Expected Fertility, Labor Market Contracts, and the Gender Wage Gap

Job Market Paper

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Abstract

This paper examines how employers' expectations about women's future fertility increase the gender wage gap in contract-based labor markets—standard settings in many occupations that involve long-horizon, complex tasks. In such environments, salaries are set in advance based on expected match productivity rather than contemporaneous output; if employers expect women's productivity to decline more than men's after childbirth, they offer lower wages today. Exploiting China's relaxation of the One-Child Policy as a quasi-experiment, I implement a difference-in-differences design and find that women's wages declined by 15.3% immediately after the reform, despite no short-term increase in actual births. To interpret these findings, I develop a search-and-matching model with on-the-job human capital accumulation, integrated with a household framework in which non-contractable fertility-driven effort choices are made. Effort links the two components by governing human capital growth and, in turn, long-run productivity in the labor market. Estimating the model on Chinese data, I find that gender differences in expected productivity—rooted in the unbalanced division of household labor—explain nearly the entire pre-reform wage gap and approximately 80% of the post-reform widening. The policy implication is stark: women-protective rules that preserve employment through legislative contract provisions may not reduce the gap; by reinforcing employers' present-value pricing, they can be offset by *ex ante* wage markdowns applied to all women.

Keywords: gender wage gap; fertility; search and match

JEL codes: J16; J31; J64

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1 Introduction

Despite convergence in educational attainment and rising female labor force participation, sizable gender wage gaps persist across countries, with little evidence of further narrowing in recent decades (Olivetti and Petrongolo, 2016; Blau and Kahn, 2017; Kunze, 2017). A central mechanism behind these gaps is the child penalty: childbirth and early child-rearing often lead women to exit the labor market or reduce hours, depressing cumulative earnings and delaying advancement into managerial roles (Adda, Dustmann and Stevens, 2017; Kleven, Landais and Søgaard, 2019; Goldin, 2021; Cortés and Pan, 2023; Kleven, Landais and Leite-Mariante, 2024). Beyond this direct, post-birth channel, a less examined mechanism is an expectation-driven child penalty: even for women without children, employers may discount wages not only for anticipated leave or replacement costs but because they expect lower post-birth productivity and effort—even if employment is uninterrupted. This paper highlights the *ex ante* emergence and persistence of the child penalty by examining how employers' expectations about future fertility—and its impact on long-run effort—shape gender wage gaps in formal, contract-based labor markets.

Empirically, I exploit the 2013 selective relaxation of China's One-Child Policy as a natural experiment to show that firms are forward-looking when wages are contracted: young women's wages declined immediately in anticipation of higher fertility, with larger declines in sectors where separation risk is low—consistent with a future productivity pricing channel rather than a replacement cost channel. To formalize these findings, I develop a wage-posting model with long-term matches, in which employers' beliefs about on-the-job human capital accumulation are shaped by a household time-allocation model that governs effort. Estimating the model using Chinese labor market data, I find that employers' gender-specific expectations about productivity growth, rooted in the unequal division of household labor, explain nearly all of the residual gender wage gap before the reform and approximately 80% of the post-reform widening. This mechanism also helps explain why "position-preserving" protections like maternity leave mandates can disappoint: rules that require firms to keep jobs for mothers lengthen contract horizons and reinforce expectations-based pricing, thereby failing to close, and potentially widening, the gender wage gap even as employment is maintained.

China's 2013 selective relaxation of the One-Child Policy provides a setting that plausibly isolates expectation-driven wage responses. The reform shifted firms' beliefs about young women's lifetime fertility while leaving short-run fertility largely unchanged, so immediate wage movements primarily reflect updates to expectations rather than contemporaneous labor-supply adjustments. Specifically, the policy permitted a second birth without fines if either parent was an only child, and its effective impact was greater in provinces with stricter prior enforcement (i.e., higher fines for additional children). I implement a difference-in-differences design comparing more-exposed and less-exposed regions before and after the reform. China's labor market is particularly well-suited to studying contracted wage setting: among tertiary-educated workers, government and state-affiliated employment is prevalent, offering tenure-like security and infrequent within-position wage changes. In this environment, post-reform wage movements are informative about how firms revise and price expected future productivity even when current productivity is unchanged.

I use the China Family Panel Studies (CFPS), restricting the sample to employed workers ages 18–35 with at least a high-school education—those most likely to hold contract-based, long-horizon jobs and to face fertility decisions. Empirical results show that young women's wages fell by 15.3% after the reform, while the same specification for comparable young men shows no significant effect. Using men as within-region, within-period controls in a triple-difference specification corroborates a 14.8% wage decline for women.

I interpret the sizable post-reform wage decline as evidence of a long-horizon, expected-productivity channel of statistical discrimination: employers reduced young women's wages in anticipation of lower future productivity—driven by increased childcare responsibilities—even when employment remained continuous. This mechanism contrasts with Amano-Patiño, Baron and Xiao (2020), where statistical discrimination arises from higher separation risk and replacement costs. In my framework, discrimination persists *without* separations, and—because wages reflect the present value of expected productivity—lower separation risk actually amplifies the markdown by extending the expected match duration. Sectoral heterogeneity reinforces this mechanism: in government-related sectors, where separation risk is minimal, young women experience a wage decline more than twice the full-sample estimate, whereas women in non-government sectors show no clear change.

To formalize this channel, I build a unitary household model with discrete market hours (non-employment vs. fixed full-time work) and continuous effort. While pay is not tied to contemporaneous effort once employed, effort governs future productivity by determining the rate of human-capital accumulation[1]. In this environment, additional births raise childcare needs that fall disproportionately on women; holding recorded full-time hours fixed, greater childcare reduces free time, lowers effort, and slows human-capital accumulation, thereby diminishing future productivity. Throughout, I treat fertility choice as governed by the social norm or policy, but effort needs to be chosen by household members to sustain family functioning and maximize household income.

I embed this gender-specific effort choice into a wage-posting model with on-the-job search. The framework builds on Burdett and Mortensen (1998), but extends it to allow productivity to evolve at the effort-determined rate. Firms post a fixed salary at the time of hire and do not renegotiate within the match; workers stochastically receive outside offers and may transition to higher-paying firms, capturing career advancement. Because future effort is not contractable and wages are rigid within matches, firms form gender-specific beliefs about effort at the posting stage, which directly shape their wage offers. A firm's expected profit equals the present value of the effective productivity path—net of the posted salary—integrated over the tenure distribution implied by offer-arrival and separation hazards. In this fixed-salary, rising-productivity environment, downward revisions to women's expected effort and productivity translate immediately into lower posted wages.

To quantify the role of expectation-based pricing in contracted labor markets, I estimate the model by matching its implied wage distributions to the observed distributions before and after the 2013 relaxation of China's One-Child Policy (CFPS 2012 vs. 2014; sample as in the reduced-form analysis). Apart from the wage distributions, the only external inputs are time-use data and the observed distribution of workers across marriage/fertility statuses in the labor force before the policy reform.

[1] This assumption mirrors Albanesi and Olivetti (2009), who posit that the utility cost of market effort rises with home hours, making household time demands a direct wedge on effective effort. Additionally, time-use evidence shows that childcare and home production compress sleep and discretionary time, the very margins that sustain focus and off-the-clock learning and working, and "greedy jobs" reward long hours and continuous availability while penalizing flexibility (Goldin, 2014).

In the 2012 baseline, nearly all workers were either childless or had one child. The estimates show that women's effort drops sharply from nearly full effort when childless to about 62% after having one child, whereas men's effort remains almost unchanged, declining only slightly to 98%. This pronounced drop in women's effort suggests that employers perceive motherhood as a shift in life orientation—from full commitment to work toward a dual focus on career and family—consistent with the traditional Chinese norm that "men handle affairs outside the home, while women manage those within". The estimated parameters imply that the annual rate of human capital growth is about 5.2% for childless workers, but falls to roughly 4.0% for mothers, compared with 5.1% for fathers during their prime working years. This unequal division of family responsibilities alone accounts for nearly the entire gender wage gap observed in 2012. Although labor market parameters also differ by gender—with men receiving outside offers more frequently while separation rates remain similar—these frictions contribute little once the household time-allocation gap is accounted for.

Re-estimating the model on the post-reform wage distribution without imposing a mechanism *ex ante*, I find strong evidence of a sizable downward revision in firms' expectations of women's future productivity. Gender gaps in offer-arrival rates also widen, consistent with increased employer reluctance to extend offers or promotions to women. Under a simple calibration—where a second child increases mothers' family-work time by 30% while leaving fathers' time unchanged, consistent with the null wage response for men—the estimates imply that employers expect roughly 58% of one-child parents to have a second child. Feeding this time-use shift and fertility composition into the 2012 labor-market environment, while holding other parameters constant, the model attributes nearly 80% of the simulated 15.5% widening in the gender wage gap to employers' downward revisions in women's expected future productivity associated with a potential second birth.

Taken together, the reduced-form and structural evidence point to a common policy lesson: position-preserving job protections are insufficient—and may even exacerbate—gender wage gaps. This class of policies includes maternity leave mandates and special protections for mothers with young children. By lengthening the effective contract horizon, such rules raise the weight employers place on expected future productivity. When women are perceived to accumulate human capital more slowly, a longer horizon translates into larger up-front wage markdowns for all women. Moreover, retaining matches that would otherwise separate lowers the average expected productivity of the protected pool, prompting broader markdowns at hiring. Policies that reduce childcare burdens and equalize parental effort—rather than merely prolong tenure for moms—are therefore more likely to address the expectations-based mechanism behind the gender wage gap, as evidenced by the shifts in social norms and the increase in fathers' parental-leave uptake documented by Albrecht et al. (2024) following Sweden's 2002 introduction of a second "daddy month". Put differently, without tackling the unequal division of household labor, maternity leave–style protections alone are unlikely to close the remaining gender wage gap.

Although the empirical setting is China and the focus is the gender wage gap, the mechanism generalizes to labor markets where long-horizon contracts are prevalent. These include government and state-affiliated employment and many high-skill occupations, where long horizons arise endogenously from costly matching, firm-specific training, and expensive replacement. In such environments, wages are set against expected productivity over the match, so employer beliefs about future effort—whether tied to anticipated childcare, immigration constraints, or health risks—carry greater weight in wage setting. In short, while this paper studies employers' pricing of fertility expectations, the logic applies broadly to contract-driven pay: when salaries are predetermined, any concern about future productivity is amplified in posted wages.

After a brief discussion of the literature, the remainder of this paper is organized as follows. Section 2 presents the empirical setting, background on China's One-Child Policy, the identification strategy, data, and main results, together with placebo and mechanism tests. Section 3 develops the theoretical framework that links household time allocation, effort, and learning-by-doing to wage posting with on-the-job search, and characterizes equilibrium. Section 4 maps the model to the data: it details the numerical solution, reports the estimation for 2012 and 2014, and conducts counterfactual decompositions. Section 5 concludes and discusses policy implications. Proofs and technical details, together with relevant discussions, are gathered in a final Appendix.

Literature Review This paper speaks to several strands of research. First, a large literature documents persistent gender wage gaps and traces a central role to children. Surveys show that gaps have narrowed only slowly despite convergence in education and labor force participation (Blau and Kahn, 2017; Olivetti and Petrongolo, 2016; Kunze, 2017), with childbirth generating sizable, long-lived penalties through reduced hours and interrupted human capital accumulation (Adda, Dustmann and Stevens, 2017; Kleven, Landais and Søgaard, 2019; Cortés and Pan, 2023; Goldin, 2021; Kleven, Landais and Leite-Mariante, 2024). Classic models of household specialization and effort (Becker, 1985; Albanesi and Olivetti, 2009; Albanesi, Olivetti and Petrongolo, 2023) and the "greedy jobs" perspective (Goldin, 2014) rationalize why home responsibilities compress focus, availability, and off-the-clock learning that sustain productivity growth at work. Correll, Benard and Paik (2007) applies a laboratory experiment to causally identify the penalization of mothers in hiring and wages, reinforcing the idea that employers perceive women as less productive due to their family responsibilities. However, while most of this literature focuses on post-birth employment outcomes, my paper emphasizes that gender-based disadvantages emerge even before childbirth and for all women regardless of their fertility intentions, particularly in less mobile labor markets where employers preemptively adjust wages based on expected, rather than actual, fertility behavior.

A second strand links gender gaps to statistical discrimination in frictional labor markets. Structural and reduced-form studies emphasize higher expected separations and replacement costs for mothers (Bowlus and Grogan, 2009; Bartolucci, 2013; Amano-Patiño, Baron and Xiao, 2020). The contribution of my paper is to shift the mechanism from expected separations to expected productivity while separation is negligible: when pay is set against the present value of match productivity, beliefs about future effort and learning-by-doing receive more weight, so markdowns can arise even without separations, and, in fact, are larger when separations are rarer and matches are longer.

Third, the paper contributes to work on China's fertility policy and women's labor outcomes. The One-Child Policy (OCP) and its local enforcement have been studied extensively (Gu et al., 2007; Scharping, 2013; Ebenstein, 2010; Huang, Lei and Zhao, 2016), and recent papers exploit relaxations to study realized fertility and labor effects, including fieldexperimental evidence on employer discrimination (He, Li and Han, 2023), city-level impacts on gaps (Agarwal et al., 2024), and post-birth outcomes (Li, 2022). In contrast, I use nationally representative survey data to capture aggregate effects and leverage the 2013 selective relaxation as a shock to expected fertility to isolate forward-looking wage setting under contracts. Rather than simply documenting a wage decline, I develop a model in which effort drives human capital growth and estimate it before and after the reform, quantifying how the unequal division of household labor is translated into expectation-driven pricing and how much of the post-reform widening it can explain.

Finally, this paper complements a growing literature showing that well-intentioned maternity-leave and anti-discrimination laws may inadvertently worsen women's labor market outcomes. Using detailed job-platform data from China, Fang, Hu and Yu (2025) show that after the 2021 extension of statutory maternity leave by 10–50 days (roughly 22%), call-back rates for young women fell by about 17%, indicating heightened hiring discrimination. Thomas (2020) develops a two-period model that predicts and empirically confirms that maternity leave provisions can lower women's promotion probabilities by pooling women with heterogeneous fertility preferences into the same candidate pool. Similarly, Di Paolo and Marcolin (2025) studies the passage of the 1978 U.S. Pregnancy Discrimination Act, which prohibited employers from discriminating on the basis of pregnancy, and finds that the reform reduced women's employment rates, suggesting that firms substituted away from hiring women of childbearing age. In the Indian context, Gupta (2023) document that extensions of paid maternity leave led firms to replace female employees with male counterparts.

This paper differs from these studies along two key dimensions. First, much of the literature identifies "child-penalty" effects on the extensive margin—employment, hours, or promotion—and finds limited or mixed wage effects. In contrast, in China's high-skilled, contract-intensive labor market, I document a sizeable decline in young women's wages after the 2013 fertility-policy relaxation, with no corresponding drop in employment. Two features plausibly underpin this pattern: (i) in a rapidly growing economy, outright non-employment among qualified women is rare, so adjustment occurs via lower starting offers rather than job loss; and (ii) although "equal pay for equal work" is formally mandated, enforcement is incomplete (World Bank, 2024), leaving room for pre-hire wage setting and job assignment to serve as the margin of statistical discrimination. These findings underscore that regulating pay equality alone cannot eliminate statistical discrimination. When wage floors constrain within-position differentiation, employers may shift discrimination to the hiring margin—reducing offers, limiting advancement, or avoiding female candidates altogether. Second, the studies mentioned above identify expected fertility effects through changes in maternity leave duration or the frequency of pregnancy-related episodes. However, the economic impact of another child should extend far beyond the childbirth period and encompass the entire child-rearing phase. The relaxation of China's One-Child Policy introduces an exogenous shift in the expected number of children while keeping maternity leave and other labor market conditions stable. Therefore, the exogenous shift used in this paper allows for a more comprehensive capture of the expected fertility effect on women's labor market outcomes, accounting for the cumulative impact of childcare and household responsibilities over time rather than the short, episodic disruption surrounding childbirth.

2 Empirical Evidence

In this section, I exploit the 2013 selective relaxation of China's One-Child Policy (OCP) as a natural experiment to estimate how an increase in *expected* fertility—by at most one additional child—affects young women's wages. The design uses three sources of variation: (i) the before–after change around the policy shift, (ii) cross-provincial differences in pre-relaxation enforcement intensity measured by *FinesRate*, and (iii) gender, with men serving as a natural control group in triple-differences (DDD) specifications. I estimate individual-level difference-in-differences (DiD) and DDD models with province and year fixed effects, as well as province–year interactions in the DDD framework.

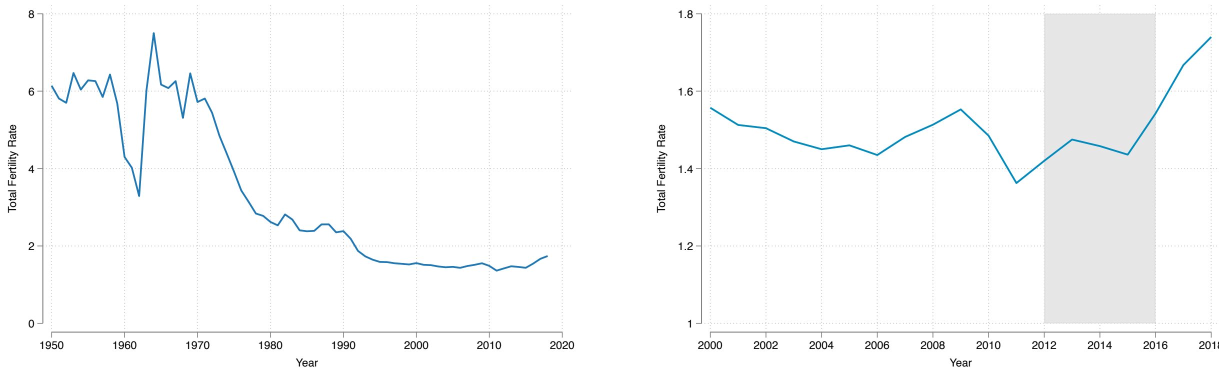
The main result is a 15.3% decline in women's wages after the relaxation in provinces more exposed to the policy shift. Importantly, neither the aggregate trend in births nor province–year DiD regressions indicate a contemporaneous rise in birth rates following the first relaxation. Taken together, the evidence points to an employer-side response to higher expected lifetime fertility—rather than a household-side labor-supply adjustment—as the proximate driver of the wage decline.

The magnitude of the wage decline is striking, and I attribute it to China's low-mobility labor market, particularly in government-related sectors that offer near-lifetime employment security. In such long-term contractual relationships, wages are set based on the present value of expected productivity rather than current output. When contracts are inflexible, longer non-adjustment horizons amplify employers' ex-ante wage markdowns for groups perceived to have lower future productivity. Consistent with this mechanism, the decline in wages is concentrated among younger women and is significantly larger in government-affiliated employment, where job separation is rare. These patterns are consistent with a forward-looking wage-setting process in which firms discount the future productivity of women *ex ante* in response to higher expected fertility, even in the absence of any immediate increase in childbirth.

The remainder of this section proceeds as follows. I first provide the institutional background on China's One-Child Policy and its subsequent relaxation. Next, I outline the empirical strategy used to exploit the policy change as a natural experiment. I then introduce the data sources and describe my analytical sample. After presenting the main empirical results, I discuss and exclude alternative explanations by robustness checks. Finally, I provide supporting evidence linking the magnitude of the estimated effects to the long employment durations characteristic of China's highly educated labor market.

2.1 Background: One-Child Policy in China and its Relaxation

China's family–planning policy began in 1971. Prior to 1979 it was largely voluntary. In 1979 the government enacted a stringent population–control policy—the One-Child Policy (OCP). Urban couples were generally limited to one child, while many rural couples could have a second child if the first was a girl. Authorities implemented a system of financial penalties and administrative sanctions to deter excess fertility, including wage deductions for salaried workers, reduced land allocations in rural areas, denial of certain public services, and, most commonly, fines for unauthorized births. The policy substantially lowered fertility: according to World Bank data, China's total fertility rate declined from 6.08 in 1970 to 2.51 by 1990 (Figure 1).



(a) 1950–2018

(b) 2000–2018

Figure 1: Trends in the total fertility rate in China. The shaded region in (b) denotes the sample period. *Sources:* United Nations, Department of Economic and Social Affairs, Population Division (2019).

Concerns about persistent low fertility and population aging later prompted gradual relaxations of the OCP. The first major step—the "selective two-child" policy—was announced in 2013, allowing a second birth if either parent was an only child; provinces implemented the change in 2014–2015. Despite expectations of a baby boom, birth rates showed little response. In November 2015 the central government adopted a universal two-child policy, effective January 2016, permitting two children for all couples.

Measuring the strength of OCP implementation Although the One-Child Policy was enforced nationwide, its implementation intensities varied significantly across provinces based on local preferences and social norms related to childbearing. The primary penalty for policy violation was a fine, which was substantial and varied from province to province. For example, Zhejiang, Fujian, and Guangdong—three consecutive and economically developed provinces along China's southeastern coast—imposed different fine rates for excess births. In Zhejiang, under the Regulations on Family Planning of Zhejiang Province enacted in 1990 and was still valid in the 2000s, couples who exceeded birth quotas were required to pay 20% to 50% of their household income annually for five years. In Fujian, around the 2000s, fines ranged from two to three times the household's total income from the previous year. In Guangdong, the 2002 regulations specified fines between three and six times the household's annual disposable income. The variation in punishment across provinces is a proxy for measuring the intensity of implementing the One-Child Policy, helping to identify the impacts of relaxing birth restrictions. In addition to economic penalties, urban residents working in the government or state-owned enterprises would lose their jobs and social welfare benefits for exceeding birth quotas. Moreover, coercive measures such as forced abortions were implemented in some regions.

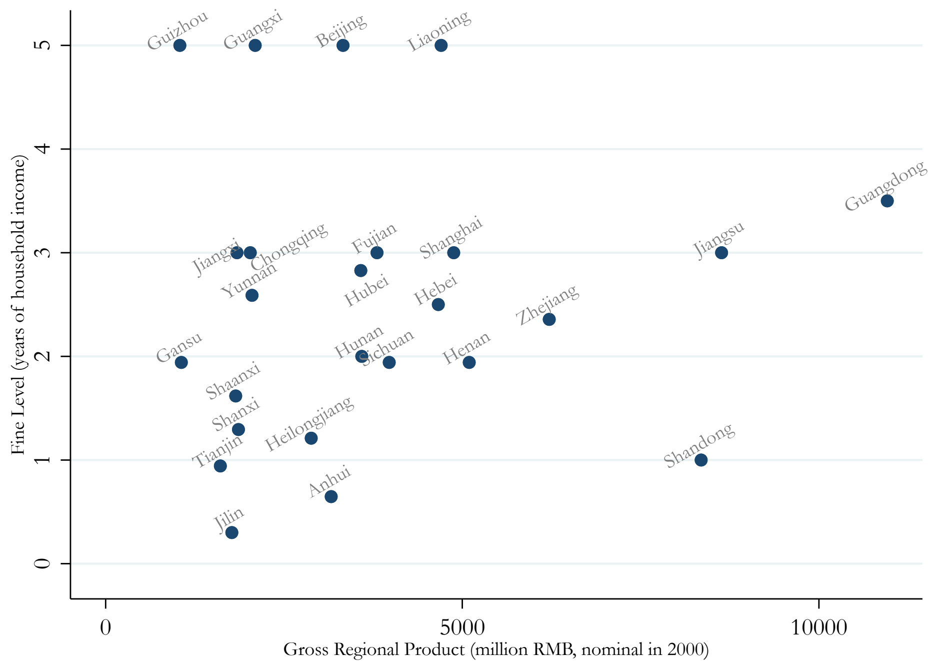


Figure 2: Harmonized One–Child Policy (OCP) fine rates by province, 2000 (multiples of average annual household income). *Sources:* Fine rates are from Ebenstein (2010), based on Scharping (2013) and CHNS; provincial gross regional product from the *National Bureau of Statistics of China*.

To obtain a unified measure of enforcement intensity, I follow the literature in using province-level "fine rates" expressed as multiples of average annual household income. Scharping (2013) compiles the official provincial schedules for 1979–2000; building on these, Ebenstein (2010) combine the schedules with China Health and Nutrition Survey data to construct annual province-specific fine rates that are widely used as an OCP enforcement proxy (see, e.g., Ebenstein (2010); Huang, Lei and Zhao (2016)). I use the 2000 cross-section of this measure—denoted *FinesRate*—as the baseline indicator of pre-relaxation enforcement intensity. Figure 2 displays provincial fine rates.

2.2 Empirical Strategy

The relaxation of the One-Child Policy provides a unique opportunity to understand how the policy relaxation affects young women's wages. I employ a difference-in-differences strategy to identify the policy impacts. *FinesRate*, the province-level monetary penalties for excess births before the relaxation, is used to measure the change in exposure and thus help define the treatment and control group.

Table 1: Fine Rates are Unrelated to Provincial Economic Conditions

	(1)	(2)
	Year = 2000	*Year = 2013*
	Dependent variable: *FinesRate*	
GDP	0.000	-0.000
	(0.000)	(0.000)
Unemployment rate	-0.349	-0.585
	(0.430)	(0.509)
Number of employed		0.002
		(0.004)
Average wage		0.000
		(0.000)
Constant	3.477**	3.647
	(1.429)	(2.635)
Observations	25	25
R^2	0.034	0.166
F-statistic	0.387	0.998
P-value	0.683	0.432

Notes: Standard errors are reported in parentheses. This table examines whether provincial enforcement intensity of the One-Child Policy (*FinesRate*) is correlated with economic conditions across provinces. Column (1) uses cross-sectional data for 2000, including provincial GDP and urban unemployment rates; Column (2) uses 2013 data, adding average urban wages and total urban employment—the year of the main policy relaxation. Data on economic variables come from the *National Bureau of Statistics of China*, and *FinesRate* is constructed from Ebenstein (2010).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

This empirical strategy assumes that OCP enforcement levels are unrelated to economic conditions that could influence wages. To assess plausibility, I regress *FinesRate* on provincial GDP, urban unemployment, average urban wages, and the urban employment count, using data from the National Bureau of Statistics of China.[2] Because GDP and unemployment are available in 2000, while average wages and urban employment are available from 2008 onward, I run cross-sections for 2000 (GDP, unemployment) and for 2013 (all four variables), the year when the main policy shift occurred. Results in Table 1 show small and insignificant coefficients; joint F-tests fail to reject that the economic covariates explain *FinesRate* (p-values 0.683 and 0.432). I therefore find no evidence that enforcement intensity is systematically related to provincial economic conditions, supporting the exclusion restriction underlying the design.

I follow a standard difference-in-differences strategy, and the estimation equation is

$$\log \text{wage}_{it} = \beta_0 + \beta_1 \text{yschool}_{it} + \beta_2 \text{age}_{it} + \beta_3 \text{age}_{it}^2 + \beta_4 \text{Treat}_{pt} + \mu_p + \gamma_t + \varepsilon_{it} \tag{1}$$

where i refers to individual worker, t calendar time, and p provinces. Using the logarithm level of nominal yearly salary income, "$\log \text{wage}_{it}$", as the dependent variable, I include years of schooling, "yschool", "age", and "squared age" as the independent variables based on the Mincer equation. Province fixed effects (μ_p) and year fixed effects (γ_t) are also included in this specification. The coefficient of interest is β_4 in front of the binary indicator Treat_{pt}, which is constructed by the time indicating variable Time_t and treatment group indicating variable FinesHigh_p:

$$\text{Treat}_{pt} = \text{FinesHigh}_p \times \text{Time}_t$$

where

$$\text{Time}_t = \begin{cases} 1, & \text{if } t > 2013 \\ 0, & \text{if } t \leq 2013 \end{cases}, \text{ and } \quad \text{FinesHigh}_p = \begin{cases} 1, & \text{if FinesRate}_p > 2.5 \\ 0, & \text{if FinesRate}_p \leq 2.5 \end{cases}$$

where 2.5 is the median of fines rates for all provinces in 2000 from Ebenstein (2010), in terms of *years of household income*. In other words, I assign provinces that had a higher

[2] The sample is restricted to the urban sector, as formal wage employment—the main outcome variable—is primarily observed in urban regions.

fine rate for excess births in 2000 to the treatment group and others to the control group. $\text{Treat}_{pt} = 1$ implies workers in province p are under treated in year t, in comparison with the same-gender workers that are either never treated or not yet treated. As the fines rates are continuously measured, I create a new variable to capture treatment intensity, denoted as $\text{Con\_Treat}_{pt} = \text{FinesRate}_p \times \text{Time}_t$, and substitute for the binary Treat_{pt} variable in regression model described by Equation 1.

I apply Equation 1 to female workers and male workers to assess differential post-policy effects by gender. As a complementary approach, I also use men's wages as the natural control group for possible wage-determining factors that are systematically different across the treated and untreated province-year combinations, and following Jayachandran and Lleras-Muney (2009) the estimating model for Triple DiDs is

$$\begin{aligned} \log \text{wage}_{it} &= \beta_0 + \beta_1 \text{yschool}_{it} + \beta_2 \text{age}_{it} + \beta_3 \text{age}_{it}^2 \\ &\quad + \beta_4 \text{Treat}_{pt} \times \text{female}_i + \mu_p \times \gamma_t + \gamma_t \times \text{female}_i + \mu_p \times \text{female}_i + \varepsilon_{it} \end{aligned} \tag{2}$$

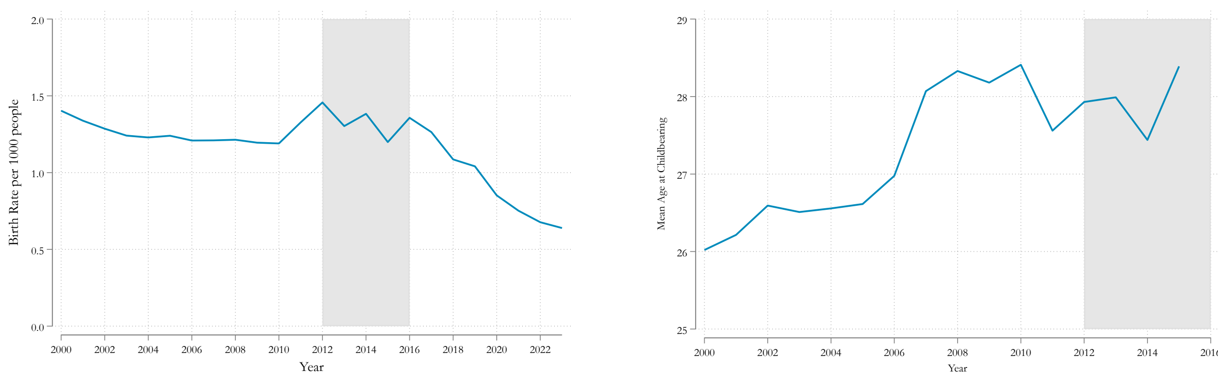
The model incorporates a full set of double interactions of fixed effects, including the province-year, gender-year, and province-gender fixed effects. This enables us to interpret the coefficient of interest, β_4, as the impact of an increase in expected fertility rates on female wages, accounting for all variations in province, year, and gender. I use the continuously measured treatment intensity Con_Treat as a second treatment specification in the estimation as well.

2.3 Data and Sample Selection

The primary dataset utilized in this paper is the China Family Panel Survey (CFPS), a representative family survey that started in 2010. Subsequent surveys were conducted biennially from 2012 onwards. I have included data from three survey rounds, spanning from 2012 to 2016. The exclusion of the 2010 survey is based on a change in employment criteria in 2012, leading to a low and incomparable fraction of employed individuals in 2010[3].

[3] The fraction of employed people in 2010 is only 62.96 percent, whereas in the later three rounds of the survey, this number increases to 83.29, 84.82, and 85.06, respectively

Furthermore, the One-Child Policy was relaxed to a universal Second Child Policy in 2016, and people realized that actual birth rates did not experience significant growth after the policy relaxation, as shown in Figure 3a. All add complexity to the interpretation of results, making the inclusion of samples post-2016 potentially challenging. The CFPS survey covers 25 provinces, excluding minority-concentrated areas such as Xinjiang, Tibet, Qinghai, Inner Mongolia, Ningxia, and Hainan. In subsequent surveys, a small number of households report living in those provinces because of migration. I exclude them due to the small size and the fact that the One-Child Policy did not initially apply to minority populations.



(a) Birth rate in China

(b) Mean age at childbearing in China

Figure 3: Fertility-related statistics in China since 2000. The shaded region denotes the sample period. *Sources:* United Nations, Department of Economic and Social Affairs, Population Division (2019).

Within each survey, I refine the sample to include individuals aged 18 to 35 years, residing in urban areas, and possessing 12 or more years of schooling. This age range aligns with the prime reproductive years for females. The educational attainment requirement is based on the premise that the expectation channel can only function effectively when employees can enter into long-term contracts with employers. In situations where employers can hire and terminate employment at their discretion, they would not adjust their job offer because of future concerns. Consequently, young individuals without a high-school diploma (with fewer than 12 years of schooling) are excluded from the main analysis.

Table 2: Summary Statistics by Year and Gender

	2012		**2014**		**2016**	
	Female	Male	Female	Male	Female	Male
Sample size	466	486	540	563	506	556
Age	28.34	28.74	27.81	28.45	28.68	29.15
Urban *hukou* (%)	85.00	84.77	71.48	74.42	71.34	73.92
Minority (%)	2.80	2.06	4.63	3.20	4.35	3.24
Years of schooling	14.37	14.26	14.59	14.55	14.72	14.68
	(1.748)	(1.806)	(1.829)	(1.877)	(1.763)	(1.947)
ln(wage)	9.99	10.23	10.12	10.43	10.20	10.53
	(0.916)	(0.921)	(0.915)	(0.980)	(1.270)	(1.114)
Total n	952		1,103		1,062	
Gender wage ratio (F/M)	0.7867		0.7334		0.7189	

Notes: Entries are means; standard deviations in parentheses. Urban, *hukou*, and minority are binary variables, whose means are displayed in percent.

Table 2 presents the summary statistics for all individuals meeting the sample selection criteria and having a valid wage record in the year they were surveyed. The sample size remains relatively consistent across the three survey rounds. The average age is approximately 28. Given that the application of the One-Child Policy varies based on people's *hukou* and ethnicity status, I provide a summary of the number of individuals with urban *hukou* status and those belonging to minority groups. It appears that, across the three rounds, the majority of individuals in the sample possess urban hukou status, less than 5% belong to minority groups, and these proportions remain relatively stable. The average years of schooling and the logarithm level of average nominal wages exhibit a slightly upward time trend. However, the gender wage ratio, defined as the wages of females divided by the wages of males, declines from 78.67% to 71.89%, indicating a widening gender wage gap.

2.4 Empirical Results

The results for the two main regression Equation 1 and Equation 2 are presented in Table 3, and all the standard errors are clustered at the province level, which is the level where the variation happens.

Table 3: Effect of OCP Relaxation on Female/Male Workers' Wages

	(1)	(2)	(3)	(4)	(5)	(6)
	Female	Male	Female	Male	Triple-DiD	
	Dependent variable: *ln_wage*					
Years of schooling	0.089***	0.067***	0.089***	0.067***	0.078***	0.078***
	(0.016)	(0.022)	(0.016)	(0.022)	(0.009)	(0.010)
Age	0.432***	0.501***	0.431***	0.501***	0.455***	0.455***
	(0.101)	(0.066)	(0.101)	(0.066)	(0.072)	(0.072)
Age^2	-0.007***	-0.008***	-0.007***	-0.008***	-0.007***	-0.007***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Treat	-0.153*	-0.031				
	(0.083)	(0.084)				
Continuous Treat			-0.059*	0.006		
			(0.031)	(0.025)		
Treat × female					-0.148*	
					(0.078)	
Cont. Treat × female						-0.075**
						(0.030)
Observations	1,467	1,519	1,467	1,519	2,986	2,986
R^2	0.200	0.216	0.200	0.215	0.239	0.239
Year fixed effects	Y	Y	Y	Y	Y	Y
Province fixed effects	Y	Y	Y	Y	Y	Y
Clustered SE: Province	Y	Y	Y	Y	Y	Y

Notes: Standard errors in parentheses. "Treat" is a binary indicator for exposure to the OCP relaxation; "Continuous Treat" is a continuous exposure measure. Triple-DiD columns report the interaction with the female indicator.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The results for Equation 1 with binary indicator variable, Treat$_{pt}$, are presented in the first two columns. The estimated coefficient for Treat$_{pt}$ is negative for female workers, indicating a statistically significant decrease of 15.3 percent in wages for young women in provinces experiencing more exposure to the policy change, as compared to unaffected females. However, for male workers, the estimated coefficient is not statistically significant from 0, suggesting that the change in policy does not impact their wages.

Columns (3) and (4) exhibit the results using continuously measured treatment variable Con_Treat_{pt}. Notably, the alteration in treatment measurement does not alter the primary finding: when assessed based on fines rates, female workers in provinces that previously imposed fines equivalent to 1 more year of household income for excess births experience a 5.9 percent decrease in wages after OCP relaxation, while if we multiply this number by the median 2.5, the result is 14.75 percent, quite comparable to what we got from binary treatment indicator. Conversely, the strictness of OCP implementation in the past did not have a significant effect on the wages of male workers.

In addition to the key coefficients of variable Treat_{pt} and Con_Treat_{pt}, other estimated results fall within the range found in the literature. Specifically, an additional year of schooling is associated with an 8.9 percent increase in wages for women and a 6.7 percent increase for men. Furthermore, wages exhibit a positive correlation with age (experience), although with a significantly diminishing return.

Triple difference-in-differences results specified in Equation 2 are presented in the last two columns. The effects of increased expected fertility rates on young females' wages are negative and significant. Under a counterfactual scenario without policy relaxation, the wage level for the same female worker would have risen by 14.8 percent. Taking the average real wage level before the policy shift for females in the treatment group as a reference point, this implies an annual wage income loss of approximately $34,650.87 \times 0.148 = 5,128.33$ RMB, which is approximately 833.87 USD using the 2013 exchange rate. If we interpret the results by the continuously-measured treatment intensity, it implies that if the province where a woman lives increased its fine by one year of household income for an excess birth, the female's annual wage income would decrease by 7.5 percent, which equals to 2598.82 RMB and 422.57 USD.

Table 4: Effect of OCP Relaxation on Female Workers' Employment Status

	Panel A: Binary			**Panel B: Continuous**		
	Female	Male	Triple-DiD	Female	Male	Triple-DiD
Years of schooling	0.173***	0.122***	0.150***	0.174***	0.122***	0.150***
	(0.018)	(0.017)	(0.012)	(0.018)	(0.017)	(0.012)
Age	-0.032	0.152*	0.058	-0.034	0.157*	0.057
	(0.057)	(0.086)	(0.060)	(0.058)	(0.086)	(0.060)
Age^2	0.001	-0.002	-0.001	0.001	-0.002	-0.001
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Treat	0.115	-0.030				
	(0.125)	(0.140)				
Treat × female			0.147			
			(0.220)			
Treat (cont.)				0.026	0.063	
				(0.049)	(0.042)	
Treat (cont.) × female						-0.035
						(0.075)
Observations	2,241	2,068	4,296	2,241	2,068	4,296
Year fixed effects	Y	Y	Y	Y	Y	Y
Province fixed effects	Y	Y	Y	Y	Y	Y
Clustered SE: Province	Y	Y	Y	Y	Y	Y

Notes: Standard errors in parentheses. "Treat" is an indicator for exposure to the OCP relaxation; "Treat (cont.)" is a continuous exposure measure. "Triple-DiD" includes the interaction with the female indicator. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Response in Extensive Employment Margin When it comes to wage change, the naturally-related question is whether the employment rates change simultaneously. If the possibilities of finding jobs for young females increase after the policy relaxation, the wage decrease could happen because more low-skilled people are in the labor market pool and the average wage level is lower. To test this hypothesis, I run the same regression equations as in Section 2.2 but now use *"have a waged job or not"* as the dependent variable and, therefore, apply a Probit model.

The results are shown in Table 4. None of the key coefficients are significant, implying that the employment rates for either males or females do not respond to the policy relaxation. The selection criteria for the labor market do not change for young females, but the payments for working decrease.

2.5 Alternative Explanations?

2.5.1 Actual vs Anticipated Fertility Increases

One potential explanation for the widening gender wage gap in treated provinces after the OCP relaxation is a differential increase in births ("motherhood penalty" channel). Prior work (e.g., Correll, Benard and Paik (2007)) documents that mothers may earn less due to reduced hours, acceptance of lower pay for schedule flexibility, or job changes that shorten commutes but lower wages. To assess this channel, I use province–year birth rates from the National Bureau of Statistics of China (live births per 1,000 population), covering 2011–2019 for the same 25 provinces as in the main analysis. Figure 3 plots the aggregate trend: after 2000, the birth rate peaks in 2012, fluctuates for several years, and then declines sharply after 2016. The sample window in this paper (2012–2016) straddles the 2013 relaxation, with the peak occurring in the pre-shock year. In other words, relative to 2012, subsequent years do not exhibit a higher number of births, which is inconsistent with a contemporaneous motherhood-penalty mechanism driving the observed wage gap widening.

I then estimate province–year DiD models analogous to Section 2.2. Let Time_t indicate the post-2013 period, FinesHigh_p equal one for provinces with above-median 2000 fine rates, and FinesRate_p denote the continuous fine measure. The binary treatment is $\text{Treat}_{p,t} = \text{Time}_t \times \text{FinesHigh}_p$; the continuous-intensity treatment is $\text{ConTreat}_{p,t} = \text{Time}_t \times \text{FinesRate}_p$. The two-way fixed effect specification is

$$\text{birth\_rate}_{p,t} = \beta_0 + \beta_1 \,\text{Treat}_{p,t} + \mu_p + \gamma_t + \varepsilon_{p,t},$$

with an analogous regression using $\text{ConTreat}_{p,t}$ in place of $\text{Treat}_{p,t}$. Columns (1)–(2) of Table 5 report pooled DiD without fixed effects; Columns (3)–(4) include province and year fixed effects. Standard errors are robust.

Across all specifications, the interaction terms are small and statistically indistinguishable from zero, indicating no detectable differential birth-rate response between treated and control provinces following the first OCP relaxation.

Since neither the aggregate series nor the province–year DiD estimates show a birth-

Table 5: Impact of OCP Relaxation on Birth Rates

	(1)	(2)	(3)	(4)
	Dependent variable: *birth_rate* (per 1,000)			
Time	0.010	0.016		
	(0.051)	(0.094)		
FinesHigh	0.027			
	(0.056)			
Time × FinesHigh	0.030		0.030	
	(0.072)		(0.021)	
FinesRate		0.022		
		(0.027)		
Time × FinesRate		0.003		0.003
		(0.034)		(0.008)
Observations	216	216	216	216
R^2	0.011	0.018	0.928	0.928
Year fixed effects			Y	Y
Province fixed effects			Y	Y
Robust SE	Y	Y	Y	Y

Notes: Province–year panel for 25 provinces, 2011–2019. Standard errors in parentheses. *Time*= 1 for post-2013 years; *FinesHigh*= 1 for provinces with above-median 2000 OCP fine rates; *FinesRate* is the continuous fine measure.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

rate response, contemporaneous fertility changes are unlikely to drive the observed wage effects. Instead, the patterns are consistent with employer-side pricing based on long-horizon expectations: following the OCP relaxation, firms anticipate higher lifetime fertility for young women and discount wages *ex ante* even in the absence of immediate births.

2.5.2 An Older-Worker Placebo

To verify that the identified wage decline among young women is driven by changes in expected fertility—rather than by a general devaluation of women's productivity—I re-estimate equations (1) and (2) for workers aged 35–54 who remain employed. These individuals have largely exited prime childbearing ages, and under the hypothesized mechanism, their wages should not respond to the relaxation of the One-Child Policy. Table 6 confirms this prediction: the coefficients on *Treat* and *Treat (cont.)* for both genders, as well as the triple-difference terms *Treat* × *Female* and *Treat (cont.)* × *Female*, are small in magnitude and statistically insignificant. This placebo test supports the interpretation that the post-relaxation wage decline is specific to younger women and operates through the expected-fertility channel, rather than reflecting a contemporaneous labor market shock affecting all women.

Table 6: Effect of OCP Relaxation on Older Workers' Wages (Ages 35–54)

	Panel A: Binary treatment			**Panel B: Continuous treatment**		
	Female	Male	Triple-DiD	Female	Male	Triple-DiD
Years of schooling	0.173***	0.122***	0.150***	0.174***	0.122***	0.150***
	(0.018)	(0.017)	(0.012)	(0.018)	(0.017)	(0.012)
Age	-0.032	0.152*	0.058	-0.034	0.157*	0.057
	(0.057)	(0.086)	(0.060)	(0.058)	(0.086)	(0.060)
Age^2	0.001	-0.002	-0.001	0.001	-0.002	-0.001
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Treat	0.115	-0.030				
	(0.125)	(0.140)				
Treat × Female			0.147			
			(0.220)			
Treat (cont.)				0.026	0.063	
				(0.049)	(0.042)	
Treat (cont.) × Female						-0.035
						(0.075)
Observations	2,241	2,068	4,296	2,241	2,068	4,296
Year fixed effects	Y	Y	Y	Y	Y	Y
Province fixed effects	Y	Y	Y	Y	Y	Y
Clustered SE: Province	Y	Y	Y	Y	Y	Y

Notes: Province–year panel; standard errors in parentheses. "Treat" is the post–OCP relaxation indicator interacted with above-median pre-policy fine rates; "Treat (cont.)" uses the continuous fine measure. "Triple-DiD" includes interactions with the female indicator and the full set of province×year, year×gender, and province×gender fixed effects.
$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

2.6 Why is the Wage Decline so Large? A Puzzle

A natural question is why an expectations-based response by employers would generate such a *large* fall in young women's wages. The canonical statistical–discrimination story emphasizes higher expected separation (replacement) costs after childbirth, which depresses starting wages. That mechanism is weak in China's high-skill labor market, where employment relationships are unusually long-lived and separations are infrequent.

Table 7: Labor market transition matrix (two-year horizon), employed individuals

	Number employed	Unemployed	Employed		Out of labor force
			same employer	changed jobs	
2010–2012	2,367	1.48%	74.31%	13.48%	10.73%
2012–2014	3,327	1.41%	62.79%	23.47%	12.32%
2014–2016	2,925	1.26%	66.56%	20.24%	11.93%
Average	2,873	1.39%	67.89%	19.06%	11.66%

Notes: The data are from China Family Panel Survey. Sample is restricted to all persons older than 16 years old, living in urban areas, appearing in two consecutive waves, and with valid non-farm employment records in both waves.

Table 7 documents this low mobility: between 2010 and 2016, on average 67.9% of workers remained with the *same* employer two years later (versus roughly 40.5% in the United States over a comparable horizon). Household survey evidence from 2010 is consistent with this: over half of respondents report that their current job is their first job, with the pattern most pronounced among the tertiary-educated. A key driver is the prevalence of government-related employment (civil service and Party organs; public institutions such as schools, hospitals, research institutes; state-owned or state-controlled enterprises), which offers near-tenure and continues to attract highly educated workers—even among younger cohorts (ages 18–35).

Taken together, China's labor market for high-skilled workers is characterized by low dynamism and prevalent long-term employment relationships. In such environments, pay is tied to the present value of match productivity, contemporaneous effort is only weakly coupled to current wages, and firing is costly or institutionally constrained. Employers therefore discount young women's wages *ex ante* if they expect postpartum productivity to be lower, even when separations do not rise.

Table 8: Wage Regressions by Government-Related Sector

	Panel A: Government-related Job				Panel B: Non-government-related Job			
	Female		Triple-DiD		Female		Triple-DiD	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable: *ln_wage*							
Years of schooling	0.036	0.037	0.052*	0.053*	0.092***	0.093***	0.091***	0.091***
	(0.030)	(0.031)	(0.028)	(0.028)	(0.021)	(0.021)	(0.010)	(0.010)
Age	0.119	0.111	0.132	0.128	0.524***	0.523***	0.517***	0.517***
	(0.101)	(0.104)	(0.113)	(0.110)	(0.121)	(0.121)	(0.076)	(0.076)
Age^2	-0.001	-0.001	-0.002	-0.002	-0.009***	-0.009***	-0.008***	-0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Treat	-0.194				-0.145			
	(0.150)				(0.100)			
Treat (cont.)		-0.136***				-0.049		
		(0.045)				(0.040)		
Treat × Female			-0.260				-0.197	
			(0.215)				(0.123)	
Treat (cont.) × Female				-0.200***				-0.070
				(0.063)				(0.042)
Observations	429	429	873	873	1,038	1,038	2,113	2,113
R^2	0.252	0.256	0.312	0.314	0.222	0.222	0.267	0.267
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Province FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Clustered SE: Province	Y	Y	Y	Y	Y	Y	Y	Y
Gov-related	Y	Y	Y	Y	N	N	N	N

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A sectoral test of the long-term pricing channel. If long-term contracting and firing frictions are the conduit, the effect should be strongest where such frictions are most salient: government-related employment. I split the sample into government-related sectors (Government/Party/people's organizations; public institutions/research institutes; SOEs/state-controlled firms) and other sectors, and re-estimate the female DiD in Equation (1) (reporting female coefficients) alongside the triple-differences specification Equation (2). I report results using both the binary treatment and the continuous intensity.

As shown in Table 8, despite smaller samples, government-related wages for young women fall significantly under the *continuous* exposure measure, with magnitudes larger than in the full sample (cf. Table 3). In contrast, wage changes in non-government sectors are statistically indistinguishable from zero. This pattern is consistent with a long-term pricing (expectations) mechanism operating most strongly where employment relationships are the stickiest.

2.7 Mechanism: Worse new jobs *vs.* Stalled Promotions

Because employment on the extensive margin does not change after the OCP relaxation, the wage decline must operate along the intensive margin. Two natural channels are: (i) new entrants accepting lower–quality jobs ("worse new jobs"), and (ii) slower within–job advancement ("stalled promotion"). I test the promotion channel using CFPS questions on supervisory responsibility—*Has subordinates?* and, if yes, *How many?*. The estimation specification is analogous to Equation (2):

$$
\begin{aligned}
Prob.\,(\text{has subordinates})_{it} = &\beta_0 + \beta_4 \text{Treat}_{pt} \times \text{female}_g \\
&+ \mu_p \times \gamma_t + \gamma_t \times \text{female}_i + \mu_p \times \text{female}_i + \varepsilon_{it} \\
\log\,(\text{num of subordinates})_{it} = &\beta_0 + \beta_4 \text{Treat}_{pt} \times \text{female}_g \\
&+ \mu_p \times \gamma_t + \gamma_t \times \text{female}_i + \mu_p \times \text{female}_i + \varepsilon_{it}
\end{aligned}
$$

Table 9: Effect of OCP Relaxation on Female Workers' Promotions

	has_subordinates		*ln_subordinates_num*	
	(1)	(2)	(3)	(4)
Female × Treat	0.163		-0.017	
	(0.264)		(0.400)	
Female × Treat (cont.)		0.096		-0.058
		(0.142)		(0.152)
Sample mean	0.200	0.200	1.700	1.700
Observations	2,003	2,003	514	514

Notes: Standard errors in parentheses.
has_subordinates is an indicator for holding a supervisory position. *ln_subordinates_num* is the log number of direct reports.
Treat denotes exposure to the OCP relaxation (indicator); *Treat (cont.)* is the continuous exposure measure.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9 shows no evidence of a promotion channel: neither the probability of supervising others nor the (log) number of direct reports changes for young women relative to men. Given the limited sample for counts, these results are suggestive but consistent with the "worse new jobs" interpretation rather than stalled promotions.

Finally, age heterogeneity adds corroborating evidence for the "worse new jobs" channel: younger women—who are more likely to be new entrants—experience significantly larger wage declines, while women ages 29–35 do not. I apply Equation (2) to young females in different age groups and present the results in Table 10, where the first and fourth columns are the same as the last two columns in Table 3 and serve as benchmark. Since the mean age at childbirth in China is around 28 in 2012 [4], I separate the sample by the age of 28. Among all treated young females, the annual wage income for females aged 18 to 28 decreases by an additional 21.5 percentage points compared to the average after the policy relaxation, while females aged 29 to 35 show no significant effect.

[4] United Nations, Department of Economic and Social Affairs, World Fertility Data (2019)

Table 10: Effect of OCP Relaxation on Female Wages by Age Group

	Panel A: Binary treatment			**Panel B: Continuous treatment**		
	≤ 35	> 28	≤ 28	≤ 35	> 28	≤ 28
	Dependent variable: *ln_wage*					
Years of schooling	0.078***	0.097***	0.060***	0.078***	0.097***	0.060***
	(0.009)	(0.018)	(0.012)	(0.010)	(0.017)	(0.012)
Age	0.455***	0.312	0.690***	0.455***	0.311	0.686***
	(0.072)	(0.348)	(0.228)	(0.072)	(0.350)	(0.229)
Age^2	-0.007***	-0.005	-0.012**	-0.007***	-0.005	-0.012**
	(0.001)	(0.006)	(0.005)	(0.001)	(0.006)	(0.005)
Treat × Female	-0.148*	0.052	-0.363**			
	(0.078)	(0.108)	(0.162)			
ConTreat × Female				-0.075**	0.008	-0.162*
				(0.030)	(0.032)	(0.084)
Observations	2,986	1,503	1,483	2,986	1,503	1,483
R^2	0.239	0.278	0.232	0.239	0.278	0.232
Year fixed effects	Y	Y	Y	Y	Y	Y
Province fixed effects	Y	Y	Y	Y	Y	Y
Clustered SE: Province	Y	Y	Y	Y	Y	Y

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3 Theoretical Model

In the previous section, I documented a 15.3% wage decline among young women in China following the relaxation of the One-Child Policy. Complementary empirical evidence suggests that this decline primarily reflects employers' downward adjustment of women's wages in response to revised fertility expectations, rather than changes in women's actual productivity or labor supply.

In this section, I develop a tractable equilibrium framework that links household time allocation to wage setting in a frictional labor market characterized by long-term contracts. The goal is to formalize the mechanism through which employers respond to changes in expected fertility and to explain why substantial wage reductions can arise even in the absence of observable changes in employment and women's initial human capital level.

The model integrates two interacting blocks. The household block delivers effort as a function of free time; effort governs learning-by-doing human capital accumulation and the effective use of accumulated capital. I then embed the difference in effort-driven productivity in a wage-posting model with on-the-job search: firms post fixed salaries at hire, matches separate either exogenously or when better offers arrive, and wages are priced off the present value of expected productivity over the match. I characterize the firm's profit function, the law of motion and cross-sectional stock of wages, prove continuity of the offer distribution, and state the equilibrium conditions. The key implication is that, even holding employment and initial human capital level fixed, differences in expected effort and accumulation translate into systematic wage differences through present-value pricing.

3.1 Household Collective Decision Model

Household problem. A household consists of one man (M) and one woman (F). Each individual has a unit time endowment. The household chooses time allocated to childcare (t_h^j) and market work (t_w^j) for $j \in \{M, F\}$ to maximize

$$\begin{aligned}
\max_{\{t_h^j, t_w^j\}_{j\in\{M,F\}}} \quad & \mathbf{1}\{\text{emp}^M = 1\}\, w^M + \mathbf{1}\{\text{emp}^F = 1\}\, w^F + \phi_H \log n + \phi_L \log\bigl(f^M + f^F\bigr) \\
\text{s.t.} \quad & \text{emp}^j = \mathbf{1}\{t_w^j \geq \underline{t}_w\}, \qquad j \in \{M, F\}, \\
& \gamma^F t_h^F + \gamma^M t_h^M \ \geq\ g(n), \\
& f^j = 1 - t_h^j - t_w^j, \qquad j \in \{M, F\}, \\
& t_h^j \geq 0, \ \ t_w^j \geq 0, \ \ t_h^j + t_w^j \leq 1, \qquad j \in \{M, F\}.
\end{aligned}$$

Here, w^j is the full-time wage for spouse j, and employment is a discrete outcome determined by the full-time threshold $\underline{t}_w$. The household derives utility from the number of children n (with weight $\phi_H > 0$) and from the *sum of partners' free time* $f^M + f^F$ (with weight $\phi_L > 0$). Childcare requires at least $g(n)$ units of effective time, where γ^j denotes spouse j's productivity in childcare.

Assumption 3.1 (Childcare productivity)**.** Women are, on average, more productive in childcare than men: $\gamma^F > \gamma^M$.

n is taken as exogenous in this section (so $\phi_H \log n$ is constant for the time-allocation problem). The function $g(n)$ is increasing in n with $g(0) = 0$, and all parameters are assumed positive unless stated otherwise.

Human capital accumulation rate. Because employment is discrete, optimal market hours satisfy $t_w^j \in \{0, \underline{t}_w\}$. Hence, among employed individuals ($t_w^j = \underline{t}_w$), variation in human capital accumulation is driven by effort ε^j, which depends on available *free time* $f^j \equiv 1 - t_h^j - \underline{t}_w$. Free time matters for at least two reasons: (i) adequate rest and recovery improve focus during fixed working hours; and (ii) many job-related investments occur off the clock (self-study, professional reading, business travel, client-maintenance activities). More free time implies more effort at work, and more effort at work accelerates the learning-by-doing process. Since childcare requirements $g(n)$ increase with the number of children n, available free time $f^j(n)$ is decreasing in n. I therefore model the accumulation rate for an individual with n children as

$$\alpha^j(n) = A\big(\varepsilon^j(n)\big), \qquad \varepsilon^j(n) = B\big(f^j(n)\big),$$

where $A : [0, 1] \to \mathbb{R}_+$ and $B : [0, 1] \to [0, 1]$ are increasing functions.

This simple household model yields several comparative-static implications. When there are no children ($n = 0$), the childcare constraint is slack. If both spouses work full-time ($t_w^j = \underline{t}_w$), then $f^M = f^F = 1 - \underline{t}_w$, and men and women accumulate human capital at exactly the same rate.

For small n, if the required childcare time $g(n)$ is low enough to be satisfied while both spouses remain employed—formally, if $g(n) \leq (\gamma^F + \gamma^M)\big(1 - \underline{t}_w\big)$—both partners continue to work full-time. Because Assumption 3.1 implies that women are relatively more productive in childcare, the efficient allocation assigns a greater share of childcare to the woman. Consequently, $f^M > f^F$, and since $A(\cdot)$ is increasing, men's human-capital accumulation exceeds women's even when both are employed full-time.

As the number of children n increases further, the childcare requirement tightens. Once it becomes infeasible—or too costly in terms of lost free time—to satisfy $g(n)$ while both spouses work at $\underline{t}_w$, the household switches to a corner solution in which one partner becomes a full-time caregiver. Because $\gamma^F > \gamma^M$, reallocating the woman to childcare yields more effective units of care per hour, making her the marginal worker more likely to exit the labor market.

Taken together, the model implies that even conditional on continued employment, higher fertility reduces the available free time $f^j(n)$ and thus lowers human-capital accumulation $\alpha^j(n) = A\big(f^j(n)\big)$. The decline is steeper for women, who shoulder a greater share of childcare, generating systematic gender differences in human-capital growth and, consequently, wages.

Employers' aggregate expectations about accumulation. With the household block in mind, a firm posting wage w to a worker of gender j faces uncertainty about the worker's future fertility $n \in \{0, 1, 2, \dots\}$ and, therefore, about the match–specific accumulation rate $\alpha^j(n) = A\big(f^j(n)\big)$. Let p_n^j denote the firm's predictive probabilities. Expected profit at w integrates over n:

$$\mathbb{E}\big[\Pi^j(w)\big] \;=\; \sum_{n\geq 0} \Pi^j\big(w; \alpha^j(n)\big)\, p_n^j.$$

Because employers form aggregate expectations and Assumption 3.1 holds, the gender-specific accumulation rates generally satisfy $\alpha^M \geq \alpha^F$.

Proposition 3.2 (Endogenous gender gap in accumulation)**.** *Under Assumption 3.1 ($\gamma^F > \gamma^M$), in any period in which both spouses are employed at $t_w^j = \underline{t}_w$,*

$$f^M \geq f^F \quad \Rightarrow \quad \alpha^M = A(f^M) \geq A(f^F) = \alpha^F,$$

with strict inequality whenever $n > 0$ and A is strictly increasing.

3.2 Labor Market Environment

Time is continuous and I focus on steady-state analysis. The economy features two segmented labor markets indexed by gender $j \in \{F, M\}$. In each submarket there is a continuum of infinitely lived, *ex ante* identical workers of measure m^j and a unit measure of firms. Differences in human capital accumulation rates α^j (stemming from the household problem above) imply potentially different wage-posting equilibria across gender j.

Each worker is either employed (1) or unemployed (0). Unemployed workers receive a benefit b^j, while employed workers earn a posted wage w^j. Regardless of employment status, job offers arrive as independent Poisson processes with rates λ_0^j for the unemployed and λ_1^j for the employed. Offers take the form of take-it-or-leave-it contracts with wage draws w^j from a continuous cdf F^j. The parameters $(b^j, \lambda_0^j, \lambda_1^j)$ may differ by gender.

Firms post wages and commit to them; there is no on-the-spot renegotiation or counter offering after an outside offer arrives.[5] Separations occur either exogenously at rate δ^j or endogenously when the worker receives a strictly higher outside offer. Thus, the separation hazard for a worker employed at wage w is

$$h^j(w) \;=\; \delta^j \;+\; \lambda_1^j\big(1 - F^j(w)\big),$$

where the second term is the arrival rate of offers exceeding w. Ties have measure zero by continuity of F^j. I interpret an outside offer as a new position on the wage ladder—either an internal promotion or a move to another firm; the model abstracts from this distinction.

3.3 Workers' Human Capital Accumulation Process

Production uses only workers' human capital: one unit of *effective* human capital produces one unit of output, so a firm's output equals the sum of its employees' effective human capital. For a worker of gender $j \in \{F, M\}$ with tenure $\tau \geq 0$ and n children, I write

$$\text{effective human capital} \;=\; \varepsilon^j(n)\, z^j(\tau),$$

where the effort (or intensity) at work $\varepsilon^j(n) \in (0,1)$ multiplies the accumulated stock $z^j(\tau)$. Effort depends on available free time—hence on n—as discussed in Section 3.1; fewer free–time resources imply lower $\varepsilon^j(n)$. Lower effort slows down the accumulation of human capital via learning-by-doing, and thus match-specific accumulation is also affected by the

[5] This "no counteroffer" assumption is standard in on-the-job search models (e.g., Burdett and Mortensen (1998)) and is also consistent with environments featuring rigid pay scales and limited within-firm bargaining (e.g., civil-service settings).

number of children, n:

$$z^j(\tau) = z_0 \exp\bigl(\alpha^j(n)\,\tau\bigr), \qquad z_0 > 0, \quad \alpha^j(n) > 0, \tag{3}$$

and accrues only while employed; upon separation, tenure resets and z^j reverts to z_0. Thus a worker's instantaneous productivity is $\varepsilon^j(n)\,z_0 \exp\bigl(\alpha^j(n)\,\tau\bigr)$.

The accumulation rate $\alpha^j(n)$ is determined in the household block as a function of efforts and therefore, free time of gender j (Section 3.1). By Proposition 3.2, $\alpha^M(n) \geq \alpha^F(n)$ whenever both spouses work. This pattern aligns with "greedy jobs" where long hours and continuous availability are rewarded while flexibility is penalized Goldin (2014): free time provides the slack for off–the–clock investment. Because family responsibilities compress women's free time and therefore, on average, their implied accumulation rates—and hence wages—are lower. Equilibrium wage schedules in segmented markets inherit these gender–specific $\varepsilon(n)\alpha^j(n)$.

3.4 Firms' Wage–Posting Problem

Firms post wages in segmented submarkets indexed by gender $j \in \{F, M\}$. Let F^j denote the cdf of posted offers with support $\bigl[R^j, \overline{w}^j\bigr]$, and let $(\lambda_0^j, \lambda_1^j, \delta^j)$ be, respectively, the offer arrival rates for unemployed and employed workers and the exogenous separation rate. Given a posted wage w, an employed worker faces a constant separation hazard

$$h^j(w) \;\equiv\; \delta^j + \lambda_1^j\bigl[1 - F^j(w)\bigr], \qquad \text{and } S^j(\tau \mid w) = \exp\bigl(-h^j(w)\tau\bigr),$$

where $S^j(\tau \mid w)$ is the survival probability in the current job up to tenure τ.

Per–worker value to the firm. A worker with tenure τ supplies match-specific effective human capital $\varepsilon^j(n), z^j(\tau) = \varepsilon^j(n), z_0 \exp!\bigl(\alpha^j(n)\tau\bigr)$ (see Section 3.3). Given a posted wage w, the firm's *per-hire* expected profit is the present value of the contemporaneous margin, integrated up to the (random) separation time:

$$\mathbb{E}\big[\pi^j(w)\big] = \int_0^\infty \big[\sum_{n=0}^{n=\overline{n}} z_0 \varepsilon^j(n) e^{\alpha^j(n)\tau} p_n^j - w\big] \; S^j(\tau \mid w)\, d\tau$$
$$= \sum_{n=0}^{n=\overline{n}} \frac{z_0 \varepsilon^j(n) p_n^j}{h^j(w) - \alpha^j(n)} - \frac{w}{h^j(w)}$$

which is finite whenever $\alpha^j(n) < h^j(w)$ for all n. A sufficient, wage–uniform condition is $\alpha^j(n) < \delta^j$ since $h^j(w) \geq \delta^j$ for all w.

Employment stock at wage w. Let m^j be the measure of type–j workers and u^j the steady–state unemployment mass. Denote by $G^j(w)$ the cross–sectional wage cdf among the employed. The law of motion for $G^j(w,t)$ is

$$\frac{\partial G^j(w,t)}{\partial t} = \underbrace{\lambda_0^j \big[F^j(w) - F^j(R^j)\big]\, u^j(t)}_{\text{inflow from unemployment}} - \underbrace{\big[\lambda_1^j\big(1 - F^j(w)\big) + \delta^j\big]\, G^j(w,t)\, \big(m^j - u^j(t)\big)}_{\text{outflow to higher offers or separations}},$$

for $w \geq R^j$ (the inflow term is zero for $w < R^j$). In a stationary equilibrium,

$$\frac{\partial G^j(w,t)}{\partial t} = 0 \quad \text{and} \quad \lambda_0^j\big[1 - F^j(R^j)\big] u^j = \delta^j\big(m^j - u^j\big),$$

so

$$G^j(w) = \frac{\delta^j\big[F^j(w) - F^j(R^j)\big]}{h^j(w)\,\big[1 - F^j(R^j)\big]},$$

where $h^j(w) \equiv \delta^j + \lambda_1^j\big(1 - F^j(w)\big)$. Let $l^j(w)$ denote the equilibrium stock of employees (per unit mass of firms) earning exactly w. Using G^j and F^j,

$$\begin{aligned}
l^j(w) &= \lim_{\epsilon \to 0} \frac{G^j(w) - G^j(w - \varepsilon)}{F^j(w) - F^j(w - \epsilon)}\,(m^j - u^j) \\
&= \lim_{\epsilon \to 0} \frac{F^j(w)\, h^j(w-\epsilon) - F^j(w-\epsilon)\, h^j(w) + F^j(R^j)\big[h^j(w) - h^j(w-\epsilon)\big]}{\big[h^j(w)\, h^j(w-\epsilon)\big]\big[1 - F^j(R^j)\big]\big[F^j(w) - F^j(w-\epsilon)\big]}\,(m^j - u^j)\,\delta^j \\
&= \lim_{\epsilon \to 0} \frac{\delta^j + \lambda_1^j\big(1 - F^j(R^j)\big)}{h^j(w)\, h^j(w-\epsilon)}\; \lambda_0^j u^j.
\end{aligned}$$

(the intermediate steps are in Appendix A.1). In equilibrium, no firm posts below R^j so $F^j(R^j) = 0$, and if F^j is continuous, which I am going to prove in the next part,

$$l^j(w) = \frac{\left(\delta^j + \lambda_1^j\right)\lambda_0^j u^j}{\left[h^j(w)\right]^2} = \frac{\left(\delta^j + \lambda_1^j\right)\lambda_0^j}{\left[h^j(w)\right]^2} \cdot \frac{\delta^j m^j}{\delta^j + \lambda_0^j}.$$

No mass points in F^j. In a wage-posting equilibrium, F^j is continuous on its support. If there were an atom at some interior w, a firm that deviates to $w + \varepsilon$ (for arbitrarily small $\epsilon > 0$) would induce a discrete fall in $h^j\big(w+\epsilon\big) = \delta^j + \lambda_1^j\big(1 - F^j(w+\epsilon)\big)$, which strictly raises the employment stock $l^j(w)$ and lengthens expected tenure per hire. The only first–order cost is the infinitesimal increase in the posted wage, which reduces the per-hire margin by ϵ. The discrete gains dominate, yielding a profitable deviation—contradicting equilibrium profit equalization. Hence:

Lemma 3.3 (No mass points in F^j on the interior of its support)**.** *Fix $j \in \{F, M\}$. In any stationary wage–posting equilibrium, the offer cdf F^j is continuous on $(R^j, \overline{w}^j)$.*

The full proof of Lemma 3.3 is provided in Appendix A.2.

Expected profit per posted wage (flow). Consider a firm that posts wage w in sub-market $j \in \{F, M\}$. Let $n^j(w)$ denote the *per–firm inflow* (per unit time) of new hires at wage w. A cohort hired at rate $n^j(w)$ has survival $S^j(\tau \mid w) = \exp[-h^j(w)\tau]$, so after tenure τ the expected number of remaining employees from that cohort is $n^j(w)\, S^j(\tau \mid w)$. In a stationary equilibrium $n^j(w)$ is time–invariant and depends only on w.

The expected profit generated by that cohort is

$$\begin{aligned}
\mathbb{E}\big[\Pi^j_{\text{cohort}}(w)\big] &= \int_0^\infty \big[\sum_n z_0 \varepsilon^j(n) e^{\alpha^j(n)\tau} p_n^j - w\big]\; n^j(w)\, S^j(\tau \mid w)\, d\tau \\
&= n^j(w) \int_0^\infty \big[\sum_n z_0 \varepsilon^j(n) e^{\alpha^j(n)\tau} p_n^j - w\big] e^{-h^j(w)\tau} d\tau \\
&= n^j(w) \left(\sum_{n=0} \frac{z_0 \varepsilon^j(n) p_n^j}{h^j(w) - \alpha^j(n)} - \frac{w}{h^j(w)} \right),
\end{aligned}$$

which is finite whenever $\alpha^j(n) < h^j(w)$. The equilibrium stock of employees at wage w (per firm), $l^j(w)$, is the integrated surviving cohort:

$$l^j(w) = \int_0^\infty n^j(w)\, S^j(\tau \mid w)\, d\tau = \frac{n^j(w)}{h^j(w)}.$$

Hence,

$$\mathbb{E}\big[\Pi^j(w)\big] = \left(\sum_{n=0} \frac{z_0 \varepsilon^j(n) p_n^j h^j(w)}{h^j(w) - \alpha^j(n)} - w \right) l^j(w). \tag{4}$$

Substituting the equilibrium stock $l^j(w)$ into (4) yields the expected profit per posted wage [6]:

$$\mathbb{E}\big[\Pi^j(w)\big] = \frac{\big(\delta^j + \lambda_1^j\big)\lambda_0^j u^j}{\big[h^j(w)\big]^2} \left(\sum_{n=0} \frac{z_0 \varepsilon^j(n) p_n^j h^j(w)}{h^j(w) - \alpha^j(n)} - w \right). \tag{5}$$

Expression (5) makes the trade-off transparent: raising w lowers the separation hazard $h^j(w)$, which (i) enlarges the employment stock $l^j(w) \propto [h^j(w)]^{-2}$ (attraction/retention) and (ii) increases the value of long tenures via $z_0 h^j(w)/\big(h^j(w) - \alpha^j\big)$. At the same time, a higher w compresses the per-hire margin through the $(-\,w)$ term. The net effect on profits is therefore ambiguous and pins down the equilibrium wage distribution.

3.5 Workers' Lifetime Utility Maximization Problem

The worker's side problem is standard as in the search and match literature. Workers maximize their life-time utility on either employed or unemployed status. I use subscripts (0) and (1) to denote them respectively. When unemployed, workers' the Bellman equation can be expressed as solution to the following asset pricing problem: the interest rate on being unemployed is equal to unemployed benefits, b^j, plus the expected gain from searching for an acceptable job that the wage level is above R^j.

$$r\, V_0^j = b^j + \lambda_0^j \int_{R^j}^{\overline{w}^j} \big[\, V_1^j(x) - V_0^j \,\big]\, dF^j(x).$$

[6] When $\alpha^j(n) = 0$ and $\varepsilon^j(n) = 1$ the expressions collapse to the standard Burdett–Mortensen case.

Similarly, when employed at wage w^j, $V_1^j(w^j)$ follows:

$$r\,V_1^j(w) = w + \lambda_1^j \int_w^{\overline{w}^j} \left[\, V_1^j(x) - V_1^j(w) \,\right] \, dF^j(x) + \delta^j \left[\, V_0^j - V_1^j(w) \,\right], \qquad w \in [R^j, \overline{w}^j].$$

As argued in Burdett and Mortensen (1998), $V_1(\cdot)$ is increasing in w^j and V_0 is independent of w^j, and thus, we could identify a reservation wage R^j such that

$$V_0^j = V_1^j(R^j), \qquad V_1^j(w) \geq V_1^j(R^j) \;\; \forall\, w \geq R^j.$$

and derive an equation in a format similar to that in Burdett and Mortensen (1998):

$$R^j - b^j = \left(\lambda_0^j - \lambda_1^j\right) \int_{R^j}^{\overline{w}^j} \left[\, V_1^j(x) - V_0^j \,\right] \, dF^j(x) \tag{6}$$

$$= \left(\lambda_0^j - \lambda_1^j\right) \int_{R^j}^{\overline{w}^j} \frac{1 - F^j(x)}{r + \delta^j + \lambda_1^j\left(1 - F^j(x)\right)} \, dx \tag{7}$$

3.6 Equilibrium

Definition 3.4 (Stationary mixed–strategy wage–posting equilibrium)**.** Fix gender $j \in \{F, M\}$ and parameters $(m^j, r, b^j, \lambda_0^j, \lambda_1^j, \delta^j, z_0, \alpha^j)$. A *stationary mixed–strategy wage–posting equilibrium* is a tuple

$$\left(F^j, G^j, u^j, R^j, \overline{w}^j\right),$$

where F^j is the cdf of posted wage offers in market j, G^j is the cross–sectional cdf of accepted wages among the employed, u^j is the mass of unemployed workers, R^j is the reservation wage, and $\overline{w}^j$ is the upper bound of the offer support, such that the following conditions hold:

(i) **Worker optimality.** Unemployed workers follow a reservation rule: accept any offer $w \geq R^j$; employed workers accept any strictly higher offer $w' > w$. Ties have measure zero by continuity. The reservation rule satisfies Equation (7).

(ii) **Firm optimality (no profitable deviation).** A measure–zero firm takes F^j—and hence $h^j(w) = \delta^j + \lambda_1^j[1 - F^j(w)]$—as given and chooses a (possibly mixed) posting strategy σ, a probability measure on $[R^j, \overline{w}^j]$, to maximize expected profits:

$$\max_{\sigma} \int \mathbb{E}\big[\Pi^j(w; F^j)\big] \; d\sigma(w),$$

where

$$\mathbb{E}\big[\Pi^j(w; F^j)\big] = \frac{(\delta^j + \lambda_1^j)\, \lambda_0^j\, u^j}{[h^j(w)]^2} \left(\sum_{n=0} \frac{z_0 \varepsilon^j(n) p_n^j\, h^j(w)}{h^j(w) - \alpha^j(n)} - w \right) \qquad \text{(cf. Eq. (5))}.$$

There exists a nonempty set $W^j \subseteq [R^j, \overline{w}^j]$ and a constant $\bar{\pi}^j$ such that

$$\mathbb{E}[\Pi^j(w; F^j)] = \bar{\pi}^j \text{ for all } w \in W^j, \qquad \mathbb{E}[\Pi^j(w; F^j)] \leq \bar{\pi}^j \text{ for all } w \notin W^j,$$

and any equilibrium mixed strategy satisfies $\mathrm{supp}(\sigma) \subseteq W^j$.

(iii) **Support and regularity.** F^j is a valid cdf supported on $[R^j, \overline{w}^j]$, with $F^j(R^j) = 0$ and (if finite) $F^j(\overline{w}^j) = 1$. There are no mass points on $(R^j, \overline{w}^j)$ (Lemma 3.3).

(iv) **Flow balance and cross–sectional consistency.** Steady–state flows satisfy

$$\lambda_0^j \big[1 - F^j(R^j)\big]\, u^j = \delta^j \big(m^j - u^j\big),$$

and the implied cross–sectional wage distribution among the employed is

$$G^j(w) = \frac{\delta^j \big[F^j(w) - F^j(R^j)\big]}{h^j(w) \big[1 - F^j(R^j)\big]}, \qquad w \in [R^j, \overline{w}^j].$$

(v) **Stationarity.** All equilibrium objects $(F^j, G^j, u^j, R^j, \overline{w}^j)$ are time–invariant and jointly consistent with the hazard rates $h^j(w)$ induced by F^j.

4 Solution Method and Estimation Results

This section brings the model to the data and quantifies the role of expected productivity in labor markets with contracted labor. I recast the equilibrium conditions in a form suitable for computation, describe the algorithm that recovers the offer distribution from parameters, and estimate these parameters by matching the model-implied wage CDFs to the CFPS distributions (2012 baseline and 2014 post-reform). I show the baseline fit, re-estimate the model after the policy relaxation, and conduct counterfactuals that (i) equalize family-work time, and (ii) update only fertility expectations to quantify how expectation-driven pricing accounts for both the baseline gap and its post-reform widening.

4.1 Numerical Solution

Fix a gender submarket j and suppress the superscript j. In equilibrium, firms' and workers' behaviors are optimal and flows are time-invariant. I rewrite the equilibrium conditions, which are equivalent to what have been introduced in Section 3 but now more suitable for deriving a numerical solution.

First, for all w in the support of the posted-offer cdf F [7],

$$\mathbb{E}[\Pi(w)] = \frac{(\delta+\lambda_1)\lambda_0 u}{\left[h(w)\right]^2}\left(\sum_{n=0} \frac{z_0\varepsilon(n)p_n h(w)}{h(w)-\alpha(n)} - w\right) = \bar{\pi}. \tag{8}$$

where $h(w) \equiv \delta+\lambda_1\left[1-F(w)\right]$ and thus, $h(R)=\delta+\lambda_1$, and $h(\overline{w})=\delta$. Equation 8 evaluated

[7]Note that the stock of currently employed workers at posted wage w per unit mass of firm is shown in the equation and is $l(w)=(\delta+\lambda_1)\,\lambda_0\,u/\left[h(w)\right]^2$, so $l(w)$ is increasing in w because $h(w)=\delta+\lambda_1\big(1-F(w)\big)$ is decreasing in w. At the endpoints, $l(R)=\lambda_0 u/\left(\delta+\lambda_1\right)$, $\quad l(\overline{w})=(\delta+\lambda_1)\,\lambda_0 u/\delta^2$. As in the canonical Burdett–Mortensen setting, higher-paying jobs retain larger employment stocks. While this monotonicity may overstate concentration at the very top in some labor markets, it is less extreme in my estimation sample, which is restricted to tertiary-educated workers under age 35. Their "upper end" of the wage distribution is not an extreme, superstar tail. Most workers are still in early–mid career, with similar tenure, ladders, and task scopes; the wage support's upper bound is not far from the bulk of the distribution. Thus, the model's "top-end clustering" should be read as many young, relatively homogeneous workers holding good (but not extreme) jobs at large platforms/public institutions/SOEs or big teams, rather than a few individuals in ultra-high-pay niches.

at the endpoints gives

$$\mathbb{E}\big[\Pi(R)\big] = \frac{\lambda_0 u}{\delta+\lambda_1}\left(\sum_{n=0} \frac{z_0\varepsilon(n)p_n(\delta+\lambda_1)}{\delta+\lambda_1-\alpha(n)} - R\right),$$
$$\mathbb{E}\big[\Pi(\overline{w})\big] = \frac{\big(\delta+\lambda_1\big)\lambda_0 u}{\delta^2}\left(\sum_{n=0} \frac{z_0\varepsilon(n)p_n\delta}{\delta-\alpha(n)} - \overline{w}\right).$$

Equalizing profits at R and $\overline{w}$ pins down the upper endpoint:

$$\overline{w} = \sum_{n=0} \frac{z_0\varepsilon(n)p_n\delta}{\delta-\alpha(n)} - \frac{\delta^2}{(\delta+\lambda_1)^2}\left(\sum_{n=0} \frac{z_0\varepsilon(n)p_n(\delta+\lambda_1)}{\delta+\lambda_1-\alpha(n)} - R\right) \tag{$*$}$$

which is well defined under $\alpha(n) < \delta$.

Equivalently, rearranging (8) yields the convenient implicit equation (constant in w on the support)

$$\sum_{n=0} \frac{z_0\varepsilon(n)p_n}{\big(h(w)-\alpha(n)\big)\,h(w)} - \frac{w}{[h(w)]^2} = \sum_{n=0} \frac{z_0\varepsilon(n)p_n}{(\delta+\lambda_1-\alpha(n))\,(\delta+\lambda_1)} - \frac{R}{(\delta+\lambda_1)^2} \tag{$**$}$$

On the worker side, remember R is the reservation wage and $\overline{w}$ the upper support. The reservation condition implies

$$R - b = (\lambda_0 - \lambda_1)\int_R^{\overline{w}} \frac{1-F(x)}{r+\delta+\lambda_1\big(1-F(x)\big)}\,dx. \tag{$***$}$$

Numerical solution (computing $F(w)$ given parameters). The equilibrium is characterized by three equations, $(*)$, $(**)$, and $(***)$. Our goal is to solve for the endogenous offer cdf $F(w)$.

Fix a gender submarket j and suppress the superscript. Given $\theta = (r, z, b, \delta, \lambda_0, \lambda_1, \alpha)$, recover the stationary F on $[R, \overline{w}]$ as follows. For a trial reservation wage $R \in [R_{\min}, R_{\max}]$, compute the upper endpoint $\overline{w}$ from $(*)$. On a fine grid $\{w_k\}_{k=1}^{K} \subset [R, \overline{w}]$, solve the implicit equal–profit condition $(**)$ for the hazard $h(w_k)$ at each node. Then back out the offer cdf pointwise via

$$F(w_k) = 1 - \frac{h(w_k)-\delta}{\lambda_1},$$

and impose $F(R) = 0$ and $F(\overline{w}) = 1$. A monotone interpolant of $\{(w_k, F(w_k))\}_{k=1}^K$ yields a continuous F on $[R, \overline{w}]$.

Given the implied F, evaluate the reservation equation $(***)$ and define the one–dimensional residual

$$\phi(R) \equiv \big(R - b\big) - (\lambda_0 - \lambda_1) \int_R^{\overline{w}} \frac{1 - F(x)}{r + \delta + \lambda_1\big(1 - F(x)\big)}\, dx.$$

Choose R^* such that $\phi(R^*) = 0$ (e.g., by a bracketing root–finder), and take the associated F as the equilibrium offer distribution.

Finally, the observed cross–sectional wage cdf G is recovered from F via the one–to–one mapping

$$G(w) = \frac{\delta\, F(w)}{\delta + \lambda_1\big(1 - F(w)\big)} \qquad \Longleftrightarrow \qquad F(w) = \frac{(\delta + \lambda_1)\, G(w)}{\delta + \lambda_1 G(w)}\,. \tag{9}$$

4.2 Identification Argument

This subsection justifies the estimation strategy. For simplicity, I omit gender superscripts unless necessary. Given the observed wage distribution $G(w)$ for either gender j, I show that—under mild regularity conditions and after fixing the discount rate r and the separation rate δ—the structural parameters

$$\theta \;=\; \Big(\{\alpha(n)\}_n,\ \lambda_0,\ \lambda_1,\ \delta,\ b,\ z_0,\ \{\varepsilon(n)\}_n\Big)$$

are identified from equilibrium restrictions for each gender j.

Suppose $G(w)$ were insufficient to identify θ. Then there would exist $\theta' \neq \theta$ that generates the same $G(w)$ on the same support $[R, \overline{w}]$. I show below, in three steps, that such a θ' cannot exist.

Step 1. Identification of $\{\alpha(n)\}_n$, $\{\varepsilon(n)\}_n$, and z_0 given (δ, λ_1) Fix (δ, λ_1) and suppose $\{p_n\}_n$ are known from the data. Given $G(w)$, we can recover $F(w)$ and hence $h(w)$ since

$$F(w) \;=\; \frac{(\delta + \lambda_1)\, G(w)}{\delta + \lambda_1\, G(w)} \quad \Longrightarrow \quad h(w) \;=\; \delta + \lambda_1\big(1 - F(w)\big) \;=\; \frac{\delta(\delta + \lambda_1)}{\delta + \lambda_1\, G(w)}.$$

Evaluating the firm's profit condition at $w = R$ and at a generic w, and eliminating $\bar{\pi}$, yields

$$w = \frac{h(w)^2}{(\delta+\lambda_1)^2}\,R + \sum_{n\geq 0} z_0\,\varepsilon(n)\,p_n\left(\frac{h(w)}{h(w)-\alpha(n)} - \frac{h(w)^2}{(\delta+\lambda_1)\,[\delta+\lambda_1-\alpha(n)]}\right). \tag{10}$$

If another parameter set $(z_0', \{\varepsilon'(n)\}_n, \{\alpha'(n)\}_n)$ with the same (δ, λ_1) generates the same mapping $w(\cdot)$ for all w, subtracting the analogue of (10) produces an identity in $h(w)$ that pins down $\{\alpha(n), z_0\varepsilon(n)\}_n$ up to a permutation. After normalizing at $\varepsilon(n_0)$, this separates z_0 from $\varepsilon(n)$, as formalized below.

Theorem 4.1 (Identification with fixed separation and offer arrival rates)**.** *Let $\{p_n\}_{n\geq 0}$ be fixed with $p_n \geq 0$ observed from data. Assume:*

(a) $h(w)$ is nonconstant over w and its range contains an interval $I = [\delta, \delta+\lambda_1]$ with $\delta > \sup_n \alpha(n)$, so that $\alpha(n) \notin I$ and $\delta + \lambda_1 - \alpha(n) \neq 0$ for all n;

(b) The values $\{\alpha(n) : 0 < \alpha(n) < \delta\}$ are pairwise distinct;

(c) Normalize $\varepsilon(n_0) = \bar{\varepsilon}$ (so individuals with no children have normalized effort equal to one).

Without loss of generality, set $(\delta + \lambda_1) = 1$ for exposition. If for every w,

$$\sum_{n\geq 0} p_n z_0 \varepsilon(n)\left(\frac{h(w)}{h(w)-\alpha(n)} - \frac{h(w)^2}{1-\alpha(n)}\right) = \sum_{n\geq 0} p_n z_0' \varepsilon'(n)\left(\frac{h(w)}{h(w)-\alpha'(n)} - \frac{h(w)^2}{1-\alpha'(n)}\right),$$

then there exists a permutation ω of $\{n : \alpha(n) \neq 0\}$ such that

$$\alpha'(\omega(n)) = \alpha(n), \qquad z_0'\varepsilon'(\omega(n)) = z_0\varepsilon(n) \quad (\forall\, \alpha(n) \neq 0).$$

Moreover, $z_0 = z_0'$ and hence $\varepsilon(n) = \varepsilon'(\omega(n))$ for all $\alpha(n) \neq 0$.

See Appendix A.3 for the proof.

Step 2. Identification of $(\lambda_1, \tilde{\alpha}, \tilde{z}_0)$ given δ Given (δ, λ_1), we have identified $\{\alpha(n), \varepsilon(n)\}$ for all n. For exposition, collapse heterogeneity by defining

$$\tilde{\alpha} \;\equiv\; \text{mean}\{\alpha(n)\}, \qquad \tilde{z}_0 \;\equiv\; \text{mean}\{z_0\varepsilon(n)\}.$$

Then the profit condition simplifies to

$$\mathbb{E}[\Pi(w)] \;=\; \frac{(\delta+\lambda_1)\lambda_0 u}{h(w)^2}\left(\frac{\tilde{z}_0\, h(w)}{h(w)-\tilde{\alpha}} - w\right) \;=\; \bar{\pi}, \qquad h(w) = \frac{\delta(\delta+\lambda_1)}{\delta+\lambda_1\, G(w)}.$$

Eliminating $\bar{\pi}$ using $G(R)=0$ (so $h(R)=\delta+\lambda_1$) gives

$$w(G) = \frac{\tilde{z}_0\, \delta(\delta+\lambda_1)}{\delta(\delta+\lambda_1) - \tilde{\alpha}\left(\delta+\lambda_1\, G\right)} \;-\; \frac{\delta^2}{\left(\delta+\lambda_1\, G\right)^2}\left[\frac{\tilde{z}_0(\delta+\lambda_1)}{(\delta+\lambda_1)-\tilde{\alpha}} - R\right]. \tag{11}$$

Let $k_1 = \lambda_1/\delta$ and $a = \tilde{\alpha}/\delta$. Then

$$w(G) \;=\; \frac{\tilde{z}_0(1+k_1)}{(1+k_1) - a(1+k_1 G)} \;+\; \frac{K}{(1+k_1 G)^2}, \qquad K \;:=\; R \;-\; \frac{\tilde{z}_0(1+k_1)}{(1+k_1)-a}.$$

By uniqueness of partial fractions, if $K \neq 0$ the pole locations and residues uniquely determine $(k_1, a, \tilde{z}_0)$; given δ, this pins down $(\lambda_1, \tilde{\alpha}, \tilde{z}_0)$.

Step 3. Identification of (λ_0, b) Given (δ, λ_1) and observed $F(\cdot)$, the reservation-wage condition identifies a linear relationship in (λ_0, b):

$$R - b \;=\; (\lambda_0 - \lambda_1)\int_R^{\overline{w}} \frac{1-F(x)}{r+\delta+\lambda_1\,[1-F(x)]}\,dx \;=:\; C\,\lambda_0 - C\,\lambda_1,$$

where C is known from $(F, \delta, \lambda_1, r)$. A second restriction follows from steady-state flow balance:

$$\lambda_0\, u \;=\; \delta\,(m-u) \quad\Longrightarrow\quad \lambda_0 \;=\; \delta\,\frac{m-u}{u}.$$

Hence λ_0 is pinned down by the observed unemployment rate u/m, after which b follows from the reservation-wage equation.

Summary

- *Step 1:* Given (δ, λ_1) and the normalization $\varepsilon(0) = \bar{\varepsilon}$, the equilibrium profit identity identifies $\{\alpha(n)\}_n$, z_0, and $\{\varepsilon(n)\}_n$ from G and h, up to permutation (with caveats for repeated or zero α).
- *Step 2:* Given δ, the mapping $G \mapsto w(G)$ identifies $(\lambda_1, \tilde{\alpha}, \tilde{z}_0)$ (except in the knife-edge

case $K = 0$).

- *Step 3:* The reservation-wage and flow-balance equations jointly identify (λ_0, b).

Altogether, the structural parameter vector θ^j is point-identified under these conditions.

4.3 Estimation

In this subsection, I use Chinese wage data from 2012 and 2014 to estimate the parameters governing the equilibrium wage distribution before and after the policy relaxation. The analysis serves three purposes. First, I estimate the pre-policy parameters to characterize the labor markets for women and men and to decompose the residual gender wage gap—after controlling for observables—to assess how much of it can be explained by the lower expected-productivity channel, which is the focus of this paper. Second, I re-estimate the parameters using post-policy data, treating the labor market as a black box, to infer how employers adjusted expectations and offer behavior following the policy change, and thus, to check whether the expectation channel really matters. Third, I conduct counterfactual exercises to examine whether, in the absence of lifetime job security (i.e., allowing for positive separation probabilities besides aging out), the observed wage decline would have been smaller.

I retain the sample used in the difference-in-differences analysis in Section 2 and construct gender-specific wage distributions before and after the OCP relaxation (2012 and 2014). For each gender–year cell, I estimate the parameter vector

$$\theta_t^j = \Big(\{\alpha^j(n)\}_n,\ \lambda_{0,t}^j,\ \lambda_{1,t}^j,\ \delta^j,\ b^j,\ z_{0,t},\ \{\varepsilon^j(n)\}_n\Big)$$

by squared minimum distance (L2 norm) between the model-implied employed-wage distribution, $G(\cdot;\theta)$, and the empirical CDF $\widehat{G}(\cdot)$. The model assumes that both genders share a common initial human capital level in year t, denoted $z_{0,t}$. Accordingly, I work with residual wages net of year[8], province, education, and industry fixed effects to align the data with the model's normalization of z_0. The assumption of a gender-common $z_{0,t}$ is motivated by

[8]Controlling for year fixed effects removes average wage differences across years but does not ensure that the normalized initial human capital $z_{0,t}$ is constant over time. In practice, $z_{0,t}$ may still vary nonlinearly across years, which the estimation allows to capture.

the fact that gender differences in educational attainment have largely disappeared or even reversed in China. Thus, there is no empirical basis to assume that young women graduating from the same or better universities start with a lower level of human capital than their male peers.

Except for the common $z_{0,t}$, all other parameters are gender-specific, including the offer arrival rates while employed ($\lambda_{1,t}^j$) and while unemployed ($\lambda_{0,t}^j$), the unemployment benefits (b^j), the exogenous separation rates (δ^j), the human capital accumulation rates conditional on marriage and fertility status ($\alpha^j(n)$), and the effort levels ($\varepsilon^j(n)$). I assume that the unemployment benefits b^j and the exogenous separation rates remain constant over time, and that the mappings from n to effort, $\varepsilon(n)$, and from effort to human capital accumulation, $\alpha(n)$, are stable across survey years.

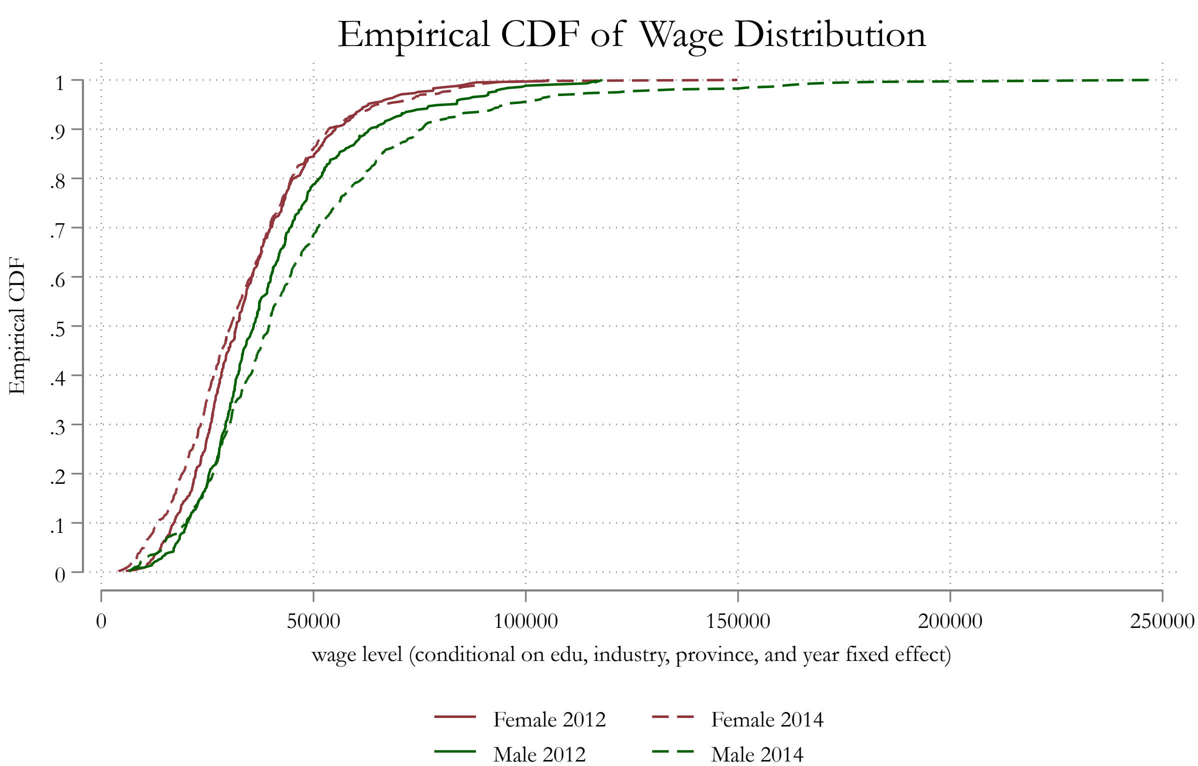


Figure 4: Employed-wage CDFs before and after the OCP relaxation

Figure 4 plots the empirical wage CDFs: solid lines represent the pre-OCP period (2012), and dashed lines represent the post-OCP period (2014). Two patterns stand out. First, the female CDF shifts only slightly overall, with a modest leftward movement in the lower quantiles. This suggests that new female entrants to the labor market found it harder to obtain high-paying jobs after the policy change and thus accepted lower wages. Second, the male CDF shifts noticeably to the right, particularly in the upper quantiles, indicating that men's wages rose, especially among high earners. Examining the full distribution, rather than focusing solely on average wages, allows the analysis to extract more information from a limited sample and to identify which parts of the wage distribution drive the observed changes in average earnings identified in the empirical part.

4.3.1 Calibration for Pre-Determined Parameters

Consistent with the identification discussion in Section 4.2, a few parameters are fixed exogenously so that the remaining objects are identified within the model.

Discounting rate. I set the annual discount rate to $r = 0.05$, as is standard in the literature.

Exogenous separation. In a wage-posting environment where firms do not fire workers within matches, "separation" is best interpreted as match termination for reasons outside the firm's control. In China's market for highly educated workers—where government-related jobs are prevalent and tenure-like employment security is common—this primarily reflects exits from the labor force or from the estimation window (e.g., aging out of the 18–35 sample), rather than displacement. I therefore set δ equal to the demography-driven "age-out" hazard.[9]

In steady state, the outflow from employment equals the inflow from unemployment: $\delta^j(m^j - u^j) = \lambda_0^j u^j$. Interpreting δ^j as the age-out rate implies that, each year, $\delta^j(m^j - u^j)$ workers leave employment and an equivalent mass of new graduates enters the labor force, keeping m^j stable. Likewise, for the unemployment pool, $\lambda_0^j u^j$ workers are hired and replaced by $\delta^j(m^j - u^j)$ new entrants, so u^j remains stationary. Treating δ^j as an "age-out" hazard introduces a life-cycle element into this otherwise static equilibrium model. New entrants—recent graduates entering the labor market—begin as temporarily unemployed,

[9]This "age-out" separation rate should be viewed as a lower bound for the true δ, since it excludes exits due to health, family, or other personal reasons—including cases where women leave the labor market to become full-time homemakers or caregivers.

receive an initial job offer, and remain in that match for the rest of their careers unless they receive and accept a better wage offer, analogous to a promotion.

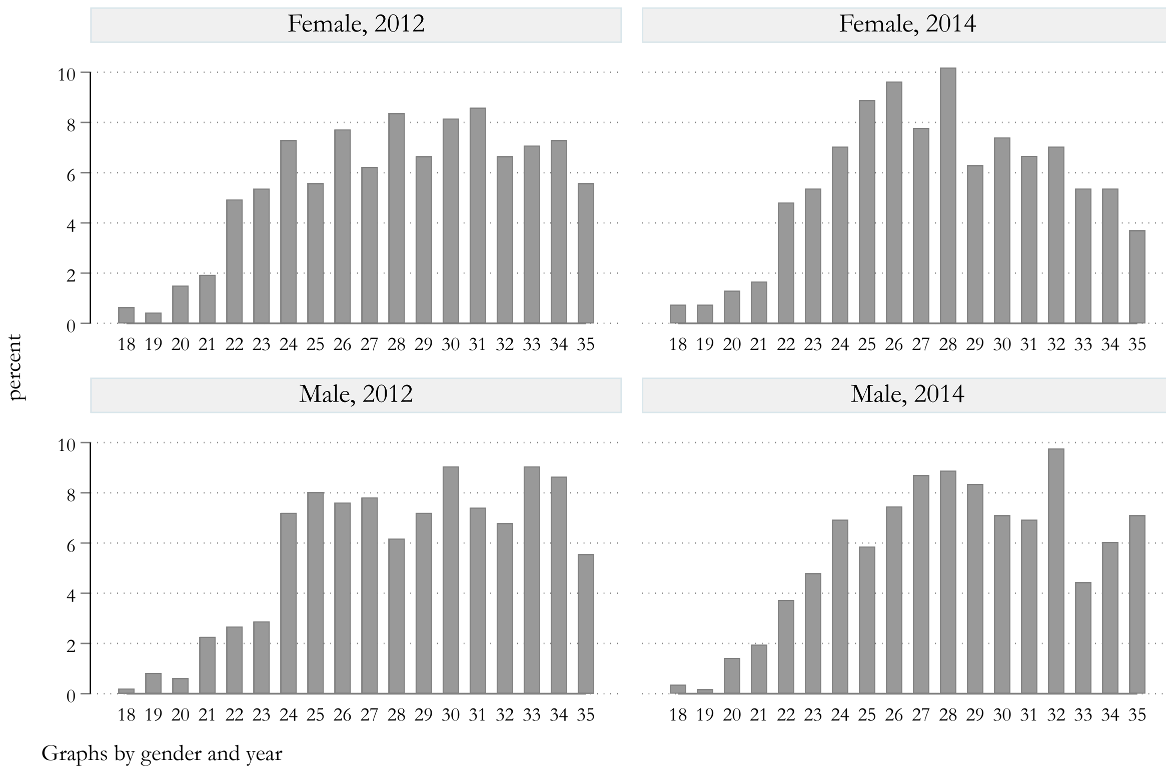


Figure 5: Age Distribution of Women and Men in the Sample (Ages 18–35). *Notes: The sample matches that used in the empirical analysis (Section 2): currently employed urban residents ages 18–35 with at least a high-school education.*

Figure 5 presents the age distribution of employed men and women aged 18–35 in 2012 and 2014. In both years, the distributions are broadly similar across genders, with most workers concentrated between their mid-20s and early 30s. Between 2012 and 2014, the overall shape of the distribution remains stable, though the female sample becomes slightly more concentrated among individuals aged 24 to 28, reflecting the entry of younger cohorts into the labor force.

To calibrate the exogenous separation rate δ, I proxy it with the average share of employed workers at terminal ages (33–35) within the 18–35 window.[10] The separation rate for women

[10] In 2012, the shares for women aged 33, 34, and 35 are 7.08%, 7.30%, and 5.58%, implying $\delta^F 2012 = 6.65\%$. For men, the corresponding shares are 9.05%, 8.64%, and 5.56%, giving $\delta^M 2012 = 7.75\%$. In 2014,

is consistently lower than that for men. Because δ determines the upper bound of the human-capital accumulation rate $\alpha(n)$, I hold it constant across years to isolate the change in $\alpha(n)$. Specifically, I set $\delta^F = 6.65\%$ and $\delta^M = 7.75\%$ [11].

Marriage and fertility-state probabilities. I calibrate the expected marriage and fertility-state probabilities, p_n^j, defined as the probabilities employers assign—at hiring—that a representative worker of gender j will spend time in a given marriage or fertility state n over the expected match horizon. Because age is not explicitly modeled as a state variable, I assume firms do not observe exact age and instead apply a flat prior over the hiring-age window $[a_L, a_H] = [18, 35]$. The observed fractions of individuals in each state within the sample thus govern the calibration of p_n^j. The states are defined as follows: $n = 0$ denotes unmarried and childless; $n = 1$ denotes married without children; and $n \geq 2$ denotes married with $n - 1$ children.[12]

Using the 2012 CFPS sample restricted to individuals in the labor force, under age 35, and with at least a high-school education, I compute the empirical distribution of these states. Among women, 31% are unmarried and childless ($n = 0$), 18% are married without children ($n = 1$), and 51% have at least one child ($n \geq 2$).[13] Only 3.23% of women and 4.53% of men report having two children before the policy relaxation; therefore, I treat all parents as belonging to a single "married with one child" category ($n = 2$). Among men, the corresponding shares are 38% for $n = 0$, 17% for $n = 1$, and 45% for $n = 2$.

Effort and accumulation mappings. Identification implies that $\alpha^j(n)$ and $\varepsilon^j(n)$ are determined up to a permutation of n. Building on the household block introduced in Section 3.1, I assume both genders share a common mapping from family-work time $t^j(n)$ to work effort and human-capital accumulation rates: $\varepsilon^j(n) = \frac{1}{1+(t^j(n)/\psi_1)^{\psi_2}} \in (0, 1], \quad \psi_1 > 0,\ \psi_2 > 0$, and $\alpha^j(n) = \rho_0 + \rho_1\, \varepsilon^j(n), \quad \rho_0 > 0,\ \rho_1 > 0$. Both $\varepsilon^j(n)$ and $\alpha^j(n)$ increase with available free time and thus decrease with family-work time. Under this specification, individuals with no family-work burden ($t^j(n) = 0$) exert full effort, $\varepsilon^j(n_0) = 1$.

the female shares are 5.37%, 5.37%, and 3.70% ($\delta^F 2014 = 4.81\%$), while the male shares are 4.44%, 6.04%, and 7.10% ($\delta^M 2014 = 5.86\%$).

[11] I use the higher estimates because the observed age-out rate represents a lower bound, and a slightly larger δ provides a more conservative calibration

[12] In the data, individuals with children are never observed as unmarried.

[13] Cohabiting and divorced individuals are grouped with the "married" category because they represent a small share of the sample—2.38% for women and 1.3% for men.

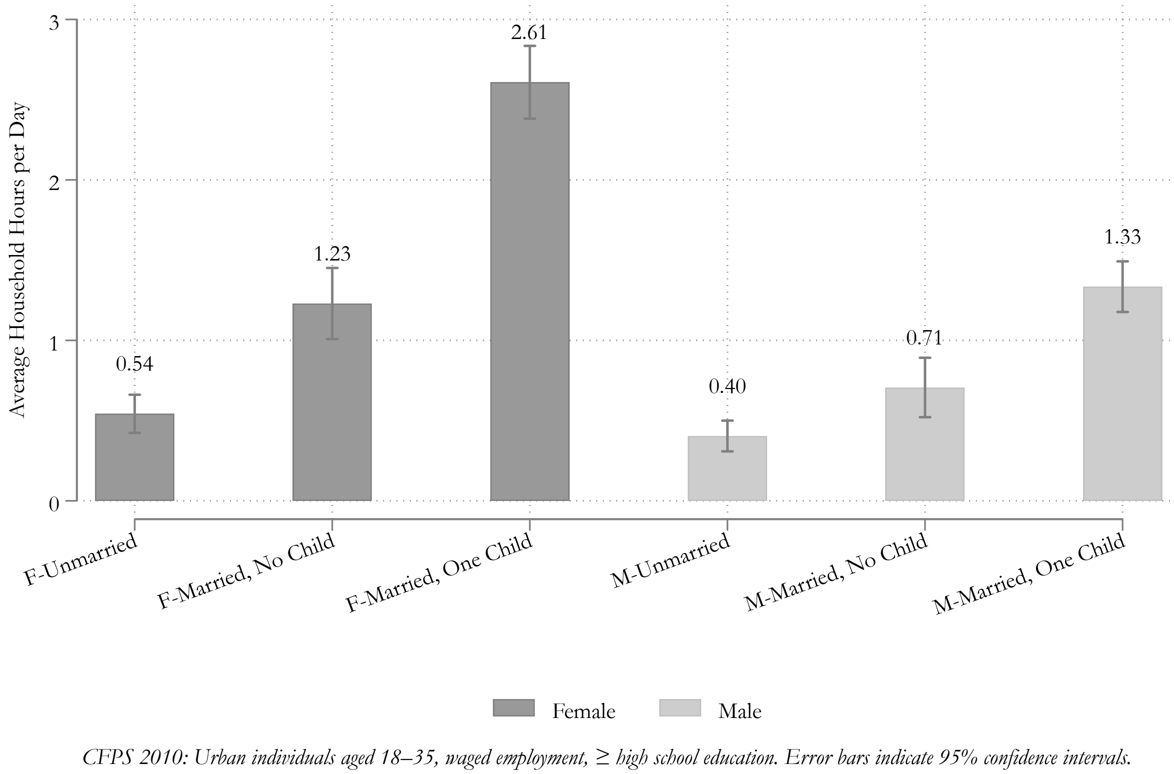


Figure 6: Average Household Hours by Gender and Family Status.

Free time is not directly observed, so I proxy it by the complement of family-work time $t^j(n)$—the sum of daily hours spent on household chores and family care—using data from the CFPS time-use module. The CFPS weekday averages indicate that, among unmarried individuals, men spend about 0.40 hours per day on family work, while women spend slightly more, around 0.54 hours. After marriage, men's average family-work time rises modestly to 0.71 hours per day, whereas women's time nearly doubles to 1.23 hours even before having children. When a child is present, men devote about 1.53 hours per day to family work, while women's time increases sharply to 2.61 hours. This stark divergence highlights a key feature of the Chinese social context: women bear the primary responsibility for household chores and childcare. Consequently, their available free time—and thus effective work effort and human-capital accumulation—declines more steeply with family formation compared to men.

Summary of externally calibrated inputs:

$$r = 0.05,\ \delta^F = 0.0665,\ \delta^M = 0.0775,$$
$$p^F_{0,2012} = 0.31,\ p^F_{1,2012} = 0.18,\ p^F_{2,2012} = 0.51;\ p^M_{0,2012} = 0.38,\ p^M_{1,2012} = 0.17, p^M_{2,2012} = 0.45,$$
$$t^F(0) = 0.54,\ t^F(1) = 1.23,\ t^F(2) = 2.61;\ t^M(0) = 0.4,\ t^M(1) = 0.71,\ t^M(2) = 1.33.$$

4.4 Estimation for 2012

The estimation algorithm follows a standard minimum-distance approach. Given the predetermined parameters discussed in the previous subsection, $\{r,\ \delta^j,\ \{p^j_n\}_n,\ \{t^j(n)\}_n\}$, I begin by guessing an initial parameter vector $\theta^{j,0} = \big(\{\alpha(n)\}_n,\ \lambda_0,\ \lambda_1,\ \delta,\ b,\ z_0,\ \{\varepsilon(n)\}_n\big)$ for each gender j. For a given guess $\theta^{j,0}$, I solve the model to obtain the implied wage-offer distribution $F^j(w;\theta^{j,0})$, convert it to the employed-wage distribution via

$$G^j(w;\theta^{j,0}) = \frac{\delta^j\, F^j(w;\theta^{j,0})}{\delta^j + \lambda^j_1\big(1 - F^j(w;\theta^{j,0})\big)},$$

and then compare the model-implied $G^j(w;\theta^{j,0})$ with the empirical wage CDF $\widehat{G}^j(w)$ using the *Anderson–Darling (AD) distance.* This procedure is iterated until the sum of AD distance for women and men is minimized.

The AD distance measures the weighted discrepancy between the model-implied and empirical CDFs, placing more weight on the tails where wage data contain the most information about mobility, promotions, and inequality. This feature is desirable in the present setting, as the data exhibit that most changes are in the tails after the policy shifts. Formally, for an empirical CDF $\widehat{G^j}(w)$ and a model-implied CDF $G^j(w;\theta)$ on the support $[R^j, \overline{w^j}]$, the AD distance for gender j is

$$\widehat{AD}^j(\theta) = \int_{R^j}^{\overline{w^j}} \frac{\big[G^j(w;\theta) - \widehat{G^j}(w)\big]^2}{\widehat{G^j}(w)\,[1 - \widehat{G^j}(w)]}\, d\widehat{G^j}(w).$$

In practice, this integral is evaluated numerically over a fine grid of wage quantiles, with the weighting term $\big[\widehat{G^j}(w)\,(1 - \widehat{G^j}(w))\big]^{-1}$ automatically emphasizing the tails. The estimator

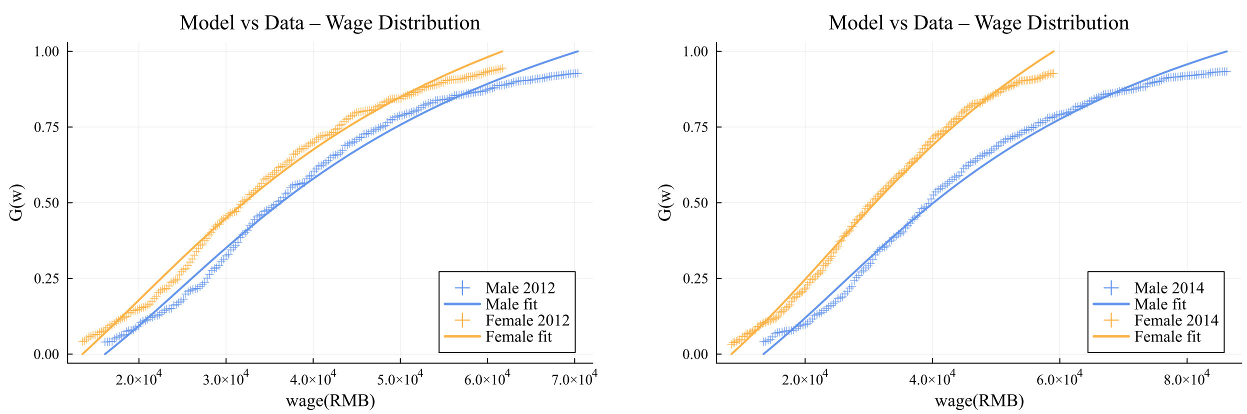
$\widehat{\theta}$ best reproduces the observed wage distributions for men and women, formally

$$\widehat{\theta} = \arg\min_{\theta} \widehat{AD}(\theta) = \sum_{j \in \{F,M\}} \widehat{AD}^{j}(\theta)$$

Under certain M–estimation regularity conditions (Newey and McFadden (1994)), the AD estimator is consistent and asymptotically normal:

$$\sqrt{n}\big(\widehat{\theta} - \theta_0\big) \xrightarrow{d} \mathcal{N}\big(0,\ \Omega(\theta_0)\big).$$

where n is the sample size. Standard errors $se(\widehat{\theta})$ can be computed from sample covariance matrix $\widehat{\Omega}$, so does the 95% confidence interval $\Big[\widehat{\theta}_i - 1.96\,\mathrm{se}(\widehat{\theta}_i),\quad \widehat{\theta}_i + 1.96\,\mathrm{se}(\widehat{\theta}_i)\Big]$.



(a) 2012: empirical vs. model CDFs by gender (b) 2014: empirical vs. model CDFs by gender

Figure 7: Model fit for employed wage distributions

The estimation results for the 2012 gender-specific wage distributions are summarized in Table 11, and the corresponding model fit is presented in Figure 7a.

Panel A of Table 11 reports the estimated parameters linking family-work time to work effort (ψ_1, ψ_2) and work effort to human-capital accumulation (ρ_0, ρ_1), as defined by

$$\varepsilon^{j}(n) = \frac{1}{1 + (t^{j}(n)/\psi_1)^{\psi_2}} \in (0, 1], \quad \psi_1 > 0,\ \psi_2 > 0,$$

and

$$\alpha^{j}(n) = \rho_0 + \rho_1\, \varepsilon^{j}(n), \quad \rho_0 > 0,\ \rho_1 > 0.$$

The positive estimates $\psi_1 > 0$ and $\psi_2 > 0$ confirm that greater family-work time reduces effective work effort. Likewise, $\rho_1 = 0.03 > 0$ implies that a worker exerting full effort ($\varepsilon^j(n) = 1$) accumulates human capital at a rate roughly 0.03 above the baseline $\rho_0 = 0.02$, corresponding to an annual firm-specific accumulation rate of about 5%.

Substituting the observed family-work time values, unmarried men and women exert nearly full effort. However, once married, the gender gap in work intensity begins to widen: men's effort remains close to 99.8%, whereas women's declines slightly to about 98.5%. The most pronounced divergence occurs with the arrival of the first child. Parenthood lowers men's effective effort modestly—to around 97.9%—but substantially reduces women's to roughly 62%. Consequently, women with children experience much slower human-capital accumulation than childless women, while the reduction for fathers is relatively small. This pattern mirrors the unequal division of household responsibilities observed in time-use data and underpins the model's mechanism that links expected family labor burdens to gendered wage differentials.

Table 11: Results for Estimated Parameters in Year 2012

Panel A: Human Capital Accumulation

Accumulation mapping parameters: $\psi_0 = 2.88$, $\psi_1 = 4.98$, $\rho_0 = 0.02$, $\rho_1 = 0.03$

$n = 0$: unmarried $n = 1$: married without kids $n = 2$: with one kid

	$e(0)$	$e(1)$	$e(2)$	$\alpha(0)$	$\alpha(1)$	$\alpha(2)$
Female	0.999	0.985	0.621	0.052	0.051	0.040
Male	0.999	0.998	0.979	0.052	0.052	0.051

Panel B: Labor Market Parameters

2012	b	λ_0	λ_1	z_0
Female	3,874 (3,849, 3,898)	0.512 (0.495, 0.529)	0.403 (0.374, 0.432)	23,352 (23,312, 23,391)
Male	3,818 (3,795, 3,842)	0.614 (0.556, 0.672)	0.506 (0.441, 0.571)	23,352 (23,312, 23,391)

Notes: Panel A reports effort $e(n)$ and human-capital accumulation rates $\alpha(n)$ for different marriage and fertility status n. Panel B reports estimated labor market parameters: unemployment benefits (b), job-offer arrival rates for unemployed (λ_0) and employed (λ_1) workers, and the common initial productivity level (z_0). All values in parentheses represent 95% confidence intervals. Monetary values are expressed in RMB per year.

Panel B of Table 11 reports the estimated labor-market parameters that characterize China's market for highly educated workers. The estimated initial human capital level, $z_0 =$ 23,300 RMB per year, represents the wage firms would pay in the absence of market frictions and human-capital accumulation ($\alpha = 0$). For comparison, the average nominal wage among employed individuals in the 2012 sample is 30,142 RMB, with a median of 27,000 RMB. Given the estimated accumulation rate of about 5% per year, a worker's productivity after five years of tenure would rise to roughly 29,700 RMB, and after ten years to about 37,900 RMB. Considering the low mobility typical of China's high-skill labor market, long tenures of ten years or more are not uncommon, making such cumulative productivity gains plausible.

The estimated unemployment benefit level, $b^j \approx 3{,}800$ RMB for both men and women, reflects not only formal unemployment insurance but also the imputed monetary value of leisure and home production. In equilibrium, the reservation wage R—the lowest wage an individual is willing to accept—must exceed this value. Consistent with this, the smallest observed wage in the sample is 3,000 RMB, and fewer than 1% of respondents report wages below 3,500 RMB.

Finally, the two job-offer arrival rates, λ_0^j and λ_1^j, capture market mobility while unemployed and employed, respectively. The estimates satisfy $\lambda_0^F < \lambda_0^M$ and $\lambda_1^F < \lambda_1^M$, indicating that women receive fewer job opportunities both when unemployed and when employed. This pattern is consistent with a less dynamic job ladder and more constrained career mobility for women relative to men.

The magnitudes of λ_0^j and λ_1^j are broadly comparable to those found in the search-and-matching literature, though direct comparisons are disputable by sample and model differences. For instance, Postel-Vinay and Robin (2002), using French administrative data for 1996–1998, report annual on-the-job offer-arrival rates (λ_1) between 0.64 and 0.67 across industries—slightly above but of similar order to the estimates obtained here.

To further evaluate whether the estimated offer-arrival rates are consistent with dynamic features of China's labor market, I use the panel dimension of the CFPS to compute employer-to-employer mobility between survey rounds (two-year intervals) as a lower bound for λ_1^j. In the model, λ_1^j represents the hazard rate of receiving a higher-paying job offer; hence, the proportion of workers experiencing substantial wage increases across waves provides an empirical upper bound. As detailed in Appendix C, these empirical bounds range from approximately 0.4 to 1.3, which aligns well with the model's estimated λ_1^j values.

4.5 Estimation for 2014

After the 2013 relaxation of China's One-Child Policy, the gender wage gap in the high-skilled labor market widened by 15.3%, as documented in the empirical analysis. To examine how employers and labor-market dynamics responded to this policy shift so that we observe such a wage change in average, I re-estimate the model for 2014 while remaining agnostic about the specific mechanisms behind the wage adjustment.

Since actual birth rates did not respond immediately to the policy relaxation, I assume that the unemployed benefits b^j remain unchanged between 2012 and 2014. This reflects the absence of any contemporaneous labor-supply adjustment that would alter households' valuation of non-working time. Moreover, because fertility behavior did not change in the short run, I also assume that workers did not adjust their family-work allocation in anticipation of future births. As discussed in Section 4.2, the exogenous separation rates δ^j are interpreted as demographic "age-out" hazards, which are essential for identifying other parameters in equilibrium. Given that the age distribution of workers remained stable between 2012 and 2014, I hold δ^j fixed at their 2012 values. Similarly, the parameters governing the mapping from family-work time to effort and from effort to human-capital accumulation are held constant.

Once the time spent on family work for individuals with two children is specified, their corresponding effort and accumulation levels can be inferred directly. Knowing the human-capital accumulation rate for workers with two children ($n = 3$) allows us to identify the probability that employers assign to a worker being in that state, $p^j(n = 3)$. In other words, as discussed in the identification argument, what we observe empirically is an "average" accumulation rate—an expectation over possible fertility states. To separate the accumulation rate $\alpha^j(n)$ for each n, we need to know the probability weights $p^j(n)$ that employers attach to each state, and vice versa. Family-work time determines $\alpha^j(n)$, so variation in expected family-work time across fertility states corresponds to variation in employers' perceived probability that a worker will have two children.

However, the time-use data contain very few observations of individuals with two children. Even among those who gave birth to a second child after the policy change, selection bias is likely: only women with high endowments or family-friendly jobs could afford to have another child and to reduce their labor supply substantially. Their reported family-work time may therefore overstate the amount that typical employers expect for an average worker with two children. To address this limitation, I impose the following assumption.

Assumption 4.2 (Time use with a second child)**.** For women, the increase in family-work time from one to two children equals 25% of the increase from zero to one child; for men, family-work time remains unchanged. Formally,

$$t^F(3) = t^F(2) + 0.25\,[t^F(2) - t^F(1)], \qquad t^M(3) = t^M(2).$$

This assumption reflects the diminishing marginal time cost of additional children commonly documented in time-use studies. Using the American Time Use Survey, Price (2008) report that mothers' weekly family-work time rises by about 27% when moving from one to two children, placing the 25% increase well within the empirical range. Holding men's time fixed is consistent with the empirical results in Section 2: women's wages decline significantly following the policy shift, while men's wages remain unaffected—implying that employers did not revise expectations about men's future productivity. Using the baseline time-use moments $t^F(0) = 0.54$, $t^F(1) = 1.23$, $t^F(2) = 2.61$; $t^M(0) = 0.4$, $t^M(1) = 0.71$, and $t^M(2) = 1.33$ (hours per weekday), the implied family-work times for two children are $t^F(3) \approx 2.955$ and $t^M(3) \approx 1.33$.

Although time-use data from the 2018 CFPS—the first post-reform wave containing the time-use module—show that mothers with two children spend roughly four hours per day on family work, this figure likely reflects realized behavior among a selective group of women rather than employers' expectations about average workers. Nonetheless, because this value may still approximate the true population mean, I consider several counterfactual levels of $t^F(3)$ ranging from 2.995 to 4.0 hours in the estimation. For each assumed $t^F(3)$, employers' perceived probability of a second child, $p^F_{2014}(3)$, adjusts endogenously through the model. By contrast, I do not estimate $p^M_{2014}(3)$, as men's wages show no significant response to changes in expected fertility, implying that $\alpha^M(3)$ and $\alpha^M(2)$ are effectively indistinguishable.

Furthermore, because the first-birth margin remained largely unaffected by the policy change, I impose the following restriction.

Assumption 4.3 (First-birth margin fixed)**.** The relaxation of the OCP does not alter first-birth decisions within the sample window. Only the conditional probability of having a second child changes, implying that $p^j(n=0)$ and $p^j(n=1)$ remain the same as in 2012, while $p^j(n=2)$ and $p^j(n=3)$ adjust.

Using the 2012 estimates as a baseline, I re-estimate the 2014 model

$$\left(z_{0,2014},\ \lambda^F_{0,2014},\ \lambda^F_{1,2014},\ \varepsilon^F(2),\ p^F_{2014}(2),\ \lambda^M_{0,2014},\ \lambda^M_{1,2014}\right)$$

by minimizing the Anderson–Darling distance between the model-implied and empirical wage distributions for 2014.

Table 12: Estimation Results for 2014 under Alternative t_3 Assumptions

$t^F(3)$	$z_{0,2014}$	λ^F_0	λ^F_1	λ^M_0	λ^M_1	$p^F_{2014,3}$	Fitness
2.955	25,963	0.2695	0.2690	0.2779	0.2445	0.509	975.16
3.450	26,542	0.2590	0.2464	0.2646	0.2551	0.384	894.58
3.750	26,537	0.2656	0.2536	0.2657	0.2563	0.324	896.62
4.000	26,538	0.2664	0.2520	0.2655	0.2561	0.297	902.33

Notes: This table reports the estimated parameters for 2014 under different assumptions about women's daily family-work time with two children (t_3, in hours). Each specification re-estimates the common productivity level ($z_{0,2014}$), female and male offer arrival rates while unemployed (λ^F_0, λ^M_0) and while employed (λ^F_1, λ^M_1), and the perceived probability that women have a second child, $p^F_{2014}(3)$. The fitness statistic corresponds to the minimized Anderson–Darling distance; lower values indicate better model fit.

Figure 7b presents the model's fit to the empirical wage CDF for 2014 (for cases where $t^F(3) = 3.45$), while Table 12 summarizes the corresponding parameter estimates under alternative assumptions about women's family-work time with two children, $t^F(3)$. Several findings emerge from the estimation.

First, across all specifications, the estimated probability that employers assign to women having a second child, $p^F_{2014,3}$, is strictly positive and quantitatively large. As expected, higher values of $t^F(3)$—corresponding to greater time devoted to household responsibilities and lower work effort—lead to smaller estimated $p^F_{2014,3}$. Even under the most time-intensive scenario ($t^F(3) = 4$ hours per weekday), which implies that the second child doubles the incremental family-work burden induced by the first child ($4 \approx 2.61 + (2.61 - 1.23)$), the model still yields a sizable $p^F_{2014,3} = 0.297$. This means that among the 51% of women expected to become mothers, employers anticipate that roughly 58% will have a second child following the policy relaxation.

Second, the results reveal a substantial "productivity depreciation" effect. When the decline in women's human-capital accumulation rate at $n = 3$ is not large enough, the model fails to match the empirical wage distribution unless the probability of a second child reaches its maximum feasible value ($p^F_{2014}(3) \approx 0.51$), implying that all women would need to have a second child to fit the data—an implausible scenario. Allowing for a sharper decline in productivity therefore improves the model fit dramatically, suggesting that employers expect a significant reduction in women's future work effort once they have two children.

Third, consistent with the identification argument, the estimates show that $t^F(3)$ and $p^F_{2014}(3)$ cannot be separately identified: different combinations of these two variables yield similar fits, while other key labor-market parameters remain stable across specifications. Only when $t^F(3)$ is set low does the model exhibit poor fit and unstable parameter estimates.

Finally, the estimated initial productivity level, $z_{0,2014}$, rises relative to 2012, capturing aggregate economic growth and reflecting the general upward shift in men's wages over the same period. This suggests that, overall wage levels in the high-skilled labor market increased with macroeconomic expansion, however, depreciation of female productivity growth due to higher expected family-work burdens made women's wage decrease.

Discussion. Treating the 2014 wage distribution as a new steady state is admittedly a strong and perhaps unrealistic assumption. In reality, firms cannot instantaneously adjust their posted wage offers within a single year, and given the high degree of labor-market immobility in China, most workers employed in 2012 would have remained in their original positions. Consequently, only new labor-market entrants would have been immediately affected by the policy relaxation.

To account for this, I experimented with a simulation-based estimation approach (reported in the Appendix). In that exercise, I drew incumbents from the 2012 wage distribution, allowed them to receive new job offers from the post-reform offer distribution characterized by the updated λ_1^j, and simulated new entrants drawing offers from $F_{2014}(w)$ also with the updated arrival rate λ_0^j. I then combined these two groups to match the observed 2014 wage distribution. However, this approach also implicitly assumes that all employers instantly re-optimize wage posting policies and start to post wages based on this new policy within a year. The resulting wage-offer distribution implied by this procedure turned out to be implausible—women's offers concentrated near the reservation wage, while men's offers are concentrated where we observe the rightward shifts. This pattern suggests it is more consistent with a transitory adjustment period than with a true post-policy steady state, and if this is not a steady state, using the guessed parameters to formulate an equilibrium wage offer distribution is ill-founded. Given there is no good way to capture the transition path, I return to the more standard approach adopted in the main analysis, estimating the 2014 distribution directly as if it reflects the new equilibrium results while not keeping part of the people fixed in their original distribution.

Despite the steady-state simplification, the estimation results convey several important insights. Empirically, men's wage distribution shifted upward in the upper quantiles, while women's distribution moved downward in the lower quantiles. In the canonical search-and-matching framework, the only way to generate a rise in male wages without altering the unemployment margin is through an increase in the initial productivity level z_0. Yet there is little reason to believe that only men's initial human capital increased after the reform, as men and women exhibited similar educational attainment and labor-market entry characteristics. Once we allow z_0 to rise for both genders, the observed decline in women's wages, absent changes in unemployment, must be attributed to slower human-capital accumulation among women.

This interpretation aligns with the model's mechanism: following the policy relaxation, employers anticipate reduced effective work effort among women. As a result, they discount women's expected productivity growth more heavily in wage offers, widening the gender wage gap. Hence, the 2014 estimates reinforce the paper's central argument that the post-reform increase in gender wage inequality stems primarily from expectation-driven differences in human-capital accumulation rates.

As a further check, I overlay the simulated wage CDFs for 2012 and 2014 to compare relative movements with the empirical CDFs in Figure 4. The simulation overlay (Figure 8) mirrors the data: the female CDF shifts left in the lower quantiles, while the male CDF shifts right in the upper quantiles.

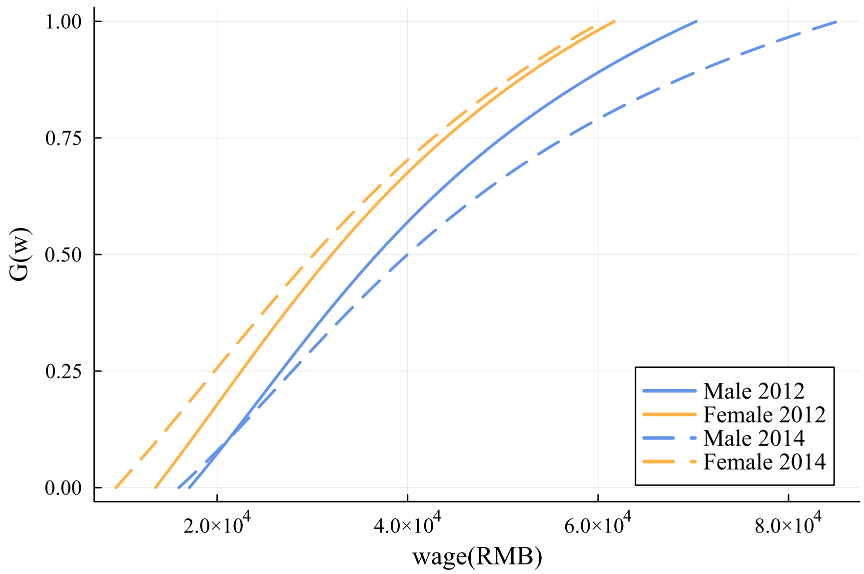


Figure 8: Simulated CDFs (2012 vs. 2014) by Gender: Overlay

4.6 Counterfactual Analysis

In this subsection, I use the estimated parameters to perform a series of counterfactual analyses designed to assess the quantitative importance of gender differences in human-capital accumulation. Specifically, I evaluate how much these differences contribute to (i) the baseline gender wage gap prior to the relaxation of the One-Child Policy, and (ii) the subsequent widening of the gap following the policy change. The exercises decompose the observed wage disparities into components attributable to differences in household time allocation, fertility distribution, and labor-market dynamics, thereby illustrating the central role of human-capital accumulation in shaping gendered wage outcomes both before and after the reform.

Using the 2012 estimates, I first assess how much of the residual gender wage gap—13.3% after controlling for education, industry, and other observables—is driven by unequal family-work time across genders. I construct a counterfactual in which men and women are assigned the same average family-work hours in 2012, holding all other parameters fixed, and solve the model to compute the implied equilibrium wages. Panel A of Table 13 shows that equalizing family-work hours would eliminate the gender wage gap entirely and even slightly reverse it. In contrast, differences in labor-market frictions—such as offer-arrival rates—play a negligible role in explaining the remaining wage differential once observables are controlled for. These results underscore that the unbalanced division of household labor accounts for the majority of the pre-reform gender wage gap.

Empirically (Section 2), women's wages declined by 15.3% after the policy relaxation. The model replicates this magnitude closely: the simulated female-to-male wage ratio falls from 0.867 in 2012 to 0.732 in 2014 (Table 13), corresponding to a 13.5-percentage-point decline—or roughly 15.5% if men's wages are held fixed. To isolate the role of employer expectations, I conduct a second counterfactual in which only the fertility distribution p_n^j is updated to its post-reform values while all other parameters remain at their 2012 levels. The resulting wage ratio of 0.761 implies that nearly 80% of the observed widening in the gender wage gap can be attributed to the expectation channel—employers discounting women's wages due to higher anticipated fertility and lower expected productivity growth.

Table 13: Gender Wage Ratio Decomposition and Comparison, 2012–2014

Scenario	**Female/Male ratio**	**Gender gap (pp)**
Panel A: 2012 Baseline Counterfactuals		
Baseline (2012)	0.867	13.3
Female with male family–work hours	1.021	−0.02
Male with female family–work hours	0.987	0.01
Female with male fertility distribution	0.901	9.9
Female with male labor market parameters	0.889	11.1
Panel B: 2012 vs. 2014		
Baseline (2014)	0.732	26.8
2012 parameters with 2014 productivity	0.761	23.8

Notes: Gender wage gap is defined as 1 − ratio and reported in percentage points (pp). Panel A presents counterfactual exercises based on the 2012 estimated parameters. Panel B compares outcomes between 2012 and 2014 under productivity and distributional shifts. For 2014, results are computed using $t^F(3) = 3.45$, the assumed family–work intensity for women with two children that yields the best model fit.

4.7 Model Implications: Job Protection Policies

The estimation results offer insight into how job protection policies may affect gender wage inequality. Such policies aim to preserve employment continuity after childbirth by requiring firms to retain women's positions during maternity or childcare leave. Since the child penalty is a key driver of the remaining gender wage gap, and women's weaker post-birth labor-market attachment limits career progression and human-capital accumulation, job protection is often viewed as a remedy. However, by committing firms to preserve positions, these policies also extend the non-adjustment horizon over which pay is effectively fixed within a position. Employers must therefore price expected average productivity over the entire match duration, not just contemporaneous output. While job protection secures women's employment, it can also intensify statistical discrimination at hiring and promotion, leading to lower initial wage offers for all women.

China's high-skilled labor market provides an illustrative case of an extreme form of job protection—lifetime job security. The results are striking. First, gender wage gaps persist despite continuous female employment. Because firms cannot dismiss workers, employers are not concerned about replacement costs when women have children; instead, they anticipate that longer-term employees facing heavier family responsibilities will divert effort toward childcare while remaining employed at guaranteed pay. As a result, firms discount women's expected productivity over the contract horizon, lowering their starting wages and promotion probabilities.

Second, job protection effectively keeps both high-effort and low-effort workers in the labor market. This raises the weight of lower-productivity matches in the average expected productivity used to set wages. In an extreme counterfactual, if employers knew that women with two children would leave the labor market, long-term job security would not reduce young women's wages *ex ante*, because the expected productivity of the employed pool would not decline.

Third, the results underscore that the "baby effect" on women's wages extends far beyond the short maternity-leave period. Because caregiving responsibilities persist throughout a child's upbringing, employers price lower productivity over a long horizon, distinguishing a *fertility shock* from a mere *maternity-leave shock*. If the latter were all that mattered, longer job contracts would dilute the penalty rather than magnify it.

Moreover, position-preserving policies can inadvertently heighten exposure to persistent shocks. By prolonging match duration, they increase the likelihood that workers encounter life events—such as childbirth—within the protected employment spell. Empirically, low-educated women are barely affected by the 2013 policy relaxation precisely because they lack long-term contracts; when employers expect short employment spells, the probability of childbirth during that spell is small, and hence no wage discount is applied.

Consequently, job protection alone may fail to close the gender wage gap and can even shift discrimination to the hiring and promotion margins. The Chinese case—where high-skilled workers enjoy near-perfect job security yet a substantial gender wage gap persists and a large wage drop after the increase of fertility rates (by at most one)—illustrates this paradox. Protecting jobs without addressing the root causes—unequal household specialization and employers' beliefs about women's future productivity—leaves wage inequality largely intact. This interpretation aligns with Goldin (2021), who emphasize that the earnings gap reflects career gaps arising from caregiving burdens and the high returns to continuous, long-hour work. Policies that ease childcare constraints and redistribute family responsibilities are therefore more likely to mitigate the gender wage gap than those that simply extend job protection.

5 Conclusion

This paper demonstrates that when pay is contracted in a long-horizon employment relationship, employers' expectations about workers' future caregiving burdens are reflected in wages in ways that can materially widen gender gaps. Exploiting China's 2013 selective relaxation of the One-Child Policy as a quasi-experiment, I document a 15.3 percent decline in young women's wages with no short-run increase in births, consistent with forward-looking wage setting rather than contemporaneous labor-supply changes. I then develop a search and match model, but extend it to allow for increasing productivity over the match and augment it with a household time-allocation block: effort depends on free time, human capital accumulates with effort, and wages are posted against the present value of an increasing productivity path over the match. Estimating the model on Chinese data, I find that the unequal division of family work alone explains essentially the entire baseline (2012) gender wage gap, and that more than 80 percent of the post-reform widening can be attributed to employers' downward revisions of women's expected productivity associated with anticipated second births.

Two broader implications follow. First, in contract-driven pay settings—government and state-affiliated employment, and many high-skill jobs where matching is costly, training is firm-specific, and replacement is expensive—wages tilt toward expectations about future productivity rather than current output. Any belief that women will accumulate human capital more slowly is amplified by the longer wage-contract horizon and shows up as larger up-front markdowns. Second, policies that merely preserve positions (e.g., job-protection mandates) lengthen the horizon over which present-value pricing applies and can therefore intensify ex-ante markdowns and stall promotions, even as employment is maintained. By contrast, policies that reduce childcare burdens—expanding affordable childcare, designing leave that equalizes caregiving across parents like Sweden's "second dad paternity leave"—directly raise expected effort and accumulation and are more likely to narrow gaps.

The analysis has limitations. Time-use inputs for family work are observed, but the second-child increment is calibrated due to the absence of a clear within-window birth response; employer expectations about second births therefore rest on an assumption and may be imprecise. On the modeling side, fertility is treated as exogenous rather than the outcome of a household decision. A natural next step is to link the household and labor-market blocks more tightly to study feedback: if employers statistically discriminate against women, lower expected returns to market work may induce higher fertility or reduced effort, which in turn validates firms' priors. Such a reinforcing cycle could help explain why, under rising childcare burdens, women disproportionately cut effort while men do not.

Overall, the evidence and the model point to a common conclusion: when salaries are predetermined and productivity grows on the job, expectation-driven pricing is an important force behind gender wage gaps. Closing those gaps requires moving the lower expectations that firms legitimately price for women, rather than only lengthening their job tenure.

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A Derivation and Proofs

A.1 Balanced employment stock $l^j(w)$ derivation

Let $l^j(w)$ denote the equilibrium stock of employees (per unit mass of firms) earning exactly w. Using G^j and F^j,

$$
\begin{aligned}
l^j(w) &= \lim_{\epsilon\to 0} \frac{G^j(w) - G^j(w-\varepsilon)}{F^j(w) - F^j(w-\epsilon)}\,(m^j - u^j) \\
&= \lim_{\epsilon\to 0} \frac{\dfrac{\big[F^j(w) - F^j(R^j)\big]\delta^j}{h^j(w)\big[1 - F^j(R^j)\big]} - \dfrac{\big[F^j(w-\epsilon) - F^j(R^j)\big]\delta^j}{h^j(w-\epsilon)\big[1 - F^j(R^j)\big]}}{F^j(w) - F^j(w-\epsilon)}\,(m^j - u^j) \\
&= \lim_{\epsilon\to 0} \frac{F^j(w)\,h^j(w-\epsilon) - F^j(w-\epsilon)\,h^j(w) + F^j(R^j)\big[h^j(w) - h^j(w-\epsilon)\big]}{\big[h^j(w)\,h^j(w-\epsilon)\big]\big[1 - F^j(R^j)\big]\big[F^j(w) - F^j(w-\epsilon)\big]}\,(m^j - u^j)\,\delta^j.
\end{aligned}
$$

Define $h^j(w) = h^j(w-\epsilon) + \Delta_\epsilon$, then

$$
\Delta_\epsilon = \lambda_1^j\big[F^j(w-\epsilon) - F^j(w)\big].
$$

Hence,

$$
\begin{aligned}
l^j(w) &= \lim_{\epsilon\to 0} \frac{\big[F^j(w) - F^j(w-\epsilon)\big]\big[h^j(w-\epsilon) + \lambda_1^j F^j(w-\epsilon)\big] + F^j(R^j)\Delta_\epsilon}{\big[h^j(w)\,h^j(w-\epsilon)\big]\big[1 - F^j(R^j)\big]\big[F^j(w) - F^j(w-\epsilon)\big]}\,(m^j - u^j)\,\delta^j \\
&= \lim_{\epsilon\to 0} \frac{h^j(w-\epsilon) + \lambda_1^j\big[F^j(w-\epsilon) - F^j(R^j)\big]}{\big[h^j(w)\,h^j(w-\epsilon)\big]\big[1 - F^j(R^j)\big]}\,(m^j - u^j)\,\delta^j \\
&= \lim_{\epsilon\to 0} \frac{h^j(w-\epsilon) + \lambda_1^j\big[F^j(w-\epsilon) - F^j(R^j)\big]}{\big[h^j(w)\,h^j(w-\epsilon)\big]\big[1 - F^j(R^j)\big]}\;\lambda_0^j\big[1 - F^j(R^j)\big]u^j \\
&= \lim_{\epsilon\to 0} \frac{\delta^j + \lambda_1^j\big(1 - F^j(w-\epsilon)\big) + \lambda_1^j\big[F^j(w-\varepsilon) - F^j(R^j)\big]}{h^j(w)\,h^j(w-\epsilon)}\;\lambda_0^j u^j \\
&= \lim_{\epsilon\to 0} \frac{\delta^j + \lambda_1^j\big(1 - F^j(R^j)\big)}{h^j(w)\,h^j(w-\epsilon)}\;\lambda_0^j u^j.
\end{aligned}
$$

In equilibrium, no firm posts below R^j so $F^j(R^j) = 0$, and if F^j is continuous, then,

$$
l^j(w) = \frac{\big(\delta^j + \lambda_1^j\big)\lambda_0^j u^j}{\big[h^j(w)\big]^2} \;=\; \frac{\big(\delta^j + \lambda_1^j\big)\lambda_0^j}{\big[h^j(w)\big]^2}\cdot\frac{\delta^j m^j}{\delta^j + \lambda_0^j},
$$

A.2 No Atoms in the Offer Distribution $F^j(w)$

Lemma A.1 (Lemma 3.3 restated). *In any stationary wage–posting equilibrium, F^j has no mass points on $(R^j, \overline{w}^j)$.*

Proof. Suppose, toward a contradiction, that F has an atom at some interior $w \in (R, \overline{w})$; i.e., for arbitrarily small $\epsilon > 0$,

$$F(w+\epsilon) = F(w) + v(w) \quad \text{with } v(w) > 0.$$

Since $h(w) = \delta + \lambda_1\big(1 - F(w)\big)$, we have

$$h(w+\epsilon) = \delta + \lambda_1\big(1 - F(w) - v(w)\big) = h(w) - \lambda_1 v(w) > 0.$$

(i.) In-firm stock strictly rises. Using the steady-state stock

$$l(w) = \frac{(\delta+\lambda_1)\,\lambda_0\,u}{[h(w)]^2},$$

it follows that

$$l(w+\epsilon) = \frac{(\delta+\lambda_1)\,\lambda_0\,u}{[h(w)-\lambda_1 v(w)]^2} = l(w) + \frac{\lambda_1 v(w)\,(\delta+\lambda_1)\,\lambda_0\,u}{h(w)^2\,[h(w)-\lambda_1 v(w)]} \;>\; l(w).$$

(ii.) Per-hire expected profit strictly rises for small ϵ. The per-hire value is

$$\pi(w) = \int_0^\infty (ze^{\tilde{\alpha}\tau} - w)\,h(w)\,e^{-h(w)\tau}d\tau = \frac{z\,h(w)}{h(w)-\tilde{\alpha}} - w \qquad (\tilde{\alpha} < h(w)).$$

where, for simplicity, $ze^{\tilde{\alpha}\tau} \equiv \sum_n z_0 \epsilon^j(n) e^{\alpha^j(n)\tau} p_n^j$ Hence

$$\pi(w+\epsilon) - \pi(w) = z\left(\frac{h(w)-\lambda_1 v(w)}{h(w)-\lambda_1 v(w)-\tilde{\alpha}} - \frac{h(w)}{h(w)-\tilde{\alpha}}\right) \;-\; \epsilon.$$

Because $v(w) > 0$ is fixed while $\epsilon \to 0$, the bracketed term is a strictly positive constant (it reflects the discrete drop in h), whereas the wage increment contributes only $-\epsilon = o(1)$.

Thus, for all sufficiently small $\epsilon > 0$,

$$\pi(w+\epsilon) > \pi(w).$$

(iii) Total expected profit strictly rises. Total profit is

$$\mathbb{E}[\Pi(w)] = \pi(w)\, l(w) = \left(\frac{z\, h(w)}{h(w)-\tilde{\alpha}} - w\right) \frac{(\delta+\lambda_1)\,\lambda_0\, u}{[h(w)]^2}.$$

Combining (i)–(ii),

$$\mathbb{E}[\Pi(w+\epsilon)] - \mathbb{E}[\Pi(w)] = \big(\pi(w+\epsilon)-\pi(w)\big)\, l(w+\epsilon) + \pi(w)\big(l(w+\epsilon)-l(w)\big) \;>\; 0,$$

for all sufficiently small $\epsilon > 0$. This yields a profitable deviation, contradicting equilibrium profit equalization. Therefore F cannot have a mass point at any interior w, and F is continuous on $(R, \overline{w})$. $\square$

A.3 Proof for Identification Theorem

Proof. Let $x := h(w)$, $\beta_n := z_0\varepsilon(n)$, and $\beta'_n := z'_0\varepsilon'(n)$. Define

$$T(x) := \sum_n p_n\beta_n\left(\frac{x}{x-\alpha(n)} - \frac{x^2}{1-\alpha(n)}\right), \qquad T'(x) := \sum_n p_n\beta'_n\left(\frac{x}{x-\alpha'(n)} - \frac{x^2}{1-\alpha'(n)}\right).$$

Since $h(w)$ takes infinitely many values in I and I avoids all poles $\{\alpha(n), \alpha'(n)\}$, the equality $T(h(w)) = T'(h(w))$ for all w implies $T(x) \equiv T'(x)$ by the identity theorem.

Writing $x/(x-\alpha) = 1 + \alpha/(x-\alpha)$ gives the partial fraction decomposition:

$$T(x) = \sum_n p_n\beta_n - x^2\sum_n \frac{p_n\beta_n}{1-\alpha(n)} + \sum_{\alpha(n)\neq 0} \frac{p_n\beta_n\,\alpha(n)}{x-\alpha(n)},$$

$$T'(x) = \sum_n p_n\beta'_n - x^2\sum_n \frac{p_n\beta'_n}{1-\alpha'(n)} + \sum_{\alpha'(n)\neq 0} \frac{p_n\beta'_n\,\alpha'(n)}{x-\alpha'(n)}.$$

Uniqueness of partial fractions implies that:

$$\alpha'(\omega(n)) = \alpha(n), \quad p_n \beta'_{\omega(n)} \alpha'(\omega(n)) = p_n \beta_n \alpha(n),$$

and thus $\beta'_{\omega(n)} = \beta_n$. With $\varepsilon(0) = \varepsilon'(0) = \bar{\varepsilon}$, we have $z_0 = z'_0$, implying $\varepsilon(n) = \varepsilon'(\omega(n))$ for all $\alpha(n) \neq 0$. $\square$

Remarks (i) If exactly one index has $\alpha(n) = 0$, that component is identified via the constant and quadratic coefficients. If multiple $\alpha(n) = 0$, only $\sum_{\alpha(n)=0} p_n z_0 \varepsilon(n)$ is identified. (ii) If some nonzero α repeats, only $\sum_{\alpha(n)=a} p_n z_0 \varepsilon(n)$ is identified.

B Computational Details in Estimation

Objective. Let $G_{\text{emp},g}(w)$ denote the empirical CDF of wages for group $g \in \{m, f\}$ and $G_g(w;\theta)$ the model-implied CDF. In the on-the-job search structure used here, the model CDF is generated from the solved offer CDF $F_g(w;\theta)$ via

$$G_g(w;\theta) = \frac{\delta^g \, F_g(w;\theta)}{\delta^g + \lambda_1^g \big(1 - F_g(w;\theta)\big)}. \tag{12}$$

Let $R_g(\theta)$ be the reservation wage and $\overline{w}_g(\theta)$ the upper support obtained from the model's closed-form bound. For each group we minimize a discretized Anderson–Darling (AD) loss that up–weights discrepancies near the CDF tails. On a fine grid $\{w_{g,j}\}_{j=1}^{M_g} \subset [R_g(\theta), \overline{w}_g(\theta)]$ the group–specific criterion is approximated by a trapezoidal sum

$$AD_g(\theta) \approx \sum_{j=1}^{M_g-1} \frac{\big(\Delta_{g,j}(\theta)\big)^2 + \big(\Delta_{g,j+1}(\theta)\big)^2}{\big(\widehat{G}_{g,j}(1-\widehat{G}_{g,j}) + \varepsilon\big) + \big(\widehat{G}_{g,j+1}(1-\widehat{G}_{g,j+1}) + \varepsilon\big)} \times \frac{w_{g,j+1} - w_{g,j}}{2}, \tag{13}$$

$$\Delta_{g,j}(\theta) := G_g(w_{g,j};\theta) - \widehat{G}_{g,j}, \qquad \widehat{G}_{g,j} := G_{\text{emp},g}(w_{g,j}),$$

with a small stabilizer $\varepsilon > 0$ to avoid exploding weights when $\widehat{G}_{g,j} \in \{0, 1\}$. The sample objective is the sum across groups,

$$AD(\theta) = \sum_{g \in \{m,f\}} AD_g(\theta). \tag{14}$$

The parameter vector θ stacks (i) group–specific reservation–wage components $\alpha^g = (\alpha_0^g, \alpha_1^g, \alpha_2^g)$, (ii) λ_0^g, λ_1^g, and (iii) a common z_0. Monotonicity and feasibility are enforced by smooth reparameterizations: $\alpha_0^g \geq \alpha_1^g \geq \alpha_2^g < \delta^g$ (via a logistic stick–breaking transform) and $\lambda_0^g > \lambda_1^g$. We obtain $\widehat{\theta}$ by multi–start differential evolution and a local Nelder–Mead refinement under these constraints.

Asymptotic normality and standard errors. By Donsker's theorem, the empirical CDF satisfies $\sqrt{n}\big(\widehat{G}_{\mathrm{emp},g}(\cdot) - G_{0,g}(\cdot)\big) \Rightarrow \mathbb{G}_g \circ G_{0,g}(\cdot)$, where $\mathbb{G}_g$ is a mean–zero Gaussian bridge. Under standard M–estimation regularity conditions the AD estimator is consistent and asymptotically normal:

$$\sqrt{n}\big(\widehat{\theta} - \theta_0\big) \xrightarrow{d} \mathcal{N}\big(0,\ \mathcal{I}(\theta_0)^{-1}\big).$$

In practice we approximate the (observed) Hessian of the sample AD criterion at the optimum,

$$\widehat{H} = \left.\frac{\partial^2 AD(\theta)}{\partial\theta\,\partial\theta'}\right|_{\theta=\widehat{\theta}}, \tag{15}$$

using finite differences, and we add a small ridge $\lambda_{\mathrm{ridge}} I$ for numerical stability. Our baseline (information–matrix) standard errors are computed from

$$\widehat{\mathrm{Var}}(\widehat{\theta}) = \big(\widehat{H} + \lambda_{\mathrm{ridge}} I\big)^{-1}, \qquad \mathrm{SE}(\widehat{\theta}_i) = \sqrt{\big[(\widehat{H} + \lambda_{\mathrm{ridge}} I)^{-1}\big]_{ii}}, \tag{16}$$

with 95% confidence intervals $\widehat{\theta}_i \pm 1.96\,\mathrm{SE}(\widehat{\theta}_i)$.

C Panel Data Results in CFPS Data

Check with panel data results One way to assess whether the estimated offer-arrival rates are consistent with observed labor-market dynamics in China is to examine how frequently the same individuals experience promotions (wage increases) or job changes across survey waves. Neither of these empirical moments directly corresponds to the promotion probability λ_1^j in the model, since in the model a worker's wage increases only when a new offer drawn from the offer distribution exceeds the current wage—either from the same employer or through a job-to-job transition. In contrast, in the data, wages may rise within the same position due to seniority pay, performance bonuses, or cost-of-living adjustments; such increases do not necessarily reflect new offers. Conversely, a job change in the data may result from either involuntary separation or a voluntary job-to-job transition. While the latter corresponds exactly to a promotion in the model, it excludes cases of within-firm promotions.

Therefore, these empirical moments serve only as approximate benchmarks for the estimated λ_1^j. On average, the promotion frequency observed in the data should correspond to the expected frequency of upward moves implied by the model, given by

$$\int_R^{\overline{w}} \lambda_1(1 - F(w))\, dF(w) = \tfrac{1}{2}\lambda_1. \tag{17}$$

Because we observe only survey waves spaced two years apart, the probability of remaining in the same wage bin over both periods satisfies $(1 - \frac{1}{2}\lambda_1^j)^2 = \Pr(\text{staying})$. This relationship provides a simple way to compare model-implied offer arrival rates with the empirical frequency of observed wage stagnation.

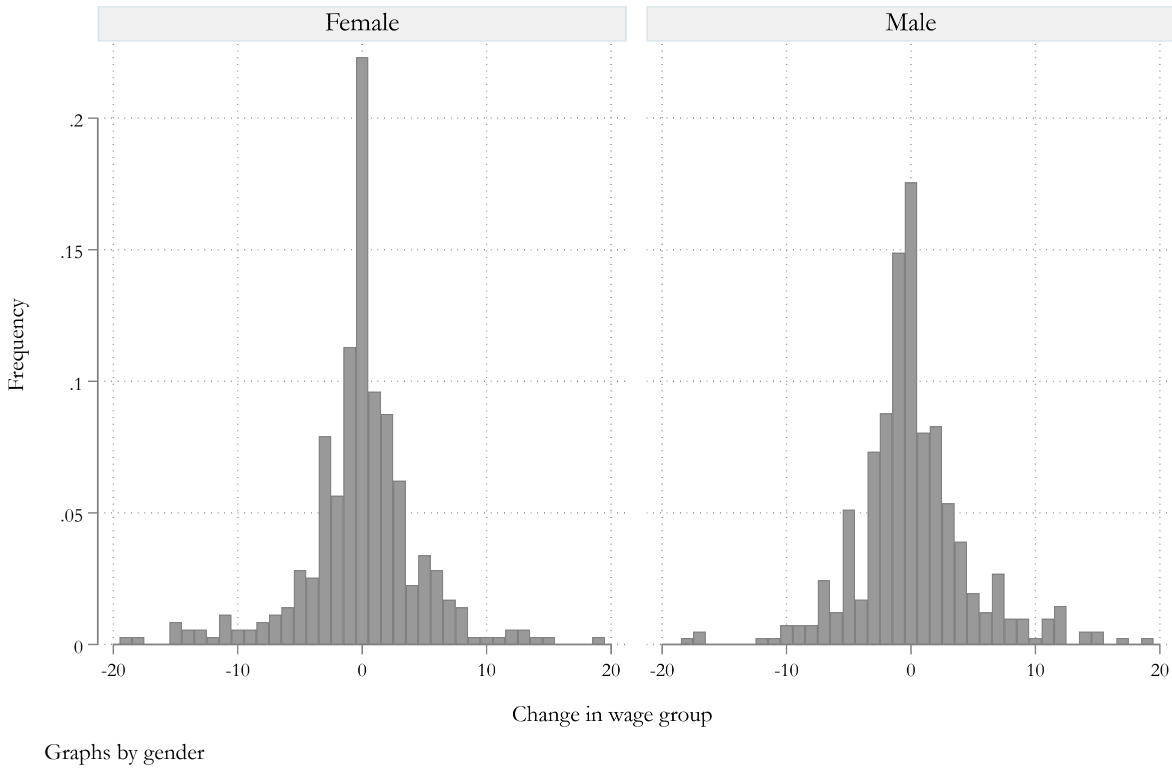

Figure 9: Change in Gender-Specific Wage Groups

Because (real) wages are continuous, the probability that an individual's wage remains exactly the same across two consecutive survey waves is virtually zero. Therefore, I divide the male and female wage distributions into 20 gender-specific bins and interpret a promotion as a wage increase large enough to move an individual from one bin to a higher one. Figure 9 presents the distribution of wage-bin changes between 2012 and 2014 for women and men. For women, among those whose wages did not decline, 12.3% remained in the same wage bin. This implies that the on-the-job offer arrival rate, λ_1, interpreted as the promotion probability, is approximately $0.649 \times 2 = 1.298$. For men, 11.5% of those whose wages did not decline remained in the same bin, implying an on-the-job offer arrival rate of $\lambda_1 \approx 0.661 \times 2 = 1.322$.

Changes in wage levels provide only an upper bound for identifying new job offers, since wage increases do not necessarily reflect promotions. However, when an employed individual switches employers, it is certain that a new offer has been accepted. Table 14 reports the proportion of individuals who remained with the same employer across two survey waves, corresponding to the probability of staying, i.e., $\big(1 - \text{Prob(switching)}\big)^2$.

Among highly educated young workers who remained in the labor force between 2012 and 2014, 44.73% stayed with the same employer. This implies an employer-to-employer transition rate of approximately 0.662 in 2012. Between 2014 and 2016, 67.75% of workers stayed with the same employer, implying a lower transition rate of 0.354 in 2014. Thus, over this period, the implied range of λ_1—the on-the-job offer arrival rate—lies roughly between 0.35 and 0.66, reflecting the low mobility characteristic of China's formal labor market for highly educated workers. These empirical moments provide a suggestive lower bound for the estimated λ_1 in the structural model.

Table 14: Job Continuity Across Surveys

	2012 → 2014	**(Employed in 2012)**
	High education	Non-high education
All ages		
Stayed in same main job	49.12%	43.27%
Not staying	45.96%	48.00%
Out of labor market	4.92 %	8.73%
Age ≤ 35		
Stayed in same main job	41.95%	28.57%
Not staying	51.83%	61.04%
Out of labor market	6.22%	10.39%
Gender breakdown (Age ≤ 35)		
Female: Stayed / no-Stay	38.35% / 61.65%	20.21% / 79.79%
Male: Stayed / no-Stay	45.22% / 54.78%	34.57% / 65.43%
	2014 → 2016	**(Employed in 2014)**
	High education	Non-high education
All ages		
Stayed in same main job	72.70%	66.21%
Not staying	21.54%	23.28%
Out of labor market	5.76%	10.51%
Age ≤ 35		
Stayed in same main job	64.20%	57.29%
Not staying	30.56%	33.33%
Out of labor market	5.25%	9.38 %
Gender breakdown (Age ≤ 35)		
Female: Stayed / no-Stay	63.52% / 36.48%	52.44% / 47.56%
Male: Stayed / no-Stay	64.85% / 35.15%	60.91% / 39.09%
	2012 → 2016	**(Employed in 2012)**
	High education	Non-high education
All ages		
Stayed in same main job	40.26%	32.00%
Not staying	50.58%	50.42%
Out of labor market	9.17%	17.58%
Age ≤ 35		
Stayed in same main job	30.53%	16.31%
Not staying	58.91%	65.24%
Out of labor market	10.56%	18.45%

Notes: Entries are column shares (percent). "Stayed in same main job" is the indicator of having the same main job across the stated waves based on the EHC-Job logic. "not-Staying" include the cases that workers changed main jobs and became unemployed. Panels "2012→2014" and "2014→2016" restrict to those employed in the baseline year (2012 or 2014, respectively). Panel "2012→2016" uses all respondents with non-missing status (no baseline employment restriction). High/Non-high education follow the study's definition.