework**		**Weekend Housework**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pre-Match	Post-Match	Pre-Match	Post-Match	Pre-Match	Post-Match	Pre-Match	Post-Match
Panel A: Property Share Gap								
IV (Treated×Post)	-0.0675***	-0.0493**	0.068**	0.0694**	1.035***	0.8718***	0.622***	0.489
	(0.0196)	(0.025)	(0.030)	(0.035)	(0.221)	(0.298)	(0.227)	(0.313)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	36,677	31,566	23,295	22,714	13,828	11,926	13,806	11,533
R-squared	0.0180	0.0102	0.065	0.1627	0.012	0.0697	0.013	0.0243
First-Stage F-stat	852	485	1272	361	337	129	335	119
Panel B:Wealth Gap								
IV (Treated×Post)	-0.0003***	-0.0002*	0.0003**	0.0003*	0.0037***	0.0030***	0.0022***	0.0018
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.001)	(0.0012)	(0.001)	(0.001)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Province FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	36,677	31,566	23,295	22,714	13,828	11,926	13,806	11,533
R-squared	0.021	0.0225	0.043	0.1455	0.034	0.0181	0.034	0.034
First-Stage F-stat	106	54	167	66	45	29	44	23

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Panel A reports 2SLS estimates using the intra-couple property share gap as the endogenous variable, while Panel B uses the intra-couple wealth gap. In both panels, the 2011 Marriage Law Reform is used as an instrument. The table compares IV estimates before and after matching for divorce, employment, wife's weekday housework, and wife's weekend housework. Standard errors are reported in parentheses.

Appendix B: Conceptual Framework

The 2011 Marriage Law shifts legal ownership of the marital home to the registered spouse, generating exogenous variation in intra-household property rights. This institutional change alters the relative bargaining positions (or threat points) of spouses and, in turn, affects household decision-making. Formally, the mechanism can be summarized as:

$$\begin{aligned}\text{Legal reform} &\Rightarrow \Delta\text{Property rights}\\ &\Rightarrow \Delta\text{Threat point}\\ &\Rightarrow \text{Predictions for divorce and home production}\end{aligned}$$

Set-up

Consider a married couple, m (the husband) and f (the wife). Each has utility

$$U_i = u_i(c_i, l_i) \quad i \in \{m, f\}$$

where c_i is private consumption and l_i is leisure (total time endowment normalized to 1). The household also enjoys the flow utility of living in a dwelling of market value H. Let $s_i \in [0,1]$ denote the *legal* share of that dwelling each spouse would receive if the marriage dissolved today. All income is pooled, so the sole distribution factor that varies exogenously is (s_m, s_f) with $s_m + s_f = 1$.

Following the collective-household literature (Chiappori, 1988; Manser and Brown, 1980; McElroy and Horney, 1981), efficient allocations solve

$$\max_{\{c_i, l_i\}} \quad \left(U_m - D_m\right)^{\phi}\left(U_f - D_f\right)^{1-\phi}$$

where D_i is spouse i's outside-option utility if she/he were to divorce today, and $\phi \in (0,1)$ is the bargaining weight that the Nash product assigns to the husband.

How the 2011 Marriage Law changes threat points

Before the 2011 judicial interpretation (equal-split regime), Chinese courts divided housing assets equally at divorce, so $s_m^{pre} = s_f^{pre}$. The reform (registered-owner regime) awards the entire dwelling to the spouse whose name alone appears on the deed. Let $\Delta_i = (s_i^{post} - s_i^{pre})$ be the shock to divorce-property for spouse i. In the vast majority of marriages, the deed lists the husband without the wife, so $\Delta_m > 0$ and $\Delta_f < 0$.

The key observation is $\frac{\partial D_i}{\partial s_i} > 0$, because a larger housing claim raises the consumption-possibility frontier after divorce. Thus the reform shifts the pair (D_m, D_f) in opposite directions, altering each spouse's threat point. Because Nash bargaining weights are monotone in threat-point utilities (McElroy, 1990; McElroy and Horney, 1981),

$$\frac{\partial \phi}{\partial (D_m - D_f)} > 0$$

This yields the following:

Proposition *(Bargaining shift).* A rise in the husband's legal housing share s_m relative to s_f increases his bargaining weight ϕ, and vice-versa.

Let $\hat{\Delta} = s_m - s_f$ be the within-couple property gap. The collective bargaining model implies three clear empirical statements:

- *Divorce hazard.* A larger $\hat{\Delta}$ strengthens the husband's threat point and weakens the wife's. This lowers the wife's incentive to exit, so the probability of divorce *falls* when the husband is the registered owner.

- *Housework allocation.* Bargaining power and non-market labor move in opposite directions: the spouse who loses power supplies more housework. Hence, as $\hat{\Delta}$ rises, the wife's housework hours increase.

3. You Are the Elite Now: Admission Effects of an Excellence Initiative in the Chinese Higher Education System*

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3.1 Introduction

A large body of literature shows that investments in higher education shape students' choices and the distribution of talent. In recent decades, numerous countries have launched universities of excellence initiatives aimed at enhancing human capital and boosting global competitiveness.[1] Evidence shows that such university-level excellence policies provide quality signals that influence application behavior (Biancardi and Bratti, 2019; Fischer and Kampkötter, 2017). At the same time, many governments also invest selectively at the discipline level. For instance, the U.S. has offered STEM-targeted grants to encourage students to enter technical fields (Blume-Kohout and Scott, 2022; Goldrick-Rab et al., 2016). Together, these studies highlight that both university-level prestige and discipline-level investments shape student decision-making and the composition of human capital.

This paper asks a new question: how does investing in and labeling excellence at the university-discipline level affect student application choices and admission competition? While many countries have invested either at the university level or at the discipline level, little is known about the consequences of university-discipline designations. China's excellence initiative provides a unique opportunity to study this question, as it designates specific university-discipline units as First-Class Disciplines (FCDs). We exploit this policy to examine whether FCD designation attracts higher-ranking applicants, intensifies competition within disciplines, and generates spillovers to non-designated fields within the same university. To our knowledge, this is the first study to evaluate the effects of government-led excellence designations at the university-discipline level.

National College Entrance Examination (NCEE), where nearly ten million students compete each year under a highly standardized, score-based admission system. Admission depends almost entirely on exam rankings, quotas

[1] Examples include: World-Class University Project in South Korea (1999); Universities with Potential for Excellence in India (2002); Excellence Initiative in Germany (2006); International Campus of Excellence in Spain (2009); UNIK-Initiative in Denmark (2009, 2013); Initiatives d'Excellence in France (2010); Top Global University Project in Japan (2014); and Excellence Initiative Research University in Poland (2019). See Guo et al. (2023) for an overview.

are centrally determined, and students must rank universities and programs in advance. The sudden release of the FCD list in 2017, based on prior discipline evaluations, provides plausibly exogenous variation in perceived quality at the university-discipline level. These institutional features allow us to compare designated and non-designated units in a quasi-experimental framework and to trace how applicants respond to new official information about program quality.

Our analysis draws on a novel dataset that compiles nationwide admission outcomes from official provincial records. We observe, for each program and year, the minimum exam score (and hence the ranking) required for admission, linked to its university and discipline. We focus on the first round of FCD designations (2017-2021) and restrict attention to provinces that maintained a consistent exam structure. This yields a rich panel of more than 50,000 university-discipline-province-year observations, allowing us to capture admission competition at fine granularity.

Empirically, we use a difference-in-differences(DID) design that compares trends in admission competition between designated and non-designated disciplines within the same field, before and after the 2017 policy. To strengthen identification, we exploit the fact that the FCD cutoff was determined by prior discipline evaluations, which reduces concerns about endogenous selection. We also examine within-university contrasts to capture potential spillover effects. This strategy allows us to isolate the causal effect of FCD designation on student application choices.

Our results show that FCD designation significantly intensifies admission competition. On average, designated programs require students to improve their exam ranking by about 1.5 percentiles, equivalent to surpassing roughly 1,800 additional peers per province. We also find spillover effects: non-designated disciplines within FCD universities become more competitive, suggesting that students view the institution as a whole as enhanced. The impacts are especially pronounced in agriculture and medicine, which were less competitive before the policy, while effects in STEM fields are more modest, given their already high baseline demand. Together, these findings indicate that university-discipline designations can reshape application behavior not only for targeted programs but also across the wider university hosting the targeted programs.

This paper contributes to two main strands of literature. First, it advances research on how quality signals in higher education shape student applications. A large body of work shows that league tables, rankings, and reputation signals influence where students apply and enroll (Bowman and Bastedo, 2009; Broecke, 2015; Gibbons et al., 2015; Griffith and Rask, 2007; Horstschräer, 2012; Luca and Smith, 2013; Sauder and Lancaster, 2006). Beyond private rankings, governments have increasingly sought to influence perceptions through excellence initiatives at the university level, such as Germany's Excellence Initiative (Fischer and Kampkötter, 2017) and Italy's Research Evaluation Exercise (Biancardi and Bratti, 2019). Evidence shows that these policies attract stronger applicants and boost the perceived prestige of selected institutions. We extend this literature by examining government designations at the university-discipline level, providing new evidence on how more granular signals of quality affect student choices in a centralized, high-stakes admissions system. Moreover, we show that such designations generate spillover effects within universities: when one discipline is certified as excellent, other disciplines in the same institution also attract stronger applicants. This finding highlights how official quality labels can enhance not only the targeted fields but also the university's broader reputation, an insight that matters for both education policy and intra-university resource allocation.

Second, we contribute to the economics of human capital formation by analyzing how university-discipline excellence designation shifts the allocation of talent across fields of study, a mechanism that has received little attention in prior work. Prior research has shown that attending elite institutions carries significant returns in terms of educational attainment, labor market outcomes, and intergenerational mobility (Long, 2008; MacLeod et al., 2017; Zimmerman, 2019). Field-specific choices also matter: students in STEM and professional programs typically earn higher wages than peers in other fields (Altonji et al., 2012; Kinsler and Pavan, 2015). Policy interventions such as scholarships, financial aid, and STEM-targeted grants have been shown to shift enrollment patterns and degree completion (Blume-Kohout and Scott, 2022; Goldrick-Rab et al., 2016). Our findings complement this literature by showing that discipline-specific excellence designations not only intensify competition in already competitive fields but also elevate less popular areas such as agriculture and medicine, thereby reshaping the future supply of skills.

The rest of the paper is structured as follows: Section 3.2 describes the background of the NCEE and the *Double First-Class Initiative* in China. Section 3.3 details the data sources, sample selection, and outcome variables. Sections 3.4 and 3.5 present our empirical strategies and results across two main dimensions. In Section 3.6, we conduct a heterogeneity analysis and robustness test. Finally, Section 3.7 concludes the paper.

3.2 Background

3.2.1 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 7th 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 upper-secondary school year, determining their NCEE track. Consequently, the track chosen has implications for their field-of-study 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

[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

size in each province, and it remains binding. After the NCEE, students receive their scores and provincial rankings. 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 might adjust their hiring lists based on 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.

3.2.2 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 disciplines (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

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

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 (Jia and Li, 2021; Li et al., 2012) 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.

3.2.3 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 a 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 an FCD are inherently included within this defined unit. This fact will not be reiterated in future discussions to avoid redundancy.

3.3 Data

3.3.1 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.

[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/

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 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.

3.3.2 Sample Selection

First, our sample selection focuses on the 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 de-

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[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 preference 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.

signed 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 and 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% 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.

3.3.3 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:

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

[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.

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. This metric 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.

3.4 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.

3.4.1 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

[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`

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 3.1 illustrates the construction of the CDE treatment and control groups. As shown in Table 3.1a, *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 3.1b 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 that 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.

3.4.2 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

Table 3.1: Treatment and Control Group Construction

(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	9	No	6	–
K	81	11	No	6	–
L	80	11	No	6	–

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 estimate the following DID specification:

$$Y_{idupt} = \beta \text{Treated}_{du} \times \text{Post}_{2017} + X_{pt}\Gamma + \phi_p + \alpha_d + \delta_t + \varepsilon_{idupt} \tag{3.1}$$

where Y_{idupt} represents the admission competition for program i in discipline d at university u, observed for applicants from province p in year t. The indicator Treated_{du} equals 1 for university-discipline pairs included in the FCD list; this status applies to all programs nested within a treated university-discipline pair. The variable $Post_{2017}$ equals 1 for years after the 2017 FCD announcement. The vector X_{pt} includes time-varying provincial covariates, such as the GDP and unemployment rate in applicants' home provinces, as well as GDP in the province where the university is located.

Province fixed effects ϕ_p absorb time-invariant differences in baseline admission competition across applicants' home provinces, reflecting that students compete only with peers from the same province. Discipline fixed effects α_d capture persistent differences in competitiveness across academic fields, and year fixed effects δ_t absorb national trends or shocks affecting all programs. Standard errors are clustered at the university level, allowing for arbitrary correlation in admission shocks within universities that share institutional reputation, resources, and applicant pools.

Because treatment is defined at the university-discipline level, our empirical design departs from the canonical DID setting in which treatment varies within a single-dimensional unit over time.[10] Instead, identification exploits variation across universities within the same discipline before and after the

[10]In settings with a single-dimensional unit of observation, a canonical DID design compares treated and untreated units before and after a policy change. In our two-dimensional setting, a mechanical application of this intuition could be interpreted as comparing treated university-discipline pairs to untreated pairs that differ in both university and discipline. Such comparisons-for example, between Physics at one university and Economics at another—are difficult to interpret in the context of students' application choices. Our design instead restricts comparisons to universities offering the same discipline, consistent with the construction of treatment and control groups in Section 3.4.1.

2017 policy. Accordingly, the comparison of interest, consistent with the treatment and control group construction described in Section 3.4.1, is between treated and untreated university-discipline pairs offering the same field of study, rather than within a given university-discipline pair over time. As a result, identification relies on differential changes over time between treated and untreated universities within each discipline, and the main effects of treatment status and the post-policy period are subsumed by discipline and year fixed effects.

The coefficient β is the parameter of interest. It captures the average change in admission competition for treated university–discipline pairs, relative to untreated pairs within the same discipline, before and after 2017. A statistically significant β therefore indicates that FCD designation increases the competitiveness of program admissions by attracting higher-ranking applicants.

Although treatment is assigned at the university-discipline level, we do not include university-discipline fixed effects in the baseline specification. Including such fixed effects would absorb all cross-sectional variation in treatment status, as each university-discipline pair appears only once per discipline and becomes treated only after 2017, leaving no identifying variation. For the same reason, we also omit university fixed effects in the baseline analysis. University fixed effects are introduced only in specifications where identification explicitly relies on within-university comparisons across disciplines, such as the spillover analysis in Section 3.5

3.4.3 Estimation Results

Given that the majority of FCD programs and university admissions are STEM-oriented (Section 3.3.2), our main analysis focuses on the natural science track. Results for the social science track are reported in heterogeneity analysis (Section 3.6.2).

Table 3.2 presents the estimated coefficients from Equation (3.1) 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 3.2 indicate that admission competition for FCD increases by 49%, attracting and admitting higher-ranking students.

Table 3.2: The Effect of FCD on Admission Competition at Disciplinary Level

	(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

Notes: This table presents DID estimates of the admission effect of FCD at the disciplinary level (Equation (3.1)) 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 3.2.2, 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.

3.4.4 Dynamic DID Analysis

To test the parallel trend assumption and examine how the treatment effect evolves over time, we estimate the following dynamic DID specification:

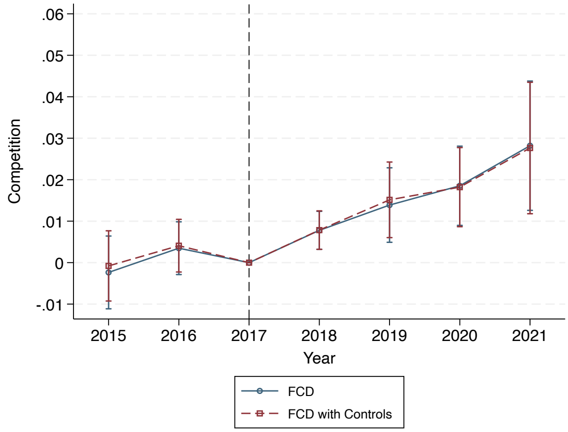
$$Y_{idupt} = \sum_{s=2015, s\neq 2017}^{2021} \beta^s \cdot (\text{Treated}_{du} \times \mathbf{1}\{t = s\}) + X_{pt}\Gamma + \phi_p + \alpha_d + \delta_t + \varepsilon_{idupt} \tag{3.2}$$

where $\mathbf{1}\{t = s\}$ is an indicator equal to 1 when the observation corresponds to year s. The year 2017 is omitted and serves as the reference year. All other variables are defined as in Equation (3.1). This event-study specification identifies dynamic treatment effects under the assumption that, in the absence of the FCD policy, treated and control university-discipline pairs would have followed parallel trends in admission competition.

We empirically assess this assumption using the pre-policy coefficients. As shown in Columns (1) and (2) of Table A1, the estimated coefficients for 2015 and 2016 are statistically insignificant, providing evidence consistent with parallel pre-treatment trends.

Figure 3.1 plots the estimated coefficients from Equation (3.2), illustrating

Figure 3.1: 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 (3.2)), 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.

the evolution of the treatment effect after controlling for discipline, province, and year fixed effects. Beginning in 2018, the dynamic coefficients became statistically significant and continued to rise, indicating that the FCD policy progressively increased the competitiveness of designated disciplines. By 2021, the minimum admission ranking for FCD programs had improved by 2.76 percentiles, meaning that students admitted at the lowest scores needed to outperform approximately 3,312 additional peers compared with the pre-policy baseline.

3.5 Spillover Effect of FCD within the University

In this section, we examine whether the FCD designation generates spillover effects to non-recognized disciplines within the same university. To isolate within-university comparisons, we restrict the sample to universities that host at least one FCD.

3.5.1 Empirical Model

We estimate the following specification[11]:

$$Y_{idupt} = \beta \text{Treated}_{du} \times \text{Post}_{2017} + X_{it}\Gamma + \phi_p + \lambda_u + \delta_t + \varepsilon_{idupt} \tag{3.3}$$

where all variables are defined same as in Equation (3.1), with the addition of the university fixed effect (λ_u). These absorb all between-university variation, ensuring that identification comes from differences between FCD and non-FCD disciplines within the same institution.

The parameter of interest is β. In the absence of spillover, we would expect β to be positive, mirroring the large effect estimated in the baseline analysis, because FCD disciplines should become more competitive relative to non-FCD disciplines within the same university after 2017. If β is instead close to zero, this indicates that non-FCD disciplines also became more competitive, preventing the FCD-non-FCD gap from widening. This pattern is consistent with a spillover effect.

3.5.2 Spillover Result

Table 3.3 reports the estimated coefficients from Equation (3.3). Column (1) includes fixed effects for year, province, and university, while column (2) incorporates additional control variables. The estimated coefficients remain statistically insignificant, small, and negative.

This null result should not be interpreted as the absence of a policy effect. In the baseline analysis, we documented a large positive impact of FCD designation on admission competition relative to comparable disciplines in other universities. The fact that this relative advantage does not appear within universities indicates that non-FCD disciplines in the same institution also ex-

[11] We exclude discipline fixed effects in the within-university spillover specification because treatment varies across disciplines within a university. Discipline fixed effects would absorb the cross-discipline variation that identifies the difference between FCD and non-FCD disciplines post-2017. Baseline level differences across disciplines do not threaten DID identification, which relies on parallel trends rather than equal levels. University and year fixed effects are sufficient for within-university comparisons.

perienced increases in competitiveness. In other words, the policy raised the attractiveness of FCD programs, but it simultaneously elevated student demand for other programs in the same universities. The lack of divergence between the two groups is therefore consistent with spillover effects.

Table 3.3: Spillover Effect of FCD on Admission Competition within the University

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

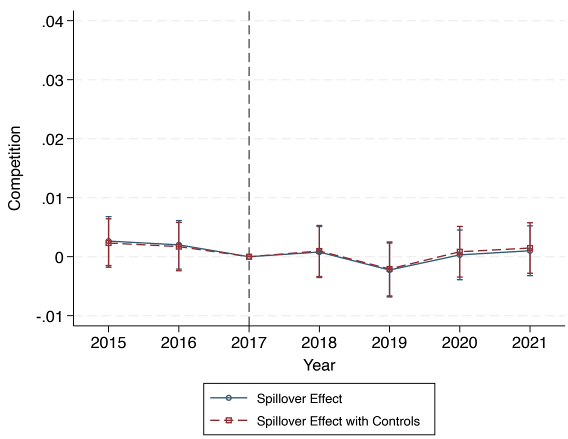
Notes: This table presents the estimated spillover effect of the FCD using the sample of universities with at least one FCD (Equation (3.1)), where we compare the FCDs to the non-FCD counterparts within the same university. Robust standard errors are reported in parentheses (clustered at the university level). Significance: *p $<$ 0.10, **p<0.05, ***p<0.01.

Two mechanisms may explain this pattern. First, the prestige associated with FCD recognition may generalize to the entire institution, leading applicants to view non-recognized disciplines as benefiting from the same improvement in perceived quality. Second, the structure of the NCEE application process, where students select universities before ranking programs within each selected university, means that increases in applications to FCD disciplines can naturally spill over to non-FCD programs, raising their admission competition as well.

3.5.3 Dynamic DID Analysis

We re-estimate the dynamic DID model in (Equation (3.2)) using the updated sample and incorporating university fixed effects. Figure 3.2 plots the resulting within-university dynamics, which are flat over time. Columns (2) and (3) of Table A1 report the corresponding estimated coefficients. All pre- and post-policy coefficients are statistically insignificant at the 95% confidence interval, indicating no differential change in admission competition between FCD and non-FCD disciplines within the same university. Notably, the post-policy coefficients are smaller in magnitude than the pre-policy ones, suggesting that the competitiveness gap between the two groups narrows after the policy. This pattern is consistent with higher-ranking students applying to both FCD and non-FCD programs within the same institution.

Figure 3.2: 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.

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

3.6.1 Heterogeneity by Disciplines

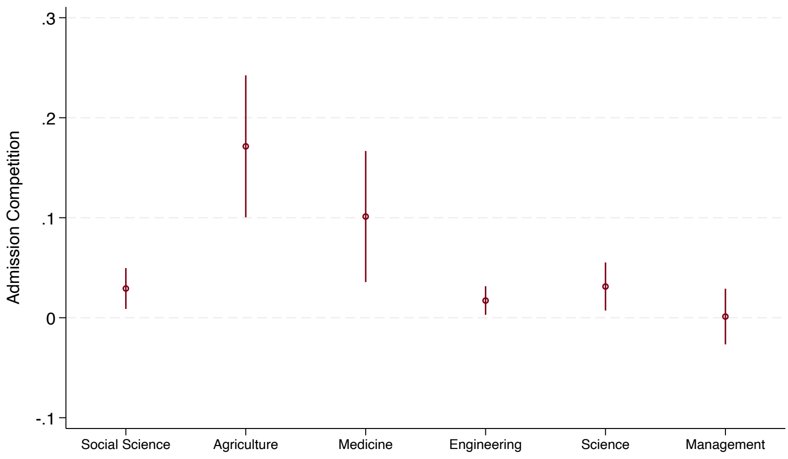
To assess the differential impact of the FCD policy across various academic disciplines, we employ an expansive classification including six primary categories for natural science track students: Social Science, Agriculture, Medicine, Engineering, Science, and Management.[12]

As shown in Figure 3.3, our results reveal varying degrees of response to FCD policies across different disciplines. Detailed estimated coefficients are presented in Table 3.4. 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.

This differential impact may be attributed to the long-established emphasis and popularity of STEM and business-related disciplines. As noted in Table 3.4, 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

[12] 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.

Figure 3.3: 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.

Table 3.4: Heterogeneity Analysis for FCD by Discipline

	(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

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.

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.

3.6.2 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 3.5 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 the universities' province 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.

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

Table 3.5: The Effect of Social Science Track FCD on Admission Competition

	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	0.9527
	(0.0542)	(0.0542)	(0.0653)	(0.0653)
Year FE	✓	✓	✓	✓
Province FE	✓	✓	✓	✓
Discipline FE	✓	✓		
University FE			✓	✓
Province GDP		-0.0002		0.002
		(0.0002))		(0.001)
Unemployment		-0.0022		0.0018
		(0.0015)		(0.0011)
Uni. Province GDP		0.0003**		-0.001
		(0.0001)		(0.0001)
N	7,653	7,653	98,001	98,001
R^2	0.513	0.549	0.460	0.521

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

estimated coefficients are positive, rather than negative as in the main analysis.

3.6.3 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.

Table 3.6: Placebo Test: Random Reassignment of Treatment Status

	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	340,668
R^2	0.50	0.53	0.67	0.68

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 3.6, 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.

3.6.4 External Validation Using Search-Based Controls

In this section, we provide external validation of our main findings by examining whether the effects of the FCD policy persist when using an alternative, behavior-based control group. This analysis does not replace our baseline identification strategy; instead, it assesses whether the patterns documented in Sections 3.4 and 3.5 are also reflected in applicant behavior when universities are compared according to how students actually perceive and evaluate alternatives.

Because we do not observe students' full preference sets when applying to universities, we construct a comparison group using related search keywords from *Baidu*, China's largest search engine.[13] These related keywords capture universities that prospective students frequently search for together, reflecting perceived substitutability from the applicants' perspective rather than similarity based on administrative classifications or geographic proximity. To avoid the results being driven by a small number of preeminent institutions, we exclude universities designated as First-Class universities, China's 42 most comprehensive universities, from the analysis. The treatment group therefore consists of universities hosting at least one FCD but not designated as First-Class universities. Using the related search keywords, we identify universities that are commonly compared with these FCD-hosting universities but do not host any FCD discipline and use them as the control group.[14]

[13]See Figure A2 for an illustration of the *Baidu*-related keywords interface used to construct the comparison group.

[14]Ideally, related keyword data at the program or discipline level would be preferable. However, *Baidu* does not provide search information at this level of granularity, which constrains the construction of behavior-based comparison groups.

We estimate a DID specification analogous to Equation (1), in which treatment varies at the university level, and universities are compared to a search-based control group constructed from applicant search behavior.[15] Table 3.7 reports the corresponding DID. Columns (1)-(4) compare programs in universities hosting at least one FCD to the search-based control universities. Consistent with the disciplinary-level results in Section 3.4, we find that programs in universities receiving FCD designations experience a statistically significant increase in average admission competition after 2017. The magnitude of these estimates is comparable to those in the baseline analysis, indicating that the disciplinary-level effects are sufficiently strong to translate into higher overall selectivity at the institutional level.

Table 3.7: Effect of FCD Policy on Admission Competition at University Level

	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

Notes: This table presents DiD estimates of the admission effect of FCD at the university level (Equation (3.4)), 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.

Columns (5)-(8) restrict the sample to non-FCD disciplines only and compare non-designated programs at universities hosting FCDs to non-designated

[15] Specifically, we estimate the following specification:

$$Y_{idupt} = \beta\,(Treated_u \times Post_{2017,t}) + X_{pt}\Gamma + \phi_p + \alpha_d + \delta_t + \varepsilon_{idupt},$$

where all variables are defined as in Equation (3.1). Although treatment varies at the university level, the outcome is measured at the program level to preserve comparability with the baseline analyses; standard errors are therefore clustered at the university level.

programs at control universities. If no spillover effects existed, the estimated coefficients would be close to zero. Instead, we find positive and statistically significant effects, suggesting that non-FCD disciplines at universities hosting FCDs also become more competitive. This result corroborates the within-university spillover evidence in Section 3.5 and confirms that the spillover operates at the university level rather than reflecting a reallocation of applicants solely across disciplines within the same institution. Section 3.7 further presents the corresponding event-study analysis, which shows a similar dynamic pattern over time.

Importantly, because search behavior may itself respond to changes in perceived quality following the policy, the search-based control group is not used for causal identification. We interpret these results as external validation: they demonstrate that the effects identified in the baseline analyses are also visible when universities are compared using an independent, behavior-based benchmark that reflects applicants' attention and comparison patterns.

3.7 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 primarily focused on the impact of university-level rankings or official evaluations on the quantity and quality 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 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 the robustness check Section 3.6.4.

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 and the robustness check 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 cause 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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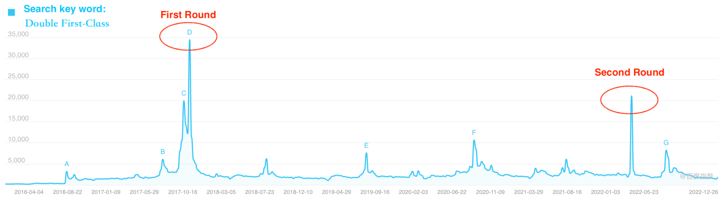
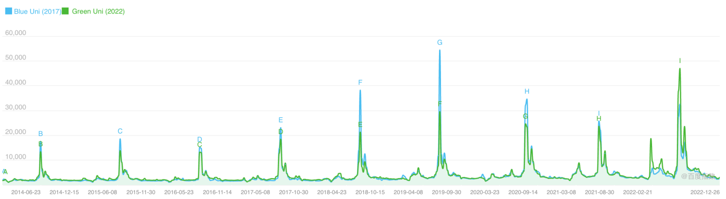
Appendix: Figures and Tables

Figure A1: Search Trend



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



(b) Search Trend of Designated Universities

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.

Table A1: Dynamic Effect of FCD Policy on Admission Competition

	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

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.

Figure A2: 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.

Table A2: Admission Quota at Provincial Level

	(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			

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: Dynamic DID Analysis — External Validation

To examine the dynamic evolution of the treatment effect in the external validation exercise, we estimate an event-study specification analogous to the baseline dynamic DID, but using the search-based control group described in Section 6.4. This analysis is intended to provide descriptive evidence on timing patterns rather than causal identification.

Specifically, we estimate the following specification:

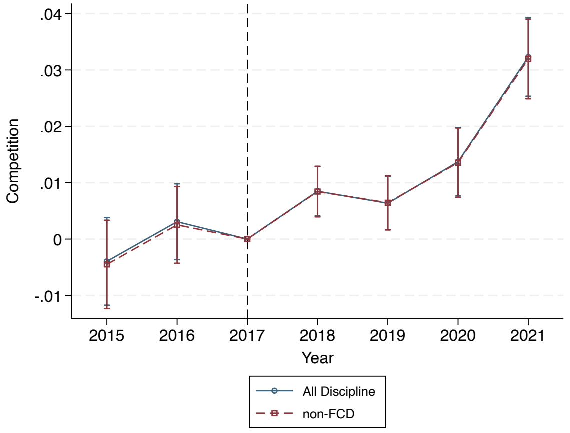
$$Y_{idupt} = \sum_{s \neq 2017} \beta^s \cdot (\text{Treated}_u \times 1\{t = s\}) + \phi_p + \alpha_d + \delta_t + \varepsilon_{idupt}, \tag{3.4}$$

where 2017 is omitted as the reference year. All variables are defined as in Equation (3.1). As in the static external validation analysis, treatment varies at the university level, while the outcome is measured at the program level. We include province fixed effects ϕ_p, discipline fixed effects α_d, and year fixed effects δ_t. Standard errors are clustered at the university level. We do not include university fixed effects because this exercise compares treated universities to search-based control universities and is not designed to exploit within-university variation.

The estimates are reported in columns (5) and (6) of Table A1 using the full discipline sample, and in columns (7) and (8) when restricting the sample to non-FCD disciplines in the treated universities. Across both specifications, the estimated pre-policy coefficients are small and statistically insignificant, indicating no evidence of differential pre-policy trends between treated and control universities.

Figure A3 plots the corresponding event-study coefficients. The blue line shows the estimated effect of the FCD policy on admission competition at the university level using the full discipline sample. Beginning in 2018, the estimated effects become positive and statistically significant and continue to increase over time, reaching approximately 3.2 percentiles (about 22%) by 2021. The red line isolates non-FCD disciplines within treated universities and closely tracks the full-sample estimates. This pattern suggests that the increase in admission competition at universities hosting FCDs is not driven solely by designated disciplines but extends to non-FCD disciplines as well,

Figure A3: 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 (3.4)). The reference year is 2017 (marked by the dashed vertical line), before the initiative's announcement.

consistent with the spillover effects documented in Section 3.5.

Sammanfattning

Denna avhandling består av tre fristående uppsatser om genus, utbildning och familjeekonomi. Uppsats I undersöker hur en sektorspecifik ekonomisk chock, IT-bubblans kollaps, formade könsskillnader i val av utbildningsinriktning. Uppsats II analyserar hur en reform av Kinas äktenskapslag år 2011 förändrade fördelningen av bostadsförmögenhet inom par och dess konsekvenser för skilsmässa, kvinnors arbetsutbud och hushållsarbete. Uppsats III, gemensamt med Tianze Liu, undersöker hur statligt ledda excellensbeteckningar på universitets- och disciplinnivå omformar studenters ansökningsval och antagningskonkurrens i Kina. Denna inledning ger icke-tekniska sammanfattningar av varje uppsats.

Uppsats I: Hur påverkar sektorspecifika chocker könsskillnader inom högre utbildning?

Kvinnor är fortfarande underrepresenterade inom informationsteknik och relaterade STEM-områden (Goldin, 2014). En växande litteratur tillskriver detta könsgap delvis flera mekanismer, däribland skillnader i komparativa fördelar och preferenser (Altonji, 1993; Zafar, 2013), könskodade uppfattningar om förmåga och social identitet (Bénabou and Tirole, 2002; Carrell et al., 2010; Murphy et al., 2007) samt differentiell exponering för förebilder och stereotyper (Beaman et al., 2009; Porter and Serra, 2020). Medan tidigare forskning visar att kvinnor och män reagerar olika på breda ekonomiska nedgångar (Blanton et al., 2019; Daskalaki et al., 2021; Kondo, 2015) är det mindre känt huruvida sektorspecifika chocker – plötsliga ökningar av den upplevda risken inom ett fält som lämnar andra fält relativt opåverkade – kan vidga könsgapen i högavkastande branscher.

Den första uppsatsen, *Sectoral Shocks and Gendered Responses in Higher Education: Evidence from the Dot-Com Collapse*, undersöker hur en stor, sektorspecifik chock kan omforma könsskillnader i utbildningsspecialisering. Jag studerar IT-bubblans kollaps år 2000–2001 som ett naturligt experiment. IT-boomen under det sena 1990-talet lockade en växande andel studenter till data- och IT-relaterade utbildningar. När bubblan brast försämrades anställningsutsikterna inom IT kraftigt, vilket ökade den upplevda risken för IT-karriärer medan de flesta andra fält förblev relativt opåverkade. Denna koncentrerade chock erbjuder en renodlad miljö för att undersöka om kvinnor och män reagerar olika på förändringar i sektorspecifik risk.

För att vägleda den empiriska analysen utvecklar jag en modell för val av utbildningsinriktning under osäkerhet, där studenter skiljer sig åt i sina riskpreferenser beroende på kön. När osäkerheten kring avkastningen inom ett fält ökar kräver individer som är mer känsliga för risk starkare incitament för att välja det fältet. Detta ramverk ger tre testbara implikationer: ett vidgat könsgap i deltagande inom det drabbade fältet, starkare positiv selektion bland dem som fortsätter att välja fältet samt omfördelning mot närliggande fält som erbjuder liknande kompetenser men lägre upplevd risk.

Den empiriska analysen använder svenska administrativa registerdata för examenskohorter från 1997 till 2007, vilka täcker både IT-boomen och den efterföljande nedgången. Data följer studenters val av utbildningsinriktning och, för dem som tar examen, deras inträde på arbetsmarknaden. Den svenska institutionella miljön är särskilt väl lämpad för denna analys: studenter ansöker direkt till specifika program, antagningen är centraliserad och meritbaserad och undervisningen är offentligt finansierad. Skillnader i utbildningsval speglar därför i huvudsak preferenser och förväntningar snarare än finansiella begränsningar.

Resultaten visar att IT-kraschen vidgade det könsrelaterade examensklyftan inom IT med cirka 4,2 procentenheter, motsvarande en relativ ökning på ungefär 50 procent. Bland dem som fortsatte att ta en IT-examen blev kvinnor mer positivt selekterade, med högre genomsnittliga betygsrangordningar jämfört med män. Vid inträdet på arbetsmarknaden framträder ett negativt och statistiskt signifikant könsgap för senare kohorter, där kvinnor blir mindre benägna än män att börja arbeta inom IT-sektorn. Givet anställning inom IT föreligger dock ingen signifikant könsskillnad i betygsrangordning, vilket tyder på konvergens i förmåga vid anställningsmarginalen. Samtidigt lämnade kvinnor inte den högre utbildningen. I stället tycks många ha omfördelat sig mot ingenjörsutbildningar, ett närliggande fält inom STEM. Tidpunkten och koncentrationen av denna förskjutning överensstämmer med omfördelning från IT mot närliggande fält snarare än ett generellt minskat deltagande.

Sammantaget belyser resultaten den upplevda riskens roll för utbildningsspecialisering och tidiga karriärutfall. Medan en stor del av den befintliga litteraturen betonar genomsnittlig avkastning som drivkraft för utbildningsval visar resultaten här att förändringar i sektorspecifik osäkerhet avservärt kan förändra könskodade mönster i specialisering. Könsgap inom STEM är därför inte fixerade utan påverkas av ekonomiska förhållanden och vidgas när ökad sektoriell risk samverkar med skillnader i hur individer reagerar på osäkerhet.

Uppsats II: Hur påverkar äganderattsförändringar ojamlikhet inom par och hushållsbeteende?

En central förutsägelse från den kollektiva modellen för hushållsbeslut är att fördelningen av resurser inom ett par – det vill säga vem som kontrollerar inkomst och tillgångar – påverkar individuellt beteende avseende arbetsutbud, konsumtion och hushållsspecialisering (Browning et al., 2014; Chiappori, 1988). Merparten av den empiriska forskningen fokuserar på inkomstflöden, men förmögenhet, särskilt bostadsförmögenhet, kan vara en lika viktig determinant för förhandlingsstyrka. I Kina har bostadsfastigheter kommit att dominera hushållens balansräkningar och utgör omkring tre fjärdedelar av hushållens totala nettoförmögenhet, vilket gör det till en naturlig kanal genom vilken juridiska äganderegler påverkar förhandling inom par (Chen et al., 2022). Eftersom bostadsrätter i Kina vanligtvis registreras i makens namn på grund av rådande sociala normer kan formellt könsneutrala förändringar i ägandelagstiftningen få tydligt könskodade effekter.

Den andra uppsatsen, *Property Rights, the Intra-Couple Wealth Gap, and Family Outcomes: Evidence from China*, studerar effekterna av Kinas reform av äktenskapslagen 2011, en rättslig tolkning från Högsta folkdomstolen som ersatte den tidigare huvudregeln om lika fördelning av gemensam egendom vid skilsmässa med en regel baserad på registrerad ägare. Eftersom lagfarter i oproportionerligt hög grad stod i männens namn genererade denna enskilda juridiska förändring en stor och plötslig förskjutning i fördelningen av juridiska äganderatter inom par.

Den empiriska analysen använder paneldata på makenivå från China Family Panel Studies (CFPS), vilken följer båda makarna inom samma hushåll över tid. Jag jämför förändringar i äganderattsklyftor inom par för par vars bostad var registrerad på enbart maken eller makan före och efter reformen, och utnyttjar denna variation i en skillnad-i-skillnader-design. Ensamregistrering är inte ett marginellt fenomen. I baslinjedata innehåller majoriteten av bostadsägande par bostaden i namn av enbart en make, oftast mannen, vilket speglar rådande sociala normer och föräldrars finansieringsmönster. Reformen förändrade därför direkt de juridiska äganderattsandelarna för en betydande andel gifta bostadsägare, vilket gör den empiriska miljön brett representativ snarare än begränsad till en smal undergrupp. För att skatta det kausala sambandet mellan dessa äganderattsklyftor och hushållsbeteende använder jag sedan den reforminducerade förskjutningen i juridiskt ägande som instrument för relativa äganderattandelar i en tvåstegs minsta kvadratmetod (2SLS).

Förstastegresultaten visar att reformen i väsentlig grad förändrade fördelningen av bostadsägande inom äktenskapet. Före 2011 betraktade lagen gemensam bostad som samfällt ägd oavsett vems namn som stod på lagfarten.

Efter reformen följde ägandeskapet den formella registreringen. Som resultat ökade reformen den genomsnittliga juridiska andelsskillnaden mellan man och hustru med 28,3 procentenheter, medan dynamiska skattningar visar att registrerade män i genomsnitt innehade 43 procentenheter mer av fastigheten än sina hustrur omedelbart efter reformen. Baserat på självrapporterade bostadsvärden motsvarade denna förskjutning en genomsnittlig förmögenhetsskillnad på 63 667 CNY, ungefär tio gånger hustruns årsinkomst i urvalet. Dynamiska skattningar visar att medan vissa par senare justerade registreringen och minskade formella äganderattsskillnader fortsätte den associerade förmögenhetsskillnaden att vidgas i takt med stigande bostadspriser.

I det andra steget undersöker jag hur dessa reforminducerade förskjutningar i ägande påverkade familjebeteende. En omfördelning av 10 procentenheter av ägandet till förmån för mannen minskar skilsmässosannolikheten med cirka 0,7 procentenheter, ökar hustruns sannolikhet för förvärvsarbete med närmare 0,7 procentenheter och ökar hennes vardagliga hushållsarbete med ungefär en timme per dag skalat till en fullskalig reformförskjutning. Heterogenitetsanalys visar att en förstärkning av den registrerade makens förhandlingsposition minskar skilsmässa oavsett om det är mannen eller hustrun som innehar lagfarten. Kvinnors arbetsutbud reagerar asymmetriskt: hustrur ökar sitt förvärvsarbete när mannens förhandlingsposition förstärks men uppvisar ingen signifikant förändring när hustruns position förstärks, vilket överensstämmer med att kvinnor kompenserar försvagade äganderatter genom ökat marknadsarbete. Hustruns hushållsarbete ökar dock oavsett vilken make som innehar större ägande, vilket tyder på att traditionella könsnormer i fördelningen av obetalt arbete är mycket beståndiga. Standardiserade jämförelser visar att skillnader i bostadsförmögenhet, snarare än enbart formella äganderattandelar, ger upphov till de största beteendemässiga responserna, vilket tyder på att tillgångars ekonomiska värde spelar en central roll för förhandlingsutfall.

Dessa resultat visar hur en formellt könsneutral lagförändring kan förstärka ojamlikhet inom hushållet när den läggs ovanpå befintliga könskodade ägandenormer, och dokumenterar att tillgångsstockar, inte enbart inkomstflöden, utgör en viktig kanal för förhandling inom hushåll.

Uppsats III: Hur påverkar excellensbeteckningar studentsortering och antagningskonkurrens?

Många regeringar har strävat efter att stärka nationellt humankapital genom att utse utvalda universitet eller discipliner som excellenscentra. Tidigare forskning om initiativ på universitetsnivå visar att sådana beteckningar påverkar upplevd prestige och kan förskjuta ansökningsmönster mot högre rankade lärosäten (Luca and Smith, 2013). Vad som är mindre känt är huruvida mer detaljerade beteckningar, på nivån av universitets- och disciplinenheter snarare än hela universitet, kan påverka hur studenter sorteras över utbildningsfält och om deras effekter sträcker sig bortom de målinriktade programmen.

Den tredje uppsatsen, *You Are the Elite Now: Admission Effects of an Excellence Initiative in the Chinese Higher Education System*, gemensamt arbete med Tianze Liu, studerar Kinas Double First-Class Initiative (DFC), som tillkännagavs 2017. Policyn utser specifika universitets- och disciplinenheter som förstklassiga discipliner (FCD:er) baserat på tidigare utvärderingspoäng. Kinas nationella högskoleprov (NCEE) erbjuder en ovanligt renodlad miljö för denna studie: antagning till samtliga universitetsprogram avgörs av ett enda standardiserat provresultat, och studenter måste rangordna program i förväg utan kännedom om sina poäng och sin rangordning bland samtliga studenter. Detta innebär att programspecifika antagningsgränser, det lägsta provresultat eller den lägsta rangordning som krävs för antagning, direkt återspeglar hur starkt sökande föredrar ett program, vilket gör dem till ett transparent mått på hur kvalitetssignaler påverkar efterfrågan.

Vår analys bygger på ett nytt dataset sammanställt från officiella provinsiella handlingar, som omfattar mer än 50 000 observationer på universitets-disciplin-provins-år-nivå. Vi jämför förändringar i antagningsgränser mellan utsedda och icke-utsedda discipliner inom samma fält före och efter 2017 års beteckning med hjälp av en skillnad-i-skillnader-design. För att hantera frågor om endogen självselektion in i FCD-programmet utnyttjar vi det faktum att beteckningen baserades på tidigare utvärderingspoäng för disciplinen, vilket ger policyvariationen en approximativt kontinuerlig och förutbestämd karaktär.

Vi finner att FCD-beteckningen signifikant höjer den minsta provrangordning som krävs för antagning med ungefär 1,5 percentiler i genomsnitt, motsvarande att överträffa cirka 1 800 ytterligare kamrater per provins. Effekten är särskilt uttalad inom jordbruk och medicin, fält som historiskt var mindre konkurrenskraftiga och där excellensbeteckningen avsevärt höjer prestigen. Effekterna inom STEM-fält, som redan var mycket eftertraktade bland sökande före policyn, är mer måttliga. Utöver de målinriktade programmen dokumenterar vi starka spillover-effekter: icke-utsedda discipliner vid universitet som har FCD attraherar också starkare sökande efter beteckningen, vilket indikerar att excellensbeteckningar höjer den upplevda kvaliteten på lärosätet som helhet, inte enbart de målinriktade programmen.

Dessa resultat visar att kvalitetssignaler på disciplinnivå kan omforma fördelningen av högpresterande studenter över fält och lärosäten, och att excellensbeteckningars rykteseffekter sträcker sig långt bortom de program som direkt omfattas av policyn. I ett bredare perspektiv tyder de på att regeringar kan använda selektiva excellensbeteckningar för att påverka utbudet av kvalificerade studenter inom strategiskt prioriterade fält och i förlängningen påverka den framtida sammansättningen av ett lands humankapital.

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