# Permanence and Performance: The Incentive Effect of Tenure on Worker Productivity

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**Abstract**

Temporary or fixed-term contracts (FTCs) are prevalent in global labor markets and often serve as stepping stones to permanent, open-ended contracts (OECs). This study investigates how transitioning from an FTC to an OEC affects worker productivity. Leveraging high-frequency production data from a Chinese garment factory—where piece-rate workers experience no changes in tasks or wages upon attaining tenure—we isolate the incentive effect of tenure. Our findings reveal a significant 5% drop in productivity immediately following the transition to permanent status, with the decline intensifying over time. This pattern suggests that workers exert additional effort under FTCs to secure permanent employment. The productivity decline is more pronounced among workers with weaker outside options, such as those with lower educational attainment or those from regions with less favorable labor markets. In contrast, we observe no such decline in a comparable plant in Vietnam where workers are guaranteed an OEC after two FTCs. These results highlight the role of tenure uncertainty in driving effort under FTC arrangements.

*Keywords*: temporary contracts, permanent contracts, incentives, labor productivity

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# 1. Introduction

Temporary employment, or fixed-term contracts (FTCs)—defined by pre-determined termination dates—is a widespread phenomenon, comprising a substantial share of the workforce in both developing (Aleksynska and Muller, 2015) and developed (Boeri and Garibaldi, 2024) countries. FTCs offer employers a flexible tool to maintain a labor buffer and respond to demand fluctuations. At the same time, many countries—including France, Spain, Germany, Italy, China, and Vietnam—have introduced labor protection policies that restrict the duration or number of FTC renewals, mandating a transition to permanent or open-ended contracts (OECs) once statutory limits are reached. As a result, FTCs are often seen as a stepping stone to permanent employment (de Graaf-Zijl, Van den Berg and Heyma, 2011; Givord and Wilner, 2015; García-Pérez, Marinescu and Vall Castello, 2019).

In this paper, we examine the incentive effect of transitioning from FTCs to permanent employment by studying the productivity dynamics of workers before and after securing tenure. Theoretically, the impact of this transition is ambiguous. On the one hand, when permanent employment depends on demonstrated performance, workers may exert additional effort to secure tenure. On the other hand, job insecurity, common among FTC workers, can induce psychological stress, weaken organizational commitment, and erode a sense of belonging, potentially reducing motivation and performance (Witte, 1999; Sverke, Hellgren and Näswall, 2002; Kim and Jo, 2024).

Estimating the tenure effect could be challenging because transition into a tenured position is often accompanied by other changes, such as salary increases, expanded responsibilities, and changes in work expectations. For example, tenured professors typically receive higher pay and take on additional service duties, which may divert attention from their core responsibilities.

Even when formal duties remain unchanged, managers may assign more complex tasks or allocate more resources to tenured workers, making it difficult to compare productivity before and after tenure.

To address these challenges, we analyze high-frequency production data from a Chinese garment factory. This setting is ideal for our study for several reasons. First, under Chinese Labor Law, firms must offer an OEC after two FTCs if they wish to retain a worker. However, tenure is not guaranteed: only about 85% of workers nearing the end of their second FTC secure permanent employment. Importantly, workers who eventually secure tenure show significantly higher productivity before their tenure is confirmed, highlighting the role of performance in obtaining permanent status.

Second, in this setting, tenure status does not coincide with other factors that typically complicate productivity comparisons. Workers are paid according to a piece rate, which remains constant before and after securing tenure, and their core responsibility—sewing garments—does not change post-tenure. Our dataset also includes detailed task-assignment data, allowing us to confirm whether tenured workers are assigned more complex tasks after obtaining tenure. Furthermore, no additional production resources are provided to workers upon obtaining tenure.

Third, the firm operates a comparable plant in Vietnam, where the same high-level managers oversee operations. Vietnam's labor laws also mandate a transition to OECs after two FTCs, but unlike the Chinese plant, all workers at the Vietnamese facility obtain permanent contracts, as the plant is newer and expanding. This provides a unique opportunity for comparison, enabling us to study productivity responses in a setting where tenure is uncertain (China) versus one where tenure is guaranteed (Vietnam).

Finally, the high-frequency and longitudinal nature of our data allows us to observe the

productivity of the same workers within a narrow window around the tenure decision, minimizing the risk that factors such as age or accumulated experience confound our estimates. Additionally, since workers in this factory can only secure tenure four years after starting—by which time productivity growth has typically stabilized—we can more confidently attribute changes in output to the tenure decision rather than to learning curves (see Levitt, List and Syverson (2013)).

Our empirical findings from the plant in China indicate a significant 5% drop in productivity immediately after the attainment of tenure, with the decline deepening over time. These results are robust to the inclusion of controls for pre-existing trends and the application of the method proposed by Callaway and Sant'Anna (2021). Crucially, we do not observe a similar productivity pattern between the first and second fixed-term contracts, suggesting that the tenure decision itself represents a key inflection point in worker behavior, rather than the contract renewal process.

We further show that the productivity decline is not driven by factors such as assignment to more complex tasks, broader task ranges, or being paired with more junior colleagues.[1] Interestingly, no similar productivity drop is observed among Vietnamese workers after they receive tenure. Since these workers are guaranteed an OEC, the absence of a productivity decline provides suggestive evidence that the uncertainty surrounding the attainment of an OEC in the Chinese setting is a key driver of the additional effort observed under FTCs.

These findings are consistent with the hypothesis that workers exert extra effort before securing tenure to improve their chances of obtaining long-term job security. We argue that the incentive to exert such effort under FTCs is closely tied to workers' outside options (see Lazear, Shaw and Stanton (2016)). Specifically, workers with fewer alternative employment prospects—such as those with lower educational attainment, migrant workers without local

[1] See Adhvaryu, Kala and Nyshadham (2022) on the role of task assignment on worker productivity.

networks, or those from cities with less favorable labor market conditions for low-skill workers—are more incentivized to work harder to secure permanent employment. Consistent with this, the post-tenure productivity decline is more pronounced among these groups. As a placebo test, we observe no such heterogeneous impacts in high-skill workers from cities with better labor market conditions.

This research contributes to the literature on the effects of fixed-term employment arrangements (see Boeri and Garibaldi (2024) for a comprehensive review). Much of the existing literature focuses on the role of FTCs as a labor buffer to respond to demand fluctuations (Bentolila and Saint-Paul, 1992; Boeri and Garibaldi, 2007). In addition, studies have examined their role in the screening and sorting of workers (Faccini, 2014; Boockmann and Hagen, 2008). However, the incentive effects related to the transition from FTC to OEC—specifically, the extra effort that workers exert while on FTC—have received comparatively little attention and are supported by limited empirical evidence. Theoretical work by Basu, Chau and Soundararajan (2021) suggests that FTCs may serve as a disciplinary tool for workers on open-ended contracts.

By highlighting the incentive effect of tenure uncertainty on worker effort under FTCs, we also contribute to the literature that examines non-wage determinants of worker productivity, leveraging personnel records (see, e.g., Bandiera, Barankay and Rasul (2010), Lazear, Shaw and Stanton (2015), Amodio and Martinez-Carrasco (2018), Frederiksen, Kahn and Lange (2020), Hoffman and Tadelis (2021), Ku (2022), Adhvaryu, Kala and Nyshadham (2022), Adhvaryu, Nyshadham and Tamayo (2023), Adhvaryu et al. (2024)).

A related strand of research explores how the use of temporary workers impacts aggregate outcomes such as total employment, earnings inequality, labor market segmentation, and firm-level productivity (e.g., Blanchard and Landier (2002), Kleinknecht et al. (2006), Bentolila et al. (2012), Hirsch and Mueller (2012), Nielen and Schiersch (2016), and Daruich, Di Ad-

dario and Saggio (2023)). The mechanisms underlying these effects on firm-level productivity typically include screening, flexibility, firm-specific human capital accumulation, and capital per worker.[2] This paper highlights an additional channel: that workers exert extra effort to enhance their chances of securing tenure, which can directly boost firm-level productivity.

Existing research shows that contract type shapes worker behavior, typically by comparing those on fixed-term and permanent contracts. Temporary workers, for instance, tend to provide more unpaid work time (Engellandt and Riphahn, 2005) and invest more in on-the-job learning (Ferreira, de Grip and Van der Velden, 2018). More recently, Garcia-Louzao, Hospido and Ruggieri (2023) finds that experience gained under fixed-term contracts yields lower returns than experience under permanent ones. We contribute to this literature by examining how productivity changes when workers transition from fixed-term to permanent contracts. Using data that tracks the same individuals before and after gaining tenure—under identical tasks and conditions—we isolate the incentive effects of tenure. While prior studies show that tenure can increase absenteeism among white-collar workers (Ichino and Riphahn, 2005; Jacob, 2013), productivity losses may also arise when workers are present but less engaged. We focus on this less visible margin of effort, controlling for attendance in a piece-rate setting where output is directly tied to pay. Unlike white-collar workers, factory workers' daily output is directly and immediately linked to their pay.

[2] A similar set of mechanisms is explored in the literature on employment protection, which affects worker composition, employment flows, firm entry rates, and capital intensity, thereby influencing firm productivity (Autor, Kerr and Kugler, 2007; Jacob, 2013; Besley and Burgess, 2004; Bjuggren, 2018; Cingano et al., 2016).

## 2. Institutional Background and Data

### *2.1. Institutional Background*

**Labor Contract Law in China and Vietnam.** China's Labor Contract Law, in effect since 2008 and slightly refined post-2010, aims to protect employees' rights and stabilize employment relationships. One core provision is that if an employee has signed two consecutive fixed-term contracts(FTC) with the same employer, the employer has to provide an open-ended contract (OEC) if it wants to retain the worker.

However, a third FTC is allowed to be signed if the employee voluntarily chooses it and no statutory termination grounds apply. In practice, some firms exploit this exception by persuading workers to "voluntarily" accept a third FTC, thereby avoiding the obligation to grant permanent status.

In the context of China's Labor Contract Law, an employer must provide severance pay when it lawfully terminates an OEC. The standard calculation is one plus number of full year of service times month's wage. Where a termination lacks legitimate grounds or fails to follow proper procedures, employees could seek remedies such as reinstatement or additional compensation through labor arbitration or civil litigation.

Labor contract laws in Vietnam share similarities with those in China, requiring firms to offer OEC after two FTCs. In the focal firm examined in our study, interviews with managers and evidence from our data indicate that every worker is offered an open-ended contract. This practice is driven by the relative difficulty of hiring skilled sewing workers in Vietnam compared to China.

**The China Factory.** This factory is a major production site for a leading global fashion brand. The contractor conducts regular on-site inspections to ensure workers' protections and overall

working conditions, resulting in relatively high standards of labor law enforcement, even if implementation of relevant legislation in China is not well enforced. From the workers' perspective, the security provided by permanent employment in this factory is highly valued, and wages exceed the industry average for other low-skill occupations.

The factory specializes in clothing processing and export, functioning as the largest garment exporter in East China, with products shipped to more than 20 countries and regions. It operates under an arrangement in which it processes orders for upstream brands and earns processing fees.

**The Vietnam Factory.** In 2016, the company established a subsidiary in Vietnam mainly due to the rising labor costs in China, replicating the same production lines and operational structures. All senior managers are from China, while sewing workers are recruited locally.

Labor market conditions in China and Vietnam differ significantly. In China, the focal factory's jobs are regarded as among the most desirable employment opportunities in local areas. In contrast, Vietnamese workers have access to a broader range of comparable opportunities offered by other foreign firms. Consequently, companies in Vietnam face persistent challenges in recruitment. Therefore, the company provides OECs to all the workers who complete the second FTCs, as these employees are generally more qualified than most new hires.

Differences in local labor market conditions also influence the pre-tenure contract period. In China, a worker typically needs to be employed for more than four years to reach a third contract. In contrast, in Vietnam, a worker generally attains this status after completing two one-year contracts.

**Workshop Organization and Production Cycle.** Garment production involves three primary stages: cutting, sewing, and finishing. Each factory comprises one cutting workshop, three

sewing workshops, and two finishing workshops. Each workshop has a designated supervisor tasked with overseeing its entire production process. Within each sewing workshop, there are roughly 10 production lines (also referred to as "teams" or "assembly lines"). The typical composition includes approximately eight standard assembly lines, as well as specialized lines for down filling and template sewing. Each assembly line normally employs about 40 workers and is headed by a team leader (or line manager).

When headquarters issues a production order, it specifies the required quantity of garments to be completed by a certain date. The factory allocates the order to the sewing workshop, which in turn assigns the workload to one or more assembly lines. Generally, a single assembly line produces only one garment style at a time, moving on to a new style once the production quota is met.[3]

**Sewing Operations and Tasks.** Sewing each garment entails numerous operations, and each operation can be broken down into distinct tasks. A garment typically involves around 100 tasks, although complexity varies by style. On each assembly line, there are roughly 30 work stations, and the line manager distributes tasks among workers on a daily basis. As shown in Figure **??** Workers perform a given operation repeatedly (e.g., attaching sleeves) on a bundle of garments, usually 10 or 20 pieces in the blanket near the worker, before passing them on to the next station. [4] On average, each worker undertakes about check2.3 distinct tasks per day.

**Compensation.** Workers' total earnings consist of four primary components: piece-rate wages, team bonuses, housing subsidies, and full attendance bonuses.[5] On average, the piece rate wage

[3]During peak seasons, some lines may need to handle multiple styles simultaneously, although such cases are rare.

[4]This system is known as a multi-piece flow production method. An alternative is single-piece flow, where each garment is immediately transferred upon completion of one operation. Multi-piece flow reduces the time spent transferring items between stations but can cause imbalances and material accumulation if tasks are not well-coordinated.

[5]Team bonuses are decided by line managers. They exercise discretion in compensating for productivity losses arising from collaboration or unforeseen events. For instance, if a team member goes on sick leave, the manager may reassign tasks to a worker who is unfamiliar with them, thereby reducing her efficiency. To offset these

accounts for around 70% of a typical worker's total earnings. It is a prevailing view among workers that higher effort directly translates into higher earnings, forming the foundation of our empirical setting.

### *2.2. Data from the Garment Factory*

**Task-level Production Data and Personnel Data.** We use daily production records from the factory's sewing workshops. Each record contains the date, worker ID, workshop and assembly line identifier, product and task codes, piece rate and output for each task. The data is at the "worker-day-task" level. Because workers usually perform multiple tasks per day and the precise time allocation across tasks is unavailable, it is not feasible to measure productivity at the "worker-day-task" level. Instead, we aggregate to the "worker-day" level to examine individual productivity in a way that accommodates variations in task allocation. Each task is automatically logged at the workstation: the worker enters her ID and the corresponding task code, and the system tracks the number of parts she completes under that task. We match the production record with the personnel data collected by the human resource department, we can obtain background information of those front-line production workers, including gender, birth year, birth place, education and date entering the factory.

**Tenure Decision and Announcement.** The human resource department will evaluate the worker near the end of the second fixed-term contract. During our sample period, the factor offer a one year+ three years two fixed term contract before renewing for the open-ended contract. They mainly evaluate workers' performance based on production data, along side with evaluations on workers' attitude towards work and violations of safety code. The human resource department will talk to the work one month or sometimes two months before the termination of the fixed

productivity gaps, managers may grant additional compensation.

term contract whether they will offer a open-ended contract. (maybe no need to say the offer can not be withdraw)

In Figure A.1, we use matched personnel data and daily wage data to compare the productivity of tenured and untenured workers six months before the renewal of the third contract. The results indicate that workers who ultimately receive tenure demonstrate higher productivity during this period. Untenured workers consist 15% of our sample, and approximately one-third of them "voluntarily" signed another fixed-term contract.

## 3. Conceptual Framework

To illustrate how job security influences workers' effort choices, we propose a simple two-period model in which the employee exerts effort in the first period to increase the probability of securing an open-ended contract, taking into account an outside option should the contract not be renewed. Let the worker's indirect utility depend on income $I$ and the dis-utility of effort $e$:

$$U(I, e) = I - \alpha_1 e - \alpha_2 e^2, \tag{1}$$

where $\alpha_1 > 0$ and $\alpha_2 > 0$ capture the marginal and quadratic cost of effort, respectively. The income is given by $I = \beta e$ with $\beta > 0$, reflecting a piece-rate compensation system in which higher effort directly raises the worker's wage.

We examine each period separately. In the second period, there is no uncertainty regarding contract renewal, so the worker solves:

$$\max_{e_2} \Big( \beta e_2 - \alpha_1 e_2 - \alpha_2 e_2^2 \Big). \tag{2}$$

From the first-order condition, $\beta - \alpha_1 - 2\alpha_2 e_2 = 0$, we obtain

$$e_2^* = \frac{\beta - \alpha_1}{2\alpha_2}, \quad u_2^* = \frac{(\beta - \alpha_1)^2}{4\alpha_2}. \tag{3}$$

Thus, $e_2^*$ is the optimal effort once the open-ended contract is already secured, and $u_2^*$ is the corresponding utility.

In the first period, the worker faces the possibility of non-renewal and hence accounts for the outside option $\mu$, which applies if the contract is not extended. Let the probability of renewal be $p(e_1) = \lambda e_1$ with $\lambda > 0$, assumed to lie in $(0, 1)$ for $e_1 \in (0, 1)$. The worker's two-period expected utility is:

$$\max_{e_1} \Big( \beta e_1 - \alpha_1 e_1 - \alpha_2 e_1^2 \Big) \; + \; p(e_1) \times u_2^* \; + \; \big[ 1 - p(e_1) \big] \times \mu. \tag{4}$$

Taking the derivative with respect to $e_1$ and setting it to zero yields:

$$\beta - \alpha_1 - 2\alpha_2 e_1 + \lambda \frac{(\beta - \alpha_1)^2}{4\alpha_2} - \mu\lambda = 0, \tag{5}$$

which implies

$$\begin{aligned} e_1^* &= \frac{\beta - \alpha_1}{2\alpha_2} + \frac{\lambda}{2\alpha_2} \Big( u_2^* - \mu \Big) \\ &= e_2^* + \frac{\lambda}{2\alpha_2} \Big( u_2^* - \mu \Big). \end{aligned} \tag{6}$$

The difference $e_1^* - e_2^*$ measures the "effort gap" between the period of contract uncertainty and the period after securing the open-ended arrangement. The simple model yields two testable predictions: 1) workers work harder before getting tenure; 2) the induced effort gap becomes larger when the outside option is weaker. Note that these predictions hold only if tenure depends positively on effort. If tenure probability is invariant to effort (i.e., $\lambda = 0$), then

we should not expect an effort gap between the pre- and post-tenure periods.

Because $u_2^* > \mu$ by assumption (i.e., the current job is preferable to the outside option), it follows that $e_1^* - e_2^* > 0$. As $\mu$ decreases (indicating worse outside options), the incentive to secure the current position becomes stronger, increasing the size of the gap $e_1^* - e_2^*$.

## 4. Effects of Tenure on Worker Productivity

### *4.1. Output Decline after Tenure*

In Figure 1, we present the main findings on how productivity evolves around the tenure announcement among workers who successfully receive tenure. In this company, workers are informed of their tenure decision 1 to 2 months before the end of their second contract (48 months after joining the company). For consistency, we define "relative month zero" in Figure 1—and throughout the analysis—as 2 months before the end of the second contract. Typically, at relative month -1, workers remain unaware of their tenure outcome; by relative month 0, they are likely informed; by relative month 1, the decision has been fully communicated; and by relative month 2, workers sign open-ended contracts. The vertical dashed line at month 0 marks the tenure announcement, dividing the pre- and post-tenure periods.

Panel (a) in Figure 1 displays the raw productivity trends surrounding the tenure announcement. The solid line represents the logarithm of daily wage residuals (after adjusting for calendar date fixed effects), while the dotted line indicates the linear productivity prediction derived from the pre-tenure experience–productivity relationship (estimated over relative months –9 to –1).

In the pre-tenure period, the actual productivity (solid line) closely tracks the predicted trend (dotted line), suggesting that productivity is well predicted by accumulated experience

before the tenure announcement. On average, productivity increases by approximately 3.6 percent over the nine-month period preceding tenure. However, immediately after tenure is granted (relative month 0), a noticeable shift occurs: the observed productivity consistently falls below the trajectory predicted by the pre-tenure trend. The persistent gap between the actual and projected productivity suggests a potential decline in worker effort or efficiency following tenure, consistent with the hypothesis that workers exert extra efforts before tenure and job security may reduce incentives for sustained high performance.

To further quantify the post-tenure decline in daily output, we implement the following event study regression:

$$Y_{it} = \sum_{m=-9, m\neq -1}^{m=12} \beta^m T_{m(it)} + \delta_i + \gamma_t + \epsilon_{it}, \tag{7}$$

where $Y_{it}$ is the log daily output for worker i on a calendar date t. $T_{m(it)}$ is an indicator that takes the value 1 if date t falls in relative month m for worker i, where the relative month is defined with respect to the tenure announcement month (as detailed earlier in this section). The coefficients $\beta^m$s are our primary parameters of interest, capturing the dynamic effects of tenure on worker productivity. To account for time-invariant individual characteristics and innate ability, we include individual fixed effects, $\delta_i$. Additionally, we incorporate calendar date fixed effects, $\gamma_t$, to control for factory-level output fluctuations, such as demand shocks, weekday-weekend variations, and other temporal factors. Standard errors are clustered at the individual level.

Similar to the approach in panel (a), the analysis sample is restricted to workers who successfully attain tenure. This allows us to compare their daily outputs before and after tenure, using the month immediately preceding the tenure announcement as the reference period. A key concern with this identification strategy is the mechanical collinearity between the relative

month (with respect to tenure announcement) and the workers' experience in the factory.

We cannot directly include a linear time trend in Equation (7) to address this concern because doing so would conflate the tenure effects with the baseline productivity trends. However, this concern is mitigated by two factors: 1) Workers in our sample have already been employed in the factory for approximately four years, by which point their productivity is likely to have stabilized, with only marginal increases expected thereafter; and 2) There is no theoretical basis to expect a sudden shift in the experience-productivity relationship precisely at the 46-month mark in the absence of a tenure announcement.

To further address this concern, we employ the method proposed by Bhuller et al. (2013), Goodman-Bacon (2021*a*), and Goodman-Bacon (2021*b*) to account for the impact of experience by controlling for pre-tenure trends. Specifically, we estimate linear pre-trends using data from relative months -9 to -1, extrapolate these trends into the post-tenure period, and subtract the projected trend from all data points. This approach isolates the tenure effects from the underlying productivity trends unrelated to tenure. The dotted line in panel (a) of Figure 1 visualizes the estimated pre-trend, which reflects the relationship between experience (in months) and output after controlling for calendar date fixed effects to account for factory-level daily fluctuations.

The results of the event study estimations are summarized in panel (b) of Figure 1. Consistent with the raw data presented in panel (a), we observe an immediate drop in output following the tenure announcement. The magnitude of this effect grows over time, starting at 2% - 3% right after tenure announcement and increasing to 7% - 10% within 6–12 months post-tenure. When comparing the post-tenure period as a whole (months 1 to 12) with the pre-tenure period (months -9 to -1), we find that output declines by approximately 4.99% after tenure announcement, statistically significant at the 1% level.[6]

[6]Month 0 is excluded from the post-tenure period because the tenure outcome is announced 1–2 months before

We also predict that the tenure effect observed in China will not be present in the Vietnam factory, where 100% of workers completing their second FTCs are promoted to OECs. This 100% tenure rate is likely be attributed to two factors: 1) the factory is still in an expansion phase and aims to retain more workers, and 2) the labor market conditions in Vietnam are more favorable for workers, driven by increasing labor demand due to the growing manufacturing sector. We analyze the Vietnam plant dataset using the same methodology. As illustrated in Figure 4, we find no significant changes in worker productivity after obtaining tenure. This suggests that when employees perceive tenure as a guaranteed outcome rather than a reward to strive for, OECs no longer serve as a strong incentive for workers to increase their effort

### *4.2. Robustness Checks*

Some additional concerns warrant discussion. First, we subtract the projected pre-trend to account for the experience–productivity relationship, raising the concern that our findings may be driven entirely by this upward pre-trend. To address this, we re-estimate Equation (7) without adjusting for the pre-trend. Panel (a) of Figure 2 presents the resulting event study estimates, which are largely consistent with the main results shown in Figure 1.

A second concern is that the sample in the event study is unbalanced across different relative months, and thus the dynamic effects observed could reflect composition changes rather than true productivity responses. To address this, we construct a balanced panel covering 13 months from relative month -6 to 6 and re-estimate our main specification on this restricted sample, which accounts for 31.54% of the observations in our primary analysis.[7] Panel (b) of Figure 2

the end of the second contract. As a result, the tenure outcome may not have been fully communicated to all workers by relative month 0, defined as 2 months before the end of the second contract.

[7]The 50.76% of sample loss arises because our production data end in July 2021; thus, for workers who joined after March 2017, we lack productivity data 6 months post-tenure. Similarly, 8.35% sample loss arises because the production data begin in January 2019; thus, for workers who joined before August 2015, we lack productivity data 6 months pre-tenure. 3.98% of the sample is lost because the workers did not work continuously for 13 months. Moreover, 5.36% of tenured workers in our analysis sample leave the company within 6 months of

presents the results, revealing a more immediate and pronounced post-tenure output decline compared to the main findings. This suggests that the primary results are mainly driven by true productivity responses, and if anything, compositional changes modestly dampen the estimated effects shown in Figure 1.

Another concern arises from the staggered rollout of tenure announcements across workers who begin their employment at different times. To address potential bias in staggered rollout estimations with heterogeneous treatment effects, we employ two alternative methods other than OLS. Panel (c) of Figure 2 presents the results. The hollow triangles represent the previous OLS estimates as a reference, the hollow diamonds reflect the estimates obtained using the method proposed by De Chaisemartin and d'Haultfoeuille (2020), and the solid red points show the estimates derived from the method proposed by Callaway and Sant'Anna (2021). As evidenced by the figure, the three estimators yield qualitatively similar trends, and the average treatment effects that pool the post-tenure period are also comparable to the OLS results, with estimated effects of -0.068 (p-value = 0.003) using De Chaisemartin and d'Haultfoeuille (2020), -0.043 (p-value = 0.103) using Callaway and Sant'Anna (2021), and -0.045 (p-value = 0.003) for the OLS results.

One potential concern is that the observed results could be influenced by the contract renewal itself, irrespective of the transition to tenure. As theoretically predicted by Iossa and Rey (2014), workers might exert increased effort immediately prior to contract renewal. As a placebo test, we redefine the relative months with respect to the renewal of the second fixed-term contract (which does not confer tenure). Panel (d) of Figure 2 shows no comparable decline after renewing this contract, suggesting that it is specifically the transition to an open-ended contract that underlies the observed effects, rather than the mere act of contract renewal.

tenure. We avoid defining the balanced panel over relative months -9 to 12 due to severe attrition, which would retain only 10% of the original sample.

### *4.3. Potential Channels behind the Output Decline*

Our findings on post-tenure productivity declines are based on days during which employees were actively working, potentially understating the total effect if absenteeism increases once job security is secured. For instance, workers may be more likely to refuse to work on weekends after obtaining tenure. To address this possibility, we analyze daily attendance patterns by adding observations for days on which employees were absent. As reported in Column (2) of Table 2, there is no statistically significant decline in attendance following tenure attainment, indicating that the observed productivity drop arises from lower output on days worked rather than from higher non-attendance.

Another possibility is that the observed output decline could be driven by task assignments from the line manager rather than a reduction in workers' own effort. For instance, managers might assign tenured workers to more challenging tasks or a broader range of task types, thereby lowering daily output. To explore this, we employ detailed task-level output data in Columns (3) and (4). Column (3) examines the average difficulty of daily tasks, and Column (4) analyzes the concentration of tasks using a monthly Herfindahl-Hirschman Index (HHI). In both cases, we find no statistically significant impact of tenure on these task assignment measures, suggesting that the productivity decline is not driven by managerial task reallocation.

It is also plausible that managers might reassign tenured workers to teams with relatively inexperienced colleagues, potentially reducing tenured workers' output due to partial output interdependence. To examine this, we use the average coworker experience (days) within each production line as the dependent variable in Column (5) of Table 2. The statistically insignificant positive coefficient does not support the hypothesis that tenured employees are systematically grouped with newer workers, indicating that this factor does not account for the observed post-tenure productivity decline.

### *4.4. Heterogeneous Treatment Effect*

We examine the heterogeneous treatment effect to explore the mechanism underlying the job security effect. As discussed in our conceptual framework, the induced effort response is expected to be stronger for workers with limited outside employment options. We measure the ease of finding a comparable job using two proxies. The first is the worker's educational attainment, less-educated workers face greater difficulty securing new employment. The second is the worker's migration status, migrant workers whose hometown is different from their workplace place a higher value on job security. In contrast, local workers experience lower reallocation costs and benefit from higher social capital, which can facilitate job transitions . Additionally, we anticipate that the labor market conditions in migrant workers' hometowns can explain the differential impact on the tenure effect.

Panel (a) of Figure 3 compares the effort gap between low-skilled and high-skilled workers, where high skill is defined as having at least a high school diploma. Consistent with our hypothesis, the effort gap is primarily driven by low-skilled workers, who face greater challenges in securing alternative employment if dismissed. Panel (b) examines workers based on their place of origin: those who grew up in the city where the factory is located, those from the same province, and those from other provinces. Similarly, we find that the effort gap is most pronounced among migrant workers. We further investigate this heterogeneity by focusing on migrant workers and testing our predictions regarding the role of outside options.

Migrant workers with stronger employment prospects in their hometowns experience less job insecurity. To quantify local labor demand, we use online job postings normalized by the city's resident population in 2020.[8] Our labor demand and supply measures come from Zhaopin.com (hereafter, Zhaopin), a leading online job portal in China. Importantly, the data

[8]The 2020 population census provides the baseline population figures.

from Zhaopin are representative of China's online labor market. Zhaopin is now one of China's two largest online job boards, with a market share of over 30% in China's online job posting industry. Zhaopin has over 230 million active individual users and approximately 6 million corporate users, covering all large and medium-sized cities in China.[9] We restrict our sample to the top 100 cities ranked by the total number of job postings in 2018 to minimize the bias caused by the low penetration rates of online job portals in smaller cities. [10]

Workers are grouped into quintiles based on the job posting density in their hometowns, and we estimate the job security effect for each group. The results in Panel (c) of Figure 3 indicate that the job security effect is strongest in regions with the lowest job availability (bottom 20th percentile) and diminishes as labor market opportunities improve. In Figure A.2 we also show the robustness check with the labor demand over labor supply as our group variable and the results do not change much. A similar pattern emerges when classifying workers by the average wage in low-skill industries in their hometowns, as shown in Panel (e). These wage estimates are derived from the China National Tax Return Data, which covers all cities and industries with higher weight on large firms.[11] Using firm-level wage data, we compute city-level average wages in low-skill industries and find results consistent with those based on job postings.

We also conduct placebo tests with job postings and average wage in high skill industries in Panel (d) and (f) with demand and average wage in high skill industries and the patterns in Panel (c) and (e) disappear.

[9] Admittedly, the online job market is not representative of China's overall labor market. Zhaopin has little presence in specific sectors, such as the agriculture industry and government sector hiring. However, this bias does not undermine our argument as long as the bias is similar across cities.

[10] The top 100 cities in our sample account for approximately 95% of the total job postings.

[11] The survey is a stratified sample that gives higher weight for large firms and conducted by the department of finance and tax authority. They double check firms answer with the internal tax return data.

## 5. Conclusions

This study provides novel insights into the productivity dynamics associated with the transition from fixed-term contracts (FTCs) to permanent contracts (OECs) by examining worker behavior in a piece-rate setting. Our analysis, based on high-frequency production data from a Chinese garment factory, reveals a significant decline in productivity following the attainment of permanent status, a pattern that is not observed in a comparable Vietnamese facility where tenure is guaranteed. This suggests that the uncertainty surrounding the transition to permanent employment plays a critical role in motivating workers to exert extra effort under FTCs.

The productivity drop observed after tenure is consistent with the hypothesis that workers exert extra efforts while on FTCs to secure long-term job security, especially when they have fewer outside options. This effect is more pronounced among workers with lower educational levels, migrant workers, and those from regions with weaker labor market conditions. By focusing on the same individuals before and after their tenure decision, we are able to offer a clear causal interpretation of the incentive effects tied to FTCs, distinct from other confounding factors such as job complexity or changes in work resources.

Our study contributes to the broader literature on labor contracts by highlighting a previously underexplored channel through which FTCs can affect firm-level productivity: the incentive to secure permanent employment. While existing research has emphasized the role of FTCs in screening, sorting, and providing flexibility, our findings suggest that tenure uncertainty can also function as an incentive mechanism, influencing worker behavior in a way that directly impacts productivity.

Overall, our results have important implications for understanding the role of labor contract policies in shaping worker incentives, particularly in industries where productivity is tightly

linked to individual performance. By focusing on tenure uncertainty, we offer a deeper understanding of how fixed-term employment arrangements influence worker effort and firm outcomes.

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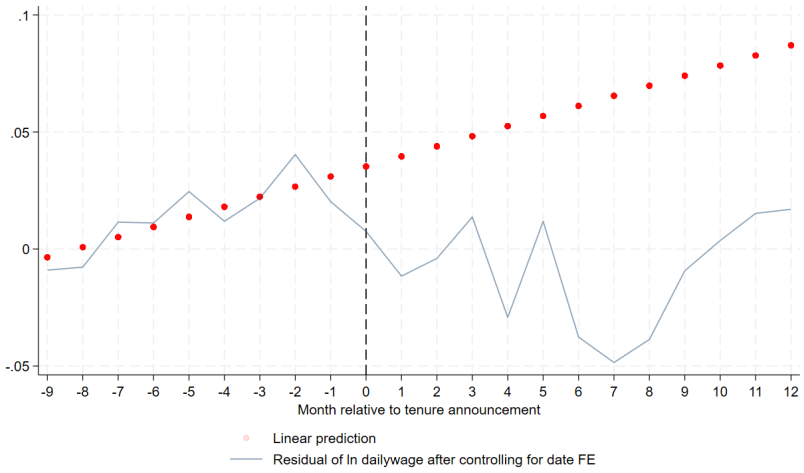
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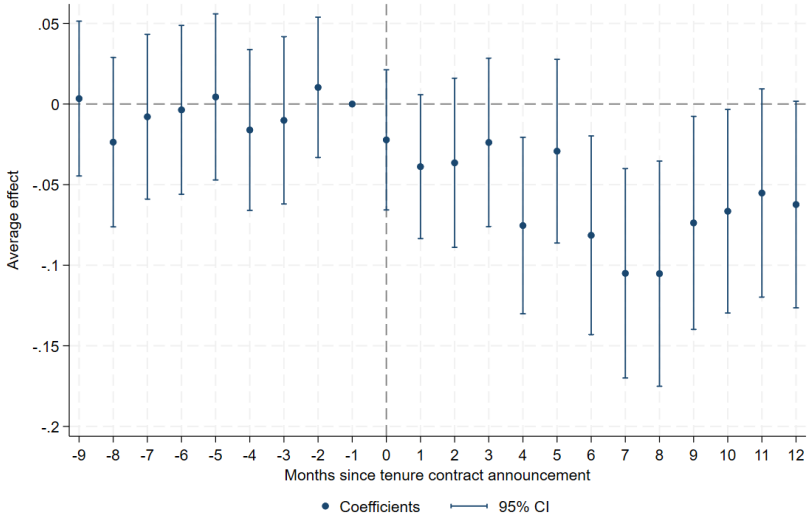
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**Figure 1:** Worker Productivity before and after Tenure

(a) Residualized ln Daily Wage and Predicted Trend of ln Daily Wage by Experience



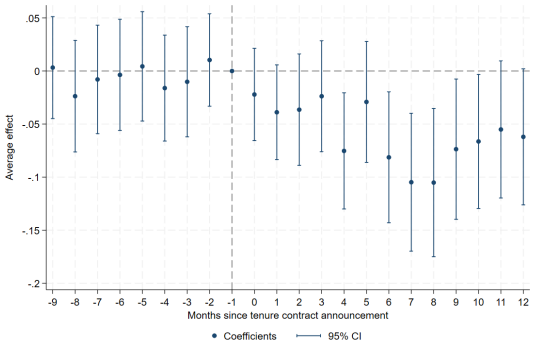

(b) Event Study



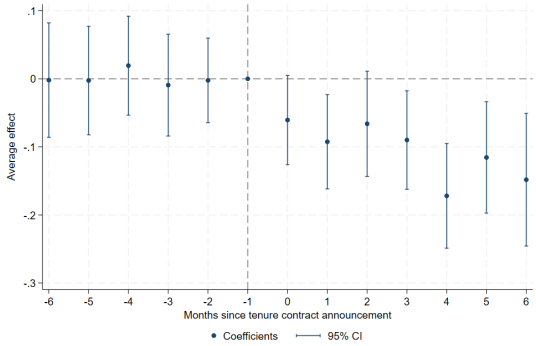

Notes: The sample restricts to workers who were tenured only. Suppose that we call the residual of ln daily wage after controlling for calendar date FE *res*. In panel (a), the blue line represents *res*. Red dots are the linear prediction of *res* by experience based on the observations from relative month -9 to -1, where the experience of workers is defined by relative month + 9. In panel (b), Month 2 is 30 days after the tenure starts. Month 1 is 30 days before the tenure starts, when the tenure is announced according to HR. Month 0 is ambiguous, since workers can be informed earlier. Panel (b) controls for individual fixed effects, calendar date fixed effects and pre-tenure experience trend. Standard errors are clustered at the individual level.

**Figure 2:** Robustness and Placebo

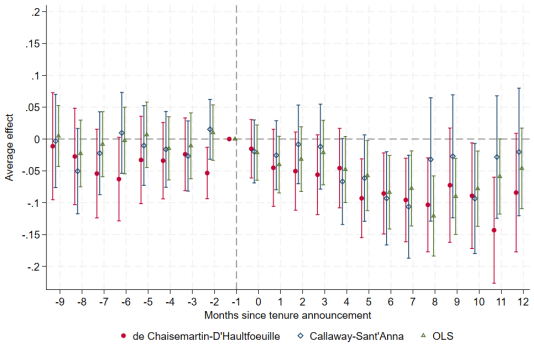
(a) No Experience Control



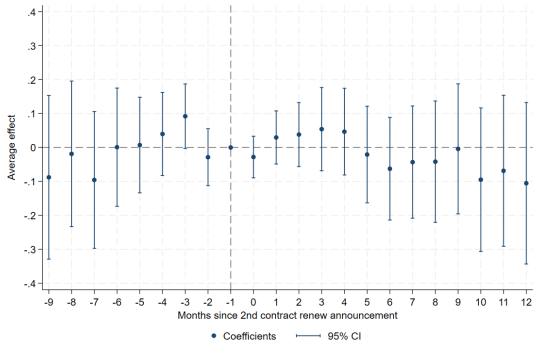

(b) Balanced Panel (-6 to +6)




(c) Alternative Estimators

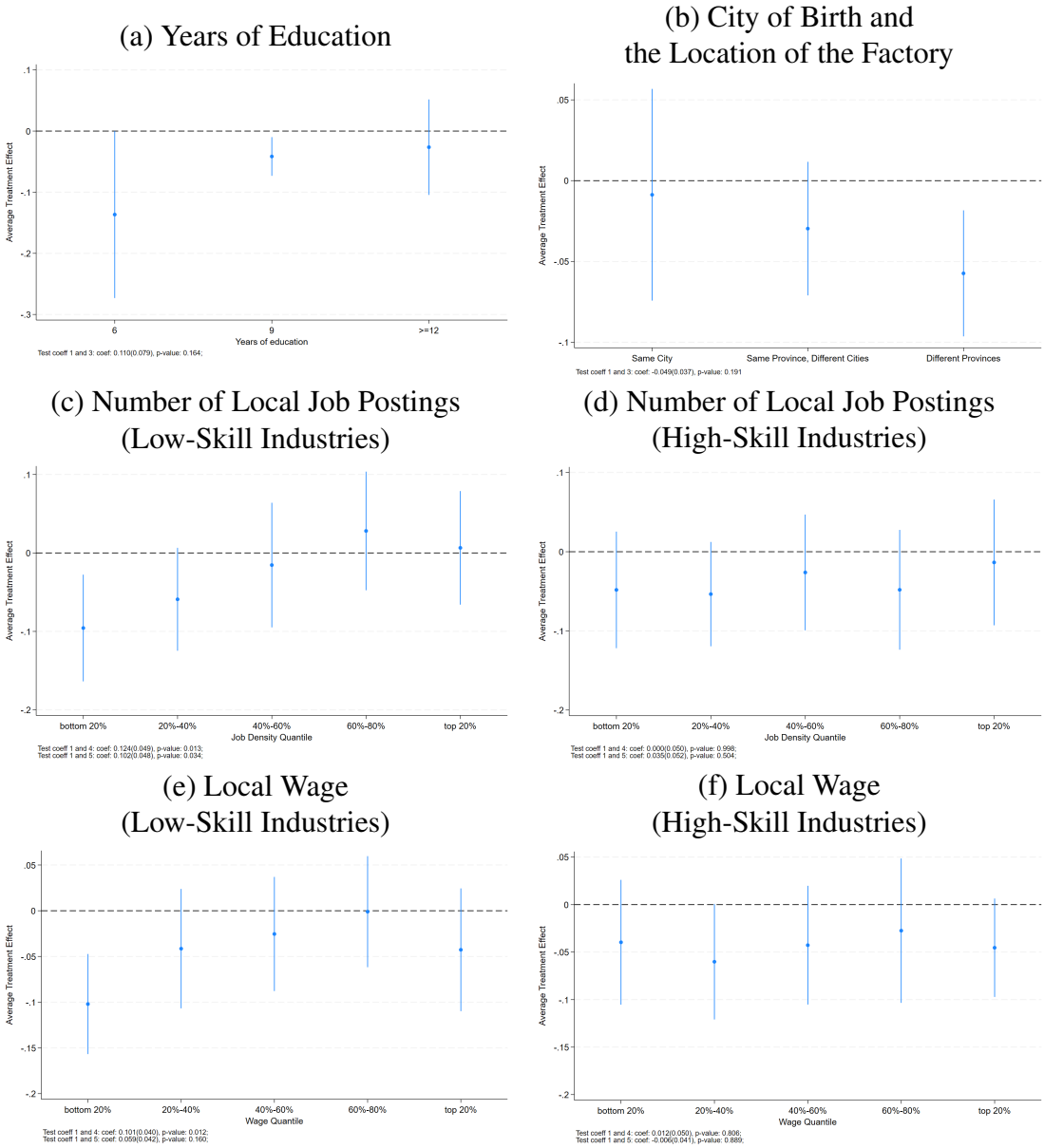



(d) Transition from the 1st to 2nd Contract




Notes: The samples for all 4 panels restrict to only workers who were tenured. For panel (a)-(c), month 2 is 30 days after the tenure starts. Month 1 is 30 days before the tenure starts, when the tenure is announced according to HR. Month 0 is ambiguous, since workers can be informed earlier. For panel (d), month 2 is 30 days after the second fixed-term contract starts. Month 1 is 30 days before the second contract starts, when the renewal is announced according to HR. Panel (b) excludes those who didn't work continuously from month -6 to +6 and obtains a balanced sample for month -6 to +6. The balanced sample contains 31.54% observations of the full sample. All 4 panels control for individual fixed effects, calendar date fixed effects and pre-tenure experience trend. Standard errors are clustered at the individual level.

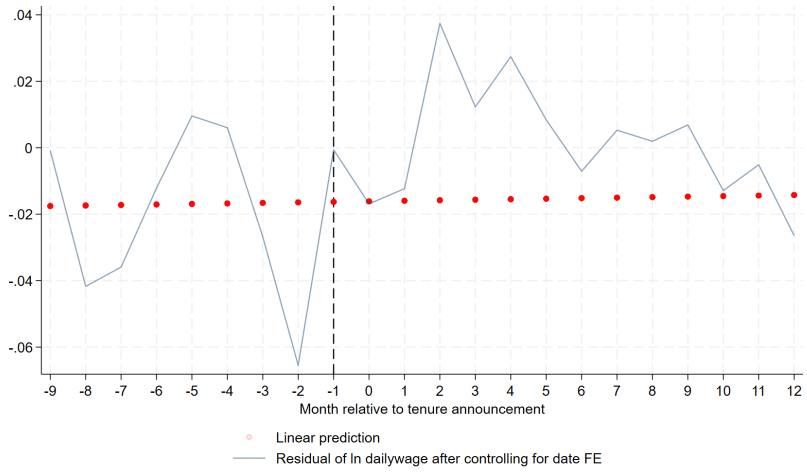
**Figure 3:** Heterogeneity by Worker Outside Options



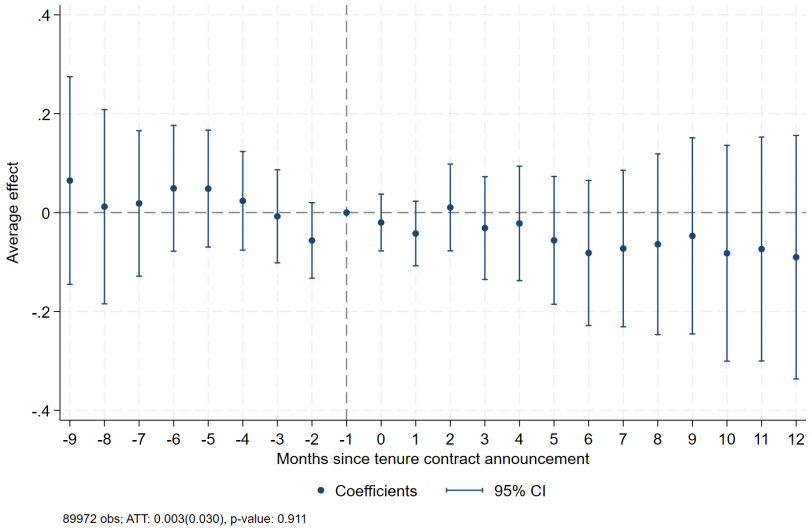

Notes: The samples for all 6 panels restrict to only workers who were tenured. For panel (c) and (d), we employ a job-post dataset at city-week level from 2018 to 2022. We take advantage of the degree requirement from the job posts and perform a more-specific match with the workers, since the education level of the workers are accessible. In panel (c) and (e), we restrict to a set of low-skill industries, including manufacture, service, agriculture, and transportation. In panel (d) and (f), we restrict to a set of high-skill industries, including IT, consulting, banking, aerospace, biotechnology and medical services. We re-scale the number of local job postings at the workers' cities of birth one year before tenure announcement by the city resident population in 2020. For panel (e) and (f), we employ a national tax survey data in 2016 and obtain the per capita wage of the local low-skill industries, including manufacture, service, agriculture, and transportation. All the quantiles are divided at the individual level. All 4 panels control for individual fixed effects, calendar date fixed effects and pre-tenure experience trend. Standard errors are clustered at the individual level.

**Figure 4:** Results from Vietnam Plant

(a) Residualized ln Daily Wage and Predicted Trend of ln Daily Wage by Experience




(b) Event Study




Notes: The sample restricts to workers who were tenured 2 years after joining the factory only. Month 2 is 30 days after the tenure starts. Month 1 is 30 days before the tenure starts, when the tenure is announced according to HR. Month 0 is ambiguous, since workers can be informed earlier. Panel (b) controls for individual fixed effects, calendar date fixed effects and pre-tenure experience trend. Standard errors are clustered at the individual level.

**Table 1:** Main Results

| VARIABLES | (1)<br>ln Daily Output | (2)<br>ln Daily Output | (3)<br>ln Daily Output | (4)<br>ln Daily Output |
|---|---|---|---|---|
| Post Tenure | -0.045*** | -0.045*** | -0.046*** | -0.042** |
| | (0.015) | (0.015) | (0.015) | (0.017) |
| Observations | 283,963 | 283,963 | 283,275 | 229,579 |
| R-squared | 0.268 | 0.257 | 0.275 | 0.275 |
| Individual FE | Yes | Yes | Yes | Yes |
| Day FE | Yes | Yes | Yes | Yes |
| Line FE | No | No | Yes | No |
| Manager FE | No | No | No | Yes |
| Control for pre-trend experience | Yes | No | Yes | Yes |
| Dependent Variable Mean | 4.634 | 4.634 | 4.634 | 4.634 |

Notes: Columns (1)-(4) each present results from a separate OLS regression and employs different specifications. All regressions control for individual fixed effects and calendar date fixed effects. Column (1) control for pre-tenure experience trend. Column (2) does not control for experience. Column (3) controls for pre-tenure experience trend and line fixed effects. Column (4) controls for pre-tenure experience trend and manager fixed effects. Robust standard errors clustered at the individual level are shown in parentheses. *** significant at the 1 percent level; ** significant at the 5 percent level; * significant at the 10 percent level.



29

**Table 2: Tenure Effects on Other Outcomes**

| VARIABLES | (1) Attendance | (2) Line Co-worker Expr (Days) | (3) Monthly HHI | (4) Task Difficulty |
|---|---|---|---|---|
| Post Tenure | 0.001 | 3.463 | -0.000 | 0.006 |
| | (0.005) | (7.030) | (0.010) | (0.030) |
| Observations | 371,373 | 283,963 | 11,791 | 11,791 |
| R-squared | 0.870 | 0.864 | 0.286 | 0.683 |
| Individual FE | Yes | Yes | Yes | Yes |
| Day FE | Yes | Yes | No | No |
| Month FE | No | No | Yes | Yes |
| Dependent Variable Mean | -0.022 | -0.022 | 0.372 | 2.410 |

Notes: Columns (1)-(4) each present results from a separate OLS regression. Column (1) uses a sample where the dataset has been supplemented with workers' non-attendance dates, while columns (2)-(4) use samples where observations exist only if the worker was present at work on that day or relative month. The supplemented non-attendance records are filled in only for the period between each worker's earliest and latest working dates. Both samples restrict to workers who were tenured only. $Attendance_{it}$ is a dummy variable that equals 1 when worker $i$ is present at work on date $t$ and 0 otherwise. The $Difficulty_{im}$ is defined as the average task difficulty for worker $i$ in relative month $m$, weighted by the time spent on each task, which is calculated by multiplying standard time by output. The $HHI_{im}$ is defined as the task hhi for worker $i$ in relative month $m$, where the ratio of each task is calculated by dividing the time spent on that task by the total working time in that month. The $Experience_{it}$ is defined as the average experience of worker $i$'s co-workers on date $t$, where co-workers are the ones who work on the same production line as worker $i$ on date $t$. All regressions control for individual fixed effects and the pre-tenure experience trend. Columns (1)-(2) control for calendar date fixed effects, and (3)-(4) control for calendar year-month fixed effects. Robust standard errors clustered at the individual level are shown in parentheses. *** significant at the 1 percent level; ** significant at the 5 percent level; * significant at the 10 percent level.

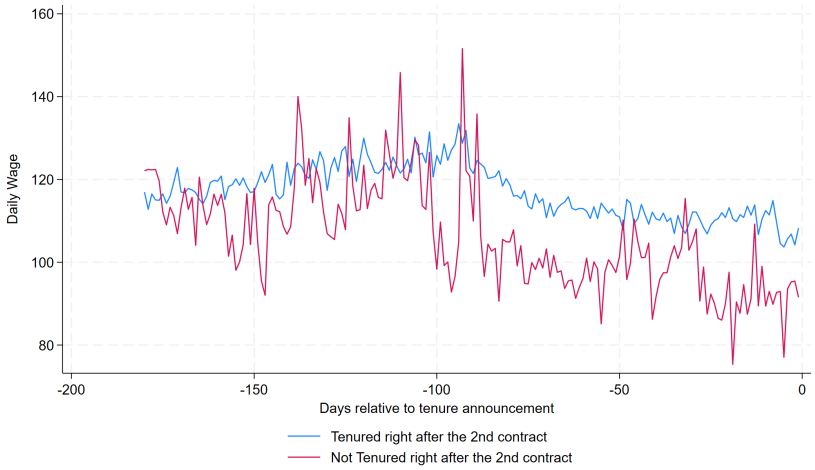


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# A. Appendix

**Figure A.1:** Comparison of Productivity

(a) 6 Months before Tenure Announcement

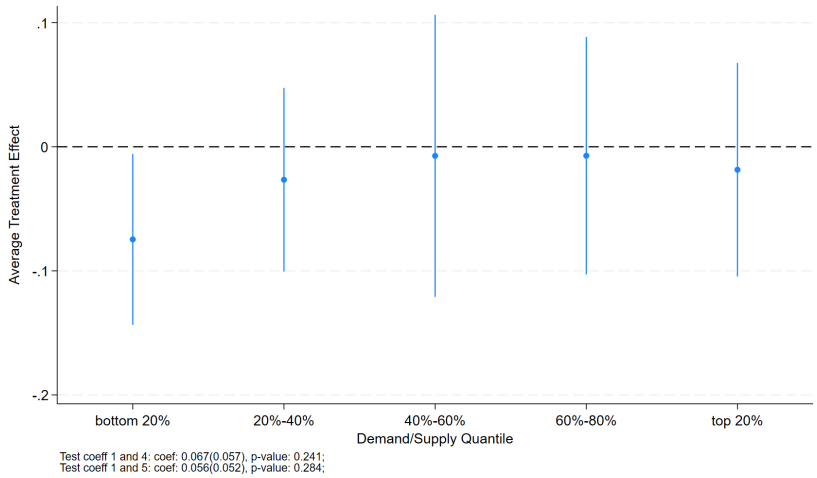



(b) 2 Months before Tenure Announcement




Notes: Panel (a) and (b) present the comparison of productivity between the workers who were tenured right after the second fixed-term contract (586 workers) and those who were not (104 workers). Panel (a) presents the comparison 6 months before tenure announcement, while panel (b) zooms in to 2 months before tenure announcement.

**Figure A.2:** Heterogeneity: Local Job Demand/Supply of Low-Skill Industries




Notes: The sample restricts to workers who were tenured only. We employ a job-post dataset along with a job-applicant dataset at city-week level from 2018 to 2022. We restrict to a set of low-skill industries including manufacture, agriculture, service and transportation. We divide the number of local job postings at the workers' cities of birth by the number of local job applicants one year before tenure announcement and obtain a demand/supply ratio. The quantiles are divided at the individual level. The panel controls for individual fixed effects, calendar date fixed effects and pre-tenure experience trend.