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ABSTRACT

Who Gets Job Offers When Minimum Wages Rise? Evidence from China

Minimum wage increases are often accompanied by firms raising qualification requirements in job postings, but whether this skill upgrading reflects changes in who applies (composition effects) or changes in whom firms select from an unchanged applicant pool (selection effects) remains unclear. Using unique data from a large online job platform in China that links job postings, applications, and job offers, we compare firm hiring practices and applicant pools before versus after province-level minimum wage increases, treated versus control provinces, and minimum-wage versus higher-wage occupations. We find that firms raise educational requirements in postings by 3-4 percentage points and increase job offers to college-educated workers by 30%, while offers to less-educated workers remain unchanged. At the same time, the application volumes and applicant characteristics remain unchanged. This pattern reveals that the shift in job offers occurs entirely through the selection effect, as the short-run labor supply response is limited even when firms actively attempt to reshape their applicant pools. Minimum wage increases thus redistribute employment opportunities among existing job seekers away from less educated workers.

JEL Classification: J23, J63, O53

Keywords: minimum wage, job postings, part-time jobs, job offers, China

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1 Introduction

There has been growing recognition that in response to minimum wage hikes, firms adjust through multiple margins beyond the traditionally emphasized employment levels (Clemens, 2021), and that there is a need to understand how minimum wages reshape who gets hired rather than simply how many. To understand these dynamics, we must look at both sides of the market: how firms adjust their hiring and employment practices and how workers respond to higher wages.

Empirical studies consistently show that when labor costs rise, firms tend to become more selective, favoring workers with stronger productivity signals (Clemens et al., 2021; Jardim et al., 2022; Butschek, 2022). Importantly, Clemens et al. (2021) notes this pattern of credential upgrading is consistent with two distinct interpretations. First, firms may become more selective in hiring from an unchanged applicant pool——what we term a *selection effect*. Second, firms may impose higher requirements to take advantage of the higher-quality applicant pool likely attracted by higher wages——a *composition effect*. Both effects produce the same hiring outcome: more qualified workers filling minimum wage positions, but the distinction between these mechanisms has important implications. Under composition effect, the hiring outcome reflects stronger competition and marketing sorting. Under selection effect, the hiring outcome instead reflects the redistribution of opportunities among existing job seekers.[1] Whether credential upgrading following minimum wage increases reflects composition effects or selection effects remains an open empirical question.

[1] It is important to note that the posting-application sequence in job hiring practices suggests firms may raise education requirements in postings to attract more educated applicants (attempted composition effect), but if the applicant pool remains unchanged, any skill upgrading in job offering must occur through increased selectivity (realized selection effect).

Our paper addresses this gap by examining how minimum wage increases in China affect both sides of the labor market: how firms adjust job characteristics and requirements, and how the quantity and quality of job applications change in response.[2] We use a novel data set of online job postings from a major Chinese part-time employment platform. This platform data includes both job postings and job-seeker registration information, allowing us to link each posting to detailed information about its applicants. Consequently, not only can we observe changes in required worker attributes, compensation structures, and job amenities in response to minimum wage increases, but we can also track how labor supply responds through changes in application volumes and applicant demographics, a dimension largely unexplored in previous studies.

In empirical analyzes, we use a difference-in-difference-in-differences (DDD) framework that takes advantage of the implementation of minimum wage increases in Chinese provinces between 2016 and 2019. We improve traditional difference-in-differences (DD) designs by adding occupational variations to the standard geographic and temporal variations. Comparing occupations with different exposure to minimum wage policies within the same location and time period strengthens causal identification by controlling for location-specific time-varying factors (e.g. regional economic shocks or concurrent policy changes) that affect all occupations uniformly.

Our findings reveal that minimum wage increases generate skill upgrading entirely through selection effects. Following wage hikes of 8-10%, firms raise educational requirements by 3-4

[2] China offers a particularly valuable setting for studying minimum wage effects due to several institutional features. Since the 2004 "Minimum Wage Regulations," China has implemented a system in which minimum wages vary between provinces and municipalities, with mandatory adjustments at least once every two years. Additionally, China's minimum wage stands at approximately 25% of the average urban wage, a relatively modest level that may induce firms to employ strategies beyond employment adjustment.

percentage points and increase job offers to college-educated workers by 30%, while offers to less-educated workers remain unchanged. Application volumes and applicant characteristics show no change along any observable dimension. This pattern confirms that rather than attracting a higher-quality pool, firms become more selective in screening an unchanged applicant pool. Although total job offers expand by 20%, all growth accrues to college-educated or non-students workers. Minimum wage increases thus redistribute employment opportunities among existing job seekers, with less-educated and less-experienced workers fare relatively worse.

Our paper contributes to the literature in the following ways. First, previous studies have relied mainly on aggregate employment or wage data at the regional or industry levels, government or company payroll information, and individual longitudinal data (Manning, 2021). Our paper takes a relatively novel approach by utilizing matched job postings and applicant data. This unique data structure allows us to observe simultaneously both employer requirements and job seeker responses following minimum wage increases. Clemens et al. (2021) provided compelling evidence that minimum wage increases raise hiring standard in job vacancy postings using US data, identifying important demand-side adjustments. Our study complements their findings by directly observing how applicant pools (does not) shift in response to minimum wage increases. We can then directly rule out the propagation of minimum wage effects through potential labor supply channels.

Second, we extend the literature on the effects of minimum wage in developing economies, where labor market institutions and enforcement mechanisms differ substantially from those in advanced economies. Previous research suggests that the effects of minimum wages vary significantly in different economic contexts. Studies in developing countries such as Hungary

(Harasztosi and Lindner, 2019), Indonesia (Alatas and Cameron, 2008), South Africa (Bhorat et al., 2014), and Brazil (Neumark et al., 2006) reveal adjustment patterns that often diverge from those observed in the US or Europe, typically showing more pronounced employment elasticities or greater heterogeneity in responses. China represents a particularly valuable case for extending this literature due to its distinctive institutional characteristics. For example, its minimum wage system was implemented relatively recently with comprehensive coverage only achieved in 2004. The enforcement mechanisms remain decentralized with varying effectiveness and informal employment is widespread. By providing evidence from China through job posting data, we can identify firm and worker adjustment channels that may be more prevalent in contexts with weaker collective bargaining and less comprehensive labor market regulation.

Third, our focus on the part-time labor market——primarily composed of college students and recent graduates——provides insights into how minimum wage policies affect a segment of the labor market that is both economically significant and relatively understudied. This demographic represents a crucial transition point in China's labor market, with approximately 8 million university graduates entering the workforce annually. Part-time employment serves multiple functions in this context: it provides supplementary income for students, offers early career experience for recent graduates, and serves as a stepping stone to full-time employment for young workers developing their skills. While most minimum wage research focuses on low-skilled, full-time workers in sectors like food service, retail, and manufacturing (Dube et al., 2016; Cengiz et al., 2019), the effects on flexible, part-time arrangements may differ substantially due to distinct labor market attachment, reservation wages, and employer expectations (Nardone, 1986; Montgomery, 1988; Kalleberg, 2000). This segment of the labor market is growing rapidly in China, with the gig economy and flexible work arrangements becoming increasingly prevalent. By examining how minimum wage policies reshape opportunities in this market, our study contributes to a more comprehensive understanding of labor market dynamics in transitional economies, where education-to-employment pathways are evolving alongside rapid economic development and regulatory changes (Hershbein and Kahn, 2018; Modestino et al., 2020).

The remainder of the paper is organized as follows: Section 2 reviews the relevant literature on minimum wage effects, with particular attention to firm selecting workers and labor adjustments. Section 3 provides background information on China's minimum wage system and its evolution. Section 4 describes our data and outlines empirical methodology. Section 5 presents the results, and section 6 concludes.

2 Worker Selection and Labor Supply Under Minimum Wages

When labor costs rise, firms tend to become more selective.[3] This selectivity is observed through multiple contexts and operates along both observable and unobserved dimensions of worker quality. At the intensive margin, firms facing higher wage costs reallocate hours toward workers with demonstrated productivity. Evidence from Seattle shows that less experienced workers suffered larger reductions in hours worked with no net earnings gains; in

[3] Clemens et al. (2021) outlines multiple channels through which minimum wage increases can generate labor-labor substitution where firms hire more skilled workers: (1) between-firm reallocation, where firms employing low-skilled workers exit or contract while firms with higher-skilled workers expand; (2) within-firm substitution, where firms replace lower-skilled workers with higher-skilled workers or increase effort requirements for existing workers; and (3) labor-capital substitution, where firms adopt self-service technologies that require complementary skilled workers to operate (Aaronson and Phelan, 2019).

contrast, more experienced workers had modest hours reductions and positive earnings gains (Jardim et al., 2022). At the extensive margin, firms raise standards for new workers along multiple dimensions. Clemens et al. (2021) provides the first systematic evidence of credential upgrading in hiring practices, showing that minimum wage increases lead U.S. firms to raise educational requirements in job postings; and correspondingly increase the average education and age of workers employed in low-wage occupations. Firms also select workers based on productivity dimensions that cannot be detected using observable measures like education, age, or experience, and such selection tends to be more pronounced at establishments with higher pre-reform screening capacity (Butschek, 2022).

Empirically, it's not clear if the selectivity is driven by selection effect or composition effect. Distinguishing between these two effects requires understanding worker responses to minimum wage increases. One important margin of labor supply adaption to minimum wage policy is worker effort adjustment. Studies have shown that workers who value their jobs most are willing to exert greater effort to retain them, and the increased effort can partially offset employers' higher labor costs (Ippolito, 2003; Zhao and Sun, 2021; Coviello et al., 2022; Ku, 2022). Another labor supply response to minimum wage increases is in the form of job-to-job reallocation among existing workers. Workers shift toward higher-quality establishments with better wage premiums and more skilled workforces (Dustmann et al., 2022), and migrate from undesirable to desirable occupations as minimum wages compress compensating differentials (Aaronson and Phelan, 2019). Does higher wages draw new workers into the labor market? Search-and-matching models of the labor market predict that increasing the minimum wage can induce workers to enter the labor force and search more intensely, potentially leading to better job matches that could offset the increased hiring costs for firms (Ahn et al., 2011).[4] The empirical evidence, however, provides only limited support for this prediction. Adams et al. (2022) shows workers do not enter the labor market to search in response to minimum wage increases, and existing job seekers only temporarily intensify their search efforts before returning to baseline behavior.

The existing evidence on labor supply responses suggests composition effects may be limited, as workers adjust effort levels and reallocate across jobs but do not appear to enter the labor market as new job seekers. Yet no study provides direct evidence by observing both job postings and application behavior to confirm that firms select more intensively from an unchanged applicant pool.

The part-time labor market also merits particular attention as a context where minimum wage effects may diverge from patterns observed in full-time employment, but remains understudied in the minimum wage literature. Part-time workers differ systematically from their full-time counterparts in demographics and labor force attachment (Nardone, 1986; Montgomery, 1988; Kalleberg, 2000). Their preference for flexibility may make them more responsive to non-wage amenities that accommodate their other commitments. Their job search may be less intensive or more selective due to time constraints and lower stakes if part-time work represents supplementary rather than primary income. Hence, minimum wage increases in part-time markets may be even less likely than in full-time markets to induce large compositional changes in applicant pools.

[4]Critically, Ahn et al. (2011) shows that those with the lowest reservation values and highest search costs, typically from less privileged backgrounds, get pushed out by workers with higher reservation wage but lower search costs who are newly incentivized to enter the market.

3 Minimum Wage Policies in China

China's current minimum wage system can trace its origins back to after its founding. In 1956, China began implementing reforms in its wage system, and the relevant reform documents clearly stipulated the starting wage for workers. However, this early minimum wage system was only applicable to state-owned enterprise employees. For the ensuing decades, workers in the private sector and self-employed individuals were not covered by the minimum wage stipulation. It wasn't until the early 1990s that a nationwide minimum wage was legally established. In 1993, the then Ministry of Labor (now the Ministry of Human Resources and Social Security) introduced and formulated the "Enterprise Minimum Wage Regulations", which for the first time clearly stated China's implementation of the minimum wage system. In 1994, the Standing Committee of the National People's Congress passed the "Labor Law of the People's Republic of China", which, in Article 48, stipulated the minimum wage system and stated that the specific standards for the minimum wage were to be determined by the governments of provinces, autonomous regions, and municipalities, and were reported to the State Council for the record. The Labor Law stipulates that employers must not pay wages lower than the local minimum wage standard.

By 2004, all of China's 31 provinces, autonomous regions, and municipalities had established a minimum wage system. The frequency of minimum wage adjustments changed from no more than once a year in 1994 to at least once every two years in 2004. Following the general principles set in the Labor Law, a major minimum age policy, the "Minimum Wage Regulations" was announced in 2004. The Regulation stipulated that the monthly minimum wage applies to full-time workers, and the hourly minimum wage standard applies to part-time workers. There's no requirement to convert between the monthly and hourly minimum wage standards. The Regulation, while allowing different administrative regions to have different minimum wage standards, did not allow varying minimum wage standards across industries, a major deviation from the 1994 regulation. Further, the 2008 "Labor Contract Law" stated that employers should sign written labor contracts with workers and provide favorable evidence for workers in case of labor disputes. Since then, the policies related to the minimum wage have been relatively stable.

Between 1995 and 2019, the national average nominal minimum wage increased about 7.5 times. Adjusted for inflation, the real minimum wage had a national average increase of 56.6% during the period.[5] The effectiveness of minimum wage policies depends critically on compliance and enforcement. Using firm-level payroll data, Jia and Du (2015) document that approximately 13% of workers in Chinese firms earn less than the local minimum wage standard, with compliance rates varying significantly across firm types and regions. Enterprise-level matched data reveal that while most firms comply with monthly minimum wage standards, adherence to overtime pay regulations remains weak (Ye et al., 2015). Most of individuals currently working seem to be aware of the minimum wage policies. Using the China National Petroleum Corporation's gas stations as a sampling frame, interviews were conducted with station managers and employees, most of whom were aged between 25 and 45. 77.5% of the total sample were aware of the minimum wage requirements. Of those who were aware of the policy, 79.3% knew the minimum wage standard in their district or county. Yet, the knowledge of minimum wage policies is rather low among the general public. Based

[5]In response to the economic crisis that began in 2008, all 31 provinces did not adjust their minimum wage in 2009. With the economic recovery in 2010, all provinces except Chongqing adjusted minimum wage upwards. The average adjustment rate in 2010 was 24.4%.

on the China Household Finance Survey, a nationally representative household survey, the average awareness rate of minimum wage standard is only about 20% among its entire adult sample.

Even with the regular hikes across the country, the minimum wage in China relative to the average wage is still rather low In 2019, based on data from the National Bureau of Statistics, the minimum wage stands at about 25% of the average wage of urban workers in 31 provinces, with the highest ratio in Henan at 32.13%, and the lowest in Tibet at 17.07%.

Recent studies have demonstrated the complexity of the impacts of minimum wage hikes in China, with intended and unintended consequences across various economic actors.[6] Firms also adjust to minimum wage increases through various channels, such as cutting fringe benefits, laying off low-skilled workers (Long and Yang, 2016), substituting labor with capital (Hau et al., 2020), and investing in financial assets (Du and Wang, 2020). However, the survival probability of the most exposed firms may decrease (Mayneris et al., 2018), and the probability of exporting and export sales may decline, particularly for firms with lower wages and capital-labor ratios (Gan et al., 2016). At the worker level, Howell (2020) provides evidence of the distributional effects of minimum wages, finding that they compress the urban wage distribution and reduce wage inequality, with larger impacts on low-skilled and ethnic minority workers.

It is evident from these studies that minimum wage policies can have positive effects on

[6]Some studies find that firms experience higher wage costs and reduced profitability (Long and Yang, 2016), while others show that minimum wage hikes can stimulate productivity improvements and innovation (Mayneris et al., 2018; Liu and Lv, 2022; Du and Wang, 2020) and increase energy efficiency (?). However, there is also evidence that financially constrained firms and firms in competitive industries may choose to forgo green technology upgrading, leading to increased pollution emission (Zhang et al., 2023). The heterogeneous effects across firms are noteworthy, with private, foreign-owned, and labor-intensive firms often experiencing more significant impacts compared to state-owned enterprises (Hau et al., 2020; Fan et al., 2018).

worker welfare and firm innovation; they may also lead to negative outcomes such as reduced employment, decreased export competitiveness, and increased pollution. The impacts are not uniform across firms, with ownership structure, labor intensity, financial constraints, and productivity levels emerging as key moderating factors. While some firms may struggle with higher labor costs and reduced profitability, others are able to adapt and even benefit from the policy changes through productivity enhancements and innovation.

4 Data

The job postings data used in this paper comes from the mobile internet part-time recruitment platform Jianzhi Mao (Moonlighting Cat).[1] This mobile app provides job information on part-time employment positions and its primary user group consists of college students, recent graduates, and other young job-seekers.

The original data file, covering the period from 2016 to 2019, contains four distinct components: (1) complete registration details of employer users; (2) a 30% sampling of job postings and recruitment records from the registered employers; (3) complete registration information of job-seeking users; and (4) all job seekers' records associated with the 30% sampled job postings. A unique job posting identification number allows each job posting to be matched with the registration information of both the employer and job-seekers. Included in the analysis are 1,079,118 job postings, covering 31 provinces and 292 cities.[7]

We extract four categories of information from the job posting and recruitment record data. The first is on the characteristics of each job position. They include information on

[7] Job postings totaled 260,755 in 2016, 302,764 in 2017, 300,697 in 2018, and 214,902 in 2019.

salary and compensation,[8] if the job provides any benefit, if the job is stable, and if the job allows flexible working hours or flexible working locations.[9] The second category of information is on job requirements. More specifically, we focus on whether the job posting specifies any requirement of applicants' education level, working experience, or age. Moreover, we also extract information on the job requirements that are non-standardized but relatively common in these job postings. Roughly these requirements can be categorized as requirements on work ethics ("hardworking", "responsible", "reliable", "conscientious" and "diligent"), behavioral expectations ("punctual", "cheerful", "patient", "obedient", "steady" and "affectionate"), and applicants' appearance ("sweet", "good-looking" and "beautiful"). Third, from the job-seeker registration data, we obtain information on the individual characteristics of the job applicants: age, gender, education level, and if they have graduated from university, if applicable. Lastly, for each job position, we can also determine whether each job seeker is ultimately hired for the position. Based on this, we can further aggregate and calculate the actual number of job offers for each job posting.

Based on the above information and using each job posting's city location, occupation code[10], and posting date, we aggregate the data to the firm–occupation–month level to construct series of outcome variables

[8]The data is standardized to an hourly wage.

[9]If the job posting makes references to any of these benefits: "five insurances" or "three insurances", "housing fund" or "one fund", "work injury insurance", "social security", "medical insurance", it indicates that the position offers benefits. If the job description mentions any of these keywords: "long-term", "stable", and "labor contract", the position is considered stable. If the job description includes any of these keywords: "flexible", "anytime", and "daily payment", the job is considered flexible in terms of working hours. If the job description mentions any of these keywords: "at home", "internet" "anywhere", "remote", and "online", the job is considered to allow flexible working locations.

[10]Occupation codes are based on the 2022 edition of the China Occupational Classification Dictionary. We manually assign each job posting to a corresponding three-digit occupation code after text analysis of job titles.

We collect data on the timing of minimum wage adjustments across Chinese provinces during 2016-2019. More specifically, we record the first minimum wage adjustment in each province occurring between the first quarter of 2017 and the fourth quarter of 2019. We exclude 2016 adjustments to maximize the use of 2016 data as the pre-adjustment period. For provinces that adjusted minimum wages in 2016, data from the adjustment quarter and all preceding quarters are removed. Figure 1 illustrates the heterogeneous implementation schedule of minimum wage increases across provinces in our regression sample. The analysis focuses on the first minimum wage adjustment for each province within this time frame, providing clean treatment variation for our empirical design. Hence, for provinces experiencing multiple adjustments during 2016-2019, we retain only the period between the first and second adjustments, excluding observations after the second adjustment to avoid contamination from subsequent policy changes. The pre-treatment period spans from the first quarter of 2016 to the actual quarter of minimum wage adjustment for each province, while the post-treatment period covers the duration from the adjustment quarter through the fourth quarter of 2019. During this period, provinces implemented minimum wage adjustments at different points, creating substantial temporal variation in policy exposure.[11]

[11]It is notable that Hebei Province did not implement any minimum wage adjustments during the period. Hebei actually adjusted its minimum wage in the second quarter of 2016 and the fourth quarter of 2019. As we only consider adjustments from 2017 onward, the 2016 adjustment is excluded from our analysis. In addition, its 2019 adjustment occurred in November, leaving little post-treatment period for analysis, so we drop Hebei's data from November-December 2019. As a result, Hebei Province has no minimum wage adjustments within our final study period.providing a consistent control unit throughout our analysis window.

5 Empirical Strategy

As Gopalan et al. (2021) pointed out, wage increases from minimum wage policies extend beyond workers earning exactly the minimum wage. As employers maintain wage hierarchies and use minimum wages as benchmarks in wage setting, the wage effect will spillover to workers earning wages above the new minimum wage level. Hence we employ a two-step approach to identify the causal effects of minimum wage increases. First, we examine which firm-specific occupations are affected by minimum wage spillover effects using a wage bin classification system and accordingly define treatment and control groups based on their pre-adjustment wage levels. Second, we implement a triple difference event study design that exploits variation across firm-specific occupations with different minimum wage exposure, cities with different adjustment timing, and quarters relative to the policy change.

5.1 Identifying Treatment and Control Occupations

To examine spillover effects of minimum wage adjustments, we keep firm-occupation pairs that posted advertisements both before and after the minimum wage adjustment. For occupation o of firm f in city c, we calculate the median pre-adjustment hourly recruitment wage W_{foc0} and obtain the corresponding hourly minimum wage W_{c0} at the city level. We then construct wage bins with increments of $\Delta = 0.5$ CNY,[12] mapping each firm-occupation pair to bins centered around W_{c0} with the wage bin indicator bin_{ijc}^{b}, where $b = 0$ represents wages in $[W_{c0}, W_{c0} + \Delta]$ and $b \neq 0$ represents $[W_{c0} + b\Delta, W_{c0} + (b + 1)\Delta]$. We examine wage

[12]The Chinese Yuan (CNY) to US Dollar (USD) average exchange rate in 2016 is 1 CNY=0.156 USD. The average hourly minimum wage adjustment in our sample is 1.8 CNY, approximately 3-4 wage bins, with the smallest adjustment being 0.8 CNY and the largest being 5.3 CNY.

bins in the range $b \in [-10, 30]$.[13][14]

To estimate the spillover range of minimum wage effects, we apply this regression:

$$\log(W_{focym}) = \alpha_0 + \sum_{b=-10}^{30} \alpha^b \times \text{Hike}_{cym} \times \text{bin}_{foc}^b + \mu_{fo} + \mu_{cy} + \mu_{cm} + \mu_{oym} + \varepsilon_{focym} \tag{1}$$

where $\log(W_{foct})$ is the logarithm of average hourly wages for occupation o of firm f in city c at year y and month o, and Hike_{cym} a post-treatment indicator that equals 1 for all periods after city c adjusted its minimum wage, and 0 for all periods before the adjustment. The coefficient α^b captures the minimum wage effect within each wage bin.

The fixed effects included in this specification includes firm-occupation fixed effects (μ_{fo}), city-year fixed effects (μ_{cy}), city-month fixed effects (μ_{cm}), and occupation-year-month fixed effects (μ_{oym}). These high dimension fixed effects serve to account for factors that affect wage outcomes. In particular, firm-occupation fixed effects account for time-invariant systematic differences in job quality and firm characteristics that determine both wage levels and minimum wage binding constraints across firm-occupation pairs. City-year fixed effects absorb city-specific economic shocks and annual trends, including local GDP growth, year-specific policy changes, and evolving labor market conditions that affect all occupations within a city in a given year. City-month fixed effects capture recurring seasonal patterns specific to each city, such as tourism cycles, agricultural seasons, or weather-related labor demand fluctuations that repeat across calendar months. Lastly, occupation-year-month fixed effects difference out occupation-specific seasonal patterns, time trends, and labor market condi-

[13] Our focus on the part-time labor market necessitates more wage bins below the minimum wage threshold, as part-time positions often have actual or calculated wages below minimum wage standards.

[14] Samples with hourly wages less than $(W_{c0} - 10\Delta)$ or greater than $(W_{c0} + 30\Delta)$ are merged into the $b = -10$ and $b = 30$ wage bins receptively.

tions that vary at the year-month level. This controls for occupation-wide factors such as national demand shifts, technological changes, and macroeconomic conditions that could correlate with minimum wage policy timing.

The regression is weighted using provincial population shares from the 2020 Chinese Census to obtain nationally representative coefficients, with standard errors clustered at the city level. The coefficients α^b capture the effectiveness of the minimum wage policy and the spillover effects.

We expect wage bins with pre-adjustment wages below the minimum wage ($b < 0$) to show significantly positive coefficients. With spillover effects, wage bins slightly above the new minimum wage should also show wage increases. Consistent with these expectations, the estimation results (Figure 2) show minimum wage adjustment effects ($\hat{\alpha^b}$) remain significant and persistent for $b \in [-10, 9]$, while coefficients become insignificant and volatile when $b \geq 10$. We therefore define our treatment group as occupations with $b \leq 9$, representing those whose wages are below or equal to the new minimum wage plus 4.5 CNY, while our control group consists of occupations whose wages exceed this threshold. We denote this group classification with the variable Treat_{foc}, where $\text{Treat}_{foc} = 1$ for $W_{fo0} \in [W_{c0} - 10\Delta, W_{c0} + 9\Delta]$, and $\text{Treat}_{foc} = 0$ for $W_{fo0} \geq (W_{c0} + 10\Delta)$.[15]

5.2 Event Study Triple Difference Model

Based on the treatment-control group classification, we construct our main triple difference regression equation using an event study framework to estimate the dynamic effects of minimum wage adjustments:

[15] In robustness checks, we use $b \leq 6$ and $b \leq 12$ respectively as the criteria for treatment group classification.

$$Y_{focym} = \beta_0 + \sum_{\substack{k=-5 \\ k\neq -1}}^{5} \beta^k \left(\pi_{cym}^k \times \text{Treat}_{foc}\right) + \mu_{fo} + \mu_{cy} + \mu_{cm} + \mu_{oym} + \varepsilon_{focym} \tag{2}$$

In this specification, Y_{focym} represents outcome variable for occupation o of firm f in city c in year y ($y \in \{2016, 2017, 2018, 2019\}$) and month m ($m \in \{1, 2, ..., 12\}$). The term π_{cym}^k represents a series of dummy variables for quarters relative to the minimum wage adjustment timing, with the quarter immediately before adjustment $k = -1$ serving as the reference period.[16] The interaction term $\pi_{cym}^k \times \text{Treat}_{foc}$ creates the difference-in-differences-in-differences (DDD) by exploiting variation across firm-specific occupations (treatment vs. control), variation across time (before and after adjustment), and variation across cities with different adjustment timing. Therefore, coefficients β_k captures how the difference between treatment and control occupations in quarter k compares to their difference in the pre-treatment period, relative to this comparison in cities without minimum wage adjustments. This event study specification allows us to examine pre-treatment trends through $\hat{\beta_{-5}}$ to $\hat{\beta_{-2}}$ to validate the parallel trends assumption and identify the persistence of minimum wage impacts over time through $\hat{\beta}_0$ to $\hat{\beta}_5$.

Compared to traditional DD approaches, the DDD framework outlined in Equation 2 provides additional identification power. DD approaches often suffer from critical limitations—geographic-time comparisons assume all firms are equally affected by minimum wage changes (diluting treatment effects), and occupation-time comparisons cannot control for location-

[16] We aggregate minimum wage adjustments to the quarterly level because Chinese minimum wages often have implementation lags of 1-2 months between announcement and enforcement, and this lag varies across provinces. Aggregating to quarterly level account for this variation while preserving the high-frequency characteristics of our data, with regression coefficients equivalent to the average monthly effects within each quarter. The timing of minimum wage adjustments across quarters is relatively balanced. The highest proportion of minimum wage adjustments occurs in the third quarter, but this proportion is approximately 35%, which shows no significant difference compared to other quarters.

specific economic shocks that drive endogenous policy timing—the DDD framework addresses these concerns simultaneously by eliminating both location-specific time-varying confounders and systematic differences between precise treatment and control occupations.

6 Results

This section presents our main empirical findings on how minimum wage increases affect China's part-time labor market based on the triple difference event study specification outlined in Equation (2). We organize the results to trace the adjustment process systematically. We begin by establishing the validity of our research design, documenting the wage effects of minimum wage increases. We then examine firm-side responses, analyzing changes in job vacancy postings, overall hiring volume, job requirements, and non-wage job characteristics. Next, we investigate worker-side responses, focusing on whether and how the volume and composition of job applications shift after minimum wage increases. Finally, we present the ultimate hiring outcomes, focusing on which types of workers capture the employment gains and documenting the selection effects that emerge from firms' screening behavior.

6.1 Wage Effects

We begin by examining whether minimum wage increases generate significant wage effects for our treatment group occupations. Table 2 presents the event study estimates of minimum wage impacts on log hourly wages across different fixed effects specifications.

The pre-treatment average impact coefficients across all specifications are small in magnitude and statistically insignificant. This suggests that treatment and control occupations followed similar wage trajectories before the minimum wage adjustments, supporting the parallel trends assumption crucial for causal identification in our DDD framework. The consistency of results across specifications (Columns 1-4) demonstrates that our findings are robust to different combinations of fixed effects.

Following the minimum wage increase, we observe immediate and significant positive wage effects. In our preferred specification with the full set of fixed effects (Column 4), hourly wages in treatment occupations increase by 8.0% in the first quarter after the policy change (T=0), relative to control occupations in the same city and time period. The wage effect remains of similar magnitude and statistically significant through the second quarter (T=2). Beyond the second quarter, the coefficients stay positive but lose statistical significance. The average post-treatment effect across all quarters is 9.8%, significant at the 10% level.

Figure 3 provides a visual representation of these dynamic treatment effects, clearly illustrating the absence of pre-trends and the sustained positive wage impact following minimum wage implementation. These results confirm that our treatment group classification successfully identifies firm-occupation pairs exposed to minimum wage hikes, establishing a solid foundation for examining subsequent adjustments in hiring behavior and job requirements.[17]

All results in the following subsections employ the same event study specification outlined in Equation (2), using the full set of fixed effects as shown in Column 5 of Table 2.

[17] These wage effects are robust to using an alternative treatment group definition based on wage bin thresholds of new minimum wage ±3 CNY and ±6 CNY (Tables A.1 and A.2, Column 1), to restricting the sample to hourly wage jobs only (Table A.3, Column 1), to using alternative estimation methods based on Callaway and Sant'Anna (2021) and Borusyak et al. (2024) (Table A.4, Column 1), and to using an alternative sample excluding provinces with fewer than four pre-treatment quarters (Table A.5, Column 1).

6.2 Firm Hiring Practices: Job Postings and Offers

We first investigate whether firms reduce labor demand by posting fewer job vacancies. Figure 4 plots the event study coefficients for the number of job postings at the firm-occupation level. Contrary to standard predictions of employment contraction, we find no evidence that firms reduce vacancy postings following minimum wage increases. The pre-treatment coefficients hover around zero and show no discernible trend, while the post-treatment coefficients remain small and statistically insignificant across all quarters. This suggests that firms maintain their recruitment intensity despite facing higher wage costs.

Even when vacancy postings remain unchanged, the actual number of accepted applicants or job offers expands significantly. Figure 5 shows following the minimum wage increase, the number of accepted applicants begins to rise, with the treatment effect reaching approximately 6% in the first quarter and growing steadily to about 20% by the fifth quarter. [18]

We now examine how job offers are distributed across different types of workers. Figure 6 Panel (a) presents treatment effects on the logarithm of accepted applicants, separately for workers with college education or above and those with below-college education. Pre-treatment coefficients for both groups fluctuate around zero. Following minimum wage increases, job offers extended to workers with college education or above increase steadily, growing by approximately 20% by the second quarter and 30% by the fifth quarter. The effects are statistically significant and persistent throughout the post-treatment period. In

[18] The expansion in total job offers is robust to alternative treatment group definitions (Tables A.1 and A.2, Column 2), to using acceptance rates instead of the number of accepted applicants (Table A.3, Column 2), to alternative estimation methods (Table A.4, Column 2), and to an alternative sample excluding provinces with fewer than four pre-treatment quarters (Table A.5, Column 2).

contrast, the job offers for workers with below-college education shows no significant change, with coefficients remaining close to zero throughout the post-treatment period.

Figure 6 Panel (b) examines job offer outcomes by student status, comparing non-students versus current students. Following minimum wage increases, job offers for non-students rise steadily, reaching approximately 30% by the fifth quarter. The effects mirror the pattern observed for educated workers in Panel (a). In contrast, job offers to current students shows no significant change. [19]

These patterns reveal that while aggregate job offers expand by 20%, this growth accrues entirely to workers with college education or above, and those who have graduated. Less-educated workers and current students see no change in job offers—they are excluded from the expanded job opportunities.

How do firms offer more jobs to some workers without posting more jobs? Figure 7 shows that firms raise their educational requirements. Panel (a) shows that the probability of job postings explicitly requiring specific education levels increases significantly after minimum wage hikes. The treatment effect grows from near zero in the pre-period to approximately 9 percentage points by the third quarter post-treatment. This represents a substantial increase given that only 15.3% of postings in our sample specify education requirements (Table 1). Panel (b) shows that work experience requirements also increase significantly following minimum wage hikes. The treatment effect rises from near zero in the pre-period to approximately 4 percentage points by the third quarter, and this increase persists through later

[19] The differential effects by education level and student status are robust to alternative treatment group definitions (Tables A.1 and A.2, Columns 3-6), to using firm acceptance rates as the outcome (Table A.3, Columns 3-6), to alternative estimation methods (Table A.4, Columns 3-6), and to an alternative sample excluding provinces with fewer than four pre-treatment quarters (Table A.5, Columns 3-6)

quarters. Together, these results indicate that firms respond to higher wages by raising both educational and experience requirements.

Figure 8 examines whether firms also adjust requirements along non-human capital dimensions. We find no evidence of systematic changes. Age requirements, work ethics requirements (e.g., "hardworking," "responsible"), behavioral requirements (e.g., "punctual," "cheerful"), and appearance-related requirements all show coefficients fluctuating around zero with no consistent patterns. These null results suggest that firms' adjustment strategy focuses specifically on measurable human capital credentials rather than broader personal attributes or subjective characteristics.

Finally, we examine whether firms offset higher wages by reducing non-wage job amenities. Figure 9 presents results for four dimensions of job characteristics. The provision of employee benefits (Panel a), promises of job stability (Panel b), and working hour flexibility (Panel c) all show no significant changes, with coefficients remaining close to zero throughout the event window. In contrast, Panel (d) reveals a significant and growing increase in location flexibility (remote work, work-from-home options). The treatment effect rises from near zero in the pre-period to approximately 0.07-0.09 by the fourth and fifth quarters, indicating that firms are about 7-9 percentage points more likely to offer flexible working locations after minimum wage hikes. Rather than cutting amenities to offset higher wages, firms appear to enhance certain job features that are potentially attractive to more educated workers.

The combination of these findings reveals a clear adjustment mechanism. Facing higher wages, firms do not reduce job postings or systematically cut job amenities. Instead, they raise human capital requirement, expand job offers by 20% and channel all the extra job opportunities to workers with college education or above, and those who have graduated. The widening gap between rising job offers and flat vacancy postings (Figure 4) suggests that, after minimum wage increases, firms are extending more offers per open position. Several mechanisms could explain this pattern. First, firms may be experiencing or expecting lower offer acceptance rates as they are targeting better-credentialed workers who have stronger outside options. Second, firms may be upgrading their workforce by extending offers to college-educated candidates and allowing less-educated incumbents to leave through natural attrition, which temporarily increases hires. Third, firms may be "stockpiling" higher-credentialed workers in anticipation of elevated turnover in this group. We cannot determine which of these mechanisms is driving the increase in offer-making. However, our results clearly show that this growth does not reach less-educated or less-experienced workers. Do these hiring patterns reflect changes in who applies for jobs, or do they represent intensified screening from an unchanged applicant pool?

6.3 Worker Search Behavior: Applications and Applicant Composition

This subsection examines whether such supply-side responses occur. Figure 10 presents the treatment effects on the logarithm of the total number of job applicants. Contrary to the expectation that higher wages would attract more applicants, we find no significant change in application volumes. While there is some suggestion of a slight increase in later quarters, the effects are imprecisely estimated and not consistently significant. This null result suggests despite an 8-10% increase in wages (Figure 3), the number of workers applying for these positions remains unchanged.

Perhaps higher wages attract a different composition of applicants even if total volume remains stable? Figure 11 examines this possibility across four dimensions of applicant characteristics. We find no evidence of compositional changes along any dimension. Panel (a) shows that applications from workers with college education or above and those with below-college education follow similar patterns, with no divergence after minimum wage increases. Panel (b) reveals no differential change in applications from non-students versus current students. Panel (c) shows no shifts in gender composition, and Panel (d) indicates no changes in age composition. In all cases, coefficients for different worker types show no difference in both pre- and post-treatment periods.

The stability of both application volume and applicant composition indicates that the changes we observe in job offer outcome cannot be attributed to shifts in labor supply. Instead, they must reflect changes in how firms screen and select from an unchanged applicant pool. Minimum wage increases therefore appear to reshape opportunities through intensified credential-based selection, concentrating new offers among higher-credentialed applicants and excluding those with lower credentials.

7 Conclusions

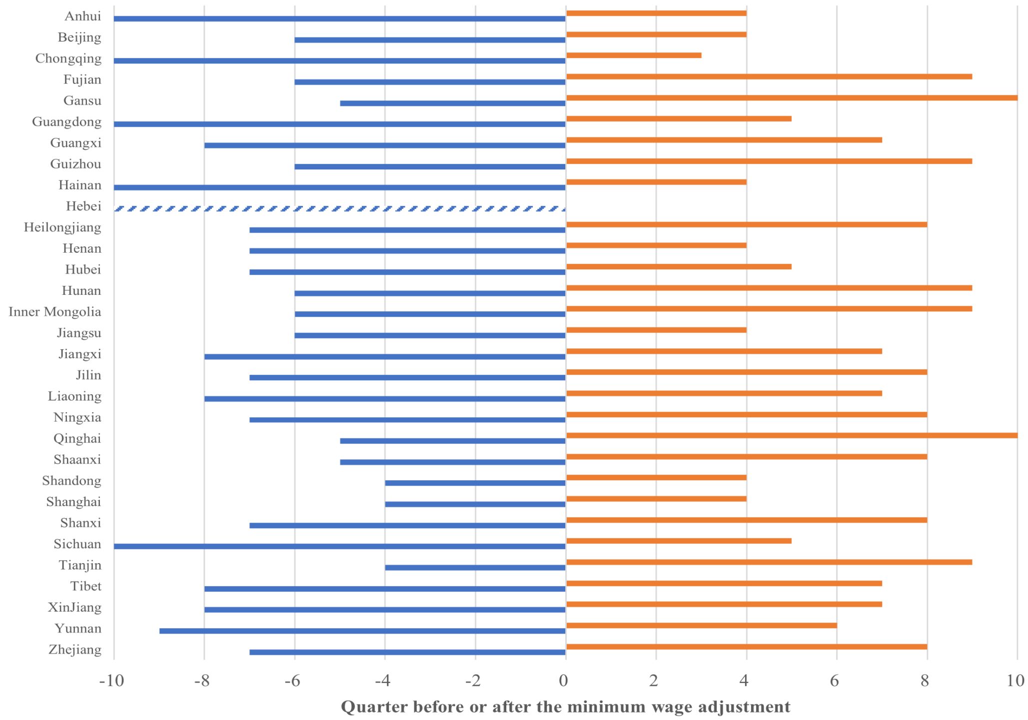
This paper examines how minimum wage increases reshape hiring in a large part-time, platform-mediated labor market in China. By linking job postings, applications, and job offers, we track the full adjustment process following province-level minimum wage hikes from 2016 to 2019. We find that firms raise educational and experience requirements and increase job offers to college-educated and non-student workers by about 30%, but the size and composition of the applicant pool remain unchanged. With labor supply essentially fixed in the short run, firms adjust entirely through intensified selection among existing applicants.

Less-educated and less-experienced job seekers do not face higher absolute rejection rates, but they lose access to the additional opportunities created after wage increases.

Our findings contribute to a growing literature documenting the heterogeneous distributional effects of minimum wage policy. While minimum wages are ostensibly worker-neutral policies, recent evidence suggests they generate differential benefits across worker groups through multiple channels. Coviello et al. (2025) demonstrates that minimum wage increases generate larger welfare gains for men than for women, even when both receive pay raises. Our paper reveals a complementary dimension of redistribution: minimum wage increases concentrate employment opportunities among workers with higher educational credentials by intensifying firms' selection from an unchanged applicant pool. These findings suggest that understanding who benefits from minimum wage policy requires looking beyond average employment and wage effects to examine how opportunities and welfare are redistributed across worker characteristics—–whether gender, education, or other dimensions that shape workers' labor market positions.

Our data structure imposes some limitations. Because we observe job offers rather than actual employment outcomes, we cannot determine acceptance rates or how firms adjust when offers are declined. As a result, our findings speak to firms' selection behavior rather than realized employment outcomes. In addition, our analysis focuses on short-run adjustments in a part-time labor market dominated by young, urban job seekers and reliant on platform-based recruitment, which may limit generalization to longer-term dynamics or traditional low-wage sectors. Nonetheless, as platform work, flexible jobs, and part-time arrangements continue to expand, more research is needed to understand how wage regulations interact with firm screening and worker search behavior in these increasingly important labor market environments.

Figure 1: The Timing of Minimum Wage Hikes Across Chinese Province in Regression Sample (2016-2019)



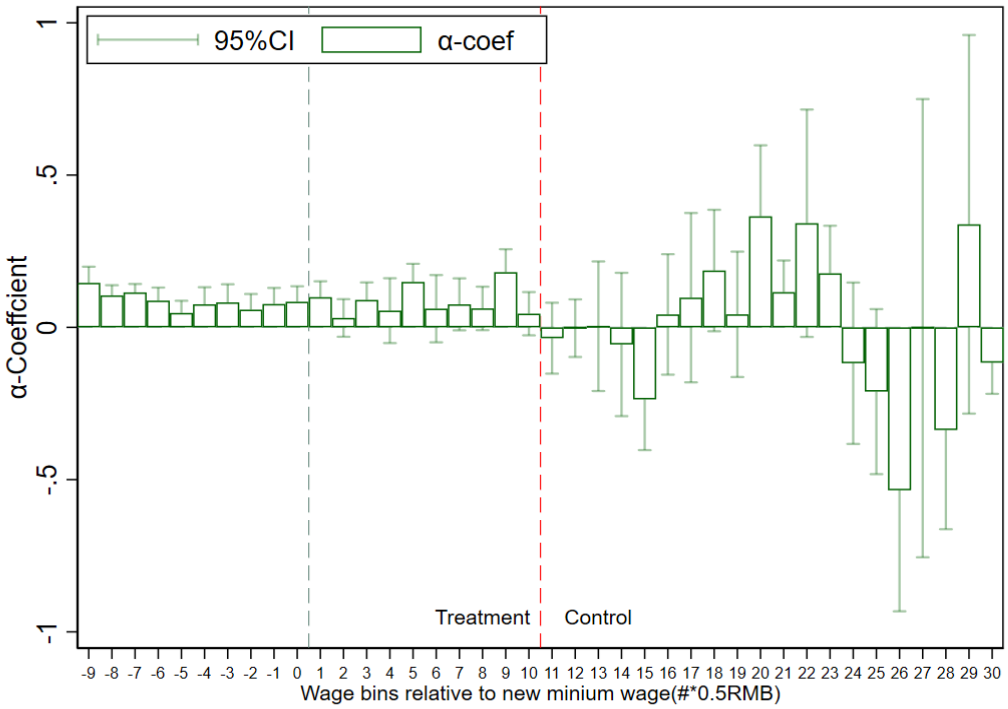
Notes: Authors' compilation from provincial minimum wage regulations and government announcements. Each province's timeline is centered on its first minimum wage adjustment during 2016-2019. The blue bar is quarters before minimum wage adjustment, the orange bar is quarters after minimum wage adjustment.

Table 1: Summary Statistics

Variables	(1) Observations	(2) Mean	(3) Std. Dev.
Hourly Wage (CNY)	231,659	16.217	9.578
Number of Job offers (thousands)	231,659	9.714	71.644
Above College	231,659	1.948	29.859
Below College	231,659	6.913	48.521
Non-Students	231,659	2.640	19.895
Students	231,659	5.931	48.099
Number of Applicants (thousands)	231,659	41.843	115.855
Above College	231,659	6.875	41.934
Below College	231,659	30.142	81.933
Non-students	231,659	10.052	29.487
Students	231,659	25.939	79.327
Demographic Characteristics of Applicants			
Average age	229,161	21.758	2.347
Male (%)	229,192	41.20	0.295
Job Requirement (%)			
Education Requirement	231,659	15.3	0.346
Work Experience Requirement	231,648	2.90	0.155
Age Requirement	231,648	12.8	31.3
Work Ethics Requirement	231,659	23.9	0.409
Behavioral Requirement	231,659	42.5	0.473
Appearance Requirement	231,659	1.5	0.115
Non-wage Job Characteristics (%)			
Providing any Benefit	231,659	3.8	0.183
Promising Job Stability	231,659	20.2	0.381
Allowing Flexible Working Hours	231,659	13.0	0.319
Allowing Flexible Working Locations	231,659	4.8	0.208

Notes: Authors' calculation based on job posting and applicant data (2016–2019) from the Jianzhi Mao platform, covering 31 provinces and 292 cities. All means reported are sample averages at the firm–occupation–month level.

Figure 2: Estimations of Effects of Minimum Wage Increases on Hourly Wages (Log) Across Different Wage Bins



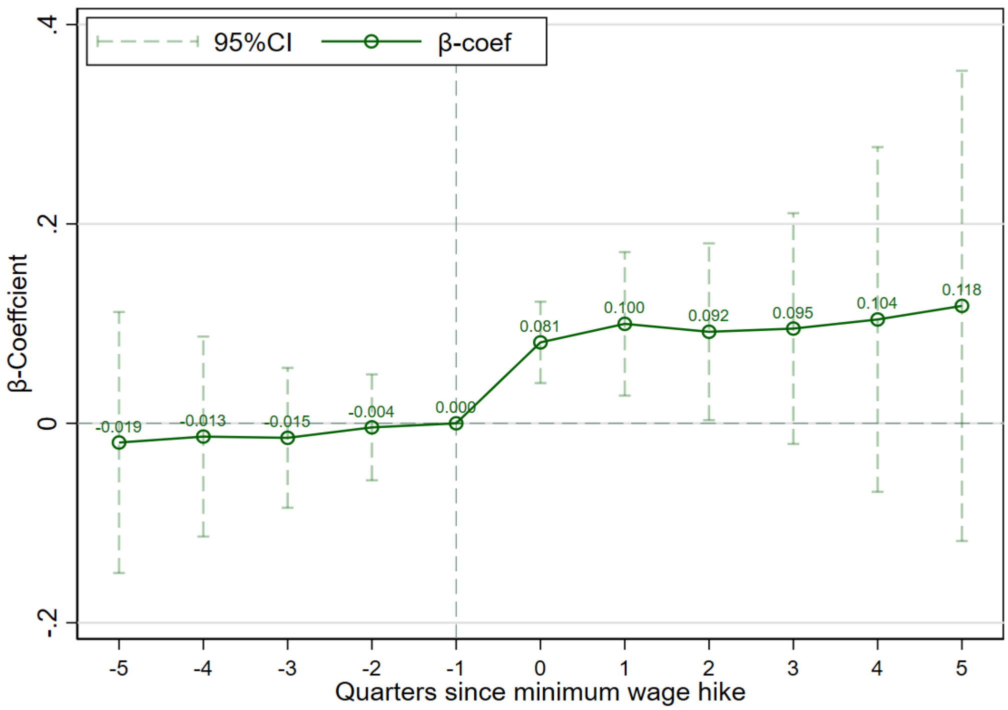
Notes: This figure presents the estimated effects on hourly wages (log) across different wage bins. The estimates are based on Equation 1, weighted by provincial population shares. Each bar represents the estimated wage effect for the occupation whose pre-adjustment wages fall within a specific wage bin (0.5 CNY increments) relative to the new minimum wage. The vertical spikes indicate 95% confidence intervals. The left (gray) dashed line denotes the new minimum wage level, and the right (red) dashed line demarcates the treatment group (wage bins -10 to 9) from the control group (wage bins 10 and above).

Table 2: Event Study Estimation: Effects of Minimum Wage Increases on Hourly Wages (Log)

	(1)	(2)	(3)	(4)
Dependent Variable: logarithm of firm level hourly wages				
Pre Average Impact	-0.023	-0.022	-0.017	-0.013
	(0.036)	(0.037)	(0.041)	(0.042)
T=0	0.068***	0.078***	0.079***	0.081***
	(0.019)	(0.021)	(0.021)	(0.021)
T=1	0.100***	0.103***	0.101**	0.100***
	(0.033)	(0.038)	(0.040)	(0.036)
T=2	0.100***	0.087**	0.098**	0.092**
	(0.035)	(0.040)	(0.045)	(0.045)
T=3	0.092*	0.091*	0.100*	0.095
	(0.053)	(0.054)	(0.060)	(0.059)
T=4	0.087	0.094	0.101	0.104
	(0.074)	(0.081)	(0.088)	(0.088)
T=5	0.112	0.106	0.127	0.118
	(0.105)	(0.112)	(0.121)	(0.120)
Post Average Impact	0.093*	0.093*	0.101*	0.098*
	(0.047)	(0.052)	(0.057)	(0.057)
Year-Month FE	Yes	Yes	Yes	
Firm-Occupation FE	Yes	Yes	Yes	Yes
City-Month FE		Yes	Yes	Yes
City-Year FE			Yes	Yes
Occupation-Year-Month FE				Yes
N	232,661	231,955	231,798	231,659
R^2	0.684	0.686	0.688	0.694
Mean(CNY)	16.735	16.712	16.703	16.703

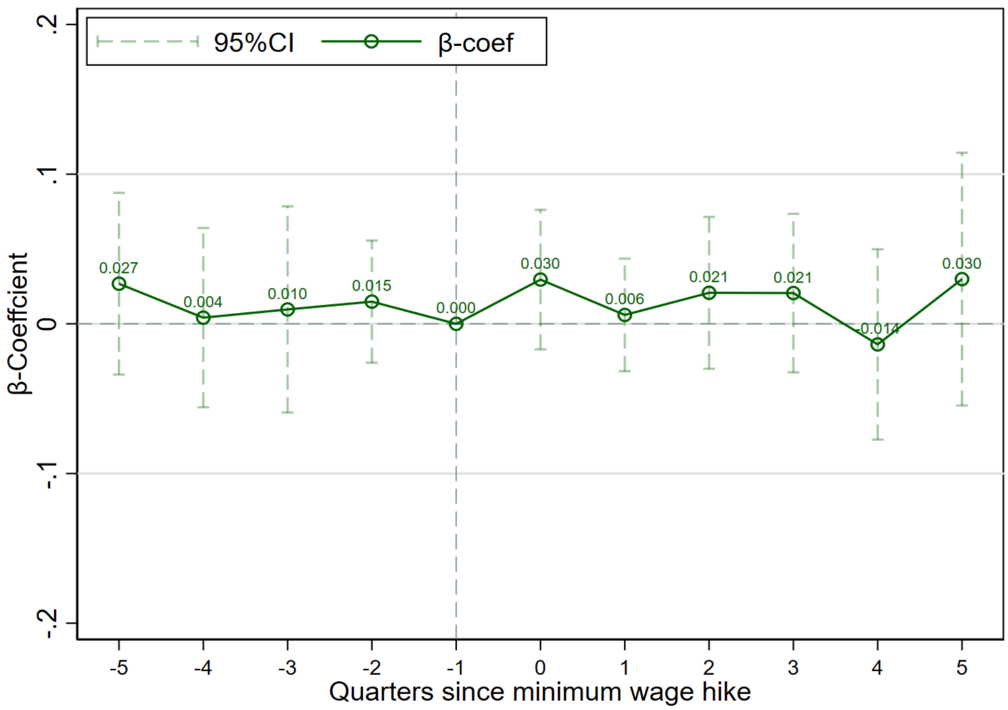
Notes: This table presents event study estimates on log hourly wages. Pre and post average impacts represent mean effects across pre- and post- event periods, respectively; T=0 through T=5 represent estimated impacts in post-event quarters. Standard errors clustered at city level. *** p<0.01, ** p<0.05, * p<0.1.

Figure 3: Effects of Minimum Wage Increases on Hourly Wages (Log)



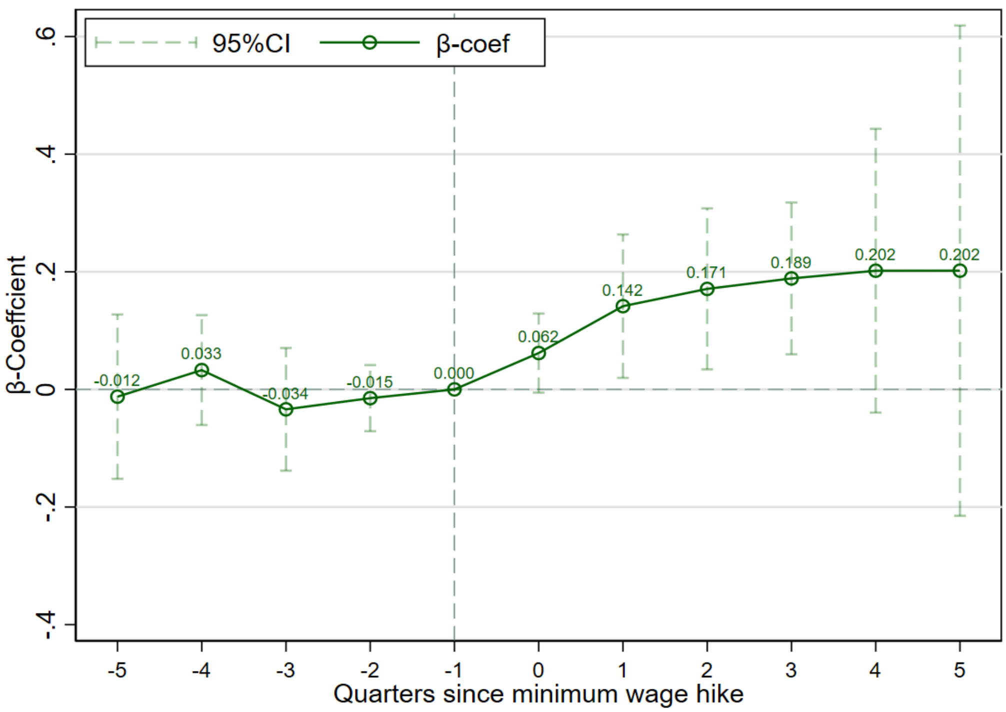
Notes: This figure presents the estimated effects on hourly wages (log). Estimates are based on Equation 2, weighted by the provincial population shares from the 2020 Chinese Census. The average hourly wage is calculated for each firm–occupation pair in each month. The baseline is set as the quarter immediately preceding the minimum wage hike. Standard errors are clustered at the city level. The x-axis represents the relative quarters since the minimum wage adjustment, and the y-axis shows the regression coefficients, with 95% confidence intervals indicated.

Figure 4: Effects of Minimum Wage Increases on the Numbers of Job Postings (Log)



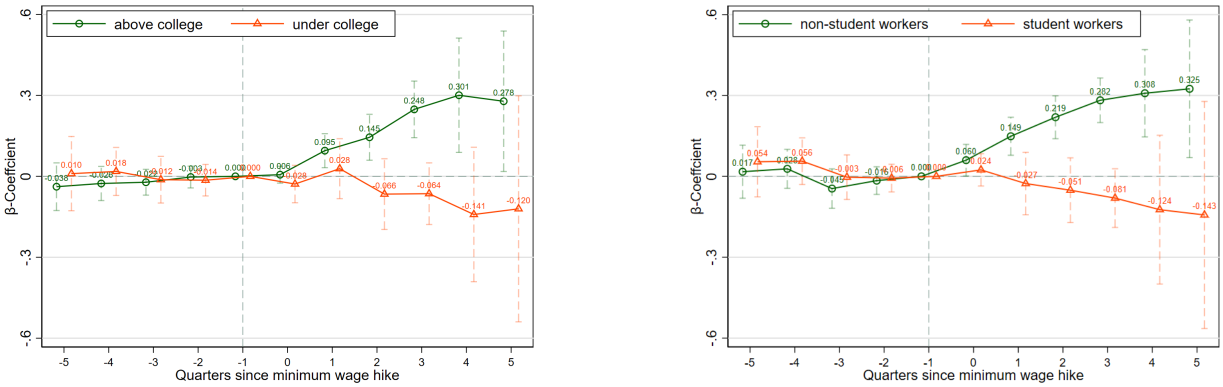
Notes: This figure presents the estimated effects on the number of job postings (log). Estimates are based on Equation 2, weighted by the provincial population shares from the 2020 Chinese Census.The number of job postings is calculated by aggregating monthly postings for each firm–occupation pair. The baseline is set as the quarter immediately preceding the minimum wage hike. Standard errors are clustered at the city level. The x-axis represents the relative quarters since the minimum wage adjustment, and the y-axis shows the regression coefficients, with 95% confidence intervals indicated.

Figure 5: Effects of Minimum Wage Increases on the Number of Job Offers (Log)



Notes: This figure presents the estimated effects on the number of job offers extended to applicants. Estimates are based on Equation 2, weighted by the provincial population shares from the 2020 Chinese Census. The number of job offers is calculated by aggregating monthly job offers extended to applicants for each firm–occupation pair. The baseline is set as the quarter immediately preceding the minimum wage hike. Standard errors are clustered at the city level. The x-axis represents the relative quarters since the minimum wage adjustment, and the y-axis shows the regression coefficients, with 95% confidence intervals indicated.

Figure 6: Effects of Minimum Wage Increases on the Number of Job Offers (Log) by Education Level and Student Status

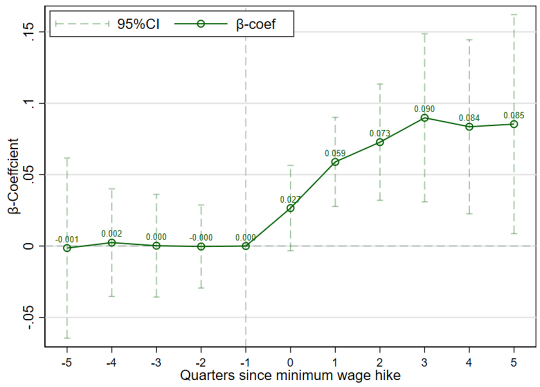


(a) By Education

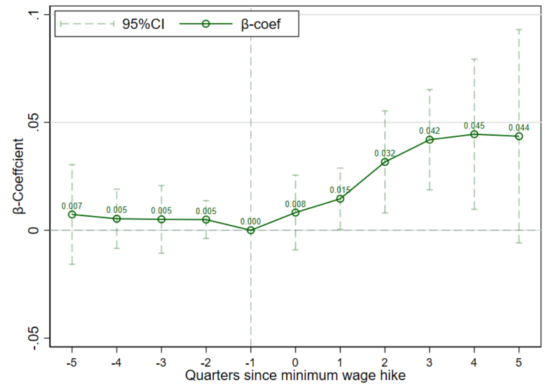
(b) By Student Status

Notes: This figure presents the estimated effects on the number of job offers by applicants' education level and student status. Estimates are based on Equation 2, weighted by the provincial population shares from the 2020 Chinese Census. The number of job offers is calculated by aggregating monthly offers for each firm–occupation pair. Panel (a) groups job offers by applicant education level (college degree or above), and panel (b) by student status. The baseline is set as the quarter immediately preceding the minimum wage hike. Standard errors are clustered at the city level. The x-axis represents the relative quarters since the minimum wage adjustment, and the y-axis shows the regression coefficients, with 95% confidence intervals indicated.

Figure 7: Effects of Minimum Wage Increases on Human Capital Requirements in Job Postings



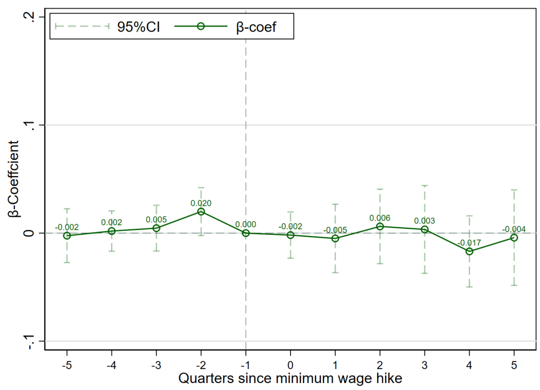
(a) Education Level Requirements



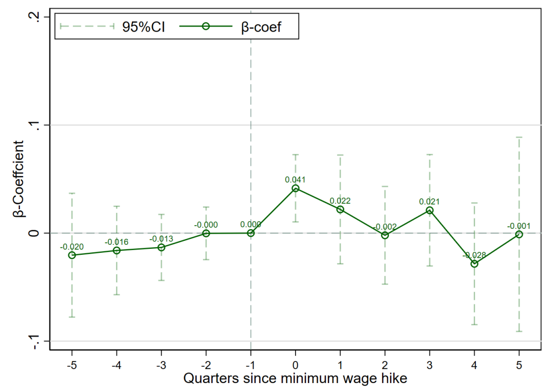
(b) Work Experience Requirements

Notes: This figure presents the estimated effects on human capital requirements. Estimates are based on Equation 2, weighted by the provincial population shares from the 2020 Chinese Census. For each firm–occupation pair in each month, we calculate the share of postings that specify education (panel a) or work experience (panel b) requirement. The baseline is set as the quarter immediately preceding the minimum wage hike. Standard errors are clustered at the city level. The x-axis represents the relative quarters since the minimum wage adjustment, and the y-axis shows the regression coefficients, with 95% confidence intervals indicated.

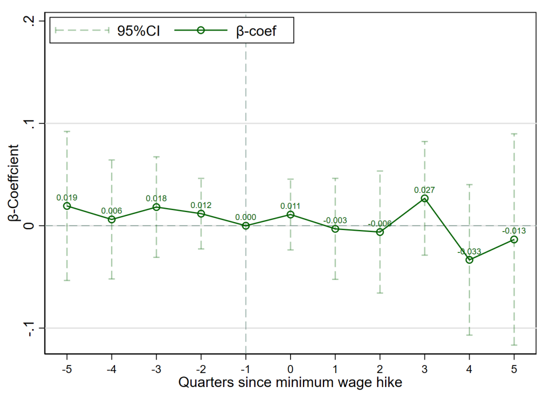
Figure 8: Effects of Minimum Wage Increases on Non-Human Capital Requirements in Job Postings



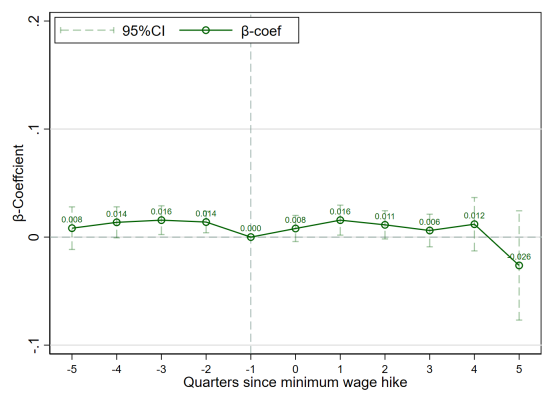
(a) Age Requirements



(b) Work Ethnics Requirements



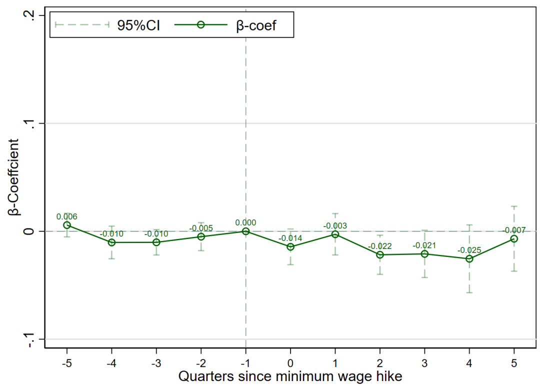
(c) Behavioral Requirements



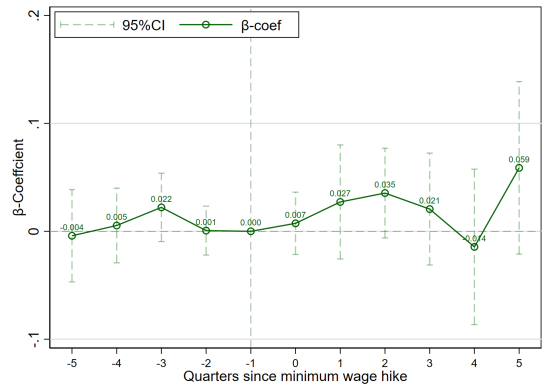
(d) Appearance Requirements

Notes: This figure presents the estimated effects on non-human capital requirements. Estimates are based on Equation 2, weighted by the provincial population shares from the 2020 Chinese Census. For each firm–occupation pair in each month, we calculate the share of postings that specify age (panel a), work ethnics (panel b), behavioral (panel c), or appearance (panel d) requirements. The baseline is set as the quarter immediately preceding the minimum wage hike. Standard errors are clustered at the city level. The x-axis represents the relative quarters since the minimum wage adjustment, and the y-axis shows the regression coefficients, with 95% confidence intervals indicated.

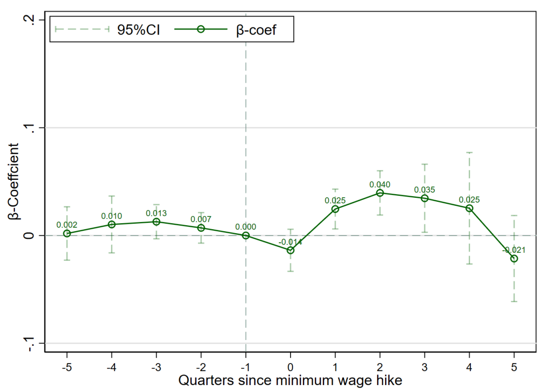
Figure 9: Effects of Minimum Wage Increases on Job Amenities and Working Conditions



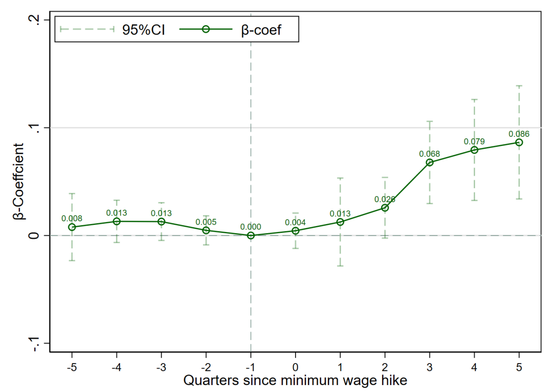
(a) Providing Employee Benefits



(b) Promising Job Stability



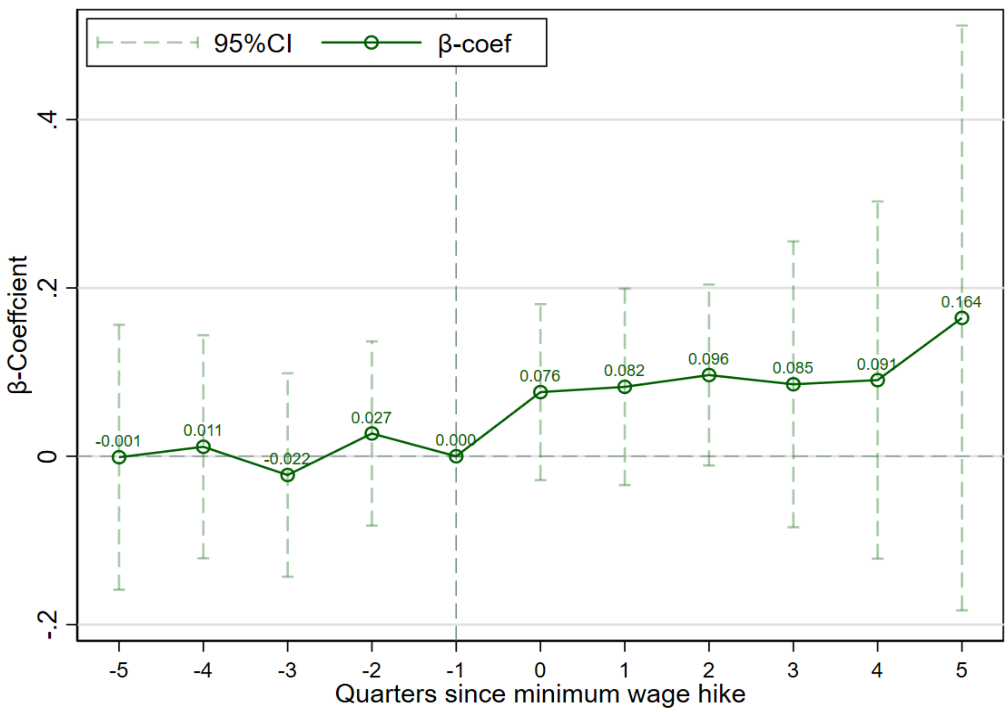
(c) Allowing Flexible Working Hours



(d) Allowing Flexible Working Location

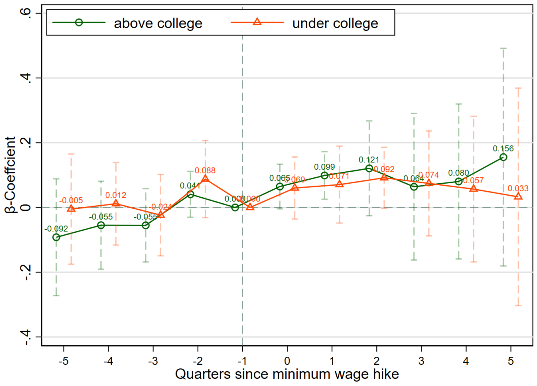
Notes: This figure presents the estimated effects on job amenities and working conditions. Estimates are based on Equation 2, weighted by the provincial population shares from the 2020 Chinese Census. For each firm–occupation pair in each month, we calculate the share of job postings that offer employee benefits (panel a), promise job stability (panel b), allow flexible working hours (panel c), or allow flexible working locations (panel d). The baseline is set as the quarter immediately preceding the minimum wage hike. Standard errors are clustered at the city level. The x-axis represents the relative quarters since the minimum wage adjustment, and the y-axis shows the regression coefficients, with 95% confidence intervals indicated.

Figure 10: Effects of Minimum Wage Hikes on the Number of Job Applicants (Log)

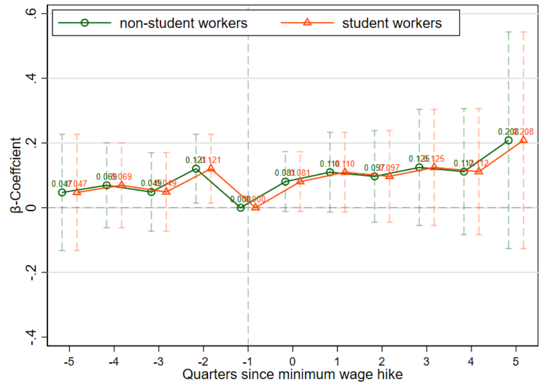


Notes: This figure presents the estimated effects on the number of job applicants. Estimates are based on Equation 2, weighted by the provincial population shares from the 2020 Chinese Census. The number of job applicants is calculated by aggregating monthly number of applicants for each firm–occupation pair. The baseline is set as the quarter immediately preceding the minimum wage hike. Standard errors are clustered at the city level. The x-axis represents the relative quarters since the minimum wage adjustment, and the y-axis shows the regression coefficients, with 95% confidence intervals indicated.

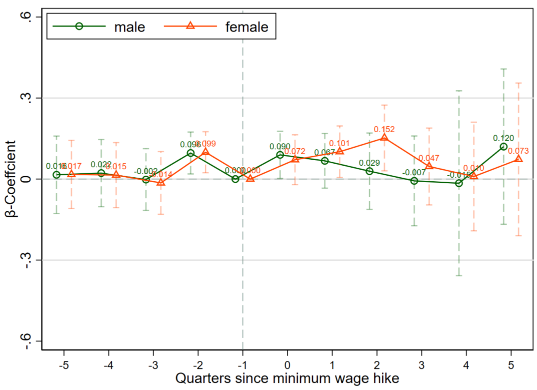
Figure 11: Effects of Minimum Wage Increases on Applicant Characteristics



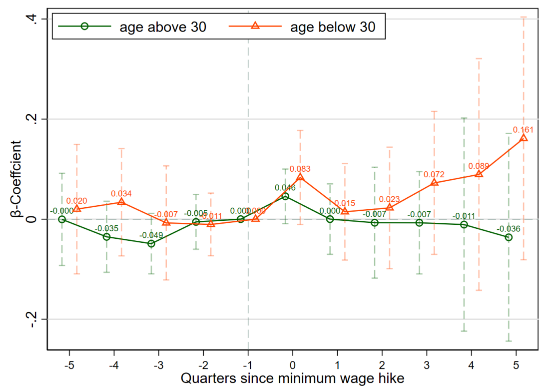
(a) By Education Level



(b) By Work Experience



(c) By Gender



(d) By Age

Notes: This figure presents the estimated effects on applicant characteristics. Estimates are based on Equation 2, weighted by the provincial population shares from the 2020 Chinese Census. The number of job applicants is calculated by aggregating monthly number of applicants for each firm–occupation pair. Panel (a) groups applicants by education level, panel (b) by student status, panel (c) by gender, and panel (d) by age. The baseline is set as the quarter immediately preceding the minimum wage hike. Standard errors are clustered at the city level. The x-axis represents the relative quarters since the minimum wage adjustment, and the y-axis shows the regression coefficients, with 95% confidence intervals indicated.

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Appendix Tables and Figures

Table A.1: Alternative Wage Bin Threshold: New Minimum Wage ±3 CNY

	(1)	(2)	(3)	(4)	(5)	(6)
	Hourly	Number of Job Offers (Log)				
	Wages	All Sample	Above College	Below College	Non-Students	Students
Pre Ave. impact	-0.011	0.001	-0.021	-0.006	-0.008	0.022
	(0.035)	(0.040)	(0.022)	(0.035)	(0.029)	(0.034)
T=0	0.054***	0.046	0.003	-0.046	0.058*	-0.001
	(0.018)	(0.040)	(0.017)	(0.038)	(0.031)	(0.034)
T=1	0.070**	0.127**	0.106***	0.009	0.127***	-0.028
	(0.029)	(0.051)	(0.023)	(0.046)	(0.039)	(0.044)
T=2	0.067*	0.143**	0.125***	-0.065	0.230***	-0.071
	(0.036)	(0.055)	(0.037)	(0.048)	(0.042)	(0.044)
T=3	0.067	0.156***	0.239***	-0.071	0.280***	-0.084**
	(0.048)	(0.056)	(0.044)	(0.046)	(0.041)	(0.039)
T=4	0.066	0.160	0.257***	-0.130	0.277***	-0.125
	(0.070)	(0.105)	(0.079)	(0.103)	(0.068)	(0.104)
T=5	0.122	0.189	0.320***	-0.132	0.325***	-0.108
	(0.095)	(0.165)	(0.094)	(0.165)	(0.100)	(0.157)
Post Ave. impact	0.074	0.137**	0.175***	-0.072	0.216***	-0.069
	(0.046)	(0.059)	(0.035)	(0.052)	(0.035)	(0.049)
Firm-Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
City-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
City-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month-Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
N	231,659	231,659	231,659	231,659	231,659	231,659
R^2	0.696	0.644	0.591	0.639	0.622	0.624
Mean(CNY)	16.217	9.714	1.948	6.913	2.640	5.931

Notes: This table presents a robustness check in which the wage bin threshold is changed from "new minimum wage + 4.5 CNY" to "new minimum wage + 3 CNY." "Pre Ave. impact" reports the average pre-event effect; "T=0" through "T=5" represent post-event quarters; "Post Ave. impact" shows the average post-event effect. Standard errors clustered at city level. *** 1%, ** 5%, * 10%.

Table A.2: Alternative Wage Bin Threshold: New Minimum Wage ±6 CNY

	(1)	(2)	(3)	(4)	(5)	(6)
	Hourly	Number of Job Offers (Log)				
	Wages	All Sample	Above College	Below College	Non-Students	Students
Pre Ave. impact	-0.006	0.002	-0.009	0.020	-0.001	0.036
	(0.037)	(0.042)	(0.027)	(0.037)	(0.032)	(0.035)
T=0	0.085***	0.110**	0.025	0.024	0.090***	0.069
	(0.022)	(0.050)	(0.020)	(0.049)	(0.034)	(0.046)
T=1	0.118***	0.123**	0.084***	0.010	0.144***	-0.034
	(0.031)	(0.050)	(0.029)	(0.051)	(0.037)	(0.046)
T=2	0.107***	0.186***	0.161***	-0.056	0.253***	-0.035
	(0.031)	(0.064)	(0.047)	(0.060)	(0.040)	(0.056)
T=3	0.118**	0.199***	0.260***	-0.059	0.314***	-0.063
	(0.049)	(0.064)	(0.066)	(0.057)	(0.054)	(0.055)
T=4	0.122	0.295**	0.402***	-0.030	0.396***	0.015
	(0.081)	(0.120)	(0.110)	(0.112)	(0.089)	(0.120)
T=5	0.115	0.204	0.278*	-0.108	0.347**	-0.103
	(0.112)	(0.255)	(0.142)	(0.257)	(0.145)	(0.260)
Post Ave. impact	0.111**	0.186**	0.202***	-0.037	0.257***	-0.025
	(0.047)	(0.071)	(0.051)	(0.067)	(0.047)	(0.067)
Firm-Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
City-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
City-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month-Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
N	231,659	231,659	231,659	231,659	231,659	231,659
R^2	0.694	0.645	0.591	0.639	0.622	0.624
Mean(CNY)	16.217	9.714	1.948	6.913	2.640	5.931

Notes: This table presents a robustness check in which the wage bin threshold is changed from "new minimum wage + 4.5 CNY" to "new minimum wage + 6 CNY." "Pre Ave. impact" reports the average pre-event effect; "T=0" through "T=5" represent post-event quarters; "Post Ave. impact" shows the average post-event effect. Standard errors clustered at city level. *** 1%, ** 5%, * 10%.

Table A.3: Alternative Hourly Wages Sample and Acceptance Rate Estimations

	(1) Hourly Wages (Hourly Wage Jobs Only)	(2) Acceptance Rate (All Job Postings) All Sample	(3) Above College	(4) Below College	(5) Non-Students	(6) Students
Pre Ave. impact	-0.004	-0.002	0.005	0.008	0.006	0.002
	(0.027)	(0.010)	(0.017)	(0.010)	(0.014)	(0.010)
T=0	0.004	0.009	0.029*	0.007	0.041***	0.003
	(0.011)	(0.010)	(0.015)	(0.012)	(0.010)	(0.011)
T=1	0.018	0.030**	0.040	0.019	0.061***	0.012
	(0.011)	(0.012)	(0.025)	(0.015)	(0.017)	(0.013)
T=2	0.040***	0.051***	0.041	0.013	0.072***	0.007
	(0.015)	(0.017)	(0.025)	(0.018)	(0.018)	(0.018)
T=3	0.043***	0.054***	0.048**	0.015	0.071***	0.019
	(0.016)	(0.017)	(0.021)	(0.017)	(0.019)	(0.016)
T=4	0.038**	0.061***	0.033	-0.033	0.026	-0.028
	(0.017)	(0.021)	(0.030)	(0.021)	(0.022)	(0.020)
T=5	0.027	0.059	0.045	-0.012	0.057	-0.015
	(0.034)	(0.036)	(0.047)	(0.039)	(0.042)	(0.037)
Post Ave. impact	0.097***	0.044***	0.039	0.002	0.055***	-0.001
	(0.027)	(0.015)	(0.024)	(0.015)	(0.018)	(0.013)
Firm-Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
City-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
City-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month-Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
N	67,953	231,659	143,192	225,773	193,308	216,933
R^2	0.902	0.677	0.644	0.672	0.658	0.663
Mean(CNY)	17.206	0.185	0.184	0.183	0.184	0.182

Notes: This table presents robustness checks using alternative sample definitions and outcome measures. Column (1) restricts the sample to job postings with hourly wage compensation only, excluding positions paid on a daily, monthly, or piece-rate basis. Columns (2)–(6) use acceptance rate (ratio of accepted applicants to total applicants) as the dependent variable instead of the number of accepted applicants. "Pre Ave. impact" reports the average pre-event effect; "T=0" through "T=5" represent post-event quarters; "Post Ave. impact" shows the average post-event effect. Standard errors clustered at city level. *** 1%, ** 5%, * 10%.

Table A.4: Alternative Estimation Methods

	(1)	(2)	(3)	(4)	(5)	(6)
	Hourly	Number of Job Offers (Log)				
	Wages	All Sample	Above College	Below College	Non-Students	Students
Callaway & Sant'Anna (2021)	0.144***	0.182*	0.174**	−0.008	0.127*	−0.035
	(0.037)	(0.095)	(0.074)	(0.102)	(0.071)	(0.071)
Borusyak et al. (2023)	0.058***	0.067***	0.064***	−0.025	0.059***	−0.001
	(0.001)	(0.022)	(0.015)	(0.021)	(0.017)	(0.020)

Notes: This table employs heterogeneous treatment effects estimators following the methodologies of Callaway and Sant'Anna (2021) and Borusyak et al. (2024) to estimate the dynamic impacts of minimum wage increases. To align with the requirements of these estimation frameworks, the sample is aggregated to the quarterly level, matching the frequency of minimum wage adjustments and ensuring compatibility with the assumptions of well-defined treatment timing and panel data structure. Standard errors clustered at city level. *** 1%, ** 5%, * 10%.

Table A.5: Alternative Sample Excluding Provinces with Fewer Than Four Pre-treatment Quarters

	(1)	(2)	(3)	(4)	(5)	(6)
	Hourly	Number of Job Offers (Log)				
	Wages	All Sample	Above College	Below College	Non-Students	Students
Pre Ave. impact	-0.017	-0.005	-0.021	0.003	-0.002	0.026
	(0.041)	(0.042)	(0.027)	(0.038)	(0.033)	(0.037)
T=0	0.078***	0.069**	0.007	-0.023	0.063**	0.029
	(0.022)	(0.034)	(0.017)	(0.036)	(0.031)	(0.030)
T=1	0.138***	0.139**	0.100***	0.025	0.149***	-0.029
	(0.038)	(0.064)	(0.032)	(0.058)	(0.036)	(0.061)
T=2	0.135***	0.172**	0.147***	-0.067	0.222***	-0.052
	(0.047)	(0.070)	(0.044)	(0.068)	(0.042)	(0.062)
T=3	0.139**	0.196***	0.254***	-0.059	0.292***	-0.077
	(0.059)	(0.066)	(0.054)	(0.059)	(0.042)	(0.056)
T=4	0.145	0.204*	0.304***	-0.141	0.311***	-0.123
	(0.088)	(0.122)	(0.108)	(0.126)	(0.083)	(0.139)
T=5	0.159	0.205	0.283**	-0.120	0.329**	-0.142
	(0.119)	(0.212)	(0.133)	(0.214)	(0.130)	(0.215)
Post Ave. impact	0.132**	0.164**	0.182***	-0.064	0.228***	-0.066
	(0.058)	(0.074)	(0.049)	(0.071)	(0.044)	(0.070)
Firm-Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
City-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
City-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month-Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
N	228653	228653	228653	228653	228653	228653
R^2	0.697	0.644	0.590	0.638	0.621	0.623
Mean(CNY)	16.257	9.801	1.972	6.969	2.663	5.985

Notes: "This table presents robustness checks excluding Shandong, Tianjin, and Shanghai, which have fewer than four quarters of pre-treatment data. "Pre Ave. impact" reports the average pre-event effect; "T=0" through "T=5" represent post-event quarters; "Post Ave. impact" shows the average post-event effect. Standard errors clustered at city level. *** 1%, ** 5%, * 10%.