Unemployment Insurance and the Allocation of Innovation

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Abstract

This paper studies whether social insurance affects the allocation of innovation across firms. Exploiting China's 2017 unemployment insurance reform, which induced larger benefit increases in provinces farther below a national policy benchmark, we show that more generous unemployment insurance reallocates innovation from listed firms to private firms. Listed firms in treated provinces experience a 12.5% decline in patent applications and an 11.4% decline in granted patents, while private firms experience increases of 20.6% and 19.0%, respectively. The effects are concentrated among safer listed firms and smaller, riskier private firms, consistent with a risk-reallocation mechanism: public insurance weakens the value of firm-provided employment stability and improves riskier firms' ability to attract inventive labor. Inventor-level evidence supports this interpretation. The reform increases inventor mobility from listed firms to private firms, but not in the reverse direction, and also encourages movements toward newly established private firms. At the provincial level, the reform increases aggregate patenting, primarily through private firms. These findings suggest that unemployment insurance does more than protect workers against income loss: by reallocating risk-bearing capacity and inventive labor, social insurance can reshape where innovation is produced.

Keywords: Unemployment Insurance Benefits, Corporate Innovation, Risk redistribution, Entrepreneurship, Knowledge Spillover

JEL Classifications: G30, G38, J65, O31, L26

1. Introduction

How do unemployment insurance policies affect the allocation of innovation in the economy? While UI primarily serves as a social safety net, its economic implications extend beyond individual welfare, influencing firms' strategic choices and labor market dynamics.[1] The standard debate focuses on its welfare and incentive effects: more generous insurance protects workers against income losses, but may also affect job search, labor supply, and firms' employment policies. This view, while important, leaves out a broader allocation question. By changing who bears downside labor-market risk, social insurance may also change who is willing to work for risky firms, who is willing to leave stable employers, and where scarce human capital is deployed. In this sense, social insurance may affect not only redistribution and worker welfare, but also the allocation of productive resources in the economy.

This allocation role is particularly important for innovation. Innovation is a major source of productivity growth and long-run economic development, but it is also risky, long-horizon, and highly dependent on mobile human capital development (Solow, 1957; Romer, 1990; Aghion and Howitt, 1992; Kogan et al., 2017). Inventors and technical employees often face a choice between stable incumbent employers and riskier private or entrepreneurial firms. Stable firms can attract and retain innovative workers partly by offering lower employment risk. Riskier firms may offer greater upside and stronger growth opportunities, but they often have less ability to insure workers against job loss or project failure. As a result, the distribution of innovation across firms depends not only on firms' technologies and financial resources, but also on how workers bear employment risk.

[1] For example, extensive research has examined how unemployment insurance influences corporate decisions in hiring (Ng et al., 2019), cost management (Shen, 2022), total factor productivity (Darrough et al., 2019), earning management (Dou et al., 2016) and financial strategies (Agrawal and Matsa, 2013; Dou et al., 2016; Devos and Rahman, 2018; Devos and Rahman, 2023).

In this paper, we study whether unemployment insurance affects this allocation of innovation across firms. More generous unemployment insurance reduces workers' exposure to job-loss risk. This can improve the ability of risky private and entrepreneurial firms to attract innovative workers by partially insuring the downside risk of joining them. At the same time, it can weaken the retention advantage of stable incumbent firms if public insurance substitutes for firm-provided employment stability. Unemployment insurance may therefore reduce innovation in safer listed firms while increasing innovation in riskier non-listed firms and new entrants. The key question is not simply whether social insurance raises or lowers innovation in the aggregate, but whether it changes where innovation is produced. Answering this question helps us understand an overlooked growth implication of social insurance policy: by reallocating risk-bearing capacity and inventive labor, social insurance may reshape the organization of innovation in the economy.

However, identifying this effect is challenging because unemployment insurance generosity is unlikely to be randomly assigned. Regions with more generous benefits may differ in labor-market conditions, fiscal capacity, industrial structure, or local innovation policies. These factors can directly affect firm innovation and inventor mobility. To address this concern, we exploit China's 2017 unemployment insurance reform as a quasi-natural experiment. The reform encouraged provinces to gradually raise unemployment insurance benefits toward 90% of the local minimum wage. Provinces differed substantially in their pre-reform distance from this benchmark, creating stronger adjustment pressure in provinces with lower pre-reform unemployment-insurance-benefit-to-minimum-wage ratios. We use this predetermined variation in reform exposure to estimate the effect of unemployment insurance on the allocation of innovation across listed firms, non-listed firms, and new entrants.

We find that more generous unemployment insurance reallocates innovation from listed firms to non-listed firms. Applying a difference-in-differences estimation, we find that for listed firms, the treated firms experienced an approximately 12.4% decline in patent applications and 11.4% decline in patent grants compared to the control firms. In contrast, non-listed firms in more exposed

provinces experience increases of approximately 20.6% in patent applications and 19.0% in granted patents. These results indicate that unemployment insurance does not simply stimulate or suppress innovation uniformly. Instead, it changes the distribution of innovative activity across firms.

We interpret these findings through a labor-market risk-reallocation mechanism. Unemployment insurance pools job-loss risk across workers and firms. Because firms differ in the employment risk they impose on workers, this risk sharing changes their relative attractiveness in the labor market. Riskier firms benefit more from public insurance because workers are partially protected against the downside risk of joining them. Safer firms, by contrast, previously offered employment stability as an implicit form of insurance. When public unemployment insurance becomes more generous, this stability becomes less valuable, weakening safer firms' ability to retain innovative workers. Consistent with this mechanism, the decline in listed-firm innovation is concentrated among safer listed firms, measured by larger size and lower return volatility. By contrast, the increase in private-firm innovation is stronger among smaller non-listed firms, which are more likely to face greater employment risk and weaker internal insurance capacity.

We provide direct evidence on the labor-market channel using inventor mobility. If unemployment insurance reallocates innovation by changing workers' willingness to bear employment risk, we should observe increased mobility of inventive labor, especially away from stable listed firms. The empirical results confirm this prediction. At the firm level, the reform increases inventor mobility among listed firms. Inventor outflows rise more than inventor inflows, leading to a decline in net inventor flow. This net loss of inventors is also concentrated among safer listed firms. At the inventor level, the reform increases the probability that inventors switch employers and move from listed firms to non-listed firms. We do not find a comparable increase in movements from non-listed firms to listed firms. This directional pattern suggests that the reform does not merely increase general labor-market turnover. Instead, it reallocates inventive human capital from listed firms toward non-listed firms.

The reallocation also extends to entrepreneurship. Newly established firms are among the riskiest organizations in the economy. They have shorter operating histories, more uncertain survival prospects, and weaker employment stability. More generous unemployment insurance can make these firms more attractive by reducing the downside risk faced by workers who join or create them. Consistent with this prediction, we find that the reform increases new firm creation at the provincial level. The effect is not limited to marginal registrations: the reform also increases the creation of high-quality new firms that remain in normal operation. Moreover, inventors from listed firms become more likely to move to newly established private firms after the reform. These results suggest that entrepreneurship is an important margin through which unemployment insurance reallocates innovative resources.

A natural concern is that the increase in unemployment insurance benefits is modest relative to the salary of high-skilled inventors. Our interpretation does not rely on a direct income-replacement effect for inventors. Instead, the mechanism operates through marginal labor-market decisions and the relative value of employment stability. Even a moderate increase in public insurance can affect the choice between remaining with a stable incumbent and moving to a riskier employer or entrepreneurial opportunity. The innovation consequences can be amplified because inventive output is organizationally embedded: it depends on firm-specific knowledge, project continuity, and coordination among inventors and complementary workers. Consistent with this interpretation, we find that the negative effect on listed-firm innovation is concentrated among firms with greater dependence on supporting team. The effect of UIB is also stronger for marginal inventors, measured with inventors with weaker attachment with the current employer. We also find little evidence that the reform increases employee compensation, reduces R&D spending, or affects innovation primarily through a labor-cost channel.

Finally, we examine whether this reallocation is associated with aggregate innovation gains or merely transfers patenting from listed firms to non-listed firms. At the provincial level, the reform increases total patent applications and granted patents. The increase is driven primarily by non-

listed firms, while listed-firm patenting does not explain the aggregate gain. This evidence suggests that the decline in listed-firm innovation is more than offset by increased innovation among non-listed firms. Unemployment insurance therefore appears to facilitate the redeployment of inventive resources from stable incumbents toward more dynamic private-sector organizations.

Our paper contributes to three strands of literature. First, we contribute to the literature on the economic effects of social insurance. A large literature studies social insurance as a mechanism for improving worker welfare, smoothing consumption, sharing labor-market risk, and shaping labor-market behavior. In the context of unemployment insurance, prior studies show that UI affects household consumption, worker search, corporate financial policies, entrepreneurship, firm value, informal employment, acquisitions, and bank deposits (Gruber, 1997; Chetty, 2008; Agrawal and Matsa, 2013; Hombert et al., 2020; Van Doornik et al., 2022, 2023; Guo et al., 2024; Arslan et al., 2025). We add to this literature by showing that social insurance also has an important innovation-allocation effect. More generous unemployment insurance reallocates innovative activity away from safer listed firms and toward riskier private and entrepreneurial firms. Importantly, this reallocation is not merely a transfer of patenting across firms. At the provincial level, the increase in private-firm innovation more than offsets the decline in listed-firm innovation, leading to higher aggregate patenting. Because innovation is a central input into long-run productivity growth, our findings point to a previously overlooked growth implication of social insurance policy: by improving the allocation of risk-bearing capacity and inventive labor, social insurance may support economic dynamism beyond its traditional role in worker protection.

Second, we contribute to the literature on labor-market protection and corporate innovation. Existing studies examine whether labor-related policies, such as bankruptcy laws, employment protection laws, wrongful discharge laws, and social insurance laws, increase or decrease corporate innovation (Acharya and Subramanian, 2009; Acharya et al., 2013, 2014; Chen et al., 2022; Wang and Yung, 2025). This literature has primarily focused on the average effect of labor protection on firms' incentives to innovate. We emphasize a different margin: labor-market protection can

change the distribution of innovation across firms. In our setting, stronger unemployment insurance reduces innovation among safer listed firms but increases innovation among riskier non-listed firms. The same policy therefore generates opposite effects across firms with different risk profiles. This distinction is important because a policy that appears to weaken innovation in one sector of the economy may simultaneously strengthen innovation elsewhere. Our results suggest that labor-market protection should be evaluated not only by its average effect on incumbent firms, but also by its effect on the allocation of innovative resources across the broader firm population.

Third, we contribute to the literature on inventor mobility, entrepreneurship, and knowledge spillovers. Prior work shows that employee mobility and inventor flows are important channels through which knowledge moves across firms and shapes innovation (Marx et al., 2009; Chemmanur et al., 2019; Liu et al., 2023). Related studies show that corporate R&D can generate entrepreneurial spillovers when employees leave established firms to join or create new ventures (Matray, 2021; Babina and Howell, 2024). We show that social insurance policy can shape these knowledge-flow channels by changing workers' willingness to bear employment risk. By reducing the relative value of firm-provided employment stability, unemployment insurance facilitates inventor movements from listed firms to non-listed firms and newly established firms. This labor-market reallocation helps explain why private-firm innovation rises after the reform and why aggregate provincial innovation increases. Our evidence therefore identifies social insurance as an institutional force that affects the movement of inventive human capital and the circulation of knowledge within local innovation ecosystems.

The remainder of the paper proceeds as follows. Section 2 describes the data. Section 3 introduces China's unemployment insurance system, the 2017 reform, and the identification strategy. Section 4 presents the baseline evidence on unemployment insurance and innovation. Section 5 examines the mechanism and inventor mobility. Section 6 discusses alternative explanations and robustness tests. Section 7 examines aggregate provincial innovation. Section 8 concludes.

2. Data

2.1 Data Sources and Sample Construction

In this paper, we combine province-level policy data, firm-level innovation data, private enterprise registration data, and inventor-level patent records to examine how unemployment insurance benefits affect the allocation of innovation and innovative labor.

We first collect provincial data on unemployment insurance benefits (UIB). Following Agrawal and Matsa (2013), we use the maximum unemployment insurance benefit as our main explanatory variable. The UIB data are hand-collected from official government websites and policy documents issued by provincial human resources and social security departments. We also construct the UIB-to-minimum-wage ratio by dividing the provincial UIB level by the local minimum wage. Minimum wage data are obtained from the WIND database. Provincial economic variables, including GDP, population, and average wages, are collected from the National Bureau of Statistics.

We construct a listed-firm innovation sample using A-share companies listed on the Shanghai and Shenzhen Stock Exchanges between 2012 and 2021. Firm-level financial information, ownership characteristics, and patent outcomes are obtained from the China Securities Market and Accounting Research (CSMAR) database. We exclude financial firms, ST, *ST, and PT firms, as well as firms with incomplete data.[2] We winsorize patent outcome variables at the 1st and 99th percentiles to reduce the influence of outliers. Listed-firm innovation is measured using the number of patent applications filed by a firm in year t and the number of these applications that are eventually granted (Acharya et al., 2013; Wu et al., 2025). We also construct citation-based measures to capture patent quality. After applying these selection criteria, our final sample contains

[2] "ST" stands for "Special Treatment," indicating companies with two consecutive years of losses; "*ST" signifies "Delisting Risk Warning," for companies with three consecutive years of losses and a delisting risk; "PT" stands for "Particular Transfer," referring to companies suspended from listing and only traded on special transfer boards.

16,882 firm-year observations.

We further incorporate innovation information for non-listed firms. Non-listed-firm patent data are obtained from the China Research Data Services Platform. We match these patent records to the national enterprise registration database to obtain detailed firm-level information, including registered province, industry classification, establishment date, registered capital, employee size, business type, and operating status. This matching procedure allows us to observe not only the innovation activities of non-listed firms but also their basic organizational characteristics. These variables are used to construct fixed effects, form matched samples, and measure firm heterogeneity in the private-firm analysis.

2.2 Summary Statistics

Table 1 reports summary statistics for the main variables used in the empirical analysis. Panel A reports descriptive statistics for provincial UIB and key economic indicators based on 300 province-year observations. The average UIB level is RMB 1,214, with values ranging from RMB 487 to RMB 2,244. This variation suggests considerable differences in social insurance generosity across provinces and over time. The mean UIB-to-minimum-wage ratio is 76%, ranging from 50% to 100%, indicating meaningful variation in the degree of income protection provided by local UI systems. This variation is central to our empirical setting because the 2017 reform targeted provinces with relatively low UIB-to-minimum-wage ratios and encouraged them to raise benefit levels toward the policy benchmark. Provincial macroeconomic variables also display substantial dispersion. GDP ranges from RMB 71 billion to RMB 12,471 billion, while the monthly average wage ranges from RMB 2,938 to RMB 16,044. These differences suggest meaningful variation in local economic conditions across provinces, which motivates the inclusion of provincial controls and high-dimensional fixed effects in the empirical analysis.

Panel B reports firm-level variables separately for listed and non-listed firms. The listed firm sample contains 16,882 firm-year observations. Listed firms file 92.12 patent applications per year,

with a standard deviation of 209.64, indicating substantial heterogeneity in innovation output across firms. The average number of granted patents is 71.33, with values ranging from 0 to 1041. These statistics show that innovation activity among public firms is highly skewed: some firms produce a large number of patents, while many firms innovate less intensively. Firm characteristics, including total assets, ROA, cash holdings, capital expenditures, and intangible assets, also vary substantially across firms. These differences capture variation in financial capacity, profitability, growth opportunities, asset structure, and investment intensity, all of which may affect both innovation activity and firms' responses to labor market policy changes.

The non-listed firm sample is larger but much less patent-intensive. It contains 68,780 firm-year observations for patent applications and 71,511 for patents granted. On average, non-listed firms file 0.88 patent applications and obtain 0.68 granted patents per year. These statistics suggest that most non-listed firms engage in limited patenting activity, while a small subset of firms is highly innovative. In terms of firm characteristics, the average employee size is 16.88, the average registered capital is RMB 2.23 million, and the firm age is 12.29 years. These patterns indicate that the private-firm sample mainly consists of relatively small and medium-sized firms, which are particularly relevant for studying whether unemployment insurance reallocates innovation toward riskier and less established firms.

3. Institutional Background and Identification Strategy

In this section, we briefly describe China's unemployment insurance system and the institutional context of the 2017 UI reform. We then assess the validity of using this reform as a quasi-natural experiment for our identification strategy.

3.1 Unemployment Insurance System in China

Since its establishment in 1999, China's unemployment insurance (UI) system has developed into an important component of the country's social security framework. The system is designed to

provide income support to workers during unemployment spells, strengthen labor market resilience, and facilitate re-employment. The Social Insurance Law, enacted in 2011, further strengthened the regulatory framework for UI by providing detailed provisions on the definition of unemployment, eligibility criteria, contribution rates and bases, and the calculation and disbursement of benefits. The law stipulates that enterprises and institutions shall contribute to the unemployment insurance fund based on their total payroll, while individual employees shall contribute based on their own wages.

Risk sharing is the core institutional feature of unemployment insurance. By pooling risks across workers, firms, industries, and regions, the system transforms idiosyncratic unemployment shocks into risks shared more broadly by society. Unemployment risk differs substantially across industries and firms. Sectors with higher employment volatility face greater exposure to job loss, whereas more stable sectors face lower risk exposure. Through mandatory and relatively uniform contribution schemes, unemployment insurance redistributes resources from more stable employment groups to workers in higher-risk sectors. In this way, the system facilitates risk transfer across sectors and strengthens the labor market's ability to absorb sector-specific shocks.

The gradual elevation of the pooling level has further expanded the risk-sharing capacity of the UI system. Over time, the coverage of the risk pool has shifted from the county or city level toward the provincial and, increasingly, national level. This institutional evolution strengthens the system's ability to diversify unemployment risk across regions. Economically developed and employment-stable regions can provide indirect support to areas undergoing structural transformation or facing employment pressure through the contribution mechanism. This cross-regional risk sharing helps reduce the likelihood that localized economic shocks lead to systemic pressure on the social protection system. The upgrading of pooling levels therefore not only enlarges the geographic scope of the risk pool but also improves the system's capacity to manage structural unemployment and aggregate labor market fluctuations.

To qualify for unemployment insurance benefits, workers must have contributed to the UI

system for at least one year and must have been involuntarily separated from their employer. Eligible workers can receive benefits for 12 to 24 months, depending on the length of their prior employment, as specified by law.[3] Monthly unemployment insurance benefits are determined at the provincial level under regionally coordinated rules. This decentralized benefit-setting structure generates substantial cross-province variation in UIB levels and in the generosity of unemployment insurance relative to local wage standards.

Figure 1 illustrates the geographic variation in provincial unemployment insurance benefits. It shows that UIB levels differ substantially across provinces and that the increase in UIB between 2012 and 2021 is not spatially uniform. Provinces vary both in their initial benefit levels and in the magnitude of subsequent benefit growth. Appendix Figure A1 further shows the provincial distribution of UIB in 2012 and 2021 separately. These maps indicate that UIB generosity varies meaningfully across regions, reflecting China's decentralized implementation of unemployment insurance policy.

Figure 2 plots the average level of unemployment insurance benefits, measured on the left y-axis, and the UIB-to-minimum-wage ratio, measured on the right y-axis, from 2011 to 2021. During this period, average UIB rose steadily from around RMB 700 to more than RMB 1,600, reflecting a substantial improvement in the income protection function of the UI system. The UIB-to-minimum-wage ratio also increased from 0.71 to 0.87, with a particularly sharp rise after 2017. This pattern indicates that UI benefits increased not only in absolute terms but also relative to local minimum wages. The strengthening of UI benefits therefore implies a more generous safety net, which may increase workers' willingness to bear labor market risk and improve labor market resilience.

[3] Specifically, if unemployment insurance premiums have been paid for more than one year but less than five years prior to unemployment, the worker is eligible to receive up to 12 months of unemployment insurance benefits. For those who have contributed for more than five years but less than 10 years, the maximum entitlement increases to 18 months. If the premiums have been paid for over 10 years, the worker can receive up to 24 months of benefits.

3.2 Unemployment Insurance Reform in 2017

In September 2017, the Ministry of Human Resources and Social Security, together with the Ministry of Finance, issued the *Guiding Opinions on Adjusting Unemployment Insurance Benefit Levels*.[4] The policy aimed to improve unemployment insurance (UI) standards by establishing a dynamic adjustment mechanism that links benefit levels to provincial economic development and the fiscal capacity of local social security systems. This mechanism was designed to ensure that unemployed workers could maintain a basic standard of living and reduce the financial burden associated with job loss. The guidance also emphasized the need to raise UIB levels and narrow interregional disparities. In particular, it called for a gradual increase in UI benefits toward a target level of 90% of the local minimum wage.

Following the implementation of the guideline, provincial governments adopted measures to raise UIB standards and improve service delivery. Table A2 reports provincial UIB levels and their ratios to local minimum wages in 2016 and 2019. As shown in the appendix, 26 of the 31 provinces increased their UIB-to-minimum-wage ratios during this period. This broad-based increase suggests that the policy effectively strengthened unemployment protection across provinces.

Importantly, the likelihood of increasing the UIB-to-minimum-wage ratio is strongly negatively related to a province's initial proximity to the 90% policy target. Provinces that were farther below the 90% benchmark before the reform were more likely to raise their ratios afterward. Table A2 shows that provinces with larger initial shortfalls from the benchmark, defined as those with ratios at or below 70%, all increased their UIB-to-minimum-wage ratios. By contrast, among provinces closer to the target, defined as those with ratios above 70%, only about 60% made such adjustments. This pattern indicates that implementation intensity varied systematically with the size of the required adjustment and that the reform operated as a convergence mechanism for

[4]For more details of the regulation, see: https://www.mohrss.gov.cn/xxgk2020/fdzdgknr/zcfg/gfxwj/shbx/201709/t20170925_278080.html.

regional UIB standards.

The increase in UIB-to-minimum-wage ratios is also accompanied by growth in absolute UIB levels. This pattern is consistent with the dual objective of the policy: bringing local UI standards closer to the 90% benchmark while also improving benefit adequacy in absolute terms. Overall, the evidence shows a strong inverse relation between a province's initial distance from the policy target and its subsequent probability of adjustment. This policy-induced convergence provides the central source of variation for our empirical analysis.

3.3 Identification Strategy

Our identification strategy rests on the cross-province variation in the intensity of policy pressure created by the 2017 national guidance on unemployment insurance benefits. The reform did not require all provinces to raise benefits by the same amount. Instead, it encouraged local governments to gradually increase unemployment insurance benefits toward 90% of the local minimum wage. This design created stronger adjustment pressure in provinces whose pre-reform UIB-to-minimum-wage ratios were farther below the policy benchmark. Provinces already close to the target had less need to adjust, while provinces with lower initial ratios were more directly affected by the reform.

We classify provinces into treatment and control groups based on their pre-reform UIB-to-minimum-wage ratios. Specifically, provinces in the bottom tercile of the 2016 ratio distribution are assigned to the treatment group, while the remaining provinces serve as the control group.[5] This classification captures pre-determined exposure to the 2017 reform: treated provinces faced the largest gap relative to the 90% benchmark and therefore the strongest policy pressure to raise UIB levels. Because treatment status is defined using pre-reform policy conditions, it is unlikely

[5] We exclude Hainan province from our analysis as its UIB level is set with a different standard. Specifically, Hainan province sets its UIB level as 150% of the local subsistence allowance.

to be mechanically driven by subsequent changes in innovation outcomes, inventor mobility, or private-sector entry.

Appendix Figure A2 maps the geographic distribution of treated and control provinces. Treated provinces are not concentrated in one region but are distributed across different parts of China. This spatial dispersion reduces the concern that our estimates are driven by a single regional shock, such as a local industrial policy, regional business cycle, or common development trend. The control group also includes provinces with different economic structures and levels of development, which supports the comparability of treated and control provinces.

Figure 3 provides further evidence on the effectiveness of the reform. Panel A plots the relative change in UIB levels for treated and control provinces from 2012 to 2021, while Panel B plots the relative change in the UIB-to-minimum-wage ratio. The shaded areas indicate 95% confidence intervals, and the vertical dashed line marks the 2017 reform. Before 2017, the two groups display broadly parallel trends in both UIB levels and UIB-to-minimum-wage ratios. After the reform, treated provinces experience a much larger increase in both measures. This divergence confirms that provinces farther below the benchmark responded more strongly to the national guidance and that the reform generated a meaningful increase in UI generosity in treated provinces.

Panel C of Figure 3 plots the relative change in minimum wage levels. Treated and control provinces follow similar trajectories throughout the sample period, including after 2017. This pattern is important because our treatment is based on the UIB-to-minimum-wage ratio. If treated provinces also experienced differential changes in minimum wages, our estimates could reflect broader wage regulation rather than changes in unemployment insurance benefits. The similar minimum wage trends suggest that the post-reform divergence in the UIB-to-minimum-wage ratio is driven mainly by increases in UIB levels rather than by changes in the denominator.

Overall, the 2017 reform provides a plausibly exogenous shock to unemployment insurance generosity. It created stronger adjustment pressure in provinces initially farther below the national benchmark, while leaving provinces closer to the benchmark less affected. The resulting post-

reform divergence in UIB generosity, together with similar pre-reform trends and stable minimum wage dynamics, supports our difference-in-differences identification strategy.

3.4 Validation of the Identification Strategy

A central premise of our empirical design is that provinces with lower pre-reform UIB-to-minimum-wage ratios faced stronger policy pressure after the 2017 reform and therefore increased unemployment insurance benefits more substantially. To validate this premise, we examine whether the reform affected the intended policy variables while leaving other provincial economic conditions largely unchanged. Specifically, we estimate the following specification:

$$Y_{plt} = \alpha + \beta Treated_p \times Post_t + \mu_p + \varphi_{lt} + \varepsilon_{plt}, \quad (1)$$

where $Y_{p,t}$ denotes one of several province-level outcomes, including the logarithm of unemployment insurance benefits, the UIB-to-minimum-wage ratio, the logarithm of the minimum wage, the number of UIB recipients, the number of listed firms, GDP, and average income. The treatment indicator $Treated_p$ equals one if a province's UIB accounted for less than 70% of the minimum wage in 2016,[6] while $Post_t$equals one for years from 2017 onward. The coefficient β captures whether treated provinces experienced differential changes in these outcomes after the reform.

Table 2 reports the results. Panel A confirms that treated provinces significantly increased both the level of unemployment insurance benefits and the UIB-to-minimum-wage ratio after the reform. In Column (2), the coefficient for log UIB is 0.084, implying that treated provinces increased UIB by approximately 8.4% relative to control provinces after the reform. In Column (4), the coefficient for the UIB-to-minimum-wage ratio indicate an increase of 4.4% points. This evidence supports the relevance of the reform as a source of variation in unemployment insurance

[6] The 70% corresponds to the bottom tercile of the provincial UIB-to-minimum-wage ratio distribution in 2016.

generosity.

Panel B examines whether the reform coincided with changes in other provincial economic variables. The coefficients on the reform interaction are statistically insignificant for the minimum wage, the number of UIB recipients, the number of listed firms, GDP, and average income. These results indicate that the reform primarily operated through changes in unemployment insurance benefits, rather than through simultaneous changes in broader provincial economic conditions. This finding helps alleviate the concern that the baseline estimates are driven by confounding local economic shocks.

4. Empirical Results

4.1 The Effect of Unemployment Insurance Benefits on Corporate Innovation

We begin by examining the baseline relationship between unemployment insurance benefits and corporate innovation using firm-level panel regressions. Patent outcomes are nonnegative count variables and contain many zeros. Log-linear models may therefore generate biased estimates when the dependent variable is transformed using logarithms. Following the suggestion by Cohn et al. (2022) and Chen and Roth (2024), we estimate the baseline specifications using Poisson pseudo-maximum likelihood regressions. Specifically, we estimate the following specification:

$$Innovation_{ipt} = \exp\left[\beta Maxui_{pt} + \gamma_s \sum Controls + Fixed\ effects\right] + \varepsilon_{ipt}, \qquad (2)$$

where subscripts *i*, *p*, and *t* denote firm, province, and year, respectively. The dependent variable $Innovation_{ipt}$ is measured by the number of patent applications filed by firm *i* in year *t*, or the number of these applications that are eventually granted. The main explanatory variable, $MaxUI_{p,t}$, is the logarithm of the provincial monthly maximum unemployment insurance benefit.[7] The

[7] Appendix Table A7 shows that the results are robust to using the UIB-to-average-wage ratio as an alternative measure of unemployment insurance generosity.

control variables include total assets, return on assets, the intangible asset ratio, cash flow scaled by total assets, and capital expenditures scaled by total assets. The baseline specifications include firm fixed effects to absorb time-invariant firm heterogeneity and year-by-industry fixed effects to control for time-varying industry shocks.

Table 3 reports the panel regression results separately for listed and non-listed firms. Panel A focuses on listed firms. The dependent variables are patent applications and granted patents. The coefficients on unemployment insurance benefits are negative across all specifications and statistically significant in the main specifications. In Column (2), where the dependent variable is patent applications, the coefficient on MaxUI is -0.232 and statistically significant at the 5% level. Economically, this estimate implies that a 10% increase in unemployment insurance benefits is associated with an approximately 2.19% decline in patent applications among listed firms. In Column (5), where the dependent variable is granted patents, the coefficient is -0.223 and statistically significant at the 5% level, implying that a 10% increase in UIB is associated with an approximately 2.10% decrease in granted patents. These estimates suggest that, even after absorbing permanent firm characteristics and industry-specific time shocks, more generous unemployment insurance benefits are negatively associated with innovation activities in listed firms.

In Columns (3) and (6), we replace the continuous measure of unemployment insurance benefits with quartile indicators. This specification allows us to examine whether the relationship between UI generosity and innovation varies across different levels of benefits:

$$Innovation_{ipt} = \exp\left[\beta_x \sum_{x=2}^{4} maxui_Qtr_{x,pt} + \gamma_s \sum Controls + Fixed\ effects\right] + \varepsilon_{ipt}, \qquad (3)$$

where $maxui_Qtr_{x,pt}$ indicates whether province p in year t falls into quartile x of the unemployment insurance benefit distribution. The lowest quartile serves as the omitted category.

For listed firms, the coefficients on the higher UIB quartiles are generally negative, and the

estimates are most pronounced in the highest quartile. In Column (3) of Panel A, the coefficient on the top UIB quartile is -0. 176 for patent applications, implying that listed firms in the highest UIB quartile have approximately 16.14% fewer patent applications than those in the lowest quartile. Column (6) reports an almost identical coefficient for patents granted, suggesting a similar decline in granted patents.

Panel B presents the corresponding results for non-listed firms. In contrast to listed firms, the coefficients on unemployment insurance benefits are positive and statistically significant across all specifications. In Column (2), the coefficient on MaxUI is 1.307 and statistically significant at the 1% level. This estimate implies that a 10% increase in unemployment insurance benefits is associated with an approximately 13.27% increase in patent applications among non-listed firms. In Column (5), the coefficient is 0.895, implying an approximately 8.9% increase in granted patents for a 10% increase in UIB. This pattern suggests that unemployment insurance benefits are positively related to innovation among non-listed firms, in sharp contrast to the negative association observed among listed firms.

The quartile specifications show a similar pattern for non-listed firms. The higher UIB quartiles are associated with stronger increase in patenting activity, especially in the third and fourth quartiles. In Column (3) of Table 3 Panel B, the coefficient on the fourth quartile is 0.489, implying approximately 63.07% more patent applications relative to the lowest quartile. In Column (6), the coefficient is 0.472, implying approximately 60.3% more granted patents relative to the lowest quartile. The divergence between listed and non-listed firms is most pronounced in provinces with more generous unemployment insurance benefits.

Overall, the results reveal a clear divergence in the baseline relation between UIB and innovation across firm types. More generous unemployment insurance benefits are associated with lower innovation among listed firms but higher innovation among non-listed firms. These findings suggest that UIB is linked to a reallocation of innovation across firm types, rather than to a uniform shift in innovation outcomes.

4.2 Quasi-natural Experiment and Difference-in-differences

The results in Section 4.1 shows that unemployment insurance benefits have a diverge effects on innovation across listed and non-listed firms. However, these estimates may still reflect unobserved provincial characteristics, local economic conditions, or labor market dynamics that are correlated with both UI generosity and corporate innovation. To address this concern, we exploit China's 2017 unemployment insurance reform as a quasi-natural experiment and estimate a difference-in-differences specification.

Specifically, we estimate the following Poisson pseudo-maximum likelihood model:

$$Innovation_{ipt} = \exp\left[\beta Treated_p \times Post_t + \gamma_s \sum Controls + Fixed\ effects\right] + \varepsilon_{ipt}, \qquad (4)$$

where $Innovation_{ipt}$ is measured by either the number of patent applications filed by firm i in province p and year t, or the number of these applications that are eventually granted. The treatment indicator $Treated_p$ equals one if a province's UIB-to-minimum-wage ratio was below 70% in 2016, and zero otherwise. $Post_t$ equals one for years from 2017 onward. The coefficient of interest β captures the differential change in innovation for firms located in provinces more strongly affected by the reform. The specifications include firm fixed effects and progressively richer time-varying fixed effects to absorb unobserved firm heterogeneity and common shocks.

Table 4 reports the difference-in-differences estimates separately for listed and non-listed firms. Panel A focuses on listed firms. Across all specifications, the coefficients on $Treat_p \times Post_t$ are negative and statistically significant. This result indicates that, after the reform, innovation declined among listed firms in treated provinces relative to listed firms in control provinces. In Column (3), where the dependent variable is patent applications, the coefficient is -0.133 and statistically significant at the 1% level. The estimate therefore implies that listed firms in treated provinces experienced an approximately 12.45% decline in patent

applications after the reform relative to listed firms in control provinces.[8] In Column (6), where the dependent variable is granted patents, the coefficient is -0.121 and statistically significant at the 1% level, implying an approximately 11.40% decline in granted patents. These estimates suggest that the reform had an economically meaningful negative effect on innovation among listed firms.[9]

Panel B presents the corresponding results for non-listed firms. In contrast to listed firms, the coefficients on the reform interaction are positive and statistically significant across all specifications. In Column (3), the coefficient is 0.187, implying that non-listed firms in treated provinces experienced an approximately 20.56% increase in patent applications relative to non-listed firms in control provinces after the reform. In Column (6), the coefficient is 0.174 and statistically significant at the 1% level, implying an approximately 19% increase in granted patents. hese magnitudes suggest that the reform-induced increase in UIB substantially strengthened innovation activity among non-listed firms.

The difference-in-differences results indicate that the 2017 unemployment insurance reform generated sharply different innovation responses across firm types. Innovation declined among listed firms but increased among non-listed firms. This pattern suggests that more generous unemployment insurance does not simply raise or reduce innovation in the aggregate. Instead, the evidence is consistent with a reallocation of innovative activity across firms: innovation weakens among listed firms but strengthens among non-listed firms.

The key identifying assumption is that, absent the 2017 reform, firms in the treated and control provinces would have followed similar trends in innovation outcomes We next assess this parallel-trends assumption using an event-study specification:

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[8] In a Poisson model, the percentage effect of a binary treatment variable is calculated as $exp\ (\beta) - 1$.

[9] Appendix Table A5 shows that the results are robust to using truncation-adjusted patent citations as an alternative measure of innovation quality. The estimates remain consistent with the findings, indicating a negative effect of higher UIB on citation-based patent quality among public firms.

$$Innovation_{ipt} = \exp\left[\sum_{t=2013}^{2021} \beta_t \times D_t \times Treated_p + Fixed\ effects\right] + \varepsilon_{ipt}, \quad (5)$$

where D_t is the year indicator. We use 2016, the year before the reform, as the omitted benchmark year. Figure 4 presents the coefficient plots estimated from Equation (5).

Panel A reports the results when the dependent variable is patent applications. For both listed and non-listed firms, the pre-reform coefficients are close to zero and statistically insignificant. This evidence suggests that firms in treated and control provinces did not exhibit systematic differences in innovation trends before the 2017 reform. After the reform, however, the estimated effects differ sharply across firm types. For listed firms, the coefficients turn negative and remain below zero, indicating a decline in patent applications after the reform. For non-listed firms, the coefficients become positive and statistically significant, suggesting an increase in patenting activity. Panel B shows a similar pattern when the dependent variable is granted patents. These event-study results support the parallel-trends assumption and reinforce the main difference-in-differences findings.

5. Mechanism Discussion

5.1 Risk Redistribution

The previous section documents opposite responses to the UI reform across listed and non-listed firms. Innovation declines among listed firms but increases among non-listed firms. In this section, we examine whether these patterns can be explained by a labor-market risk redistribution mechanism.

The basic idea is that unemployment insurance acts as a public form of downside protection. When unemployment insurance becomes more generous, workers require less compensation to accept jobs with greater employment risk. In this sense, unemployment insurance can operate as an implicit subsidy to riskier firms by reducing the risk premium workers demand for joining them

(Van Doornik et al., 2022). More broadly, by reducing workers' downside risk, unemployment insurance may improve the ability of riskier, talent-intensive firms to attract innovative workers (Pagano and Picariello, 2023).

This mechanism is especially relevant for innovative labor. Safe firms traditionally attract and retain workers by offering more stable employment relationships and lower layoff risk. This stability is valuable for innovative employees because innovation projects often involve long development cycles, uncertain outcomes, and firm-specific knowledge accumulation. However, when public unemployment insurance becomes more generous, workers rely less on firm-provided employment stability. This argument is consistent with Ellul et al. (2018), who show that government-provided unemployment insurance and firm-provided employment insurance are substitutes. As public insurance becomes more generous, the value of stability offered by safe firms declines, making workers more willing to consider riskier employers that may offer greater upside or better innovation opportunities.

This mechanism generates two predictions. First, among listed firms, the negative effect of the UI reform should be concentrated among safer firms. These firms benefit most from the pre-reform stability premium and therefore lose more when public insurance weakens the value of firm-provided stability. By contrast, riskier listed firms should be less negatively affected because higher unemployment insurance partially offsets the employment risk they impose on workers. Second, among non-listed/private firms, the positive effect of the reform should be stronger for riskier firms. These firms have more to gain because the reform reduces the downside risk that previously made them less attractive to innovative workers.

Table 5 tests these predictions by examining whether the treatment effect varies with firm risk. Instead of relying only on subsample regressions, we also estimate full-sample specifications that interact the reform indicator with high-risk status. This allows us to test directly whether riskier firms respond differently from safer firms.

Panel A uses firm size to proxy for risk among listed firms. Following the empirical corporate

finance literature, we use total assets as a measure of firm size (Dang, Li, and Yang, 2018). Larger listed firms are classified as lower-risk firms because they are generally more established and offer more stable employment relationships, while smaller listed firms are classified as higher-risk firms. The results show that the negative effect of the reform is concentrated among larger, safer listed firms. In the subsample regressions, the reform reduces patent applications by about 13.24% and patents granted by about 12.63% among low-risk listed firms. By contrast, the coefficients for high-risk listed firms are small and statistically insignificant. The full-sample interaction results lead to the same conclusion. The positive interaction terms indicate that the effect of the reform is significantly less negative for smaller, riskier listed firms. These findings suggest that safer listed firms are more adversely affected by the UI reform, consistent with the loss of their employment-stability advantage.

Panel B uses stock return volatility as an alternative proxy for firm risk, following Ellul et al. (2018). Firms with lower return volatility are classified as low-risk firms, while firms with higher return volatility are classified as high-risk firms. The results are again consistent with the risk redistribution mechanism. Among low-risk listed firms, the reform significantly reduces both patent applications and patents granted. The estimated declines are approximately 16.97% for patent applications and 18.37% for patents granted. In contrast, the coefficients for high-risk listed firms are much smaller and statistically insignificant. The interaction terms in the full-sample specifications are positive and significant, indicating that the reform has a significantly weaker negative effect on high-risk listed firms. Overall, Panels A and B show that the decline in listed-firm innovation is not a uniform response to the UI reform. It is concentrated among firms with safer employment profiles.

The same logic also helps explain why non-listed/private firms respond in the opposite direction. Compared with listed firms, non-listed firms are generally smaller, riskier, and less able to provide stable employment. Before the reform, this risk made it harder for them to attract innovative workers. More generous unemployment insurance partially insures workers against this

risk and therefore improves the relative attractiveness of these firms. From this perspective, the increase in innovation among non-listed firms is not a separate phenomenon from the decline in listed-firm innovation. Both patterns reflect the same underlying force: public insurance reduces the value of employment stability and shifts innovative labor toward riskier firms.

Panel C examines this prediction within the non-listed/private firm sector. Although non-listed firms are generally riskier than listed firms, there is still meaningful risk heterogeneity within this group. We classify smaller non-listed firms as high-risk firms because they tend to have weaker organizational stability, shorter operating histories, and greater employment uncertainty. The results show that the positive effect of the reform is stronger among these high-risk firms. In the subsample regressions, the coefficient for patent applications is 0.265 among low-risk private firms and 0.616 among high-risk private firms, implying increases of approximately 30.34% and 85.15%, respectively. For patents granted, the corresponding coefficients are 0.289 and 0.547, implying increases of approximately 33.51% and 72.81%.

The interaction specifications confirm that high-risk private firms benefit more from the reform. In the full-sample specification, the coefficient on the reform indicator captures the effect among low-risk private firms, while the interaction term captures the incremental effect for high-risk private firms. The interaction terms are positive, indicating that the reform effect is significantly stronger among smaller and riskier private firms. These results are consistent with the idea that unemployment insurance improves risky firms' ability to attract innovative workers by reducing workers' exposure to employment risk.

Taken together, Table 5 provides evidence that the effect of the UI reform varies systematically with firm risk. Among listed firms, the negative effect is concentrated among safer firms, which previously benefited more from employment stability as a retention advantage. Among non-listed/private firms, the positive effect is stronger among smaller and riskier firms, which previously faced greater difficulty attracting innovative workers. These opposite responses are therefore consistent with a common mechanism: more generous unemployment insurance

redistributes employment risk and reallocates innovative resources away from safer incumbents toward riskier firms.

5.2 Inventor Mobility and Directional Reallocation

5.2.1 *Inventor Flow at Listed Firms*

In this section, we provide further evidence on risk redistribution and the allocation of innovation. If more generous unemployment insurance reduces workers' dependence on firm-provided employment stability, we should observe an increase in movements in innovative workers after the reform. In particular, more generous public UI should weaken safer listed firms' retention advantage and make inventors more willing to move toward riskier employers. Therefore, the prediction is not simply that inventors become more mobile after the reform, but that mobility should have a clear direction: inventive labor should move away from listed firms and toward non-listed firms.

We test this prediction using inventor mobility constructed from patent records. Following the patent-based labor mobility literature (Marx et al., 2009; Chemmanur et al., 2019), we operationalize inventor mobility by constructing a matched inventor-firm panel where transitions are identified when an inventor's consecutive patent applications list different corporate assignees.

We begin with patent-level information on inventor names and applicant firms and then construct inventor-firm linkages based on consecutive patenting records. Given the prevalence of name duplication in China, we employ a multi-step procedure to accurately identify unique inventors. First, within a given firm, we assume that each inventor's name corresponds to a unique individual; thus, identical names appearing within the same firm are treated as one person. Second, we rely on inventors' employment tenure and assume that an inventor is affiliated with only one firm during a given period. Third, we utilize co-inventor networks, under the assumption that inventors sharing the same name and at least one common co-inventor are the same individual. Finally, we analyze the technological fields of patents, positing that inventors tend to specialize in

a particular domain. Thus, if an inventor's patents across different firms fall within the same technological field, we treat them as one person. After establishing unique inventor identifiers, we merge inventors with firm-level information and provincial policy exposure based on the geographic location of the employing firm in 2016.

We then aggregate the inventory level movement data to firm-year level for listed firms and construct four measures: *Inventor Mobility*, which captures the total number of inventors who moved to and from the focal employers; *Inventor Outflow*, which measures the number of inventors leaving the firm; *Inventor Inflow*, which measures the number of inventors joining the firm from another employer; and *Net Inventor Flow*, defined as the difference between *Inventor Inflow* and *Inventor Outflow*. All above variables normalized by the number of inventors in year *t-1*.

Table A3 Panel A reports summary statistics for the listed-firm-year inventor-mobility variables. The average inventor total mobility is 1.04, indicating that listed firms experience substantial turnover in their patent-based inventor stock. The mean inventor outflow is 0.58, while the mean inventor inflow is 0.45. Inventor outflows exceed inflows on average, resulting in a negative mean net inventor flow of -0.13. These patterns suggest that listed firms are not only receiving new inventors but also continuously losing existing inventors, and that the average listed firm experiences a net loss of inventive human capital during the sample period. This provides a useful baseline for interpreting whether the UI reform further accelerates inventor reallocation away from listed firms.

We then re-estimate our regression in Equation (4) with the dependent variable replaced by firm-level inventor flow for listed firms. Table 6 reports the results. Panel A shows that the UI reform significantly increases inventor mobility in listed firms. In Column (1), the coefficient on the reform indicator is 0.164 and statistically significant at the 1% level. This coefficient represents a 16.4% relative increase of the mean total inventor flow. Columns (2) and (3) decompose this increase into outflows and inflows. Higher UIB increases inventor mobility in treated provinces

relative to control provinces: inventor outflows rise by about 10%, while inventor inflows increase by about 6.4%. This asymmetric response implies that listed firms do not simply participate in a more active labor market; they lose more inventors than they gain. Consistent with this interpretation, Column (4) shows that the reform reduces net inventor flow by 0.037, significant at the 5% level. The negative effects of UIB on inventor outflow at the listed firms are consistent with the overall decrease in patent activities at the listed firms in section 4.

Panels B and C of Table 6 further examine whether this net inventor loss is concentrated among safer listed firms. This test directly follows the risk redistribution mechanism. If safer firms lose more of their retention advantage after listed UI becomes more generous, as suggested by Ellul et al. (2018), their net inventor flow should decline more strongly. Panel B uses firm size as the proxy for firm risk. The coefficient for low-risk firms is -0.050 and statistically significant at the 5% level, indicating that higher UIB significantly reduces net inventor flow in treated provinces relative to control provinces, with the decline concentrated among larger and safer listed firms. The coefficient for high-risk firms is positive and statistically insignificant. This full-sample interaction term means that the reform effect on net inventor flow is 8.6% higher for high-risk listed firms than for low-risk listed firms. The implied effect for high-risk listed firms is slightly positive, while the effect for low-risk firms is clearly negative.

Panel C uses return volatility as an alternative measure of firm risk. The results are highly consistent. Low-risk firms experience a significant decline in net inventor flow, while the coefficients for high-risk firms show a much smaller and statistically insignificant coefficient. The positive interaction term indicates that high-risk listed firms experience a substantially smaller decline in net inventor flow than low-risk listed firms. These results reinforce the interpretation that the reform erodes the inventor-retention advantage of safer listed firms.

5.2.2 *Inventor-level Evidence*

We next turn to the inventor-year level panel to examine the direction of inventor reallocation. The inventor-level sample is constructed from inventors who are observed working for listed firms at

least once during the sample period. We first construct two indicators that capture the probability that an inventor changes her employer. *D(Switch)* is an indicator equal to one if an inventor changed its employer in year t compared to the previous year. D(*Left Baseline Firm*) is an indicator equal to one if an inventor is no longer affiliated with the firm for which the inventor worked in 2016. These variables capture whether inventors become more mobile after the reform.

We further construct another two indicators to capture the direction of reallocation across firm types. To examine movements from listed firms to non-listed firms, we focus on inventors who worked for listed firms in 2016. D(Move to Non-Listed Firm=1) is an indicator that equals one if an inventor moves from a listed firm in year t−1 to an unlisted firm in year t. D(Work in Non-Listed Firm=1) is a status indicator equals one if the inventor works for an unlisted firm in year t. Similarly, we also focus on inventors who worked for non-listed firms in 2016. D(Move to Listed Firm=1) equals one if an inventor moves from a non-listed firm in year t−1 to a listed firm in year t. D(Work in Listed Firm=1) equals one if the inventor works for a listed firm in year t. These directional variables allow us to distinguish genuine reallocation from general labor-market churning.

Table A3 Panel B reports summary statistics for the inventor-level mobility and directional reallocation variables. About 11% of inventor-year observations involve an employer switch, and 25% indicate that the inventor is no longer affiliated with the baseline firm. Among baseline listed-firm inventors, 3% of inventor-year observations involve a transition to a non-listed firm, and 8% are associated with employment in a non-listed firm. Among baseline private-firm inventors, 9% of inventor-year observations involve a transition to a listed firm, and 42% are associated with employment in a listed firm. These statistics show that inventor mobility is common, while directional transitions across listed and non-listed firms are more selective. They provide a useful benchmark for interpreting the inventor-level estimates in Table 7.

Table 7 reports the results of inventor-level mobility and directional reallocation. Panel A first shows that the reform increases overall inventor mobility. In Columns (1) and (2), the coefficients

on the interaction term are both positive and statistically significant, implying that inventors in the treated provinces become more likely to switch employers after the reform compared with inventors in the control provinces. Similarly, Columns (3) and (4) also show that the treated inventors are more likely to leave the firms where they work prior to the reform. These results provide direct evidence that the UI reform increases inventor mobility.

Panel B examines whether this mobility is directed toward non-listed firms. The sample focuses on inventors employed by listed firms in 2016. The results show that inventors are more likely to move to non-listed firms after the reform. In Column (2), the coefficient of the interaction term is 0.005 and statistically significant at the 1% level. Relative to the average probability of moving to a non-listed firm (3%), this estimate represents an economically meaningful increase in movements toward non-listed firms. Columns (3) and (4) show that inventors are also more likely to be employed by non-listed firms after the reform. The increase in inventor movements toward non-listed firms captures a direct labor-market margin of risk redistribution.

Panel C examines the reverse direction of inventor reallocation. In these tests, we restrict our sample to those inventors that were employed by non-listed firms in 2016. If the reform merely increased general labor-market turnover, we should observe stronger movements in both directions: from listed firms to non-listed firms and from non-listed firms to listed firms. The evidence does not support this interpretation. The coefficients on moving to listed firms and working in listed firms are small and statistically insignificant. Combined with Panel B, this result reveals a clear directional asymmetry in inventor mobility. The reform increases inventor movements from listed firms toward non-listed firms, but does not generate a corresponding increase in movements from non-listed firms toward listed firms.

This asymmetry is central to the risk redistribution mechanism. It suggests that more generous unemployment insurance does not simply make inventors more mobile. It changes the direction of innovative labor allocation by weakening the relative value of employment stability in listed firms and making riskier non-listed firms more attractive. As inventive human capital flows out of listed

firms without a comparable reverse flow back into them, listed firms experience a loss of innovation capacity. At the same time, non-listed firms receive additional inventive labor, which helps explain the increase in private-firm innovation documented in the baseline results.

Overall, Tables 6 and 7 provide direct labor-market evidence for the risk redistribution mechanism. At the firm level, listed firms experience higher inventor mobility, larger outflows, and a decline in net inventor flow. At the inventor level, inventors become more likely to switch employers and move toward non-listed firms, while there is no comparable increase in movement toward listed firms. These findings show that more generous unemployment insurance reduces the value of employment stability provided by safe firms, weakens their ability to retain inventors, and facilitates the movement of inventive talent toward riskier non-listed firms. This labor-market reallocation helps explain why the reform reduces innovation among listed firms while increasing innovation among non-listed firms.

5.3 Entrepreneurship

The reallocation of inventive labor does not necessarily stop at existing non-listed firms. If unemployment insurance reduces workers' downside risk, it might also affect the entrepreneurship. Newly established firms are among the riskiest organizations in the economy. They have shorter operating histories, weaker employment stability, and more uncertain survival prospects. For innovative workers, joining or creating such firms involves substantial career risk. More generous unemployment insurance can reduce this risk by providing a stronger safety net in the event of failure. Therefore, the reform may not only redirect inventors from listed firms to non-listed incumbents, but also encourage innovative labor and resources to move toward new firms.

This prediction is consistent with Hombert et al. (2020), who show that unemployment insurance can stimulate entrepreneurial activity by lowering the downside risk of starting a business. It is also related to the broader view that unemployment insurance can act as a subsidy to risk-taking by reducing workers' exposure to unemployment risk (Van Doornik et al., 2022). In

our setting, entrepreneurship represents a particularly important margin of risk redistribution. If listed firms lose part of their retention advantage after the reform, some of the reallocated innovative labor may flow not only to existing non-listed firms but also to young entrepreneurial firms.

We first examine whether the reform stimulates new firm creation using the quasi-natural experiments at the provincial level. Specifically, we estimate the following regression equation:

$$Ln(\#\ of\ new\ firms)_{pt} = \beta Treated_p \times Post_t + \gamma_s \sum Controls + Fixed\ effects + \varepsilon_{pt}, \qquad (6)$$

where $Ln(\#\ of\ new\ firms)_{pt}$ is the log of the number of newly established firms in province p and year t. Provincial control variables and fixed effects are sequentially introduced to enhance the robustness and interpretability of the results. The specifications include province fixed effects, provincial controls, and progressively richer year-by-group fixed effects, including year-by-income tercile, year-by-region, year-by-GDP tercile, and year-by-population tercile fixed effects. The coefficient of interest β captures the differential change in entrepreneurial entry in treated provinces after the reform.

Table 8 reports the results. Panel A shows that the reform significantly increases new firm creation. The effect remains positive and statistically significant after controlling for provincial characteristics and adding progressively richer fixed effects. The coefficient economically implies that treated provinces experience an approximately 50.8% increase in new firm creation after the reform relative to control provinces. This magnitude suggests that more generous unemployment insurance meaningfully stimulates entrepreneurial entry.

A natural concern is that the increase in new firm creation may simply reflect marginal or short-lived registrations rather than meaningful entrepreneurial activity. To address this concern, we further examine high-quality new firm creation, measured by newly established firms that remain active in later years. The results continue to be positive and statistically significant. In Column (4), the coefficient is 0.517 and statistically significant at the 5% level, implying an

approximately 51.7% increase in high-quality new firm creation. This evidence indicates that the entrepreneurial response is not merely a mechanical increase in registrations. Instead, the reform appears to promote the formation of more persistent and economically viable new firms. This result aligns with the findings of Hombert et al. (2020).

We then examine whether this provincial-level entrepreneurial expansion is connected to the reallocation of inventive workers. If entrepreneurship is part of the risk redistribution channel, inventors leaving listed firms in the treated provinces should become more likely to join newly established private firms after the reform. To test this prediction, we estimate the following inventor-level specification:

$$Flow\ to\ New\ Firm_{i,p,t}^{(a)} = \alpha + \beta Treated_p \times Post_t + \gamma_s \sum Controls + Fixed\ effects + \varepsilon_{pt}, \quad (7)$$

where $Flow\ to\ New\ Firm_{i,p,t}^{(a)}$ is an indicator equal to one if inventor i moves from a listed firm in year $t-1$ to a private firm in year t, where the destination private firm has been established for no more than a years. We consider three alternative age windows: two years, three years, and five years. All specifications include inventor, year-industry and provincial fixed effects. The coefficient β captures whether inventors initially associated with listed firms become more likely to move to newly established private firms after the reform.

Table 9 reports the results. The dependent variable captures the probability that an inventor leaves a listed firm and joins a newly established private firm. Across all three definitions of newly established private firms, the reform significantly increases inventors' transitions from listed firms to young private firms. The estimated coefficients imply a relatively 0.03% to 0.11% increase in probability that an inventor leaves a listed firm and join a newly formed private firm depending on various definitions of newly formed firms. Given that movements from listed firms to newly established private firms are rare events (mean value =0.01), these estimates indicate a meaningful increase in the flow of inventive labor toward entrepreneurial firms.

The results suggest that more generous UIB broadly improves young private firms' ability to attract inventors from listed firms. This pattern is consistent with the entrepreneurship channel: by reducing the downside risk of leaving stable employment, more generous unemployment insurance makes young and risky private firms more viable destinations for innovative workers. This evidence strengthens the risk redistribution interpretation. This mechanism helps explain the diverge innovation effects documented earlier: listed firms lose part of their inventive labor force, while private and newly established firms gain access to workers who can contribute to innovation. Entrepreneurship therefore represents a key margin through which unemployment insurance reallocates innovative resources from safer incumbent firms toward riskier and younger firms.

5.4 Economic Significance of a Modest UI Increase

A natural concern is whether the 2017 UI reform is large enough to affect the behavior of high-skilled inventors. The policy-induced increase in unemployment insurance benefits is modest relative to the salary of an inventor. Our interpretation, however, does not rely on a direct income-replacement effect at the inventor level. Instead, the reform affects innovation by changing the relative value of employment stability and by altering the allocation of inventive labor at the margin.

This distinction is important. The relevant economic margin is not whether unemployment insurance benefits can replace the income of a high-paid inventor. Rather, the question is whether more generous public insurance weakens the implicit premium workers attach to stable employment relationships. Public unemployment insurance and firm-provided employment stability can act as partial substitutes (Ellul et al., 2018). When public insurance becomes more generous, safer firms lose part of the retention advantage that comes from offering lower employment risk. This change can affect workers who are close to the margin between staying with a stable incumbent employer and moving to a riskier non-listed firm or entrepreneurial opportunity.

The inventor-mobility evidence supports this interpretation. The reform increases inventor mobility in listed firms, and the increase in outflows exceeds the increase in inflows. At the inventor level, the reform also raises the probability that inventors move from listed firms to non-listed firms, while generating no comparable increase in movements from non-listed firms to listed firms. These patterns suggest that the reform does not simply increase general labor-market turnover. Instead, it changes the direction of inventive labor allocation by weakening the relative value of employment stability in listed firms.

In this section, we provide some suggestive evidence on the economic significance of UI increase. First, if the UI increase operates through marginal labor-market adjustments, the mobility response should be stronger among marginal inventors whose labor-market choices are more sensitive to downside risk. To test this conjecture, we construct a measure for marginal inventor based on their observed patenting history with the firm. We define inventors whose first observed patent with the current firm appears during 2014–2016 (one to three years prior to the reform) as "weakly-attached" inventors as they are more likely to have short tenures with their current employers. If modest UI changes affect inventors near the employer-switching margin, the reform-induced increase in mobility should be more pronounced among these relatively weakly attached inventors.

Results in Panel A of Table A6 supports this prediction. The higher-UIB-induced increase in inventor mobility is more pronounced among marginal inventors than among non-marginal inventors, both for employer switching and for leaving the baseline firm. The full-sample interaction estimates are also positive and statistically significant, indicating that recently observed inventors respond more strongly to the reform. This pattern is consistent with the mobility-margin interpretation: modest UI changes are more likely to affect inventors with weaker firm-specific attachment.

Additionally, unemployment insurance is generally more valuable for lower-income workers because a given increase in benefits represents a larger share of their earnings and provides more

meaningful downside protection. Thus, a modest increase in UIB may be more relevant for R&D supporting employees whose wages are lower and whose decisions to move to riskier firms are more sensitive to public insurance. At the same time, these supporting employees are closely relevant to innovation production. Ordinary or blue-collar workers can influence firm innovation as they may contribute production knowledge, support scientists and engineers, and affect innovative employees' productivity through project execution and organizational routines (Bradley et al. 2017).

The implication is firms with more research supporting employees per inventor should be more exposed to the effect of increase in UIB. When supporting workers become more willing to move from safer listed firms to riskier private-sector opportunities, the stability of listed firms' R&D teams may weaken. For inventors whose projects rely heavily on supporting personnel, disruptions to the surrounding team can reduce the value of staying with the original firm and make inventor departures more likely. We therefore examine whether inventor net losses are larger in firms with higher research supporting team per inventor.

Results in Panel B of Table A6 is consistent with this prediction. We measure the research support with the average number of supporting R&D employees per inventor in 2015 and 2016, standardized across sample firms. The net loss of inventors in the treated firms are more pronounced for firms with higher research support per inventor. In addition, the relative drop in both patent application and grants are also stronger for firms with higher research support per inventor. Overall, the results are consistent with the view that the effect of UIB on inventor mobility can operate through the broader R&D team environment: when inventors rely more heavily on supporting personnel, changes in the stability of the surrounding R&D workforce are more likely to translate into inventor departures.

The findings in this section help address the concern that the UI increase is small relative to inventor salaries. The evidence is not consistent with a simple direct income effect on high-paid inventors. Instead, it supports a labor-market reallocation mechanism. A moderate increase in

unemployment insurance can affect innovation because it changes marginal mobility decisions and because the loss of inventive labor has amplified effects in firms that depend heavily on a limited group of inventors.

6. Alternative Explanation and Robustness Tests

6.1 Can Labor Cost Explain the UI Effect?

In the previous section, we present evidence that the contrasting effects of UIB on listed and non-listed firms are consistent with the risk redistribution channel. A possible alternative explanation, however, is that the decline in listed-firm innovation after the UI reform is driven by higher labor costs. More generous unemployment insurance may improve workers' outside options and strengthen their bargaining power. If firms respond by raising wages, higher labor costs may crowd out resources for innovation and reduce patenting activity.

This labor-cost mechanism generates three testable predictions. First, the reform should increase employee compensation or labor expenses among firms in treated provinces. Second, the negative effect on innovation should be stronger among labor-intensive firms, which are more exposed to wage pressure and labor-related expenses. Third, firms may reduce R&D investment if higher labor costs crowd out resources allocated to innovation.

Table 10 tests these predictions. Panel A examines the effect of the UI reform on employee compensation, using both the logarithm of average employee salary and total salary scaled by sales as dependent variables. Across all specifications, the coefficients on the reform interaction are small and statistically insignificant. In the more demanding specifications, the coefficient is 0.009 for log average employee salary and close to zero for total salary scaled by sales. These estimates provide little evidence that the UI reform increases firms' wage bills or employee compensation. This result weakens the basic premise of the labor-cost channel.

Panel B examines whether the negative innovation effect is stronger among labor-intensive

firms. This test is informative because the labor-cost explanation has a clear prediction: if the reform reduces innovation by raising general labor costs, high-labor-intensity firms should be more negatively affected. These firms employ more workers relative to assets and should therefore be more exposed to wage pressure and employee-related expenses.

The evidence does not support this prediction. The negative effect is concentrated among low-labor-intensity firms. The estimated coefficients are -0.194 for patent applications and -0.167 for granted patents. By contrast, the coefficients for high-labor-intensity firms are smaller and statistically insignificant. The interaction estimates further show that the reform effect differs across labor-intensity groups. The stronger decline among low-labor-intensity firms indicates that the negative innovation effect is not concentrated among firms with greater exposure to aggregate labor-cost pressure. This pattern is difficult to reconcile with the labor-cost mechanism.

Panel C examines whether increases in UIB reduce firms' R&D investment. The dependent variables include log R&D expenditure, R&D scaled by total assets, and R&D scaled by sales. Across all specifications, the coefficients are statistically insignificant, indicating that firms do not reduce R&D spending following increases in UIB. This finding is also difficult to reconcile with the labor-cost explanation. If higher wage expenses crowded out innovation-related resources, firms should reduce R&D investment as an adjustment margin. Instead, R&D spending remains stable while patent output declines. This pattern suggests that the reform affects innovation outcomes through the allocation or productivity of innovative human capital, rather than through a reduction in innovation inputs.

Overall, the evidence provides little support for the labor-cost channel. The decline in listed-firm innovation does not appear to be driven primarily by higher wage costs or by a crowding-out of R&D investment.

6.2 Robustness Tests

In this section, we examine whether our main results are robust to alternative sample constructions

and model specifications.

6.2.1 Matched Sample

Although firms do not directly determine province-level unemployment insurance policies, firms with different characteristics may be unevenly distributed across treated and control provinces. To address this concern, we construct matched samples separately for listed and non-listed firms and then re-estimate the difference-in-differences specification.

Table A4 reports pre-reform balance tests for listed firms. Panel A shows that, before matching, firms in treated provinces have higher patent applications and granted patents, larger total assets, and slightly lower capital expenditure ratios. These differences suggest that pre-existing firm characteristics should be carefully accounted for.

For listed firms, we implement a propensity score matching procedure using firm characteristics measured in 2016, the year before the reform. Specifically, we estimate the propensity score based on patent applications, patents granted, firm size, intangible asset ratio, return on assets, cash holdings, and capital expenditure. We then match each treated firm to up to two control firms using nearest-neighbor matching with a caliper of 0.01 and impose the common-support restriction. Panel B of Table A4 reports the post-matching balance tests. The matched sample substantially improves comparability between firms in treated and control provinces, especially in pre-reform innovation outcomes and key financial characteristics.

For non-listed firms, detailed financial information is not available in the same way as for listed firms. We therefore construct a matched sample using cell-based exact matching based on firm registration characteristics. To avoid post-treatment selection, we restrict the matching pool to non-listed firms established before the 2017 reform. We classify firms into cells defined by industry, employee-size quintiles, registered-capital quintiles, and firm-age quintiles, with firm age measured as of 2016. Within each cell, we randomly match firms in treated provinces to firms in control provinces on a one-to-one basis and retain only cells that contain both groups. This

procedure ensures that matched non-listed firms are comparable in industry affiliation, operating scale, capitalization, and pre-reform maturity.

Panels A and B of Table A8 report the results using the matched samples for listed and non-listed firms, respectively. For listed firms, the coefficients on the reform interaction remain negative and statistically significant for both patent applications and granted patents. For non-listed firms, the coefficients remain positive and statistically significant. These results are consistent with our baseline findings, suggesting that the main results are not driven by observable differences between firms in treated and control provinces.

6.2.2 Additional Sample Restrictions

A potential measurement concern is that unemployment insurance exposure depends on the province in which employees work, while our treatment assignment is based on the province in which a firm is headquartered. This issue may be more relevant for firms whose employees are geographically dispersed. To mitigate this concern, we exclude industries in which employees are more likely to work across multiple locations, such as wholesale, retail, and transportation. Panel C of Table A8 shows that the results remain stable after excluding these geographically dispersed industries. The coefficients remain negative and statistically significant for listed firms and positive and statistically significant for non-listed firms. This evidence suggests that the baseline findings are unlikely to be driven by measurement error in provincial policy exposure.

We also examine a subsample of firms located in border cities. Firms in neighboring border cities are likely to operate in similar geographic and economic environments, but may be subject to different provincial unemployment insurance policies. This setting provides a more localized comparison and helps control for unobserved regional heterogeneity. Panel D of Table A8 reports the border-city results. For listed firms, the coefficients remain negative and statistically significant in most specifications. For non-listed firms, the coefficients remain positive, although the statistical significance varies across specifications. Overall, the border-city evidence continues to

support the central finding that the reform reduced innovation among listed firms while increasing innovation among non-listed firms.

6.2.3 Alternative Model Specification

Our baseline difference-in-differences design defines treated provinces as those in the bottom tercile of the 2016 UIB-to-minimum-wage ratio distribution. This classification captures provinces that faced the strongest policy pressure under the 2017 reform. In this section, we use an alternative continuous measure of reform exposure based on each province's pre-reform distance from the 90% policy benchmark.

Specifically, we define reform intensity as the gap between the 90% benchmark and a province's UIB-to-minimum-wage ratio in 2016. Provinces with lower pre-reform ratios had larger policy gaps and therefore faced stronger pressure to raise unemployment insurance benefits after the 2017 national guidance. This specification allows us to test whether innovation responses vary systematically with the intensity of reform exposure. We estimate the following model:

$$Patents_{ipt} = \exp\left[\beta Distance_p \times Post_t + \gamma_s \sum Controls + Fixed\ effects\right] + \varepsilon_{ipt}, \quad (8)$$

where $Distance_p$ represents 90% minus UIB-to-minimum-wage ratio in 2016. A larger value of $Distance_p$ indicates a larger pre-reform shortfall from the policy benchmark and therefore stronger exposure to the 2017 reform. All other variables, controls, and fixed effects are defined as in the baseline specification.

Table 11 reports the results. The findings remain consistent with the baseline difference-in-differences estimates. For listed firms, the coefficients on the continuous reform-intensity measure are negative and statistically significant. In the specification with firm controls, the coefficient is -0.455 for patent applications and -0.427 for granted patents. These estimates indicate that listed firms located in provinces with larger pre-reform policy gaps experience larger declines in innovation after the reform. Economically, a 10 percentage-point larger gap from the 90%

benchmark is associated with an approximately 4.45% decline in patent applications and an approximately 4.18% decline in granted patents among listed firms after the reform.

For non-listed firms, the coefficients are positive and statistically significant. The coefficient is 1.709 for patent applications and 1.294 for granted patents. These estimates imply that a 10 percentage-point larger pre-reform policy gap is associated with an approximately 18.64% increase in patent applications and an approximately 13.81% increase in granted patents among non-listed firms after the reform.

These results support our identification strategy. The baseline findings are not driven by the particular binary classification of treated and control provinces. Instead, the estimates exhibit a dose-response pattern: provinces farther below the 90% benchmark before the reform experience stronger post-reform innovation reallocation from listed firms toward non-listed firms. This pattern is consistent with the institutional design of the reform, which created stronger adjustment pressure in provinces with larger pre-reform shortfalls from the national benchmark.

6.2.4 Controlling for Additional Fixed Effects

Finally, we control for additional fixed effects to address the concern that firms with different ownership structures, sizes, capitalization levels, or ages may follow different innovation trends over time. If these trends are correlated with provincial exposure to the UI reform, the baseline estimates may capture differential firm-type trends rather than the effect of unemployment insurance.

Table A9 introduces additional interaction fixed effects to absorb more flexible time-varying heterogeneity. For listed firms, Panel A adds year-by-SOE and year-by-size-tercile fixed effects. These specifications control for differential innovation trends associated with ownership structure and firm size. The coefficients remain negative and statistically significant across specifications, indicating that the decline in listed-firm innovation is not explained by these time-varying factors.

For non-listed firms, Panel B adds year-by-registered-capital-tercile and year-by-age fixed

effects, in addition to the baseline fixed effects. These controls account for differences in firm scale and maturity among non-listed firms. The coefficients remain positive and statistically significant, suggesting that the increase in private-firm innovation is robust to a more demanding set of fixed effects.

7. UIB and Provincial Level Innovation

The previous sections show that the unemployment insurance reform reallocates innovation across firms. Listed firms experience a decline in innovation, while private, young, and riskier firms gain innovative activity and become more attractive destinations for inventive labor. These findings raise an important aggregate question: does a more generous UIB simply shift innovation away from listed firms, or does it also increase innovation at the provincial level? The net effect is ambiguous ex ante and depends on whether the decline in listed-firm innovation is offset by, or dominated by, the increase in innovation among non-listed and entrepreneurial firms.

To examine this question, we estimate the effect of the UI reform on aggregate provincial innovation. Table 12 reports the results. Panel A examines provincial patent applications, while Panel B examines granted patents. The first two columns of each panel focus on aggregate innovation across all firms within a province. In Column (2), the coefficient for provincial patent applications is 0.278 and statistically significant, implying that treated provinces experience an approximately 27.8% increase in total patent applications after the reform relative to control provinces. Panel B shows a similar pattern for granted patents, with an estimated increase of approximately 14.5%. These estimates indicate that the UI reform does not reduce total provincial innovation. Instead, aggregate innovation increases after the reform.

The remaining columns decompose the aggregate effect by firm type. Columns (3) and (4) examine aggregate innovation among listed firms. The estimated coefficients are negative for both patent applications and granted patents, which is directionally consistent with the firm-level evidence that listed-firm innovation declines after the reform. However, the estimates are

statistically insignificant at the province-year level. This lack of precision is not surprising, as the aggregate analysis collapses firm-level variation into province-year patent counts and therefore relies on substantially fewer observations. Aggregation also changes the weighting of the estimates because listed-firm patenting within a province may be driven by a small number of large listed firms. We therefore interpret these results as showing that listed firms do not drive the positive aggregate innovation response.

Columns (5) and (6) show that the aggregate increase is concentrated among non-listed firms. In Column (6) of Panel A, the coefficient for private-firm patent applications is positive and statistically significant, implying that non-listed firms in treated provinces experience an approximately 29.9% increase in patent applications after the reform. In Column (6) of Panel B, the coefficient for private-firm granted patents implies an approximately 22.8% increase. These effects are economically meaningful and closely align with the aggregate provincial increase, indicating that non-listed firms are the main source of the positive aggregate innovation response.

Taken together, the findings in Table 12 strengthen the interpretation that UIB reshapes the labor-market equilibrium through which innovative workers are allocated across firms. The increase in private-firm innovation more than offsets the decline among listed firms, leading to higher aggregate innovation at the provincial level. This pattern is consistent with the idea that when inventive labor moves from established listed firms to private and entrepreneurial firms, knowledge accumulated within incumbents can be redeployed in new organizational settings. From a policy perspective, these findings suggest that social insurance reforms can have broader innovation effects by reshaping the allocation of innovative resources and fostering a more dynamic, risk-tolerant entrepreneurial ecosystem.

8. Conclusion

This paper examines how unemployment insurance benefits affect corporate innovation and the allocation of innovative resources. Using China's 2017 unemployment insurance reform as a quasi-

natural experiment, we show that more generous unemployment insurance generates sharply different innovation responses across firm types. Listed firms experience a significant decline in patenting activity, while non-listed firms experience a substantial increase in both patent applications and granted patents. These results indicate that unemployment insurance does not uniformly suppress or stimulate innovation. Instead, it reshapes the allocation of innovation across firms.

The central mechanism is a change in labor-market equilibrium. Before the reform, safer listed firms benefited from their ability to provide stable employment relationships, which helped them retain innovative workers. As unemployment insurance becomes more generous, the relative value of firm-provided employment stability declines. At the same time, riskier private and entrepreneurial firms become more competitive in attracting inventive labor. Consistent with this interpretation, we find that the negative effect on listed-firm innovation is concentrated among safer firms, while the positive effect on private-firm innovation is stronger among smaller and riskier private firms.

Evidence from inventor mobility further supports this labor-market reallocation channel. Higher UIB increases overall inventor movement and inventor outflows from listed firms. The resulting net loss of innovative human capital is concentrated among relatively safe listed firms. Individual-level tests also reveal an asymmetric pattern of inventor mobility: higher UIB encourages movements from listed firms to non-listed firms, but does not generate a comparable increase in movements from non-listed firms to listed firms.

At the regional level, more generous UIB does not lead to an aggregate innovation loss. We find that higher UIB increases new firm creation and strengthens young private firms' ability to attract innovative workers. As a result, treated provinces experience increases in both total patent applications and granted patents. These findings suggest that unemployment insurance can generate broader innovation gains by shifting innovative resources from safer incumbents toward more dynamic private and entrepreneurial firms.

More broadly, our findings suggest that unemployment insurance may play an important role in shaping the allocation of innovative activity across firms. By pooling unemployment risk more broadly, unemployment insurance reduces the extent to which workers must rely on individual firms for employment stability. This form of risk sharing can weaken the labor-market advantage of safer incumbent firms and improve the ability of private and riskier firms to attract innovative workers. In doing so, social insurance may help redirect inventive human capital toward firms with stronger growth opportunities but weaker internal insurance capacity. Our evidence suggests that this reallocation can increase innovation in the private sector and, under certain conditions, contribute to aggregate innovation. These findings point to a broader implication of social insurance policy: beyond protecting workers against income loss, it may also support economic dynamism by improving the allocation of risk-bearing capacity, talent, and innovative resources across the economy.

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Figure 1. Geographic Change of Provincial Unemployment Insurance Benefits

This figure maps monthly unemployment insurance benefits (UIB) across mainland China and reports the change in UIB between 2012 and 2021.

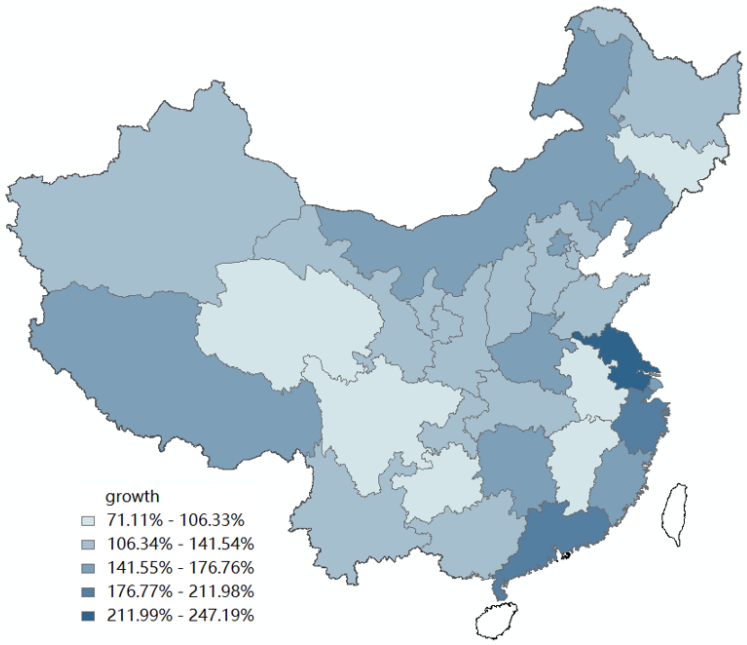


Figure 2. Evolution of Unemployment Insurance Benefits in China

This figure plots the evolution of unemployment insurance benefits in China from 2011 to 2021. The solid blue line shows the average provincial monthly maximum unemployment insurance benefit (left axis). The dashed red line shows the average provincial UIB-to-minimum-wage ratio (right axis).

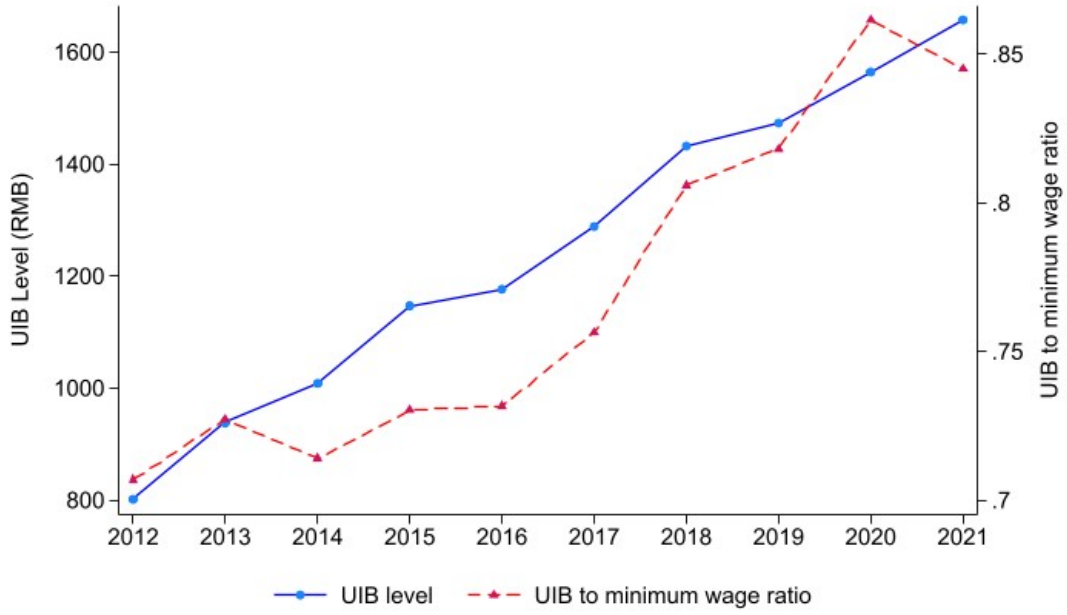
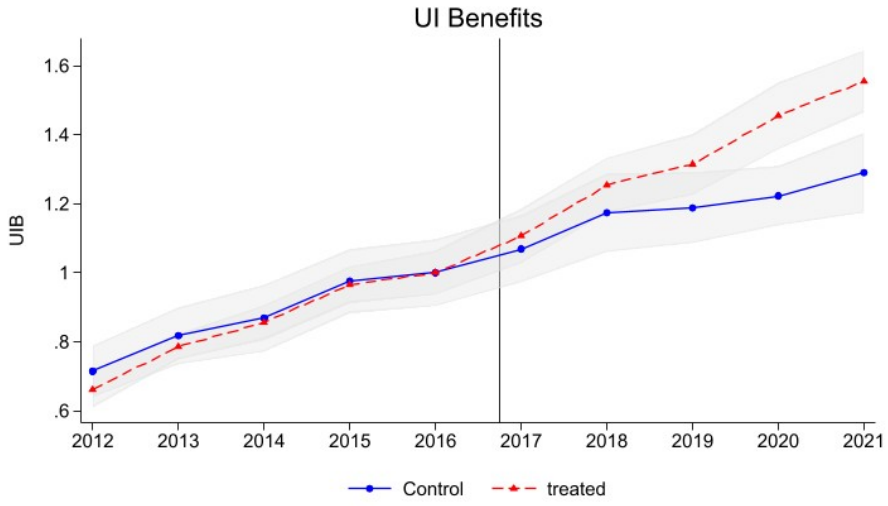


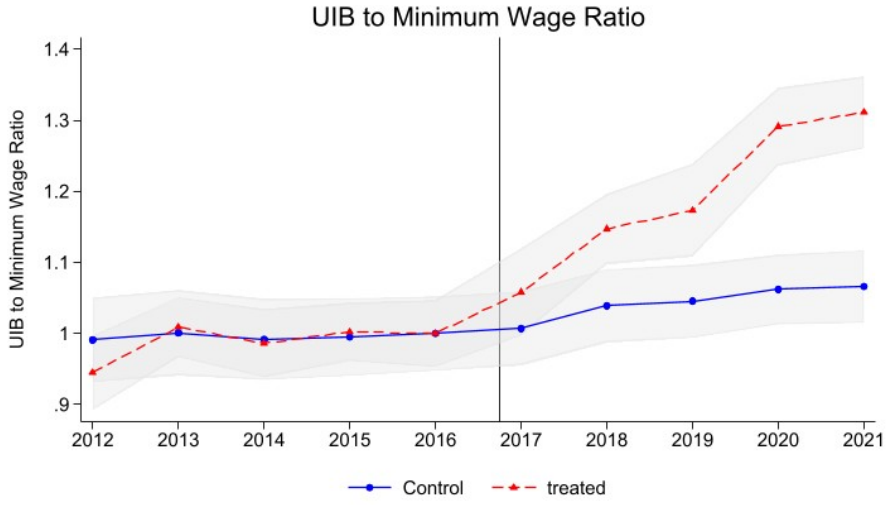
Figure 3. Dynamics of Unemployment Insurance Benefits and Minimum Wages Around the 2017 Reform

These figures plot the evolution of unemployment insurance variables for treated and control provinces from 2012 to 2021, with all series normalized to their 2016 values. Treated provinces are those whose 2016 UIB-to-minimum-wage ratio was below 70%. Panel A plots unemployment insurance benefits (UIB), Panel B plots the UIB-to-minimum-wage ratio, and Panel C plots the minimum wage. The vertical dashed line marks 2017, the year of the policy reform. Shaded areas denote 95% confidence intervals.

Panel A. Unemployment Insurance Benefits Relative to 2016



Panel B. UIB-to-minimum-wage Ratio Relative to 2016



Panel C. Minimum Wage Relative to 2016

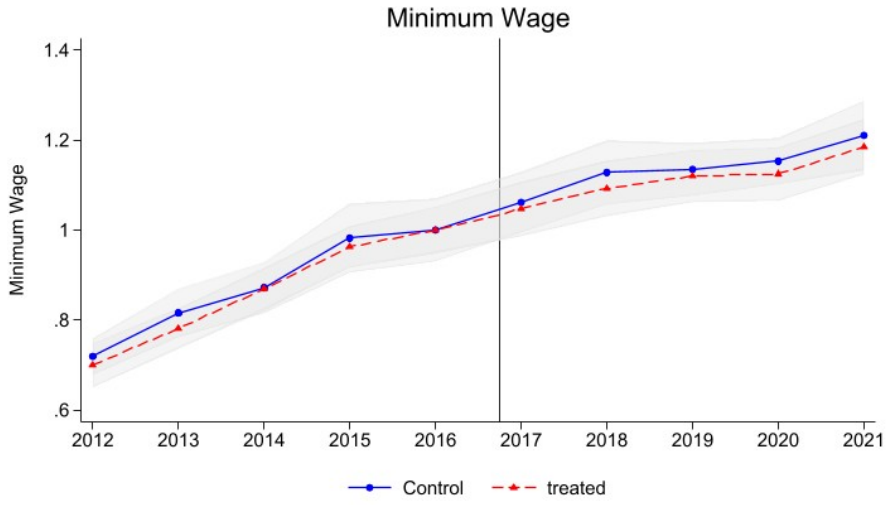
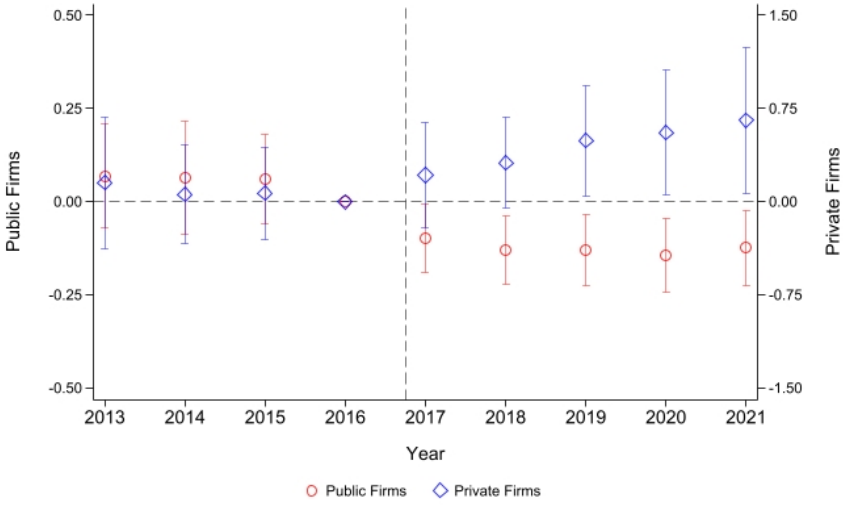


Figure 4. Event-Study Estimates of the UI Reform and Corporate Innovation

These figures present the event-study estimates of the effect of the 2017 unemployment insurance reform on corporate innovation. The dependent variables are the number of patent applications filed in year t (Panel A), and the number of patents granted (Panel B). Event time is defined relative to the 2017 reform, with 2016 omitted as the reference year. Coefficients are estimated using Poisson regressions. Vertical bars denote 95% confidence intervals, and the vertical dashed line marks the reform year.

Panel A. Patent Applications



Panel B. Patents Granted

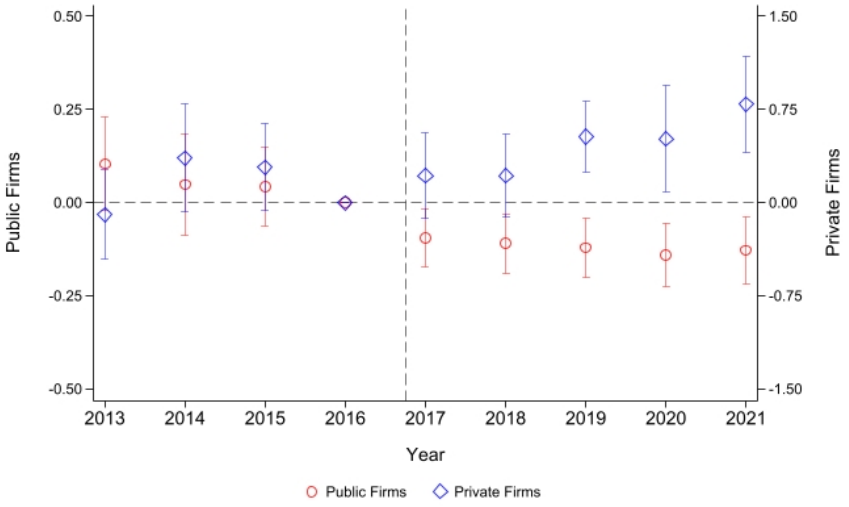


Table 1. Summary Statistics

This table reports summary statistics for main variables used in the analysis. Panel A reports province-year variables, including unemployment insurance benefits (UIB), the UIB-to-minimum-wage ratio, minimum wage, GDP, population, and average wage. Panel B reports firm-level variables separately for listed firms and non-listed firms. For listed firms, the table reports patent applications, patents granted, citation-based patent quality, total assets, capital expenditure to assets, cash holdings to assets, intangible assets to total assets, and return on assets. For non-listed firms, the table reports patent applications, patents granted, employee size, registered capital, and firm age. Variable definitions are provided in Appendix Table A1.

Panel A. Province Level

	N	Mean	SD	Min	Max
UIB	300	1213.53	330.78	486.85	2244.09
UIB-to-Minimum-Wage Ratio	300	0.76	0.11	0.50	1.00
Minimum Wage	300	1572.01	299.68	847.13	2559.29
GDP (billion)	300	2690.30	2242.97	71.02	12471.95
Population (million)	300	46.00	28.92	3.15	126.84
Average Wage	300	5900.06	2180.47	2938.15	16044.43

Panel B. Firm Level

	N	Mean	SD	Min	Max
Listed Firm					
Patent Applications	16882	92.12	209.64	0	1377
Patents Granted	16882	71.33	160.63	0	1041
Patent Citations	16882	0.66	1.30	0.00	6.20
Total Asset (billion)	16882	19.66	96.56	0.29	2671.74
Capital Expenditure to Asset	16882	0.05	0.04	0.00	0.22
Cash to Asset	16882	0.19	0.13	0.02	0.67
Intangible Assets Ratio	16882	0.05	0.05	0.00	0.30
ROA	16882	0.04	0.05	-0.16	0.22
Non-Listed Firm					
Patent Applications	68780	0.88	3.16	0	22
Patents Granted	71511	0.68	2.32	0	16
Employee Size	40448	16.88	29.05	1	197
Registered Capital (million)	66176	2.23	6.51	0.01	50.00
Age	68780	12.29	7.39	0.00	34.00

Table 2. Validation of Identification Strategy

This table reports robustness tests for identification strategy. The dependent variables are the log of unemployment insurance benefits (*Log UIB*), the *UIB-to-minimum-wage ratio*, the log of minimum wage *(Log Minimum wage*), the number of UIB recipients, the number of listed firms, GDP, and average income. The treatment indicator $Treated_p$ equals one if a province's UIB accounted for less than 70% of the minimum wage in 2016, while $Post_t$ equals one for years from 2017 onward. Provincial control variables include the log of GDP, population, and average wage. All specifications include year and province fixed effects. T-statistics based on standard errors clustered at the provincial level are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Panel A. Unemployment Insurance Benefits and UIB-to-Minimum-Wage Ratio

	Log UIB		UIB-to-minimum-wage Ratio	
	(1)	(2)	(3)	(4)
$\boldsymbol{Treated_p \times Post_t}$	0.088**	0.084**	0.048**	0.044*
	(2.57)	(2.55)	(2.08)	(1.94)
Provincial Controls	No	Yes	No	Yes
Fixed Effects				
Year	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes
N	270	270	270	270
within R^2	0.071	0.146	0.054	0.141

Panel B. Provincial Economic Conditions

	Log Minimum wage	Log Recipients	Log listed firm number	Log GDP	Log Average Income
	(1)	(2)	(3)	(4)	(5)
$\boldsymbol{Treated_p \times Post_t}$	0.009	0.053	-0.021	-0.017	-0.024
	(0.47)	(0.40)	(-0.37)	(-0.40)	(-1.49)
Provincial Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects					
Year	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes
N	270	265	270	270	270
within R^2	0.002	0.002	0.003	0.004	0.023

Table 3. Unemployment Insurance Benefits and Corporate Innovation: Panel Regression

This table reports the impact of unemployment insurance benefits (UIB) on corporate innovation from 2012 to 2021 in listed firms and non-listed firms. The dependent variables are the number of patent applications filed in year t (Patent Applications), and the number of these applications that are eventually granted (Patents Granted). The main explanatory variable is the log of the provincial monthly maximum unemployment insurance benefit (Maxui). In Columns (3) and (6), Maxui is replaced by quartile indicators. Control variables include firm size, capital expenditure to asset, cash holdings to asset, intangible asset ratio, return on assets (ROA) for listed firm. T-statistics based on standard errors clustered at the province-by-year level are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Panel A. Listed Firm

	Patent Applications			Patents Granted		
	(1)	(2)	(3)	(4)	(5)	(6)
Maxui	-0.358***	-0.232***		-0.351***	-0.223***	
	(-4.234)	(-2.914)		(-4.192)	(-2.854)	
Maxui_2			0.029			0.033
			(1.314)			(1.541)
Maxui_3			-0.087***			-0.082***
			(-3.124)			(-2.952)
Maxui_4			-0.176***			-0.178***
			(-4.406)			(-4.600)
Firm Controls	No	Yes	Yes	No	Yes	Yes
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year*Industry	Yes	Yes	Yes	Yes	Yes	Yes
N	16882	16882	16882	16835	16835	16835
pseudo R^2	0.862	0.868	0.869	0.854	0.860	0.861

Panel B. Non-Listed Firm

	Patent Applications			Patents Granted		
	(1)	(2)	(3)	(4)	(5)	(6)
Maxui	1.784***	1.307***		1.278***	0.895***	
	(5.603)	(4.041)		(4.736)	(3.132)	
Maxui_2			0.034			0.028
			(0.311)			(0.290)
Maxui_3			0.402***			0.359***
			(2.954)			(2.985)
Maxui_4			0.489***			0.472***
			(3.244)			(3.171)
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year*Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year*Employee Size	Yes	Yes	Yes	Yes	Yes	Yes
Year*Business Type	No	Yes	Yes	No	Yes	Yes
Year*Business Status	No	Yes	Yes	No	Yes	Yes
N	68780	68780	68780	71511	71511	71511
pseudo R^2	0.303	0.315	0.315	0.268	0.278	0.278

Table 4. Unemployment Insurance Reform and Corporate Innovation: Difference-in-Differences

This table reports difference-in-differences estimates of the effect of the 2017 unemployment insurance reform on firm innovation. The dependent variables are the number of patent applications filed in year *t* (*Patent Applications*), and the number of these applications that are eventually granted (*Patents Granted*). The treatment indicator $Treated_p$ equals one if a province's UIB accounted for less than 70% of the minimum wage in 2016, while $Post_t$ equals one for years from 2017 onward. Control variables include firm size, capital expenditure to asset, cash holdings to asset, intangible asset ratio, return on assets (ROA) for listed firm. T-statistics based on standard errors clustered at the province-by-year level are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Panel A. Listed Firm

	Patent Applications			Patents Granted		
	(1)	(2)	(3)	(4)	(5)	(6)
$\boldsymbol{Treated_p \times Post_t}$	-0.244***	-0.141***	-0.133***	-0.233***	-0.125***	-0.121***
	(-7.404)	(-4.451)	(-4.228)	(-7.307)	(-4.135)	(-4.289)
Firm Controls	No	Yes	Yes	No	Yes	Yes
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	No	Yes	Yes	No
Industry	Yes	Yes	No	Yes	Yes	No
Year*Industry	No	No	Yes	No	No	Yes
N	16882	16882	16882	16835	16835	16835
pseudo R^2	0.887	0.893	0.903	0.879	0.886	0.896

Panel B. Non-Listed Firm

	Patent Applications			Patents Granted		
	(1)	(2)	(3)	(4)	(5)	(6)
$\boldsymbol{Treated_p \times Post_t}$	0.369***	0.243**	0.187*	0.310***	0.222**	0.174*
	(3.450)	(2.370)	(1.844)	(2.982)	(2.159)	(1.711)
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year*Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year*Employee Size	Yes	Yes	Yes	Yes	Yes	Yes
Year*Business Type	No	Yes	Yes	No	Yes	Yes
Year*Business Status	No	No	Yes	No	No	Yes
N	68780	68780	68780	71511	71511	71511
pseudo R^2	0.301	0.308	0.314	0.268	0.273	0.278

Table 5. Risk Redistribution and Firm Risk Heterogeneity

This table reports the impact of higher unemployment insurance benefits (UIB) on corporate innovation, focusing on firms with different ex ante risk profiles. The dependent variables are the number of patent applications submitted by the company in year t (*Patent Applications*), as well as the number of patents applied for in year t and ultimately granted by the company (*Patents Granted*). The treatment indicator $Treated_p$ equals one if a province's UIB accounted for less than 70% of the minimum wage in 2016, while $Post_t$ equals one for years from 2017 onward. Control variables include total assets, capital expenditure to asset, cash to asset, intangible asset ratio, return on assets (ROA). Panels A and B report heterogeneous treatment effects across firms with different ex ante risk profiles. Firms are classified by total assets and return volatility. Panel C reports heterogeneous results for non-listed firms based on employee size. T-statistics based on standard errors clustered at the province-by-year level are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Panel A. Firm Size in Listed firm

	Patent Applications			Patents Granted		
	Low Risk	High Risk	Full Sample	Low Risk	High Risk	Full Sample
	(1)	(2)	(3)	(4)	(5)	(6)
$\boldsymbol{Treated_p \times Post_t}$	-0.142***	0.028	-0.141***	-0.135***	0.082	-0.133***
	(-4.321)	(0.388)	(-4.291)	(-4.558)	(1.056)	(-4.512)
$\boldsymbol{Treated_p \times Post_t \times High\ Risk}$			0.183**			0.246***
			(2.345)			(3.123)
$\boldsymbol{Post_t \times High\ Risk}$			-0.011			-0.049
			(-0.237)			(-1.041)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year*Industry	Yes	Yes	Yes	Yes	Yes	Yes
N	13085	3645	16882	13044	3639	16835
pseudo R^2	0.906	0.787	0.903	0.899	0.770	0.896

Panel B. Return Volatility in Listed firm

	Patent Applications			Patents Granted		
	Low Risk	High Risk	Full Sample	Low Risk	High Risk	Full Sample
	(1)	(2)	(3)	(4)	(5)	(6)
$\boldsymbol{Treated_p \times Post_t}$	-0.186***	-0.130***	-0.175***	-0.203***	-0.050	-0.194***
	(-5.280)	(-3.418)	(-4.748)	(-5.776)	(-1.482)	(-5.427)
$\boldsymbol{Treated_p \times Post_t \times High\ Risk}$			0.126***			0.226***
			(2.577)			(4.867)
$\boldsymbol{Post_t \times High\ Risk}$			-0.034			-0.045
			(-0.813)			(-1.178)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year*Industry	Yes	Yes	Yes	Yes	Yes	Yes
N	9481	7266	16882	9455	7240	16835
pseudo R^2	0.918	0.879	0.903	0.911	0.868	0.896

Panel C. Firm Size in Non-Listed Firm

	Patent Applications			Patents Granted		
	Low Risk	High Risk	Full Sample	Low Risk	High Risk	Full Sample
	(1)	(2)	(3)	(4)	(5)	(6)
$\boldsymbol{Treated_p \times Post_t}$	0.265**	0.616***	0.249**	0.289***	0.547***	0.273**
	(2.250)	(3.932)	(2.081)	(2.699)	(3.698)	(2.529)
$\boldsymbol{Treated_p \times Post_t \times High\ Risk}$			0.285*			0.271*
			(1.717)			(1.766)
$\boldsymbol{Post_t \times High\ Risk}$			-0.275***			-0.246***
			(-3.188)			(-3.424)
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year*Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year*Employee Size	Yes	Yes	Yes	Yes	Yes	Yes
Year*Income Tercile	Yes	Yes	Yes	Yes	Yes	Yes
Year*Business Type	Yes	Yes	Yes	Yes	Yes	Yes
Year*Business Status	Yes	Yes	Yes	Yes	Yes	Yes
N	18365	20898	39785	18739	21407	40589
pseudo R^2	0.289	0.337	0.297	0.272	0.293	0.268

Table 6. Unemployment Insurance Benefits and Inventor Mobility in Listed Firms

This table reports the estimates of the impact of higher unemployment insurance reform on inventor flow in listed firms. The dependent variables are the number of inventors who leave firm *i* in year *t* divided by the patent-based inventor stock of firm *i* in year t-1 (*Inventor Outflow*), and the number of inventors who join firm i in year t divided by the patent-based inventor stock of firm i in year t-1 (*Inventor Inflow*). *Inventor Mobility* is the sum of *Inventor Outflow* and *Inventor Inflow*, and *Net Inventor Flow* is defined as *Inventor Inflow* minus *Inventor Outflow*. The treatment indicator $Treat_p$ equals one if a province's UIB accounted for less than 70% of the minimum wage in 2016, while $Post_t$ equals one for years from 2017 onward. Panel A examines firm-year inventor-flow outcomes. Panel B examines heterogeneous effects on *Net Inventor Flow* by firm size in Columns (1)–(3) and by return volatility in Columns (4)–(6). High-risk firms are defined as firms with smaller total assets or higher return volatility. Controls include firm size, capital expenditure, cash holdings, intangible assets, and ROA. All specifications include firm fixed effects, year-by-industry fixed effects and year-by-SOE fixed effects. T-statistics based on standard errors clustered at the province-by-year level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Unemployment Insurance Reform and Firm-Level Inventor Flows

	Inventor Mobility	Inventor Outflow	Inventor Inflow	Net Inventor Flow
	(1)	(2)	(3)	(4)
$\boldsymbol{Treated_p \times Post_t}$	0.164***	0.100***	0.064**	-0.037**
	(2.933)	(3.345)	(2.257)	(-2.076)
Firm Controls	Yes	Yes	Yes	Yes
Fixed Effects				
Firm	Yes	Yes	Yes	Yes
Year*Industry	Yes	Yes	Yes	Yes
Year*SOE	Yes	Yes	Yes	Yes
N	10671	10671	10671	10671
R^2	0.604	0.608	0.548	0.360

Panel B. Heterogeneous Effects on Net Inventor Flow

	Net Inventor Flow					
Risk Measurement	Firm Size			Return Volatility		
	Low risk	High risk	Full Sample	Low risk	High risk	Full Sample
	(1)	(2)	(3)	(4)	(5)	(6)
$\boldsymbol{Treated_p \times Post_t}$	-0.050**	0.054	-0.053***	-0.062**	-0.018	-0.063***
	(-2.501)	(1.008)	(-2.746)	(-2.577)	(-0.626)	(-2.643)
$\boldsymbol{Treated_p \times Post_t \times High\ Risk}$			0.086*			0.056*
			(1.712)			(1.674)
$\boldsymbol{Post_t \times High\ Risk}$			-0.034			0.015
			(-1.217)			(0.666)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year*Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year*SOE	Yes	Yes	Yes	Yes	Yes	Yes
N	8000	2560	10671	5925	4582	10671
R^2	0.374	0.394	0.360	0.394	0.358	0.360

Table 7. Unemployment Insurance Benefits and Inventor Reallocation: Inventor-Level

This table reports difference-in-differences estimates of the effect of higher unemployment insurance benefits (UIB) on inventor mobility and the direction of inventor reallocation at the inventor level. The treatment indicator $Treated_p$ equals one if a province's UIB accounted for less than 70% of the minimum wage in 2016, while $Post_t$ equals one for years from 2017 onward. Panel A examines overall inventor mobility using two inventor-level measures: *Employer Switch*, an indicator equal to one if the inventor works for a different employer than in the previous year, and *Left Baseline Firm*, an indicator equal to one if the inventor is no longer employed by the firm for which he worked in 2016. Panel B focuses on inventors employed by listed firms in 2016 and examines whether they are more likely to move to non-listed firms after the reform. *Flow to Non-Listed Firms* equals one if an inventor moves from a listed firm to a non-listed firm between year t−1 and year t, and *Non-Listed Firm Status* equals one if the inventor works for a non-listed firm in year t. Panel C focuses on inventors not employed by listed firms in 2016 and examines whether they are more likely to move to listed firms after the reform. *Flow to Listed Firms* equals one if an inventor moves from a non-listed to a listed firm between year t−1 and year t, and *Listed-Firm Status* equals one if the inventor works for a listed firm in year t. T-statistics based on standard errors clustered at the inventor level are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Panel A. Overall Inventor Mobility

	Employer switch		Left Baseline Firm	
	(1)	(2)	(3)	(4)
$\boldsymbol{Treated_p \times Post_t}$	**0.021*****	**0.022*****	**0.025*****	**0.029*****
	(29.748)	**(28.979)**	**(20.219)**	**(21.825)**
Fixed Effects				
Inventor	Yes	Yes	Yes	Yes
Year	Yes	No	Yes	No
Year*Industry	No	Yes	No	Yes
Province	Yes	Yes	Yes	Yes
N	5382381	4336531	3316022	2729498
R^2	0.247	0.244	0.653	0.670

Panel B. Reallocation Toward Non-Listed Firms

	D(Move to Non-Listed Firm=1)		D(Work in Non-Listed Firm=1)	
	(1)	(2)	(3)	(4)
$\boldsymbol{Treated_p \times Post_t}$	**0.006*****	**0.005*****	**0.014*****	**0.008*****
	(17.068)	**(13.804)**	**(14.902)**	**(7.302)**
Fixed Effects				
Inventor	Yes	Yes	Yes	Yes
Year	Yes	No	Yes	No
Year*Industry	No	Yes	No	Yes
Province	Yes	Yes	Yes	Yes
N	4585685	3701240	4585685	3701240
R^2	0.154	0.154	0.408	0.414

Panel C. Reallocation Toward Listed Firms

	D(Move to Listed Firm=1)		D(Work in Listed Firm=1)	
	(1)	(2)	(3)	(4)
$\boldsymbol{Treated_p \times Post_t}$	**-0.003****	**-0.002**	**0.003**	**0.006**
	(-2.394)	**(-1.547)**	**(0.609)**	**(1.162)**
Fixed Effects				
Inventor	Yes	Yes	Yes	Yes
Year	Yes	No	Yes	No
Year*Industry	No	Yes	No	Yes
Province	Yes	Yes	Yes	Yes
N	796696	635282	796696	635282
R^2	0.176	0.165	0.517	0.443

Table 8. Unemployment Insurance Benefits and Entrepreneurship

This table reports the impact of higher unemployment insurance benefits (UIB) on entrepreneurship activity at the provincial level. The dependent variables are the log of the number of new enterprises created in province *p* (*Enterprise Created*), and truncation-adjusted new enterprises established in year t and still operating normally through 2024 (*High Quality Enterprise Created*). The treatment indicator $Treated_p$ equals one if a province's UIB accounted for less than 70% of the minimum wage in 2016, while $Post_t$ equals one for years from 2017 onward. Panel A examines the effect of UIB on overall new firm creation across provinces. Panel B focuses specifically on high-quality new firm creation at the provincial level. Provincial control variables include the log of GDP, population, and average wage. T-statistics based on standard errors clustered at the provincial level are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Panel A. The Effect of Unemployment Insurance Benefits on New Firm Creation

	Enterprise Created			
	(1)	(2)	(3)	(4)
$\boldsymbol{Treated_p \times Post_t}$	0.313*	0.342*	0.464***	0.508***
	(1.73)	(1.84)	(2.85)	(3.38)
Provincial controls	Yes	Yes	Yes	Yes
Fixed Effects				
Province	Yes	Yes	Yes	Yes
Year*Income Tercile	Yes	Yes	Yes	Yes
Year*Region Tercile	No	Yes	Yes	Yes
Year*GDP Tercile	No	No	Yes	Yes
Year*Population Tercile	No	No	No	Yes
N	225	225	225	225
within R^2	0.108	0.146	0.315	0.360

Panel B. The Effect of Unemployment Insurance Benefits on High-quality New Firm Creation

	High Quality Enterprise Created			
	(1)	(2)	(3)	(4)
$\boldsymbol{Treated_p \times Post_t}$	0.293*	0.370*	0.483**	0.517**
	(1.86)	(1.87)	(2.48)	(2.79)
Provincial controls	Yes	Yes	Yes	Yes
Fixed Effects				
Province	Yes	Yes	Yes	Yes
Year*Income Tercile	Yes	Yes	Yes	Yes
Year*Region Tercile	No	Yes	Yes	Yes
Year*GDP Tercile	No	No	Yes	Yes
Year*Population Tercile	No	No	No	Yes
N	225	225	225	225
within R^2	0.108	0.164	0.285	0.323

Table 9. Unemployment Insurance Benefits and Inventor Flows to Newly Established Firms

This table reports difference-in-differences estimates of the effect of higher unemployment insurance benefits (UIB) on inventors' transitions from listed firms to newly established non-listed firms. The dependent variable *D(Flow to Newly Established Non-Listed Firms=1)* is an indicator equal to one if an inventor moves from a listed firm in year t−1 to a non-listed firm in year t, where the destination firm has been established for no more than 2, 3, or 5 years. The treatment indicator $Treated_p$ equals one if a province's UIB accounted for less than 70% of the minimum wage in 2016, while $Post_t$ equals one for years from 2017 onward. The sample is restricted to inventors employed by listed firms in 2016. All specifications include inventor, year-by-industry and provincial fixed effects. T-statistics based on standard errors clustered at the inventor level are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	D(Flow to Newly Established Non-Listed Firms=1)		
New-firm window	⩽2 years	≤3 years	≤5 years
	(1)	(2)	(3)
$\boldsymbol{Treated_p \times Post_t}$	0.0003**	0.0007***	0.0011***
	(2.007)	(3.324)	(4.928)
Fixed Effects			
Inventor	Yes	Yes	Yes
Year*Industry	Yes	Yes	Yes
Province	Yes	Yes	Yes
N	3701240	3701240	3701240
R^2	0.1384	0.1399	0.1425

Table 10. Tests of the Labor Cost Channel

This table reports evidence on the labor cost channel. The dependent variables are the log of average staff salary, total salary scaled by sales, the number of patent applications filed in year *t* (*Patent Applications*), the number of these applications that are eventually granted (*Patents Granted*), R&D scaled by total assets, and R&D scaled by sales. The treatment indicator $Treated_p$ equals one if a province's UIB accounted for less than 70% of the minimum wage in 2016, while $Post_t$ equals one for years from 2017 onward. Panel A examines the effect of UIB on employee compensation. Panel B explores heterogeneity by labor intensity, measured by the number of employees scaled by total assets in 2016. Panel C examines the effect on R&D investment. T-statistics based on standard errors clustered at the province-by-year level are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Panel A. UIB and Employee Compensation

	Log Average Staff Salary		Total Salary/Sales	
	(1)	(2)	(3)	(4)
$\boldsymbol{Treated_p \times Post_t}$	0.006	0.007	0.001	0.002
	(0.690)	(0.779)	(1.179)	(1.642)
Firm Controls	Yes	Yes	Yes	Yes
Fixed Effects				
Firm	Yes	Yes	Yes	Yes
Year	Yes	No	Yes	No
Industry	Yes	No	Yes	No
Year*Industry	No	Yes	No	Yes
N	17421	17361	17421	17361
R^2	0.855	0.861	0.861	0.876

Panel B. Heterogeneity by Labor Intensity

	Patent Applications			Patents Granted		
	High Labor-intensity	Low Labor-intensity	Full Sample	High Labor-intensity	Low Labor-intensity	Full Sample
	(1)	(2)	(3)	(4)	(5)	(6)
$Treat_p \times Post_t$	-0.126***	-0.145***	-0.124***	-0.123***	-0.132***	-0.115***
	(-4.059)	(-3.298)	(-2.708)	(-3.787)	(-3.442)	(-2.748)
$Treat_p \times Post_t \times High\ Labor - intensity$			-0.002			-0.002
			(-0.039)			(-0.044)
$Post_t \times High\ Labor - intensity$			0.057			0.036
			(1.361)			(0.833)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year*Industry	Yes	Yes	Yes	Yes	Yes	Yes
N	7925	8770	16882	7891	8751	16835
pseudo R^2	0.880	0.919	0.903	0.872	0.913	0.896

Panel C. UIB and R&D Investment

	R&D /Sales		R&D /Total Asset	
	(1)	(2)	(3)	(4)
$Treated_p \times Post_t$	-0.019	-0.041	-0.000	-0.000
	(-0.327)	(-0.717)	(-0.713)	(-0.577)
Firm Controls	Yes	Yes	Yes	Yes
Fixed Effects				
Firm	Yes	Yes	Yes	Yes
Year	Yes	No	Yes	No
Industry	Yes	No	Yes	No
Year*Industry	No	Yes	No	Yes
N	17424	17364	17424	17364
R^2	0.877	0.882	0.884	0.890

Table 11. Alternative Model Specifications

This table reports additional robustness tests for the difference-in-differences estimates using alternative model specifications. The dependent variables are the number of patent applications filed in year t (*Patent Applications*), and the number of these applications that are eventually granted (*Patents Granted*). Control variables include firm size, capital expenditure to asset, cash holdings to asset, intangible asset ratio, return on assets (ROA). T-statistics based on standard errors clustered at the province-by-year level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Patent Applications		Patents Granted	
	(1)	(2)	(3)	(4)
Listed Firm				
$\boldsymbol{Distance_p \times Post_t}$	-0.644***	-0.455**	-0.584***	-0.427**
	(-3.476)	(-2.248)	(-3.597)	(-2.305)
Firm Controls	No	Yes	No	Yes
Fixed Effects				
Firm	Yes	Yes	Yes	Yes
Year*Industry	Yes	Yes	Yes	Yes
N	16882	16882	16835	16835
pseudo R^2	0.896	0.902	0.889	0.895
Non-Listed Firm				
$\boldsymbol{Distance_p \times Post_t}$	1.866***	1.709***	1.366***	1.294***
	(3.080)	(3.197)	(2.713)	(2.806)
Fixed Effects				
Firm	Yes	Yes	Yes	Yes
Year*Industry	Yes	Yes	Yes	Yes
Year*Employee Size	Yes	Yes	Yes	Yes
Year*Business Type	No	Yes	No	Yes
Year*Business Status	No	Yes	No	Yes
N	67994	67994	67389	67348
pseudo R^2	0.298	0.312	0.266	0.276

Table 12. The Effect of Unemployment Insurance Benefits on Aggregate Innovation

This table reports the impact of more generous unemployment insurance benefits on aggregate provincial innovation. Panel A uses provincial patent applications as the dependent variable, and Panel B uses provincial patents granted. The analysis is further decomposed by firm type into listed and non-listed firms. The treatment indicator $Treated_p$ equals one if a province's UIB accounted for less than 70% of the minimum wage in 2016, while $Post_t$ equals one for years from 2017 onward. Provincial control variables include the log of GDP, population, and average wage. All specifications include province-level controls, province fixed effects and year-by-income-tercile fixed effects, with higher-order fixed effects added progressively across columns. T-statistics based on standard errors clustered at the provincial level are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Panel A. The Effect of Unemployment Insurance Benefits on Provincial Patent Application

	Provincial Patent Applications		Patent Applications for Listed Firms		Patent Applications for Non-Listed Firms	
	(1)	(2)	(3)	(4)	(5)	(6)
$\boldsymbol{Treated_p \times Post_t}$	0.275***	0.278*	-0.061	-0.103	0.278***	0.299**
	(2.87)	(1.95)	(-0.93)	(-1.15)	(2.71)	(1.98)
Provincial Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Province	Yes	Yes	Yes	Yes	Yes	Yes
Year*Income Tercile	Yes	Yes	Yes	Yes	Yes	Yes
Year*Region Tercile	Yes	Yes	Yes	Yes	Yes	Yes
Year*GDP Tercile	No	Yes	No	Yes	No	Yes
Year*Population Tercile	No	Yes	No	Yes	No	Yes
N	270	270	270	270	270	270
pseudo R^2	0.989	0.992	0.995	0.996	0.986	0.990

Panel B. The Effect of Unemployment Insurance Benefits on Provincial Patent Granted

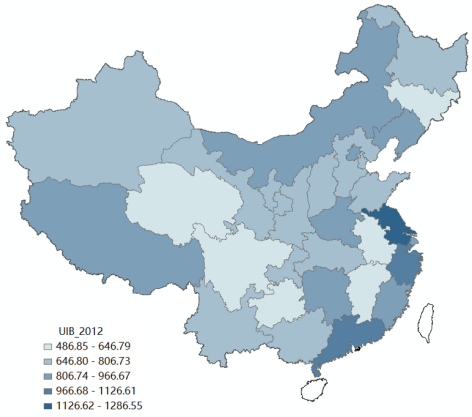
	Provincial Patents Granted		Patents Granted for Listed Firms		Patents Granted for Non-Listed Firms	
	(1)	(2)	(3)	(4)	(5)	(6)
$\boldsymbol{Treated_p \times Post_t}$	0.058	0.145**	-0.105	-0.066	0.130**	0.228***
	(1.05)	(2.41)	(-1.30)	(-0.68)	(2.40)	(3.89)
Provincial Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Province	Yes	Yes	Yes	Yes	Yes	Yes
Year*Income Tercile	Yes	Yes	Yes	Yes	Yes	Yes
Year*Region Tercile	Yes	Yes	Yes	Yes	Yes	Yes
Year*GDP Tercile	No	Yes	No	Yes	No	Yes
Year*Population Tercile	No	Yes	No	Yes	No	Yes
N	270	270	270	270	270	270
pseudo R^2	0.996	0.997	0.993	0.994	0.994	0.996

Appendix

Figure A1. Provincial Unemployment Insurance Benefits in Mainland China

These figures map monthly unemployment insurance benefits (UIB) across provinces in mainland China. Panel A reports the provincial distribution of UIB in 2012. Panel B reports the provincial distribution of UIB in 2021.

Panel A. Provincial Distribution of Unemployment Insurance in 2012



Panel B. Provincial Distribution of Unemployment Insurance in 2021

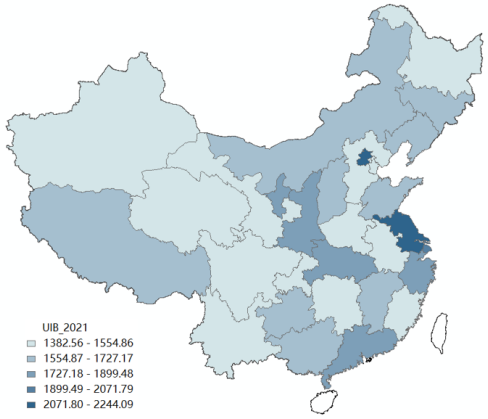


Figure A2. Geographic Distribution of Treatment and Control Provinces

This figure shows the geographic distribution of treatment and control provinces in mainland China. Treatment provinces are those whose UIB-to-minimum-wage ratio in 2016 was below 70%. Darker shading indicates treatment provinces, and lighter shading indicates control provinces.

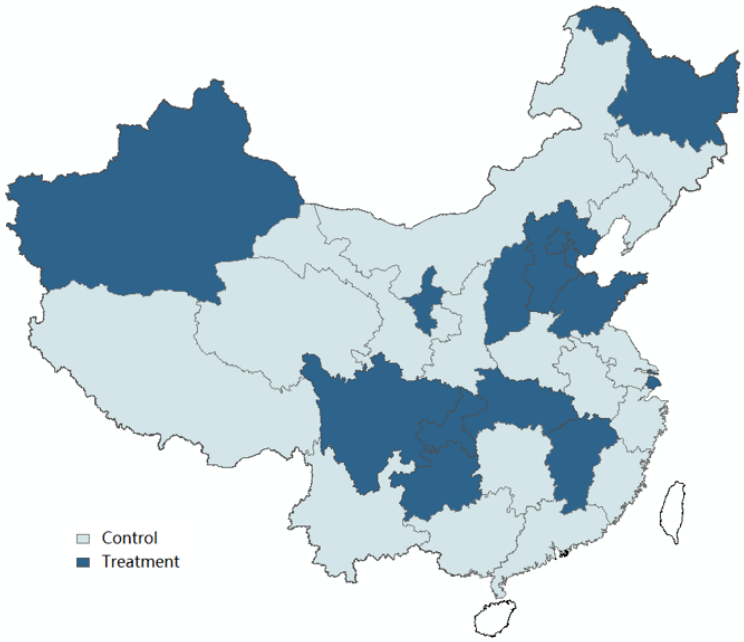


Table A1. Variable Definitions

Variables	Definition
Measures of Innovation	
Patent Applications	The total number of patent applications in the year.
Patents Granted (for Listed Firm)	The number of patent applications in the year and eventually granted.
Patents Granted (for Non-Listed Firm)	The number of patents granted in the year.
Patent Citation	The number of citations received by a firm's patents adjusted for citation truncation and normalized by the yearly mean.
Enterprise Created	The log of the number of enterprises registered in the province.
High Quality Enterprise Created	The log of the number of truncation-adjusted new enterprises established in year t and still operating normally through 2024.
Provincial Patent Applications	The annual number of patent applications filed by all companies in the province.
Patent Applications for Listed Firms	The annual number of patent applications filed by all listed companies in the province.
Patent Applications for Non-Listed Firms	The annual number of patent applications filed by all non-listed companies in the province.
Provincial Patents Granted	The annual number of patents granted by all companies in the province.
Patents Granted for Listed Firms	The annual number of patents granted by all listed companies in the province.
Patents Granted for Non-Listed Firms	The annual number of patents granted by all non-listed companies in the province.
Measures of Inventor Mobility	
Inventor Outflow	Number of inventors who leave firm i in year t divided by the patent-based inventor stock of firm i in year t-1.
Inventor Inflow	Number of inventors who join firm i in year t divided by the patent-based inventor stock of firm i in year t-1.
Inventor Mobility	Inventor Outflow plus Inventor Inflow.
Net Inventor Flow	Inventor Inflow minus Inventor Outflow.
Employer switch	An indicator equal to one if the inventor works for a different employer than in the previous year.
Left Baseline Firm	An indicator equal to one if the inventor is no longer employed by the firm for which he worked in 2016.
D(Move to Non-Listed Firm=1)	An indicator equal to one if an inventor moves from a listed firm to a non-listed firm between year t−1 and year t.
D(Work in Non-Listed Firm=1)	An indicator equal to one if the inventor works for a non-listed firm in year t.
D(Move to Listed Firm=1)	An indicator equal to one if an inventor moves from a non-listed to a listed firm between year t−1 and year t.
D(Work in Listed Firm=1)	An indicator equal to one if the inventor works for a listed firm in year t.
D(Flow to Newly Established Non-Listed Firms=1)	An indicator equal to one if an inventor moves from a listed firm in year t−1 to a non-listed firm in year t, where the destination firm has been established for no more than 2, 3, or

	5 years.
Measures of Unemployment Insurance Benefits and Control Variables	
UIB	The provincial monthly maximum unemployment insurance benefit.
Maxui	The log of UIB.
UIB-to-minimum-wage Ratio	Provincial maximum unemployment insurance benefits / Provincial minimum wage.
Distance	90% minus UIB-to-minimum-wage ratio.
$Treat_p$	An indicator equal to one if a province's UIB accounted for less than 70% (bottom tercile) of the minimum wage in 2016.
$Post_t$	An indicator equal to one for years from 2017 onward.
Log Total assets	The log of total assets.
Cash to Asset	Cash holdings divided by total assets.
Intangible Assets Ratio	Intangible assets divided by total assets.
ROA	Net profit divided by total assets.
Capital Expenditure to Asset	Capital expenditure divided by total assets.
Return Volatility	The volatility of annual stock returns.
Marginally Inventors	An indicator equal to one if an inventor's first observed patent with the baseline firm appears during 2014–2016.
Research Supporting Workforce	The pre-reform average ratio of supporting R&D employees to inventors in 2015 and 2016, standardized across sample firms.
Log Minimum Wage	The log of provincial minimum wage.
Log GDP	The log of provincial GDP.
Log Population	The log of provincial population.
Log Average Wage	The log of provincial average urban income.
Log listed firm number	The log of the number of listed firms in the province.
Log Recipients	The log of the number of people who receive unemployment insurance benefits.

Table A2. Province-Level Unemployment Insurance Benefits and UIB-to-Minimum-Wage Ratios in 2016 and 2019

This table reports province-level unemployment insurance benefit (UIB) levels and UIB-to-minimum-wage ratios in 2016 and 2019. The table documents the extent to which provinces adjusted UIB levels after the 2017 reform and highlights cross-province variation in policy implementation.

	2016		2019	
Province	ratio	UIB	ratio	UIB
Anhui	0.75	1140	0.90	1395
Beijing	0.70	1321	0.83	1815
Fujian	0.80	1200	0.80	1360
Gansu	0.74	1081	0.90	1458
Guangdong	0.80	1516	0.90	1890
Guangxi	0.80	1120	0.80	1344
Guizhou	0.70	1120	0.80	1432
Hainan	0.55	780	0.57	945
Hebei	0.56	930	0.57	1090
Henan	0.80	1280	0.80	1520
Heilongjiang	0.65	962	0.80	1344
Hubei	0.70	1085	0.80	1400
Hunan	0.80	1112	0.85	1445
Jilin	0.71	1056	0.85	1513
Jiangsu	1.00	1770	1.00	2020
Jiangxi	0.65	1000	0.80	1340
Liaoning	0.80	1224	0.90	1629
Inner Mongolia	0.80	1312	0.90	1584
Ningxia	0.65	962	0.75	1245
Qinghai	0.86	1090	0.90	1350
Shandong	0.58	1000	0.80	1528
Shanxi	0.70	1130	0.80	1360
Shaanxi	0.75	1110	0.90	1620
Shanghai	0.69	1520	0.73	1815
Sichuan	0.70	1050	0.80	1424
Tianjin	0.54	1050	0.65	1330
Xizang	0.80	1120	0.90	1485
Xinjiang	0.63	1051	0.71	1297
Yunnan	0.72	1138	0.78	1298
Zhejiang	0.80	1488	0.80	1608
Chongqing	0.70	1050	0.80	1440

Table A3. Summary Statistics for Inventor

This table reports summary statistics for the firm-level and inventor-level variables used in the mobility and reallocation analyses. Panel A reports firm-level inventor-flow variables for listed firms. The dependent variables are the number of inventors who leave firm *i* in year *t* divided by the patent-based inventor stock of firm *i* in year

t-1 (*Inventor Outflow*), and the number of inventors who join firm i in year t divided by the patent-based inventor stock of firm i in year t-1 (*Inventor Inflow*). *Inventor Mobility* is the sum of *Inventor Outflow* and *Inventor Inflow*, and *Net Inventor Flow* is defined as *Inventor Inflow* minus *Inventor Outflow*. Panel B reports inventor-level mobility and directional reallocation variables. *Employer Switch* is an indicator equal to one if an inventor works for a different employer than in the previous year. *Left Baseline Firm* is an indicator equal to one if an inventor is no longer employed by the firm with which the inventor was affiliated in 2016. *D(Move to Non-Listed Firm = 1)* and *D(Move to Listed Firm = 1)* indicate whether an inventor moves to a non-listed firm or a listed firm between year t − 1 and year t, respectively. *D(Work in Non-Listed Firm = 1)* and *D(Work in Listed Firm = 1)* indicate whether an inventor is affiliated with a non-listed firm or a listed firm in year t, respectively. *D(Flow to Newly Established Non-Listed Firms = 1)* is an indicator equal to one if an inventor moves from a listed firm in year t − 1 to a non-listed firm in year t, where the destination firm was established within 3 years. All variables are defined in Appendix A.

Panel A. Firm Level

	N	Mean	SD	Min	Max
Inventor Mobility	10931	1.00	1.40	0.00	6.88
Net Inventor Flow	10931	-0.13	0.43	-1.50	1.00
Inventor Outflow	10931	0.56	0.77	0.00	3.63
Inventor Inflow	10931	0.43	0.68	0.00	3.29

Panel B. Inventor Level

	N	Mean	SD	Min	Max
Employer switch	7728194	0.11	0.31	0	1
Left Baseline Firm	5537102	0.25	0.43	0	1
D(Move to Non-Listed Firm=1)	6541817	0.03	0.17	0	1
D(Work in Non-Listed Firm=1)	6541817	0.08	0.27	0	1
D(Move to Listed Firm=1)	1186377	0.09	0.28	0	1
D(Work in Listed Firm=1)	1186377	0.42	0.49	0	1
D(Flow to Newly Established Non-Listed Firms=1)	6541817	0.01	0.08	0	1

Table A4. T-Tests for Differences by Treatment Status

This table reports mean-difference tests between treatment and control groups using pre-reform variables observed for listed firms in 2016. Panel A reports the unmatched sample, and Panel B reports the matched sample. The treatment indicator equals one if a province's UIB accounted for less than 70% of the minimum wage in 2016. Variables include the log of provincial maximum UIB, the distance from the 90% benchmark, patent applications, patents granted, firm size, intangible assets, ROA, cash holdings, and capital expenditure.

Panel A. Pre-Reform Differences in 2016

	Control		Treatment			
	N	Mean	N	Mean	diff	2-sided P-value
Log UIB	893	7.24	645	7.05	-0.19	0.00
Distance (90% minus ratio)	893	0.10	645	0.24	0.13	0.00
Patent Applications	893	68.54	645	104.28	35.73	0.00
Patents Granted	893	53.35	645	78.53	25.18	0.00
Log Total Asset	893	22.14	645	22.52	0.38	0.00
Intangible Assets Ratio	893	0.05	645	0.05	0.00	0.36
ROA	893	0.04	645	0.04	0.00	0.18
Cash to Asset	893	0.17	645	0.18	0.00	0.91
Capital Expenditure to Asset	893	0.05	645	0.04	0.00	0.03

Panel B. Pre-Reform Differences after Matching

	Control		Treatment			
	N	Mean	N	Mean	diff	2-sided P-value
Log UIB	611	7.24	638	7.05	-0.19	0.00
Distance (90% minus ratio)	611	0.10	638	0.24	0.13	0.00
Patent Applications	611	75.97	638	90.63	14.66	0.18
Patents Granted	611	59.39	638	69.53	10.14	0.24
Log Total Asset	611	22.27	638	22.49	0.22	0.00
Intangible Assets Ratio	611	0.05	638	0.05	0.00	0.60
ROA	611	0.04	638	0.04	0.00	0.31
Cash to Asset	611	0.17	638	0.18	0.00	0.83
Capital Expenditure to Asset	611	0.04	638	0.04	0.00	0.33

Table A5. Unemployment Insurance Benefits and Patent Citations

This table reports the relation between higher unemployment insurance benefits and patent citations. The dependent variable is truncation-adjusted patent citations. Columns (1) and (2) use the log of the provincial monthly maximum unemployment insurance benefit (*Maxui*) as the main explanatory variable. Columns (3) and (4) use the difference-in-differences specification based on the 2017 reform. The treatment and post indicators are defined as in Table 4. Firm controls and fixed effects are reported in the table. T-statistics based on standard errors clustered at the province-by-year level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Patent Citations			
	(1)	(2)	(3)	(4)
Maxui	-0.303***	-0.229**		
	(-3.282)	(-2.570)		
$\boldsymbol{Treated_p \times Post_t}$			-0.164***	-0.128***
			(-5.668)	(-4.462)
Firm Controls	No	Yes	No	Yes
Fixed Effects				
Firm	Yes	Yes	Yes	Yes
Year*Industry	Yes	Yes	Yes	Yes
N	16278	16278	16278	16278
pseudo R^2	0.507	0.509	0.507	0.509

Table A6. Additional Evidence on Inventor Mobility under Modest UIB Changes

This table provides additional evidence on why modest changes in unemployment insurance benefits may affect inventor mobility. Panel A reports individual inventor-level estimates by marginally inventor weakly attachment to the baseline firm. Marginally inventors are defined as inventors whose first observed patent with the baseline firm appears during 2014–2016. The dependent variables are Employer Switch, an indicator equal to one if the inventor works for a different employer than in the previous year, and Left Baseline Firm, an indicator equal to one if the inventor is no longer affiliated with the firm for which he worked in 2016. Panel B reports firm-level estimates by the intensity of the research supporting workforce. Research supporting workforce captures a firm's pre-reform inventor support intensity. It is constructed as the average number of supporting R&D employees per inventor in 2015 and 2016, standardized across sample firms. The dependent variable in Panel B is Net Inventor Flow, defined as Inventor Inflow minus Inventor Outflow. The treatment indicator $Treated_p$ equals one if a province's UIB accounted for less than 70% of the minimum wage in 2016, while $Post_t$ equals one for years from 2017 onward. T-statistics are reported in parentheses. Standard errors are clustered at the inventor level in Panel A and at the province-by-year level in Panel B. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Marginally Inventors

	Employer switch			Left Baseline Firm		
	Marginal	Non-Marginal	Full Sample	Marginal	Non-Marginal	Full Sample
	(1)	(2)	(3)	(4)	(5)	(6)
$\boldsymbol{Treated_p \times Post_t}$	0.023***	0.019***	0.019***	0.048***	0.018***	0.014***
	(18.285)	(20.812)	(19.972)	(19.067)	(11.692)	(9.664)
$\boldsymbol{Treated_p \times Post_t \times Marginal}$			0.007***			0.038***
			(4.091)			(13.572)
$\boldsymbol{Post_t \times Marginal}$			0.016***			0.072***
			(25.670)			(64.199)
Fixed Effects						
Inventor	Yes	Yes	Yes	Yes	Yes	Yes
Year*Industry	Yes	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes
N	1588935	2747588	4336531	925803	1803690	2729498
R^2	0.242	0.248	0.244	0.700	0.651	0.672

Panel B. Research Supporting Workforce

	Net Inventor Flow	Inventor Mobility	Inventor Outflow	Inventor Inflow	Patent Applications	Patents Granted
	(1)	(2)	(3)	(4)	(5)	(6)
$\boldsymbol{Treated_p \times Post_t}$	-0.052**	0.209***	0.119***	0.075**	-0.099***	-0.083***
	(-2.118)	(2.640)	(2.999)	(2.005)	(-3.040)	(-2.930)
$\boldsymbol{Treated_p \times Post_t}$	-0.059*	0.157	0.095*	0.053	-0.052*	-0.060**
$\boldsymbol{\times High\ Supporting}$	(-1.771)	(1.455)	(1.815)	(1.031)	(-1.822)	(-2.135)
$\boldsymbol{Post_t}$	0.035*	0.129*	0.042	0.078**	0.137***	0.136***
$\boldsymbol{\times High\ Supporting}$	(1.927)	(1.815)	(1.274)	(2.188)	(6.552)	(6.320)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year*Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year*SOE	Yes	Yes	Yes	Yes	No	No
N	10293	10293	10734	10293	12732	12730
R^2/ pseudo R^2	0.340	0.573	0.575	0.524	0.903	0.895

Table A7. Alternative Measurement for Unemployment Insurance Benefits

This table reports robustness tests using the UIB-to-average-wage ratio as an alternative measure of unemployment insurance generosity. The main explanatory variable is the UIB-to-average-wage ratio. The dependent variables are the number of patent applications filed in year *t* (*Patent Applications*), and the number of these applications that are eventually granted (*Patents Granted*). Firm controls and fixed effects are reported in the table. T-statistics based on standard errors clustered at the province-by-year level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Patent Applications		Patents Granted	
	(1)	(2)	(3)	(4)
Listed Firm				
UIB/average-wage	-1.272**	-0.746	-1.166**	-0.589
	(-2.465)	(-1.632)	(-2.329)	(-1.370)
Firm Controls	No	Yes	No	Yes
Fixed Effects				
Firm	Yes	Yes	Yes	Yes
Year*Industry	Yes	Yes	Yes	Yes
N	16882	16882	16835	16835
pseudo R^2	0.896	0.903	0.889	0.896
Non-Listed Firm				
UIB/average-wage	7.103***	4.957***	4.914***	3.143***
	(5.694)	(3.893)	(4.219)	(2.624)
Fixed Effects				
Firm	Yes	Yes	Yes	Yes
Year*Industry	Yes	Yes	Yes	Yes
Year*Employee Size	Yes	Yes	Yes	Yes
Year*Business Type	No	Yes	No	Yes
Year*Business Status	No	Yes	No	Yes
N	68780	68780	71511	71511
pseudo R^2	0.303	0.315	0.268	0.278

Table A8. Robustness Test to Sample Restrictions

This table reports robustness tests based on alternative sample restrictions. The dependent variables are the number of patent applications filed in year *t* (*Patent Applications*), and the number of these applications that are eventually granted (*Patents Granted*). The treatment indicator $Treated_p$ equals one if a province's UIB accounted for less than 70% of the minimum wage in 2016, while $Post_t$ equals one for years from 2017 onward. Panels A and B report matched difference-in-differences estimates for listed firms and non-listed firms, respectively. Panel C excludes industries in which employees are more likely to be geographically dispersed. Panel D restricts the sample to firms located in boundary cities. Control variables include firm size, capital expenditure to asset, cash holdings to asset, intangible asset ratio, return on assets (ROA). T-statistics based on standard errors clustered at the province-by-year level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Matching Difference-in-Differences Estimates for Listed Firms

	Patent Applications	Patents Granted
	(1)	(2)
$\boldsymbol{Treated_p \times Post_t}$	-0.101***	-0.082***
	(-3.399)	(-2.781)
Firm Controls	Yes	Yes
Fixed Effects		
Firm	Yes	Yes
Year*Industry	Yes	Yes
N	11582	11540
pseudo R^2	0.906	0.898

Panel B. Matching Difference-in-Differences Estimates for Non-Listed Firms

	Patent Applications	Patents Granted
	(1)	(2)
$\boldsymbol{Treated_p \times Post_t}$	0.494***	0.429***
	(4.186)	(3.885)
Fixed Effects		
Firm	Yes	Yes
Year*Industry	Yes	Yes
Year*Employee Size	Yes	Yes
Year*Business Type	Yes	Yes
Year*Business Status	Yes	Yes
N	12424	12727
pseudo R^2	0.271	0.261

Panel C. Excluding Geographically Dispersed Industries

	Patent Applications			Patents Granted		
	(1)	(2)	(3)	(4)	(5)	(6)
	Listed Firm					
$\boldsymbol{Treated_p \times Post_t}$	-0.245***	-0.138***	-0.126***	-0.235***	-0.122***	-0.114***
	(-7.440)	(-4.243)	(-3.895)	(-7.323)	(-3.897)	(-3.932)
Firm Controls	No	Yes	Yes	No	Yes	Yes
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	No	Yes	Yes	No
Industry	Yes	Yes	No	Yes	Yes	No
Year*Industry	No	No	Yes	No	No	Yes
N	15472	15472	15472	15451	15451	15451
pseudo R^2	0.889	0.896	0.905	0.881	0.888	0.897
	Non-Listed Firm					
$\boldsymbol{Treated_p \times Post_t}$	0.370***	0.240**	0.184*	0.319***	0.229**	0.180*
	(3.450)	(2.340)	(1.806)	(3.048)	(2.210)	(1.757)
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year*Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year*Employee Size	Yes	Yes	Yes	Yes	Yes	Yes
Year*Business Type	No	Yes	Yes	No	Yes	Yes
Year*Business Status	No	No	Yes	No	No	Yes
N	67843	67843	67843	70516	70516	70516
pseudo R^2	0.299	0.306	0.312	0.267	0.272	0.278

Panel D. Boundary-City Analysis

	Patent Applications			Patents Granted		
	(1)	(2)	(3)	(4)	(5)	(6)
			Listed Firm			
$Treated_p \times Post_t$	-0.350***	-0.232***	-0.172***	-0.367***	-0.243***	-0.175***
	(-4.730)	(-3.671)	(-2.881)	(-4.863)	(-3.795)	(-2.875)
Firm Controls	No	Yes	Yes	No	Yes	Yes
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	No	Yes	Yes	No
Industry	Yes	Yes	No	Yes	Yes	No
Year*Industry	No	No	Yes	No	No	Yes
N	7558	7558	7558	7514	7514	7514
pseudo R^2	0.905	0.913	0.925	0.901	0.909	0.920
			Non-Listed Firm			
$Treated_p \times Post_t$	0.354***	0.338***	0.283**	0.414***	0.407***	0.344***
	(3.099)	(2.988)	(2.538)	(3.628)	(3.714)	(3.208)
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year*Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year*Employee Size	Yes	Yes	Yes	Yes	Yes	Yes
Year*Business Type	No	Yes	Yes	No	Yes	Yes
Year*Business Status	No	No	Yes	No	No	Yes
N	23082	23082	23082	24298	24298	24298
pseudo R^2	0.251	0.261	0.267	0.234	0.243	0.251

Table A9. Additional Fixed Effects

This table reports additional robustness tests for the difference-in-differences estimates. The dependent variables are the number of patent applications filed in year t (*Patent Applications*), and the number of these applications that are eventually granted (*Patents Granted*). Panels A and B augment the DID specifications with additional interaction fixed effects for listed firms and non-listed firms, respectively. T-statistics based on standard errors clustered at the province-by-year level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Listed Firms

	Patent Applications			Patents Granted		
	(1)	(2)	(3)	(4)	(5)	(6)
$Treated_p \times Post_t$	-0.132***	-0.169***	-0.169***	-0.121***	-0.154***	-0.153***
	(-4.222)	(-5.532)	(-5.584)	(-4.290)	(-5.505)	(-5.481)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year*Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year*SOE	No	Yes	Yes	No	Yes	Yes
Year*Size Tercile	No	No	Yes	No	No	Yes
N	16882	16514	16514	16835	16467	16467
pseudo R^2	0.903	0.904	0.905	0.896	0.897	0.898

Panel B. Non-Listed Firms

	Patent Applications			Patents Granted		
	(1)	(2)	(3)	(4)	(5)	(6)
$Treated_p \times Post_t$	0.187*	0.183*	0.179*	0.174*	0.186*	0.187*
	(1.844)	(1.822)	(1.719)	(1.711)	(1.795)	(1.732)
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year*Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year*Employee Size	Yes	Yes	Yes	Yes	Yes	Yes
Year*Business Type	Yes	Yes	Yes	Yes	Yes	Yes
Year*Business Status	Yes	Yes	Yes	Yes	Yes	Yes
Year*Registered Capital	No	Yes	Yes	No	Yes	Yes
Year*Age	No	No	Yes	No	No	Yes
N	68780	66145	66145	71511	68686	68686
pseudo R^2	0.314	0.316	0.320	0.278	0.279	0.284