Gig Jobs as a Buffer: How Employment Contract and Production Evolve in Firms[1]

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Abstract: Long-term contracts insure employees against income uncertainties (Holmström, 1983), but at the cost of sacrificing potential opportunities for excessive earnings. As the gig economy rises, employees increasingly prefer short-term contracts, viewing gig jobs on platforms as a buffer against such risks. Consequently, firms adapt by shortening contract durations and expanding temporary employment, potentially transforming management and production practices. Using China Employer-Employee Survey (CEES) data and a staggered difference-in-differences model with food delivery platform entry as a shock, we find: (1) the entry of food delivery platforms significantly reduces employment contract likelihood and duration, with stronger effects for frontline and non-technical workers; (2), these impacts are weaker for those who are more risk-averse or have consumption commitments (e.g., house mortgages), as well as those who are more patient or enjoy better promotion prospects; (3) the impacts are stronger for OEM manufacturers, who can actually take advantage of this shift in the labor market, but weaker for high-tech firms; (4) in response, the average wage for long-term contracts increases, while that for short-term contracts decreases; (5) in addition, firms significantly reduce on-the-job training but increase the adoption of robots in production. By reshaping the labor market, the gig economy not only creates flexibility even in traditional sectors such as manufacturing but also poses challenges for traditional modes of management and production.

Key words: employment contract duration, gig economy, manufacturing, on-the-job training, robot adoption

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1. Introduction

Employment without formal contracts or with only short-term agreements has traditionally been associated with industries where the gig economy thrives, food delivery, ride-hailing, and instant logistics. In these sectors, flexible employment arrangements are the norm rather than the exception. Workers move fluidly between platforms, accepting jobs on demand without long-term commitments to any single employer. By contrast, traditional manufacturing has long been characterized by stable employment relationships: workers typically hold formal contracts, receive firm-specific training, and have access to promotion ladders. This employment model reflects both firms' need for accumulated firm-specific human capital and workers' preferences for job security and predictable income streams. The contrast between these two models, flexible gig work versus stable manufacturing employment, has seemed fundamental to understanding modern labor markets.

Recent evidence from China, however, reveals a striking departure from this traditional pattern. Manufacturing employment is experiencing a systematic shift toward shorter contracts and informal arrangements, particularly among frontline workers. According to the 2025 wave of the Enterprise Survey for Innovation and Entrepreneurship in China (ESIEC), 27 percent of manufacturing workers now lack formal employment contracts, a figure nearly identical to the 28 percent observed across all sectors. This proportion represents a substantial increase from earlier years and signals a fundamental transformation in manufacturing labor markets. Field research by Zhang (2025) documents even more dramatic patterns in China's major manufacturing clusters. In the Yangtze River Delta and Pearl River Delta regions, on-demand workers comprise one-third of the manufacturing workforce on average, rising to two-thirds during peak production seasons. In large plants employing over 10,000 workers, this proportion can reach 80 percent. These patterns suggest not isolated incidents but rather a systematic restructuring of employment relationships in one of the world's most important manufacturing sectors.

Understanding this transformation is important for several reasons. From the firm's perspective, contract duration fundamentally shapes human capital accumulation. Manufacturing firms have traditionally relied on long-term employment relationships to justify investments in worker training and skill development. When workers stay with firms

for extended periods, the returns to firm-specific training can be captured; when turnover accelerates and contracts shorten, these investments become less attractive. Contract structure also determines firms' ability to respond to economic uncertainty. Flexibility in workforce composition provides valuable options during demand fluctuations, but may come at the cost of reduced productivity from less experienced or less committed workers. The balance between these considerations affects not only labor costs but also production efficiency, quality control, and innovation capacity.

For workers, contract duration directly influences the stability-flexibility tradeoff that defines employment choice. Long-term contracts provide insurance against income uncertainty and create opportunities for career advancement, but constrain workers' ability to pursue alternative opportunities. Short-term or informal arrangements offer flexibility but expose workers to unemployment risk and search costs. Changes in the equilibrium contract structure therefore have direct implications for worker welfare, income volatility, and career trajectories. Given that China produces nearly 30 percent of global manufacturing output and employs over 100 million manufacturing workers, understanding these employment dynamics carries implications well beyond China's borders.

Moreover, the rise of flexible employment in manufacturing represents the convergence of two major labor market trends: the expansion of the gig economy and the evolution of traditional industrial employment. While extensive literature examines gig platforms in isolation, less is known about how platform growth affects employment relationships in other sectors. If the manufacturing sector, perhaps the archetypal example of stable, long-term employment, is experiencing systematic shifts toward flexibility, this suggests that gig economy effects extend far beyond direct platform participation. Understanding these spillovers is essential for predicting how labor markets will evolve as platform economies continue to expand globally.

This paper offers a supply-side explanation for the shortening of manufacturing employment contracts in China. We propose that the rapid expansion of the gig economy, particularly food delivery platforms, fundamentally alters workers' employment preferences by providing a buffer against unemployment risk. The classical contract theory literature, building on Holmström (1983) and Azariadis (1975), emphasizes that long-term contracts

serve an insurance function: they protect risk-averse workers from income uncertainty in exchange for reduced labor market flexibility. This insurance-flexibility tradeoff has traditionally favored long-term contracts for workers who value income stability. However, when gig platforms achieve sufficient scale, they change this calculus by offering readily available alternative employment. A worker can transition to food delivery or ride-hailing at virtually any time and begin earning income within hours, substantially reducing the downside risk of unemployment. With this buffer in place, the insurance value of long-term manufacturing contracts diminishes, shifting worker preferences toward shorter, more flexible arrangements that preserve the option to pursue alternative opportunities.

To test this hypothesis, we exploit the staggered entry of food delivery platforms across Chinese cities as a quasi-natural experiment. Using comprehensive data from the China Employer-Employee Survey (CEES), which provides detailed information on individual employment contracts, worker characteristics, and firm attributes, we implement a difference-in-differences design that compares changes in contract structure between cities before and after platform entry. The timing of platform expansion was largely driven by strategic business considerations unrelated to local manufacturing labor market conditions, providing plausibly exogenous variation in workers' access to gig employment opportunities.

Our analysis yields five main findings. First, the entry of food delivery platforms significantly reduces both the likelihood that manufacturing workers hold formal employment contracts and the duration of contracts among those who do. The effects are economically substantial: platform entry reduces contract likelihood by approximately 8 percentage points and shortens average contract duration by 3-4 months. These heterogeneity patterns are not incidental: each margin we examine corresponds to one of the conditions under which the gig-as-buffer mechanism is theoretically operative, so that the heterogeneity tests collectively serve as tests of the mechanism itself. Second, these impacts exhibit considerable heterogeneity across worker types. Effects are concentrated among frontline and non-technical workers, precisely those for whom gig work represents a credible outside option, while managerial and skilled technical workers show minimal response. These impacts are weaker for those who are more risk-averse or have consumption commitments (e.g., house mortgages), as well as those who are more patient or enjoy better promotion prospects. Third,

firm characteristics matter: OEM manufacturers, whose production processes require less firm-specific human capital, experience larger contracting changes and may even benefit from increased workforce flexibility. High-tech firms, in contrast, show weaker responses, suggesting efforts to maintain long-term employment relationships despite shifting worker preferences. We further trace how firms adjust to the shift in workers' contract preferences along three margins—wages, training, and robot adoption—which together characterize the firm-side equilibrium response to the labor-side shock. Fourth, we document systematic wage effects that vary by contract type. Wages for long-term contract workers increase following platform entry, consistent with firms paying a premium to retain stable workers when outside options improve. Wages for short-term contract workers, however, show weaker increases or even declines, reflecting the interaction between labor supply competition and contract-specific bargaining dynamics. Fifth, firms respond to contracting changes by reducing investments in on-the-job training, consistent with shortened payback periods, and by accelerating adoption of industrial robots. This automation response aligns with the directed technological change literature (Acemoglu, 2002): when retaining human workers becomes more difficult or expensive, firms substitute toward capital-intensive production methods.

Our work builds on several strands of literature. First, we contribute to research on the gig economy and platform labor markets. Existing studies have documented workers' preferences for flexibility (Chen et al., 2019; Mas and Pallais, 2017, 2020; He et al., 2021), quantified the consumer surplus from platforms (Cook et al., 2021), and examined labor supply elasticities in gig work (Barrios et al., 2022). For China specifically, He et al. (2021) demonstrate workers' willingness to accept lower wages for schedule flexibility, while Mo and Li (2022) and Li et al. (2022) analyze platform effects on income inequality and labor force participation. We extend this literature by examining spillover effects on non-platform sectors, demonstrating that gig economy impacts extend well beyond direct platform participation. Second, we contribute to contract theory and the literature on employment relationships. Building on foundational work by Azariadis (1975) and Holmström (1983) on the insurance role of long-term contracts, and Postlewaite et al. (2008) on how consumption commitments affect contract preferences, we show how external labor market conditions, specifically, the availability of alternative employment through platforms, reshape the

equilibrium contract structure. While this literature has emphasized how individual and firm characteristics determine contract choice, we highlight a novel mechanism operating through improved outside options. Third, we inform research on firm-specific human capital and training. The classical analysis of Becker (1962) and recent empirical work by Lazear (2009) and Konings and Vanormelingen (2015) emphasize that training investments depend on expected worker tenure. We provide new evidence on how external labor market shocks, through their effects on contract duration, alter training incentives. Our finding that training declines following platform entry illustrates the potential for negative feedback loops: shorter contracts reduce training, which makes workers less valuable and easier to replace, potentially accelerating the shift away from long-term employment. Finally, we contribute to the literature on technology adoption and automation. Following Acemoglu (2002) and Acemoglu and Restrepo (2020, 2021, 2022), we examine how labor market conditions shape firms' technology choices. While much of this literature focuses on labor costs or skill availability, we show that employment contract structure also matters: difficulty retaining workers through long-term contracts accelerates robot adoption, providing a supply-side complement to existing demand-side explanations for automation.

Our analysis makes three main contributions. First, we provide a supply-side explanation for the emergence of flexible employment in manufacturing, documenting how the gig economy reshapes worker preferences and thereby affects traditional sector employment relationships. This complements existing demand-side explanations that emphasize firms' desires for flexibility in the face of volatile product demand. Second, we trace the implications of contract changes through multiple dimensions of firm management and production: incentive structures (insurance and promotion), human capital accumulation (training), and technology adoption (automation). This comprehensive approach reveals how a shock to employment relationships propagates through organizational practices. Third, we provide new empirical evidence on a globally significant phenomenon, the transformation of manufacturing employment in the world's largest manufacturing economy, with implications for how labor markets may evolve as platform economies expand worldwide.

The remainder of this paper proceeds as follows. Section 2 develops our theoretical framework, deriving testable predictions about how gig economy expansion affects

employment contracts, wages, training, and technology adoption. Section 3 introduces institutional background, and Section 4 describes our data sources, variables that we use and documents summary statistics. Section 5 presents our empirical strategy and identification approach. Sections 6 and 7 reports results on contract likelihood and duration, along with heterogeneity analyses. Section 8 examines wage effects, training responses, and robot adoption. Section 9 concludes and discusses welfare implications and policy considerations.

2. Conceptual Framework

The rise of the gig economy represents a fundamental shift in labor market structure, with implications extending far beyond the platform economy itself. In this section, we develop a conceptual framework to understand how the expansion of gig work, particularly in China's food delivery and ride-hailing sectors, affects employment contract choices in traditional manufacturing industries. Our framework builds on the classical labor contract literature while incorporating the novel role of gig platforms as a readily available outside option for workers.

2.1 Employment Contracts as a Flexibility-Certainty Tradeoff

The foundational insight from contract theory is that employment contracts involve a tradeoff between flexibility and certainty (Azariadis, 1975; Holmström, 1983). Long-term contracts provide workers with insurance against income uncertainty, a valuable form of consumption smoothing for risk-averse individuals. When firms offer long-term employment guarantees, they essentially absorb macroeconomic risk that would otherwise fall on workers, stabilizing income streams even during economic downturns. Additionally, long-term contracts create opportunities for promotion and career advancement, providing dynamic incentives that enhance worker productivity over time (Gibbons and Waldman, 1999, 2006).

However, these benefits come at a cost. Workers bound by long-term contracts sacrifice the flexibility to pursue alternative employment opportunities. If better job prospects emerge elsewhere, contract terms, including notice periods, penalties for breach, and potential reputational damage in local labor markets, create friction that may prevent workers from seizing these opportunities. In China's context, labor law typically requires a one-month notice period for resignation, which can result in lost opportunities when timing is critical.

Short-term contracts or informal employment arrangements offer the opposite tradeoff. Workers retain substantial flexibility to adjust their employment in response to changing circumstances, whether pursuing better-paying positions, accommodating family obligations, or achieving preferred work-life balance. However, this flexibility comes with exposure to unemployment risk and job search costs. Without the insurance provided by long-term contracts, workers bear the full burden of income volatility.

Traditional contract theory predicts that risk-averse workers will prefer long-term contracts despite their rigidity, as the insurance value outweighs the option value of flexibility. This prediction has been broadly consistent with observed employment patterns in manufacturing and other traditional sectors, where permanent contracts with job security provisions have been the norm for core workers.

2.2 The Gig Economy as a Buffer Stock of Employment

The fundamental mechanism we propose is that large-scale gig platforms fundamentally alter the flexibility-certainty tradeoff by providing a buffer stock of readily available employment. When platforms like Meituan (food delivery) and Didi (ride-hailing) achieve sufficient market penetration, they create a labor market characterized by immediate job availability with minimal search frictions. A worker can transition into gig work at virtually any time and begin earning income within hours or days, rather than the weeks or months typically required for traditional job search.

This "gig-as-buffer" mechanism operates through two channels. First, it provides partial insurance against unemployment risk. While gig work may not offer the same income stability as a long-term manufacturing contract, it substantially reduces the worst-case scenario that workers face without formal employment. The ability to earn income quickly through gig platforms diminishes the insurance value of long-term contracts. Second, gig platforms reduce job search costs when workers decide to leave their current positions. Rather than facing extended periods of unemployment or costly search processes, workers can transition to gig work as a bridge to their next traditional employment opportunity.

Critically, this buffer function only operates when the gig economy reaches sufficient scale. If gig platforms are small or geographically limited, they cannot reliably serve as an outside option for most workers. However, when platforms achieve the market penetration

seen in China's major cities, where food delivery and ride-hailing services are ubiquitous and continuously hiring, they become a credible alternative that enters workers' employment calculus.

From the worker's perspective, this changes the optimal contract choice. With gig work as a buffer, the flexibility of short-term contracts becomes more valuable because unemployment risk is mitigated. Workers no longer need long-term contracts to insure against income uncertainty; instead, they can opt for more flexible arrangements that allow them to respond to changing circumstances, whether pursuing better opportunities, managing family responsibilities, or adjusting work intensity over time.

2.3 Bargaining Power and Contract Equilibrium

The gig economy also affects employment contracts through its impact on bargaining power. The availability of gig work strengthens workers' outside options, shifting the terms of negotiation between firms and employees. When workers can credibly threaten to leave for gig employment, firms face greater pressure to accommodate worker preferences, including preferences for shorter contract durations and more flexible arrangements.

This bargaining channel is particularly important for understanding why firms might agree to reduce contract durations even if they would prefer long-term commitments. In equilibrium, firms must balance their desire for stable workforces against the cost of attracting and retaining workers who have improved outside options. If firms insist on long-term contracts when workers prefer flexibility, they may face higher wage demands or difficulty filling positions. As a result, both the incidence of long-term contracts and their average duration may decline. These mechanisms lead to our first testable hypothesis:

Hypothesis 1: The rise of the gig economy decreases the likelihood of formal employment contracts in traditional industries and shortens their duration.

2.4 Heterogeneous Effects across Worker Types

Hypothesis 1 rests on a chain of behavioral assumptions about workers, and its mechanism can therefore be probed by examining whether the predicted contract response varies systematically with the conditions that make the chain operative. Three such conditions are essential. First, gig employment must constitute a credible income substitute for the worker in question: only when platform earnings are broadly comparable to formal-sector wages can the

option of switching plausibly serve as informal insurance. Second, the worker must be sufficiently risk-averse, since it is the desire to insure against income shocks—rather than to maximize expected income—that gives long-term contracts their value in the first place. Third, the worker must place limited weight on the dynamic, deferred returns embedded in long-term employment, such as promotion prospects and firm-specific human-capital accumulation; for sufficiently patient or career-oriented workers, these forward-looking benefits dominate the short-run insurance motive and blunt the mechanism. When any one of these conditions weakens, the predicted negative effect of gig-economy expansion on contract duration should attenuate. Sections 2.4, 2.5, and 2.6 develop this logic along the three margins in turn—skill and income comparability, risk aversion and consumption commitments, and time preference and promotion prospects—and derive from each a heterogeneity prediction that doubles as a test of the underlying mechanism. Together, the three subsections constitute a unified set of worker-side mechanism tests for Hypothesis 1.

The gig-as-buffer mechanism does not affect all workers equally. For gig employment to serve as a credible outside option, workers must view platform work as a realistic alternative, which depends on their skills, income level, and comparative advantage. The effect should be concentrated among workers whose characteristics and earning potential align with those of typical gig workers.

For frontline production workers, particularly those in non-managerial and non-skilled positions, gig work represents a reasonable outside option. Their income levels and skill requirements are comparable to platform workers, making the transition feasible. Food delivery or ride-hailing could plausibly provide similar or better earnings than their current positions, especially in the short run. By contrast, managers and skilled technical workers face much larger wage gaps between traditional employment and gig work. For these workers, platform employment is not a credible alternative, and the gig economy's expansion has minimal impact on their contract preferences. This heterogeneity generates a second testable prediction:

Hypothesis 2: The negative impact of the gig economy on employment contract duration is stronger for non-managerial and non-skilled workers.

2.5 Risk Aversion and Consumption Commitments

We turn next to the second condition underlying Hypothesis 1: that workers are sufficiently risk-averse for the insurance value of long-term contracts to be a binding consideration. The insurance function of long-term contracts matters most for risk-averse workers, suggesting that the gig economy's impact should vary with individual risk preferences. While gig platforms provide a buffer against the worst outcomes of unemployment, they do not eliminate income volatility. Platform earnings fluctuate with demand, weather, competition, and other factors outside workers' control. This residual risk means that highly risk-averse workers should continue to value the more complete insurance provided by long-term contracts, even as the gig economy expands.

Consumption commitments amplify risk aversion in contract choice. Following Postlewaite et al. (2008), workers with fixed financial obligations, particularly mortgage payments, have stronger preferences for income stability. Housing mortgages represent large, inflexible monthly expenses that create substantial hardship if income drops unexpectedly. Moreover, in China's context, mortgage approval often depends on proof of stable employment, creating an additional mechanism linking long-term contracts to property ownership.

For workers with consumption commitments, the partial insurance provided by gig platforms may be insufficient. While platform work can generate income, its variability makes it unsuitable for meeting fixed obligations with high reliability. These workers require the more complete insurance of long-term contracts and should be less responsive to gig economy expansion. Conversely, workers without major consumption commitments face less severe consequences from income volatility and should be more willing to trade contract security for flexibility when gig options become available. These considerations yield two related predictions:

Hypothesis 3a: The negative impact of the gig economy on employment contract duration is weaker for more risk-averse workers.

Hypothesis 3b: The negative impact of the gig economy on employment contract duration is weaker for property owners.

2.6 Time Preferences and Promotion Opportunities

The third condition underlying Hypothesis 1 concerns workers' valuation of the deferred

returns embedded in long-term employment. Long-term contracts create opportunities for career advancement and skill development that short-term arrangements typically do not (Gibbons and Waldman, 1999, 2006). Promotion prospects represent future benefits that require patience to realize, workers must remain with the firm long enough to be considered for advancement and to develop the relationships and firm-specific knowledge that support upward mobility. Consequently, workers with strong time preferences (patient workers) should place greater value on long-term contracts because they more fully capture the option value of future promotion.

The gig economy's impact should therefore vary with time preferences. Workers who heavily discount the future (impatient workers) place less weight on potential promotions and more weight on current flexibility and income. For these workers, the availability of gig employment tips the balance decisively toward short-term contracts, as they gain flexibility without sacrificing much value from foregone advancement. Patient workers, in contrast, should remain more committed to long-term contracts that preserve promotion opportunities, even as gig options expand.

This logic extends to firm characteristics. In firms where promotion opportunities are more plentiful or rapid, long-term contracts are more valuable because the probability of realizing advancement benefits is higher. Workers in such firms should be less affected by gig economy expansion, as the opportunity cost of switching to short-term contracts remains substantial. Conversely, in firms with limited promotion prospects, perhaps due to flat organizational structures or low growth rates, the dynamic benefits of long-term contracts are minimal, making workers more responsive to the flexibility enabled by gig platforms. These arguments generate two hypotheses:

Hypothesis 4a: The negative impact of the gig economy on employment contract duration is weaker for more patient workers.

Hypothesis 4b: The negative impact of the gig economy on employment contract duration is weaker for workers with higher probabilities of promotion.

2.7 Heterogeneous Effects across Firm Types

Section 2.7 develops the firm-side counterpart to the worker-side analysis in Sections 2.4–2.6. The shift in workers' contract preferences changes contract duration only as part of a market

equilibrium, and that equilibrium differs across firm types because firms differ in the kind of human capital they employ. OEM manufacturers, which rely on general human capital with low search costs, already prefer flexible arrangements and may be relatively unharmed—even helped—by a workforce more amenable to short-term contracts; high-tech firms, which rely on task-specific human capital and face high replacement costs, bear the larger cost of the shift. From the firm's perspective, the value of long-term contracts depends critically on the importance of firm-specific human capital. Firms that rely on specialized skills, proprietary processes, or deep organizational knowledge benefit substantially from workforce stability. Training workers in firm-specific competencies represents an investment that pays returns only if workers remain with the firm long enough to apply their knowledge productively. Such firms should resist the shift toward short-term contracts, even as worker preferences change.

High-technology firms typically fall into this category. Their production processes often involve complex technical knowledge, quality standards, or innovative practices that require substantial on-the-job learning. Even frontline workers in high-tech manufacturing may need weeks or months of training to reach full productivity, creating strong incentives to retain workers through long-term contracts. These firms face difficult choices as the gig economy expands: they can either maintain long-term contracts by offering premium compensation to offset workers' increased preference for flexibility, or accept higher turnover costs from shortened contracts.

In contrast, firms engaged in routine assembly or OEM (original equipment manufacturer) production have minimal firm-specific human capital requirements. Workers can be trained quickly, and tasks are sufficiently standardized that replacing departing workers imposes little cost. For these firms, the gig economy's pressure toward short-term contracts may actually be advantageous. Shorter contracts provide flexibility to adjust workforce size in response to demand fluctuations without the rigidity of long-term commitments. Rather than resisting the trend toward shorter contracts, OEM manufacturers may embrace it as a way to share demand risk with workers while reducing their own exposure to business cycle volatility. This yields a fifth hypothesis:

Hypothesis 5: The negative impact of the gig economy on employment contract duration is

stronger for OEM manufacturing firms but weaker for high-tech firms.

2.8 Change in Wage: Competition and Contract Effects

Section 2.8 turns to the firm-side equilibrium response taken jointly. Faced with workers' altered contract preferences, firms adjust along three connected margins: wages (this subsection), investment in worker-specific training (Section 8.2), and adoption of automating capital (Section 8.3). The three margins are not independent reactions but components of a single reoptimization of the firm's production and personnel strategy. The gig economy's expansion affects manufacturing wages through two distinct channels. First, a competition effect operates through labor supply: as workers leave manufacturing for gig platforms, reduced labor supply in traditional sectors puts upward pressure on wages. This is a standard market-clearing mechanism that should raise compensation across all contract types.

Second, a contract effect operates through changes in relative demand for different contract types. As discussed above, firms with significant firm-specific human capital need to retain or attract long-term contract workers even as worker preferences shift toward flexibility. To maintain their long-term workforce in the face of improved outside options, these firms must raise wages sufficiently to compensate workers for accepting binding contracts. This contract effect reinforces the competition effect for long-term workers, potentially producing substantial wage increases.

For short-term contract workers, the two effects work in opposite directions. While the competition effect raises wages through reduced labor supply, the contract effect creates downward pressure. As more workers prefer short-term arrangements, the supply of workers willing to accept flexible contracts increases relative to firms' ability to create additional short-term positions (particularly in capital-intensive manufacturing where adjusting workforce composition takes time). This excess supply of short-term workers dampens wage growth, potentially offsetting the competition effect.

Importantly, this analysis applies to short-run partial equilibrium, holding technology and capital relatively fixed. In the longer run, firms may adjust their production techniques, potentially reducing demand for all types of labor or changing the skill composition of employment. Our focus here is on the medium-term period during which the gig economy expands but before substantial technological adjustment occurs. This reasoning generates our

sixth hypothesis:

Hypothesis 6: The rise of the gig economy raises wages for workers on long-term contracts, but the effect for those on short-term contracts is weaker.

2.9 Firm Responses: Training and Technology Adoption

The shift toward shorter employment contracts creates incentives for firms to reduce investment in on-the-job training. Training represents a fixed cost that generates returns over the period during which trained workers remain employed. Following Becker (1962) and Lazear (2009), firms are willing to invest in firm-specific training only when they expect to recoup costs through increased worker productivity. As contract durations shorten and turnover rates rise, the expected payback period shrinks, making training investments less attractive.

This creates a feedback mechanism: shorter contracts reduce training incentives, which in turn makes workers less valuable and easier to replace, potentially accelerating the shift away from long-term employment relationships. Some firms may attempt to maintain training programs by focusing them exclusively on workers with long-term contracts, creating a two-tier workforce. However, if the fraction of long-term workers declines, aggregate training provision should fall. This generates a seventh hypothesis:

Hypothesis 7: The rise of the gig economy reduces the likelihood and intensity of on-the-job training.

A complementary response involves technology adoption, particularly automation and robotics. Acemoglu (2002) and subsequent work on directed technological change demonstrate that factor scarcity induces innovation and adoption of technologies that substitute for the scarce input. When firms face difficulty retaining workers through long-term contracts, or when the wage premium required to maintain long-term workers becomes prohibitive, they have stronger incentives to adopt labor-saving technologies.

Robot adoption becomes particularly attractive when the alternative is a high-turnover workforce with limited firm-specific skills. Robots do not require training, do not leave for gig platforms, and their productivity does not decline with shortened employment relationships. The option value of automation increases precisely when the option value of long-term employment relationships decreases. Consequently, industries or firms most

affected by the shift toward shorter contracts should exhibit higher rates of robot adoption. This represents a potential path toward a new long-run equilibrium with less employment overall but greater capital intensity. While our empirical analysis focuses on medium-term adjustments, the technology adoption hypothesis points toward longer-term structural change:

Hypothesis 8: The rise of the gig economy increases the likelihood of robot adoption.

2.10 Welfare Implications and Distributional Considerations

The welfare effects of gig economy expansion are theoretically ambiguous and likely differ across time horizons. In the short run, workers may benefit from increased flexibility without bearing the full costs of reduced job security, particularly if gig platforms successfully buffer unemployment risk. The ability to choose shorter contracts while maintaining access to income through platforms represents an expansion of workers' choice sets, suggesting welfare improvements through revealed preference, workers who switch to short-term contracts or gig work presumably prefer these arrangements to their previous long-term contracts.

Firms may also gain in the short run. Those engaged in routine manufacturing can reduce their exposure to demand risk by maintaining more flexible workforces. The ability to adjust employment more readily in response to business cycle fluctuations has option value that partially offsets any costs from reduced workforce stability.

However, longer-run welfare effects are more concerning. Workers may lose valuable opportunities for skill development and career advancement as training investments decline and promotion ladders shorten. The shift away from long-term relationships may reduce accumulated firm-specific human capital, potentially lowering productivity growth. For firms, weakened organizational attachment could undermine company culture, reduce institutional knowledge transfer, and make it harder to maintain quality standards or innovation capacity.

These considerations suggest potential coordination failures: individual workers rationally choose flexibility given the availability of gig options, but the aggregate outcome may involve underinvestment in skills and relationships that would benefit both workers and firms in the long run. Whether these dynamic losses outweigh short-run flexibility gains remains an empirical question that extends beyond our current analysis but motivates careful attention to the magnitude and distribution of effects across different contract types and worker categories.

The theoretical framework developed in this section generates eight testable hypotheses regarding the gig economy's impact on traditional manufacturing employment relationships. The following sections present our empirical strategy for testing these hypotheses using data from China's manufacturing sector during the period of rapid gig economy expansion.

3. Institutional Background

3.1 The Rise of the Gig Economy in China

China's labor market has undergone a profound structural shift since the early 2010s with the rapid ascent of the gig economy, a form of work intermediation powered by digital platforms that algorithmically match workers with on-demand, short-term tasks. This transformation was driven by widespread smartphone adoption, mobile payments, and the emergence of large digital platforms that sharply reduced matching frictions between labor supply and demand. Unlike traditional informal employment, platform-based work in China is organized through centralized intermediaries that coordinate millions of workers and consumers in real time, enabling standardized task allocation and rapid geographic scaling. By the mid-2010s, platform-mediated employment had become a quantitatively important component of urban labor markets, particularly for low- and medium-skilled workers seeking flexible income opportunities. According to the Ninth National Survey on the Status of the Workforce released by the All-China Federation of Trade Unions in 2023, the number of gig workers exceeded 84 million, accounting for roughly 21% of the national workforce.

3.2 Food-Delivery Platforms: Central Role in the Gig Economy and Capital-Driven Rise as an Exogenous Shock

While the gig economy spans multiple sectors, including ride-hailing, logistics, and household services, food delivery occupies a central position in this transformation. Food-delivery platforms combine high-frequency consumer demand with labor-intensive last-mile logistics, making them especially effective at absorbing flexible labor. By 2021, the number of food-delivery couriers nationwide had reached approximately 13 million, representing nearly one percent of China's population (China Labour Bulletin, 2023). For many low-skilled urban workers, especially migrants and those in volatile employment, food delivery represents a highly accessible outside option: the entry barriers are minimal, typically

requiring only a smartphone and an electric bicycle (often provided or rented through the platform), with minimal formal credentials or firm-specific training. China Labour Bulletin's research report on China's food-delivery industry indicates that active delivery riders typically earn between 5,000 and 8,000 yuan per month in major cities, with peak-period earnings often exceeding entry-level manufacturing wages, making platform work a financially viable alternative for low-skilled workers.

Evidence from Meituan's own reporting underscores both the close substitutability between delivery work and many low-skilled jobs and the sector's role as a short-horizon outside option. A senior executive at the Meituan Research Institute notes that riders are drawn largely from services, manufacturing, and construction, and that platform delivery is frequently undertaken as part-time work or as a temporary "stopgap" during job transitions. Consistent with this transitional role, close to half of riders report cumulative delivery tenure of less than three months, while only about 11 percent accumulate at least 260 working days. These patterns suggest that the entry of a major food-delivery platform into a city does not merely introduce a new consumer service. It establishes a large-scale, digitally coordinated gig labor market that expands outside options for a broad segment of the local low-skilled workforce and can therefore affect reservation wages and employment relationships in traditional sectors.

The explosive geographic diffusion of food-delivery platforms across Chinese cities in the mid-2010s was not primarily an organic, demand-driven process, but rather the outcome of an intensely capitalized race for market dominance among China's leading internet conglomerates. Although the industry took roughly a decade to evolve from inception to mass adoption, the core expansion phase was remarkably compressed, unfolding largely within a two- to three-year window beginning in 2014. During this period, platforms entered a phase of concentrated rollout fueled by successive rounds of large-scale financing. For instance, Meituan raised several hundred million U.S. dollars from investors including Alibaba and Sequoia Capital, reaching a valuation of approximately USD 7 billion after its Series D round. Ele.me similarly attracted multiple investment rounds between 2014 and 2015 from CITIC, Tencent, JD.com, Dianping, and Sequoia Capital, before being fully acquired by Alibaba in 2018.

Business observers characterized this episode as "burning-money warfare," in which platforms aggressively subsidized consumers, merchants, and riders to accelerate geographic penetration and capture market share. This strategy produced rapid nationwide expansion accompanied by sustained operating losses, the exit of smaller competitors, and eventual market consolidation into a duopoly dominated by Meituan and Ele.me. Consistent with this narrative, Meituan Waimai, launched in November 2013, expanded its services to more than 240 cities within two years, while Ele.me reached over 200 cities by early 2015. Importantly, this rollout was strategically decoupled from local labor market conditions: entry timing was dictated by platforms' national competition for ecosystem dominance and financed by centralized investment cycles, rather than by city-specific economic fundamentals.

This capital-driven rollout translated mechanically into a large and sudden increase in local demand for delivery labor. Food delivery relies on physically intensive, one-to-one order fulfillment: riders travel to restaurants to pick up orders and then deliver them to individual customers, a production process that remains difficult to scale without proportional increases in frontline labor. As platforms expanded into new cities, they therefore had to recruit couriers quickly and at scale to build delivery capacity and ensure short delivery times, often alongside subsidies that further boosted order volume. Consistent with this logic, Meituan reports that its average daily active riders rose from roughly 14,000 in 2015 to over 700,000 by 2019. In parallel, consumer-side expansion was rapid: the number of online food-ordering users increased from about 256 million in 2016 to more than 540 million by 2021.

A crucial feature of this expansion is its capital-driven nature, which provides the central identification logic for our study. Because platform entry into a given city was primarily shaped by corporate financing cycles and national competitive strategy, rather than by contemporaneous local labor market trends, the timing of entry offers plausibly exogenous variation in the sudden availability of large-scale, low-skill gig work. We therefore exploit the staggered arrival of the first major food-delivery platform across Chinese prefecture-level cities as a quasi-natural experiment, using it to measure the localized shock of gig-economy expansion on manufacturing firms and their workers.

4. Data, Variables and Descriptives

Our analysis combines three primary data sources: (1) city-level gig-platform entry dates constructed from online job postings; (2) matched worker- and firm-level data from the China Employer-Employee Survey (CEES); (3) baseline city characteristics from official statistical yearbooks.

4.1 Gig-platform Entry Data from Online Job Postings

To measure the expansion of the gig economy at the city level, we construct a prefecture-by-year indicator for the presence of major food delivery platforms using historical online job posting data. Our data are drawn from five leading recruitment websites (Zhaopin, 51job, Liepin, 58.com, and Ganji), covering the period from 2014 to 2022.

As food delivery platforms expanded geographically, demand for platform-related personnel rose sharply, generating a wave of recruitment activity across cities. We exploit this feature to infer platform entry timing. Using a keyword-matching algorithm combined with manual verification, we identify the earliest recruitment advertisement related to food delivery services posted by 13 major platforms in each city, including Ele.me, Meituan-Dianping, TaoDiandian, Baidu Waimai, Koubei Waimai, Dianping, and other dominant market participants that collectively accounted for the vast majority of industry market share during our study period.

Importantly, we do not restrict attention to business development or delivery-specific postings. Instead, we manually verify early advertisements released by platforms' parent companies, including positions such as human resources staff and merchant onboarding roles (e.g., part-time photographers), which typically precede large-scale operational deployment and signal the initiation of platform activity in a new market. We define the date of the first such recruitment posting as the city's platform entry time and treat the city as exposed to the gig-platform shock from that point onward.[2]

[2] Mo and Li (2022) define city-level platform entry based on the first food-delivery-related job postings observed on Zhaopin, 51job, and Liepin during 2014-2019. Relative to their approach, our measure draws on a broader set of recruitment platforms and incorporates manual verification of early postings by platforms' parent companies, which allows us to capture initial deployment activity that often precedes standard business-development recruitment. As a result, our entry dates tend to be earlier and closer to the onset of platform operations. As a robustness check, we replicate all main analyses using the Mo and Li (2022) entry definition and obtain qualitatively similar results.

4.2 Worker-level and Firm-level Data from CEES

Our primary worker-firm data come from the China Employer-Employee Survey (CEES), a large-scale longitudinal matched employer-employee survey of manufacturing firms and their workers in five provinces: Guangdong, Jiangsu, Hubei, Sichuan, and Shaanxi. These provinces span China's major industrial regions and represent a broad range of development levels (Cheng et al., 2024).

The 2015 and 2016 waves draw the initial firm sample from the Third National Economic Census (2014) and cover 573 firms and 5,028 workers. The 2018 wave re-interviews previously contacted firms and adds newly sampled firms, yielding a combined sample of 1,978 firms and 16,379 workers. Within each firm, CEES randomly selects 16 employees from the firm roster and stratifies sampling by occupation; approximately 30 percent of respondents are middle or senior managers.

The CEES waves we use include 2015, 2016, and 2018. Using workers' reported job start dates, we retrospectively construct annual worker-firm panels for the period 2013-2018. For workers who have not yet entered a firm in a given year, outcomes are coded as missing.[3] From these data, we build two complementary panels: an individual-level panel that links workers to their employing firms, and a firm-level panel that aggregates outcomes naturally defined at the enterprise level (e.g., robot adoption and robot capital intensity). We merge the CEES records with data on platform entry based on each firm's city location and survey year. The final estimation sample consists of 85,860 worker-year observations and 8,909 firm-year observations.

4.3 Variables

Our empirical analysis examines outcomes across three interconnected dimensions: individual employment contracts, wages, and firm-level adjustments in training and technology.

[3] In cases where retrospective reconstruction yields multiple records for the same baseline variable, we use the earliest observed value. A natural concern with this retrospective construction is sample selection: workers who appear in the panel for earlier years are necessarily those who remained employed at a CEES firm long enough to be observed in a survey wave, and these survivors are disproportionately drawn from workers on long-term contracts. This selection works against finding our main result, since it tilts the historical sample toward the very workers who are least likely to switch into short-term arrangements when the gig economy expands. The implied attenuation bias means that our estimates of the negative effect of gig-platform entry on contract duration should, if anything, understate the true magnitude of the effect.

Employment contract outcomes. We construct three primary indicators to capture contractual formality and stability at the worker level: (i) *Employment Contract*, a dummy variable equal to one if the worker reports having either a standard labor contract or a labor-dispatch contract with the firm in a given year. (ii) *Contract Duration*, measured in months based on the reported term of the current fixed-term contract and is observed only for workers with non-missing contract information. (iii) *Long-term Contract*, a dummy variable equal to one if the worker holds an open-ended contract or a fixed-term contract exceeding 36 months, a threshold consistent with Chinese labor law conventions and commonly used to distinguish substantial employment commitments from short-term arrangements. All contract variables are organized into annual panels using workers' job-entry years and employment tenure.

Worker compensation. Worker compensation is measured using self-reported monthly pre-tax income, including regular wages and bonuses. Each survey wave retrospectively records earnings for the previous one to two years, allowing us to construct a worker-year wage panel for 2013–2018. Our main outcome *Monthly Income*, is the natural logarithm of self-reported monthly pre-tax income.

Firm investment in human capital. We measure firm investment in human capital using two variables: (i) *On-the-job Training*, a dummy equal to one if the worker reports having participated in any firm-sponsored training since joining the current employer, and (ii) *Training Duration*, records the cumulative number of training days since job entry. Both variables are mapped into annual panels using workers' employment tenure.

Robot adoption. At the firm level, we capture technological substitution with two measures: (i) *Robot Adoption*, a dummy equal to one if the firm reports having introduced industrial robots by a given year, constructed based on firms' reported first year of robot use, and (2) *Share of Robot Capital*, defined as the book value of robot capital stock divided by the firm's total fixed assets (in percentage points). Robot capital stock is constructed using the perpetual inventory method with robot-specific investment flows, assuming an 11-year service life following International Federation of Robotics guidelines.

Control variables. We include a comprehensive set of controls to isolate plausibly exogenous variation from platform entry. Worker, firm, and city characteristics are measured in the initial wave or year and are interacted with year fixed effects to allow for time-varying

impacts on the outcomes. Specifically, firm characteristics are initialized using the first year the firm is observed in CEES; city characteristics are measured in 2010 and held fixed thereafter. Individual characteristics are treated as time-invariant where appropriate (e.g., gender, schooling, hukou, migrant status, marital status, property ownership, and occupational category), while age increases mechanically by one each year.

The worker-level controls include age and age squared, years of schooling, and indicators for female, rural hukou status, migrant status, marital status, property ownership, and being a non-managerial or non-skilled worker, defined as non-managerial frontline production workers and sales workers. We also control for household composition using family size and the dependency ratio, defined as the number of non-working household members divided by total family size. Firm-level characteristics include indicators for state-owned and foreign ownership, firm age, and the logarithms of employment size and fixed capital stock. City-level controls include the logarithms of disposable income per capita and road area per capita, the share of employment in catering and services, the share of secondary industry in GDP, and the internet penetration rate.

4.4 Descriptive Statistics

Table 1 presents the summary statistics for the key variables. Panel A summarizes worker-level outcomes and covariates based on 85,860 worker-year observations. The mean of the employment contract indicator is 0.879, and the average contract duration is 27.4 months among observations with non-missing contract terms. The shares of long-term contracts and employee leasing are 0.196 and 0.195, respectively. The mean of the on-the-job training indicator is 0.262, and average training duration is 4.7 days. Average monthly income is 4,753 yuan. Worker characteristics show a mean age of 36.3 years, a female share of 0.459, a rural hukou share of 0.559, a migrant share of 0.366, a married share of 0.800, and a property ownership share of 0.574. The share of non-managerial and non-skilled workers is 0.474.

[Insert Table 1 around here]

Panels B and C summarize firm-level and city-level characteristics used as baseline controls. Panel B reports firm outcomes and baseline firm characteristics. Based on 8,909 firm-year observations, the mean robot deployment indicator is 0.162, and the average share of robot capital in total fixed assets is 1.92 percent. The firm-level on-the-job training indicator has a

mean of 0.900, and average training duration is 9.8 days. Baseline firm characteristics measured in the first year a firm is observed in CEES indicate a state-owned share of 0.098, a foreign-owned share of 0.184, an average firm age of 8.5 years, baseline employment size of 584 workers, and baseline fixed capital of 133.6 million yuan. Panel C reports baseline city characteristics measured in 2010 for the 60 cities in our sample. Disposable income per capita averages 52,384 yuan, road area per capita averages 11.2 square meters, the share of workers in the catering service industry is 0.589 percent, the secondary sector share in GDP is 51.0 percent, and internet penetration averages 32.5 percent.

5. Empirical Strategy

5.1 Identification Strategy

Our empirical analysis aims to estimate the causal effect of gig-economy expansion on the structure of employment relationships in traditional manufacturing. The eight hypotheses developed in Section 2 organize this estimation into three groups. Hypothesis 1 specifies the average effect on contract incidence and duration and constitutes the central test of the gig-as-buffer mechanism. Hypotheses 2 through 5 sharpen this test along worker- and firm-side margins predicted by the model: each heterogeneity dimension corresponds to one of the conditions under which the mechanism is theoretically operative, and each is therefore informative not only about distributional impacts but also about whether the mechanism itself is at work. Hypotheses 6 through 8 turn to the firm-side equilibrium response and ask whether wages, training investment, and automation adopt margins move in the directions implied by a labor force whose contract preferences have shifted.

Identification of these effects requires variation in gig-economy exposure that is plausibly orthogonal to unobserved determinants of manufacturing employment relationships. As argued in Section 3.2, the staggered entry of major food-delivery platforms into Chinese prefecture-level cities provides such variation. Entry timing was driven by the national competitive strategies of platform conglomerates and by the timing of their financing rounds, rather than by city-specific labor market fundamentals. The capital-driven nature of the rollout means that the timing of treatment is, conditional on time-invariant city characteristics and aggregate shocks, unlikely to reflect local trends in contract structure or in the demand for flexible labor. We use

this staggered entry as a quasi-natural experiment and estimate causal effects by comparing within-firm changes in outcomes around the date a firm's city receives its first major platform, relative to firms in cities not yet exposed.

The amount of identifying variation is substantial. As shown in Figure 1, platform entry is dispersed across cities and across time within the sample window. Entry activity peaks between the third and fourth quarters of 2014, with cumulative coverage reaching approximately 240 cities by the fourth quarter of 2014, and platform expansion continuing into 2015. The combination of broad cross-sectional reach and concentrated but staggered timing yields meaningful within-city, over-time variation in gig-economy exposure that we exploit in the estimation below.

Building on this identification logic, the remainder of Section 5 specifies our estimation in two steps. Section 5.2 introduces the baseline two-way fixed-effects specification, which delivers an average treatment effect of platform entry on contract and other outcomes and serves as the main vehicle for testing Hypothesis 1. Section 5.3 then presents an event-study specification that traces the dynamics of these effects around the entry date, allowing us to assess pre-trends, evaluate the plausibility of the parallel-trends assumption underlying the baseline estimator, and characterize the timing with which workers and firms adjust.

5.2 Baseline Specification

The rapid expansion of these platforms was driven by large-scale capital injections from major internet conglomerates rather than local labor market conditions specific to individual cities, providing a source of plausibly exogenous variation in the availability of large-scale flexible gig work. To identify its causal effects on workers and firms, we exploit year and regional variations in prefecture's platform entry as a quasi-natural experiment and use the following baseline specification:

$$y_{ifct} = \alpha_0 + \alpha_1 Gig_{ct} + \lambda_f + \gamma_t + X_{1,ct} + X_{2,fct} + X_{3,ifct} + e_{ifct} \quad (1)$$

where y_{ifct} denotes an outcome for worker i in firm f, located in city c in year t. Outcomes include employment contract indicators and duration, wages, and training at the worker level, as well as robot adoption and robot capital intensity at the firm level (denoted as y_{fct}). Gig_{ct} is a binary treatment indicator that switches from 0 to 1 in the year (and remains 1 thereafter) that a food-delivery platform enters the city where firm f is located. λ_f denotes the firm fixed

effects that absorb all time-invariant firm heterogeneity, and γ_t denotes year fixed effects that capture aggregate shocks common to all firms. The vector $X_{1,ct}$ includes baseline city characteristics interacted with year dummies, log disposable income per capita, log road density, the share of workers in catering services, the share of secondary industry in GDP, and internet penetration, as well as city-specific time trends including both linear and quadratic terms, which flexibly absorb differential local trends across cities. $X_{2,fct}$ consists of interactions between initial firm characteristics, ownership type, firm age, and the logarithms of employment size and fixed capital, and year dummies, allowing firms with different baseline attributes to follow distinct time paths. $X_{3,ifct}$ includes time-varying worker characteristics, namely age and age squared, as well as interactions between baseline worker and household characteristics and year dummies. These baseline characteristics include years of schooling, indicators for rural hukou, migrant status, marital status, property ownership, and being a non-managerial or non-skilled worker, together with household size and the dependency ratio. Standard errors are clustered at the city level to account for correlated shocks within geographic units.

5.3 Event-study Specification

The coefficient α_1 captures the average effect of gig-platform entry on outcomes, identified from within-firm changes over time relative to firms in cities not yet exposed. Our identification relies on the assumption that, absent platform entry, outcomes in treated and not-yet-treated cities would have followed parallel trends after conditioning on firm fixed effects, year fixed effects, and the rich set of interacted baseline controls. To empirically assess this assumption and examine dynamic adjustment, we estimate the event-study specification:

$$y_{ifct} = \alpha_0 + \sum_{k\neq -1} \beta^k I[t - T_c = k] + \lambda_f + \gamma_t + X_{1,ct} + X_{2,fct} + X_{3,ifct} + e_{ifct} \quad (2)$$

where T_c denotes the year of platform entry in city c, and k indexes event time, the omitted category is the year immediately preceding entry, and all other controls are defined exactly as in equation (1). The coefficients β^k trace the evolution of outcomes before and after platform arrival, allowing us to test for differential pre-trends and characterize the timing and persistence of treatment effects. The pre-treatment leads ($k < -1$) should be statistically indistinguishable from zero if the parallel trends assumption holds.

With treatment adoption staggered over time, recent econometric literature highlights potential biases in traditional two-way fixed effects estimators when treatment effects exhibits

heterogeneity because of the negative weight issue (see, for instance, Goodman-Bacon, 2021; de Chaisemartin and d'Haultfoeuille, 2024; Wooldridge, 2025). To alleviate this concern, we complement our baseline estimates with two robustness exercises. First, we implement the stacked DID regression approach of following Cengiz et al. (2019), which constructs separate event-time samples for each treated cohort and avoids using already treated units as controls. Second, we apply the heterogeneous difference-in-differences estimator proposed by Wooldridge (2025), which explicitly accommodates variation in treatment timing and dynamic treatment effects across cohorts.

6. Effects on Employment Contracts

6.1 Baseline Results

This section provides the central test of Hypothesis 1: whether the rise of the gig economy reduces the prevalence and duration of formal employment contracts in traditional manufacturing. We begin by examining how gig-platform entry affects firms' employment contracts. Figure 2 presents event-study estimates for four outcomes: the probability of having an employment contract, the log contract term, employee leasing, and the probability of holding a long-term contract.

[Insert Figure 2 around here]

Across all panels, we find no evidence of differential pre-trends in the years leading up to platform entry. Estimated coefficients in the pre-period are small and statistically indistinguishable from zero, supporting the parallel trends assumption. Following entry, employment contracts adjust gradually but persistently. Panel A shows a decline in the probability of having an employment contract, which emerges in the first year after entry and continues to widen over time. Panel B documents a parallel reduction in contract duration, with log contract terms falling steadily in the post-entry period. In contrast, Panel C shows a sharp increase in employee leasing beginning immediately after entry, while Panel D indicates a persistent decline in long-term employment contracts. These dynamic patterns suggest a sustained shift away from stable employment relationships toward more flexible labor arrangements following gig-platform expansion.

Table 2 reports corresponding average treatment effect estimates. Column (1) shows that

gig-platform entry reduces the probability of having an employment contract by 9.3 percentage points. Relative to the sample mean of 87.9 percent, this represents a decline of approximately 10.6 percent. Column (2) reports a 14.9 percentage point decline in the probability of holding a long-term contract, which corresponds to a 76 percent reduction relative to the baseline mean of 19.6 percent. Column (3) indicates that contract duration falls by 12.9 log points, which implies an average reduction of about 3.3 months in contract length relative to the sample mean contract term of 27.4 months.

[Insert Table 2 around here]

Together, the event-study and DID estimates provide consistent evidence that gig-platform entry induces firms to reduce formal and long-term employment while increasing reliance on flexible labor arrangements. These effects emerge shortly after platform arrival and persist over subsequent years, indicating that platform expansion leads to durable changes in firms' employment practices rather than transitory adjustments.

6.2 Robustness Checks

Heterogeneous DID estimation. Although two-way fixed effects regressions of the form in equation (1) are the workhorse specification for staggered adoption designs, they have been shown to deliver consistent estimates only under relatively strong assumptions about the homogeneity of treatment effects across cohorts and over time. When treatment effects are heterogeneous, the TWFE coefficient can be interpreted as a weighted average of multiple two-by-two DID comparisons, potentially assigning weight to comparisons between newly treated and already treated units, and therefore need not recover the average treatment effect on the treated. Motivated by these concerns, we assess the robustness of our baseline findings using alternative DID estimators that remain valid under treatment effect heterogeneity. In particular, we implement the heterogeneous DID approach of Wooldridge (2025), which flexibly allows effects to vary by treatment cohort and event time and aggregates group-time treatment effects in a manner that is robust to staggered adoption.

Appendix Table A1 reports the results. Across the primary outcomes, including employment contract coverage and contract duration, the Wooldridge estimates closely track the baseline TWFE results in both sign and magnitude. Gig-platform entry remains associated with declines in formal and long-term employment relationships and increases in flexible labor

arrangements. The estimated effects are economically meaningful and statistically distinguishable from zero. Overall, allowing treatment effects to vary flexibly across cohorts and over event time does not alter the qualitative pattern of contract restructuring documented in the baseline analysis, suggesting that our main findings are not driven by biases from staggered adoption under heterogeneous or dynamic effects.

Alternative measure of platform entry timing. A potential concern with our baseline treatment definition is measurement error in the timing of gig-platform entry. Our main approach infers city-level entry dates from the earliest platform-related recruitment advertisements across five major online job boards and incorporates manual verification of early postings by platforms' parent companies. While this procedure is designed to capture the earliest operational presence of major platforms in each city, alternative coding rules could shift entry dates and, in turn, affect event-time alignment and estimated treatment effects.

To assess robustness to this concern, we replicate the analysis using the alternative entry-timing measure in Mo and Li (2022). Their approach defines platform entry as the date of the first food-delivery–related job posting observed on three recruitment platforms (Zhaopin, 51job, and Liepin) during 2014–2019. Relative to our baseline measure, this definition is more conservative in capturing early entry because it relies on food-delivery tags and does not incorporate postings by parent companies that may precede formal business development recruitment. It therefore tends to date entry later in the rollout process.[4]

Table A2 reports results using the Mo and Li (2022) entry timing while holding outcomes, fixed effects, and controls identical to equation (1). The estimated effects remain qualitatively unchanged. Gig-platform entry continues to predict significant declines in employment contract coverage and duration, increases in flexible labor arrangements, and reductions in long-term contracts. Effect magnitudes are comparable to those obtained under our baseline definition, and statistical significance is preserved across the main outcomes.

Overall, these results indicate that our core findings are not sensitive to the precise dating

[4] Appendix Figure A2 replicates Figure 1 using an alternative definition of city-level platform entry based on Mo and Li (2022). While both measures exhibit highly similar diffusion dynamics, our baseline measure identifies earlier initial entry, reflecting broader coverage of early recruitment activity. Under the Mo and Li (2022)'s definition, cumulative platform presence reaches 197 cities by the end of 2014, compared with approximately 240 cities using our preferred measure.

of platform entry. Even under a more conservative definition that likely captures a later stage of platform rollout, the pattern of contract restructuring remains intact, reinforcing the interpretation that gig-platform expansion causally reshapes employment relationships.

Placebo estimates. To further assess whether our baseline results could be driven by spurious correlations or chance alignment between platform entry and labor market outcomes, we conduct placebo tests based on randomly assigned treatment timing and treatment units.

Specifically, we implement a mixed placebo design in which we randomly assign fictitious platform entry years between 2013 and 2018 and randomly select placebo-treated workers from the full sample. For each draw, we re-estimate equation (1) using the same specification as in the baseline analysis. We repeat this procedure 500 times to construct the empirical distribution of placebo coefficients for each employment outcome. Appendix Figure A2 plots the resulting distributions for employment contract status, log contract duration, employee leasing, and long-term employment contracts. The vertical solid red lines denote the true estimated effects from Table 2, while the histograms and kernel density curves summarize the placebo estimates.

Across all four outcomes, the placebo distributions are tightly centered around zero, with little mass near the true estimates. In each case, the actual coefficient lies far in the tail of the placebo distribution, with associated p-values effectively equal to zero. This pattern indicates that estimates of comparable magnitude rarely arise under random assignment, and provide strong evidence that our baseline findings are unlikely to be driven by sampling variation or mechanical correlations in the data. Instead, they support the interpretation that the observed contract restructuring reflects a genuine response to gig-platform entry rather than artifacts of the research design.

7. Heterogeneous Analysis: Disentangling Mechanisms

The baseline results establish that gig-platform entry is associated with a shift away from formal and long-term employment relationships. This average effect, however, may mask substantial heterogeneous responses across workers and firms. Platform expansion simultaneously alters workers' outside options and firms' employment strategies, and the relative importance of these channels depends on job characteristics, workers' economic constraints, and firms' production environments. To shed light on the underlying mechanisms, this section examines how contract

responses vary along margins that govern workers' exposure to gig competition, their need for income security and career attachment, and firms' reliance on firm-specific human capital. This heterogeneity analysis allows us to move beyond average effects and identify the margins along which gig-platform entry most strongly reshapes employment relationships.

7.1 Job Sensitivity: Non-managerial and Non-skilled Workers

We begin by examining heterogeneity across job types. Gig employment primarily involves standardized, low-skill tasks, making platform-based jobs a closer substitute for frontline manufacturing positions than for managerial or skilled occupations. For workers engaged in non-managerial and non-skilled jobs, gig platforms offer an accessible alternative source of income with similar task requirements and greater flexibility. For managerial and skilled workers, by contrast, platform work is unlikely to represent a meaningful outside option given their higher levels of human capital and compensation. To capture this margin, we interact the gig-platform entry indicator with a dummy for non-managerial and non-skilled workers. This variable directly reflects a worker'This subsection tests Hypothesis 2, which predicts that the contract response is concentrated among workers for whom platform earnings constitute a credible income substitute. s position in the occupational hierarchy and serves as our primary measure of exposure to platform competition.

The regression results are reported in Table 3. Across all contract outcomes, the responses are substantially larger for frontline workers. In column (1), the interaction coefficient indicates that non-managerial and non-skilled workers experience an additional 4.5 percentage point decline in the probability of holding any employment contract relative to managerial and skilled workers. Combined with the baseline effect, this implies a pronounced contraction in formal employment among frontline workers following platform entry.

Column (2) reveals particularly large effects on long-term employment: the likelihood of holding a long-term contract declines by an additional 14.9 percentage points for non-managerial and non-skilled workers. Column (3) shows that contract duration also falls more sharply for this group, with an additional reduction of 3.3 log points.

Taken together, these estimates show that the reorganization of employment relationships documented in Section 5.1 is driven primarily by frontline workers. For this group, gig-platform expansion materially strengthens outside options, reducing reliance on traditional contracts and

accelerating the transition toward flexible employment. In contrast, managerial and skilled workers exhibit substantially weaker responses, consistent with the fact that their labor is less substitutable with gig work. These patterns indicate that supply-side adjustments among workers with high job substitutability play a central role in the aggregate decline of formal and long-term employment.

[Insert Table 3 around here]

7.2 Worker's Risk Preference and Consumption Commitments

This subsection tests Hypothesis 3: if risk aversion and consumption commitments anchor the value of long-term contracts, the gig-economy effect should attenuate for more risk-averse workers and for those with binding consumption obligations. We next turn to heterogeneity in workers' risk preference and consumption commitments. Individual preferences fundamentally shape the trade-off between contractual flexibility and income security. We next examine the mechanism by two key dimensions: risk tolerance and consumption commitment.

Even in the absence of fixed financial obligations, workers differ in their aversion to income volatility and in how they discount future benefits. For more risk-averse workers, the insurance value inherent in a long-term contract remains paramount, making the imperfect income security of gig work a poor substitute.

To capture the dimension, we draw on CEES survey modules on risk attitudes, which is measured using respondents' self-assessed willingness to take risks, elicited by the question "Some people like taking risks while others prefer to avoid risks. If you rank your willingness to take risks from 0 to 10, where 0 means very unwilling to take risks and 10 means very willing, what is your score?" We define an indicator for high risk aversion as having a risk score weakly below the sample median, and low risk aversion otherwise.

[Insert Tables 4-1 and 4-2 around here]

Across contract outcomes, both preference measures significantly moderate the impact of platform entry. Workers with higher risk aversion exhibit smaller declines in employment contracts and contract duration.

Following a similar logic, while gig platforms expand access to flexible employment, income from platform work remains inherently uncertain and lacks many of the protections associated with formal contracts. Workers facing substantial fixed expenditures may therefore

remain attached to long-term employment relationships even as gig opportunities expand. Housing-related financial obligations are particularly salient in this regard, as mortgage payments require stable and predictable income streams and are often contingent on maintaining formal employment status. As a result, workers with property ownership are likely to place greater value on income security and exhibit weaker responses to the flexibility benefits offered by gig-platform entry.

To capture this margin, we interact gig-platform entry with an indicator for property ownership. This variable proxies for consumption commitments and financial constraints that limit workers' willingness to trade contractual stability for flexibility. Table 4-2 reports the corresponding results. Across all contract outcomes, property owners exhibit substantially attenuated responses to platform entry. In column (1), the decline in the probability of holding any employment contract is 7.4 percentage points smaller for property owners than for non-owners. Column (2) shows that the decline in long-term contracts is mitigated by 3.7 percentage points while Column (3) shows that contract duration also falls less for this group, with a 4.3 log-point smaller reduction relative to workers without property.

These estimates imply that workers with housing commitments are significantly less willing to substitute formal employment with gig-enabled flexibility. Even when platform work becomes readily available, property owners continue to rely on traditional contracts, reflecting the need for stable income to meet fixed financial obligations. In contrast, workers without property ownership respond more strongly to gig-platform expansion, shifting away from formal and long-term employment toward more flexible arrangements.

Together with the job-type heterogeneity documented above, these findings highlight the interaction between outside options and income security in shaping employment contracts. Frontline workers without housing commitments experience the largest contract adjustments, while those with substantial consumption obligations remain anchored to traditional employment relationships.

7.3 Worker's Time Preference Promotion Prospects

If these conditions hold, the negative effect of gig expansion on contract duration should be muted precisely for patient and promotion-prospective workers. We next examine heterogeneity in time preference and career incentives. More patient workers, who place a higher value on

future career advancement and firm-specific skill accumulation embedded in long-term employment, are expected to be less responsive to the immediate gains in flexibility offered by platform work. In CEES, patience is measured using an intertemporal trade-off question that asks respondents how willing they are to "give up something beneficial today in order to obtain greater benefits in the future," also coded on a 0-10 scale, where 0 indicates "completely unwilling" and 10 indicates "very willing." We define high patience as having a patience score weakly above the sample median, and low patience otherwise. We interact gig-platform entry with indicators for high risk aversion and high patience, respectively. Table 5 reports the results.

[Insert Tables 5-1 and 5-2 around here]

We find more patient workers experience attenuated reductions in contract duration and long-term employment, together with smaller increases in flexible labor arrangements.

Furthermore, beyond current wages and job stability, long-term employment relationships also provide access to internal promotion ladders and opportunities for skill accumulation. Workers who face stronger advancement prospects within their firms may therefore be less willing to substitute long-term contracts with gig-enabled flexibility, as doing so risks forfeiting future career gains that cannot be replicated through platform work.

To capture promotion prospects, we construct a binary indicator based on workers' reported promotion experience within the firm. Specifically, the CEES questionnaire asks whether the respondent has ever obtained an occupational promotion at the current employer; we define workers reporting any promotion as having high promotion prospects and interact this indicator with gig-platform entry. Table 5-2 reports the results.

Across all contract outcomes, workers with higher promotion prospects exhibit significantly attenuated responses to gig-platform entry. In column (1), the decline in the probability of holding an employment contract is reduced by 13.0 percentage points for workers with upward mobility relative to those without. Column (2) reveals that the decline in long-term contracts is also substantially muted, while Column (3) shows that contract duration falls by 6.7 log points less for this group.

Overall, these estimates suggest that career attachment acts as a powerful countervailing force to gig-induced flexibilization. Workers who have experienced promotion within the firm

appear reluctant to trade away stable employment relationships, consistent with the view that long-term contracts carry implicit returns through advancement and firm-specific skill accumulation that are difficult to replicate through gig employment. This pattern complements the results in Sections 6.1-6.2 that contract erosion is concentrated among workers with strong outside-option exposure and low demand for insurance, whereas workers with stronger dynamic career incentives exhibit substantially greater resistance to shifting toward flexible employment.

7.4 Firm-side Heterogeneity: Worker Replaceability and Production Technology

This subsection tests Hypothesis 5, which holds that firms relying on general human capital and facing low search costs (notably OEM manufacturers) absorb the labor-side shock differently from firms relying on firm-specific human capital (notably high-tech producers). We finally turn to heterogeneity on the firm side. While the preceding analyses focus on workers' responses to improved outside options, firms also actively adjust their employment practices in response to changes in labor market conditions. The extent of these adjustments depends critically on how easily workers can be replaced and on the role of firm-specific human capital in production. In environments where tasks are standardized and labor is readily substitutable, firms face lower costs of turnover and have stronger incentives to adopt flexible employment arrangements. By contrast, in firms that rely heavily on specialized skills or firm-specific knowledge, retaining workers becomes more valuable, limiting the scope for contract flexibilization.

To capture these differences, we exploit variation in firms' production technologies. We classify firms as high-tech if they operate in technology-intensive industries, and separately identify firms engaged in original equipment manufacturing (OEM), where production processes are highly standardized and workers are more easily replaced. We interact gig-platform entry with indicators for high-tech firms and OEM firms, respectively, and report the results in Tables 6-1 and 6-2.

[Insert Table 7 around here]

The estimates reveal stark contrasts across firm types. In high-tech firms, the negative effects of gig-platform entry on employment contracts and contract duration are significantly attenuated. Columns (1) to (3) in Table 6-1 show that the declines in contract coverage and

contract length are substantially smaller in these firms. These patterns suggest that when production depends on firm-specific human capital, firms resist the shift toward flexible employment even as workers' outside options improve.

In contrast, OEM manufacturing firms exhibit amplified responses. Columns (1) to (3) indicate larger declines in contract likelihood and duration relative to non-OEM firms. These estimates imply that firms operating in standardized production environments are more willing to reorganize employment toward short-term and flexible arrangements when gig platforms expand.

These firm-side patterns underscore that production technology is an important moderator of how gig-platform entry translates into organizational change. In settings where labor is easily replaceable, firms shorten contracts and expand flexible employment more aggressively. In contrast, when production relies more on firm-specific human capital, employment relationships are substantially more stable.

Taken together, the heterogeneity patterns across workers and firms point to a common economic margin governing the impact of gig-platform entry. Contract adjustments are largest among workers whose jobs are most substitutable with gig employment, who face weaker consumption commitments, and who exhibit lower aversion to income risk and shorter time horizons. These workers are also less likely to have strong internal career incentives. On the firm side, contract responses are amplified in production environments where labor is more easily replaceable and attenuated where firm-specific human capital plays a larger role. Overall, contract responses are concentrated in settings with high labor substitutability and low attachment, and are substantially smaller where workers value security and career progression and where firms rely on firm-specific human capital.

8. Effects on Worker Compensation and Firm Responses

8.1 Worker Compensation

This subsection tests Hypothesis 6: that wages adjust asymmetrically across contract types, rising for long-term contract workers and falling for short-term workers, as firms reprice the two contracts in the new equilibrium. The preceding sections document a substantial reorganization of employment relationships following gig-platform entry, characterized by a

shift away from long-term contracts toward more flexible arrangements. We next examine how these contractual changes reshape the wage structure within the manufacturing sector. Because contracts and wages are jointly determined, average wage responses may conceal important heterogeneity across workers who remain in stable employment versus those who transition into flexible or informal arrangements. Understanding these wage effects is essential for assessing the distributional consequences of gig-platform expansion. Table 7 reports DID estimates of the impact of gig-platform entry on log monthly income separately by contract status, which allows us to distinguish compensation changes among workers on long-term contracts from those without contracts or under employee leasing. Panel A presents results for the full sample, while Panel B restricts attention to non-managerial and non-skilled workers.

[Insert Table 8 around here]

Panel A shows strikingly asymmetric wage responses across contract types. Column (1) indicates that workers holding long-term contracts experience a significant increase in earnings following platform entry, with wages rising by 18.3 log points. In contrast, column (2) shows that workers without formal contracts or short-term contract arrangements which are shorter than one year suffer a substantial wage decline of 16.8 log points. These estimates indicate that gig-platform expansion is associated with wage gains for workers who remain in stable employment relationships, but sizable earnings losses for those who shift into flexible arrangements.

Panel B reveals that these patterns are even more pronounced among frontline workers. For non-managerial and non-skilled workers, wages rise by 21.5 log points among those holding long-term contracts, while falling by 20.2 log points among workers without contracts or with only short-term contracts. As in Panel A, no significant wage response is observed for workers in other contractual categories. This amplification among frontline workers mirrors the heterogeneity documented in Section 5.2 and highlights that workers most exposed to gig competition also experience the largest wage polarization.

Overall, these results suggest that gig-platform entry is associated with increasing wage dispersion across employment types. Workers who retain long-term contracts benefit from higher earnings, potentially reflecting increased bargaining power or firms' efforts to retain core employees. At the same time, workers who move into flexible or informal arrangements

experience substantial wage losses, consistent with reduced job stability and weaker access to firm-sponsored wage premia. This divergent outcome stems from the interplay of a generalized competition effect, where the gig economy tightens overall labor supply to the traditional sector, and a strategic retention effect, wherein firms raise wages specifically for core, hard-to-replace workers on long-term contracts to deter turnover. For easily substitutable flexible positions, however, the gig economy expands latent labor supply, suppressing wage growth. Consequently, the gig economy reshapes intra-firm inequality, and this pattern is especially pronounced among frontline workers, underscoring that the distributional consequences of gig expansion extend beyond employment stability to earnings inequality.

8.2 Firm Responses: Training

This subsection tests Hypothesis 7, which predicts that firms reduce investment in worker-specific training as the expected duration of employment relationships shortens. The wage and contract adjustments documented above suggest that gig-platform entry reshapes not only workers' employment outcomes but also firms' internal production decisions. Changes in employment stability and compensation may affect firms' incentives to invest in worker-specific human capital and to reorganize production technologies. We therefore next examine how firms respond along two key margins: on-the-job training and automation.

We begin by studying firms' training behavior. On-the-job training represents a form of relationship-specific investment whose returns depend critically on employment duration and worker retention. As gig-platform entry accelerates contract shortening and expands flexible employment, firms may become less willing to incur upfront training costs, particularly when worker attachment becomes more transitory. Table 8 reports estimates of the impact of gig-platform entry on on-the-job training, using both worker-level and firm-level panels. Panel A presents results at the individual level, while Panel B aggregates outcomes at the firm level.

[Insert Table 9 around here]

Panel A shows that gig-platform entry significantly reduces both the likelihood of receiving any firm-sponsored training and the duration of training among those who receive it. Specifically, platform entry lowers the probability of on-the-job training by 4.4 percentage points. Relative to a baseline training rate of 26.2 percent, this represents a decline of approximately 17 percent. Column (2) further indicates a substantial contraction in training

intensity: training duration falls by 52.9 log points, implying a reduction of roughly 41 percent in days of training conditional on participation. Panel B reveals closely aligned patterns at the firm level. Firms exposed to gig-platform entry are 1.6 percentage points less likely to provide on-the-job training, and average training duration declines by 51.7 log points. The consistency between worker- and firm-level estimates indicates that these effects reflect firm-wide adjustments rather than compositional changes driven solely by worker sorting.

Viewed together, these results provide direct evidence of reduced investment in worker-specific human capital following gig-platform expansion. As employment relationships become shorter and more flexible, firms scale back training provision, consistent with diminished expected returns to relationship-specific investments. This contraction in training complements the earlier findings on contracts and wages, highlighting that gig-platform entry reshapes not only the terms of employment but also firms' long-run workforce development strategies.

8.3 Firm Responses: Automation and Robot Adoption

An alternative margin of adjustment is automation: as employment relationships become shorter and firms scale back training, substituting labor with capital becomes relatively more attractive, particularly in tasks that are routine or easily standardized. This subsection tests Hypothesis 8: that firms substitute toward automation and robot adoption when the cost of retaining long-term human workers rises. We next examine whether firms respond to gig-platform entry by adjusting production technologies, and consider both whether a firm deploys any robots and the share of robot capital in total fixed assets.

[Insert Table 10 around here]

The results reported in Table 9 indicate a statistically and economically significant increase in automation following platform entry. Column (1) shows that gig-platform expansion raises the probability of robot adoption by 3.3 percentage points. Relative to a baseline adoption rate of 16.2 percent, this corresponds to an increase of approximately 20 percent. Column (2) further indicates a substantial rise in robot capital intensity: the share of robot capital in total fixed assets increases by 0.84 percentage points, implying a sizable reallocation of firms' investment portfolios toward automation technologies.

Together with the training results, these findings reveal a coherent pattern of firm-side adjustment. As gig-platform entry weakens long-term employment relationships and reduces

firms' incentives to invest in worker skills, firms respond by reallocating resources away from labor-specific investments and toward automation technologies. This shift reflects a broader reorganization of production in which firms rely less on accumulated worker expertise and more on capital-based solutions, highlighting that the impact of the gig economy extends beyond workforce composition to the technological trajectory of traditional firms.

9. Conclusions and Discussion

This paper documents a fundamental shift in manufacturing employment relationships driven by the rise of China's gig economy. We show that the explosive growth of platform-based gig work since 2014 has systematically shortened contract durations and increased informal employment in a sector previously characterized by stable, long-term contracts.

Our theoretical framework offers a simple insight. Employment contracts traditionally represent a tradeoff: long-term contracts insure against income risk but constrain mobility; short-term arrangements preserve flexibility but expose workers to unemployment. A thriving gig economy disrupts this calculus. When workers can transition easily into delivery work and earn immediate income, they gain unemployment insurance without sacrificing flexibility. This reshapes preferences over traditional employment contracts.

The empirical evidence supports this mechanism. Exploiting staggered entry of food delivery platforms across cities, we find that gig economy expansion significantly reduces contract prevalence and duration in manufacturing. Effects concentrate among frontline workers, for whom gig work is most viable, and weaken for those with mortgages. OEM manufacturers experience larger shifts; high-tech firms show muted responses. Firms respond with compensating wage differentials: long-term contract wages rise while short-term wages fall. More fundamentally, firms cut training and accelerate robot adoption.

An alternative reading of these patterns would emphasize labor demand rather than labor supply. The shortening of employment contracts, the contraction of firm-sponsored training, and the acceleration of automation could in principle be driven by demand-side forces—most notably the falling cost of industrial robots, intensifying trade fluctuations, and the broader reorganization of global production networks—rather than by a shift in workers' willingness to enter long-term arrangements. We do not dispute that such demand-side forces are present,

and our results are fully consistent with their operating in parallel. Three considerations, however, suggest that the labor-supply channel we emphasize is likely to be a main driving force, with the demand-side mechanisms reinforcing rather than substituting for it. First, the large-scale adoption of industrial robots and the most acute episodes of trade volatility in China are predominantly recent phenomena, whereas the trend toward shorter and more informal employment relationships in our sample begins well before these forces come to dominate the manufacturing landscape. Second, the supply-side account naturally explains the asymmetric wage adjustment we document—rising wages for long-term contract workers alongside falling wages for short-term and informal workers—whereas a pure demand-side story has difficulty rationalizing the wage gain at the long-term contract margin: if firms simply needed less labor, wages on long-term contracts should not be rising. Third, the heterogeneity patterns we document line up tightly with the worker-side conditions under which the gig-as-buffer mechanism is theoretically operative (income comparability, risk aversion, and time preference), which is exactly the signature one would expect if workers' contract preferences are the proximate mover. Taken together, we read the evidence as suggesting that labor-supply adjustments triggered by the gig economy are the proximate driver of the patterns we document, while demand-side forces operating in the background tend to amplify these adjustments along the same direction.

These findings carry broader implications. First, the gig economy's labor market impacts extend far beyond platform services. Workers who never participate in gig work alter their employment decisions knowing such options exist. This spillover amplifies the gig economy's influence on labor markets. Second, while workers gain flexibility, reduced training may diminish skill accumulation and productivity. Accelerated automation raises questions about employment and inequality. Third, our evidence suggests policy debates should consider how gig economy growth affects traditional sectors, not just gig workers themselves.

Several limitations merit note. We identify effects of food delivery platform entry; other platform types may differ. Longer-term consequences for careers, productivity, and competitiveness remain uncertain. Whether these patterns emerge elsewhere depends on institutional contexts that differ substantially from China's.

The transformation we document is likely in early stages. As platforms expand

geographically and into new services, their influence on traditional employment may grow. Understanding this evolution matters for anticipating changes in labor markets, skill formation, and production technology. Our analysis suggests the gig economy's most profound impacts may arise not from direct employment it creates, but from how it reshapes workers' alternatives and thereby transforms employment relationships throughout the economy.

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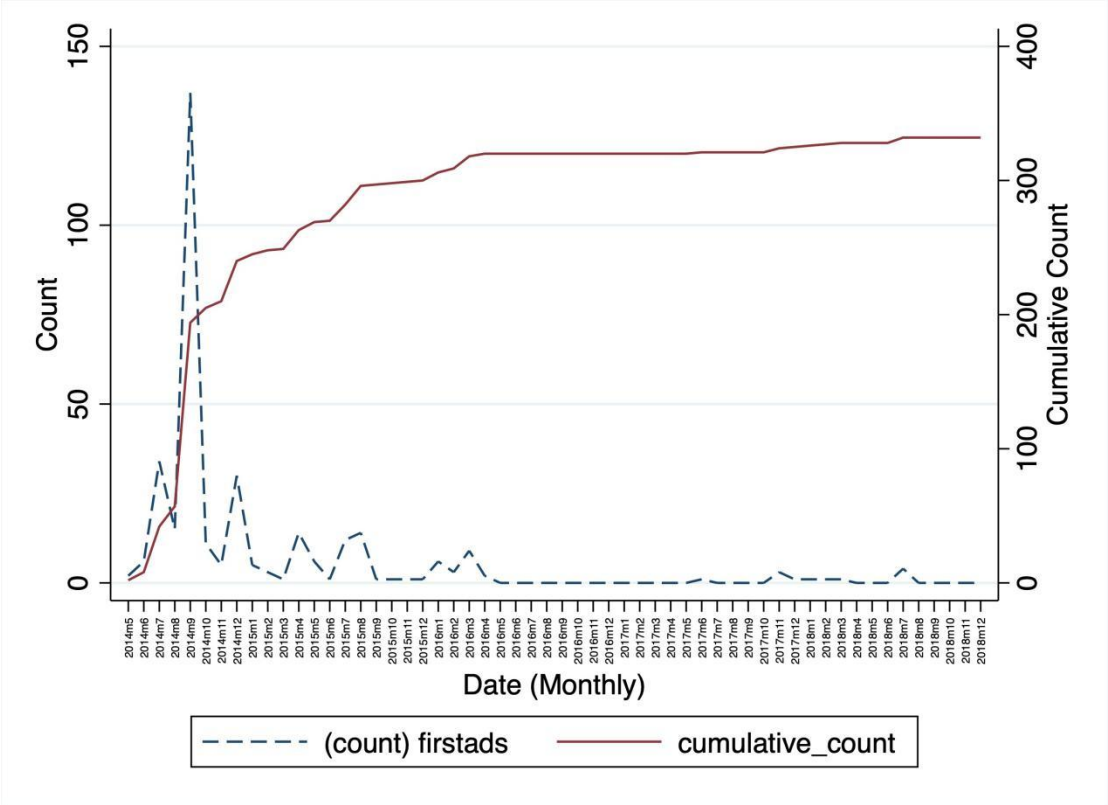
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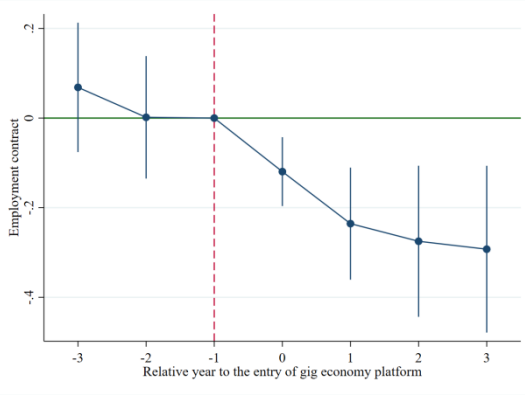
Figure:

Figure 1. City Entry of Major Food-Delivery Platforms Over Time: Monthly New Entries and Cumulative Coverage

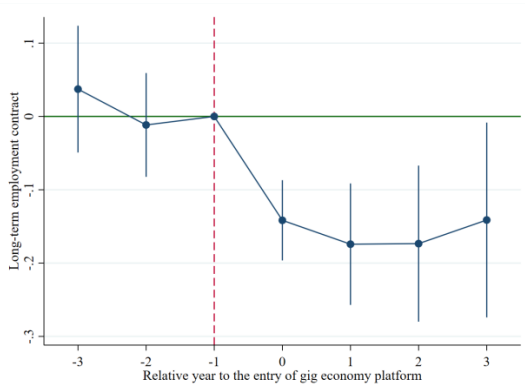


Notes: This figure plots the timing of city entry by major food-delivery platforms. The horizontal axis reports calendar months. The left y-axis measures the number of cities that experience their first platform entry in a given month (monthly new entries). The right y-axis measures the cumulative number of cities that have been entered by at least one platform up to and including that month (cumulative coverage). The blue dashed line corresponds to monthly new entries (the count of "first-entry" cities, constructed from the earliest recruitment advertisement date in each city), and the red solid line corresponds to cumulative coverage. A city is defined as "entered" in the month when we first observe a recruitment advertisement related to food-delivery services posted by any of the major platforms in that city.

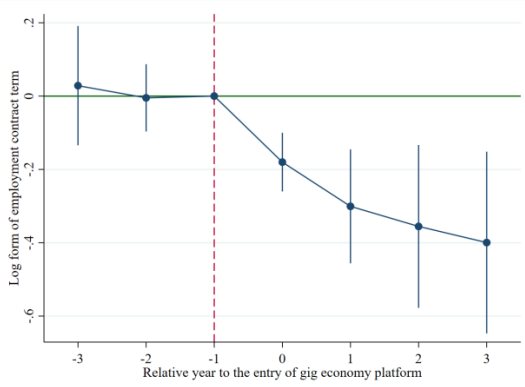
Figure 2. Dynamic effects of gig economy platform on employment contract



A. Employment contract

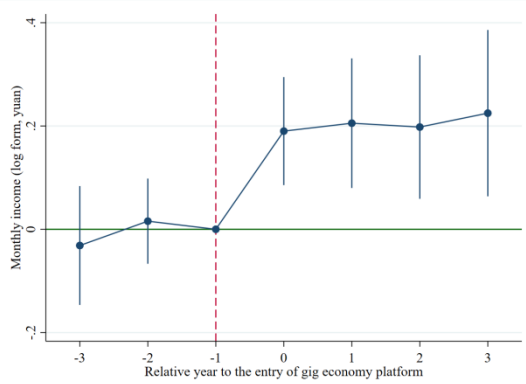


B. Long-term employment contract

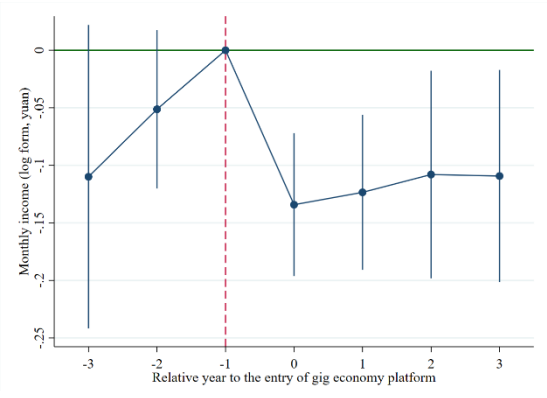


C. Log form employment contract term

Figure 3. Dynamic effects of gig economy platform on monthly income

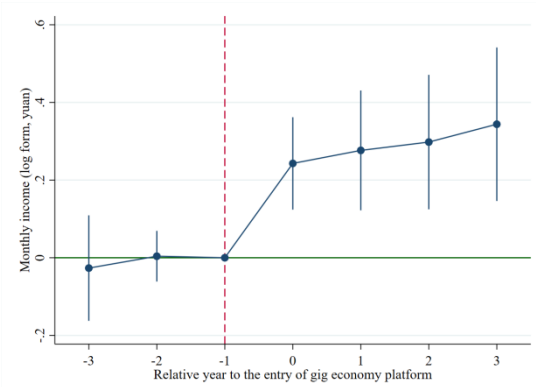


A1. Long-term contracts

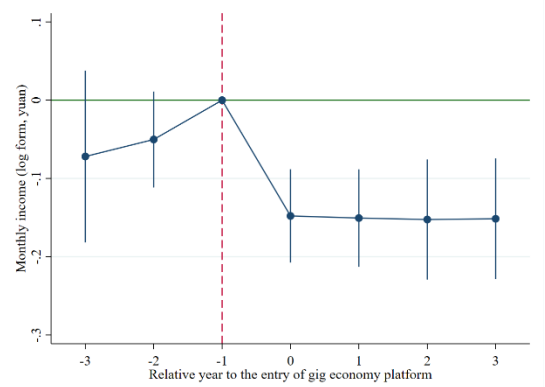


A2. No contracts/short-term contracts

A. For all workers



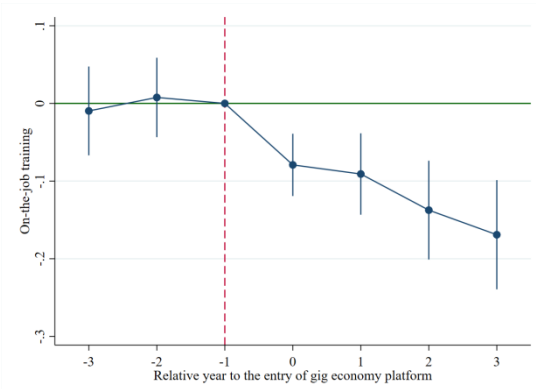
B1. Long-term contracts



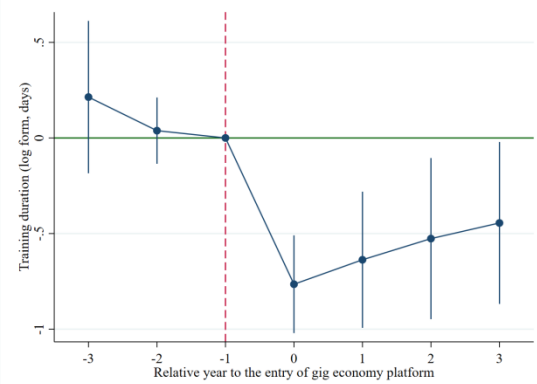
B2. No contracts/short-term contracts

B. For non-managerial and non-skilled workers

Figure 4. Dynamic effects of gig economy platform on on-the-job training

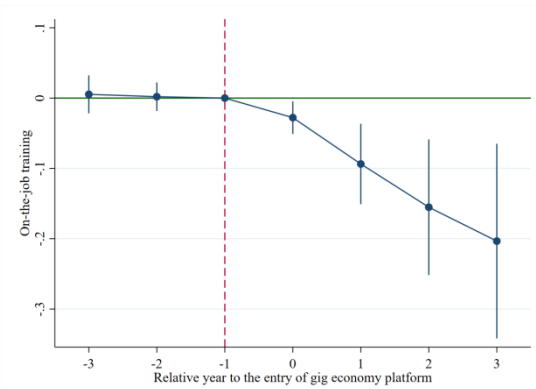


A1. On-the-job training

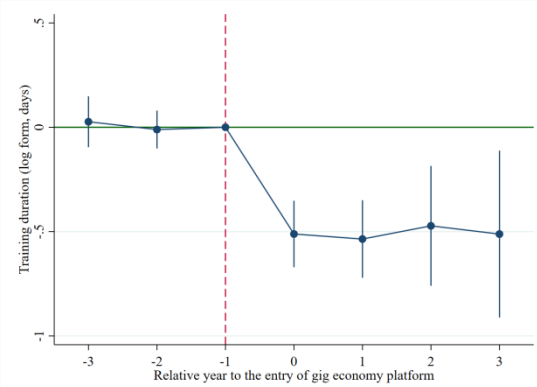


A2. Log form of training duration

A. Individual-level panel dataset



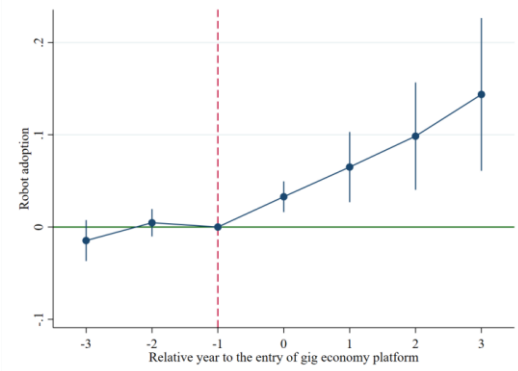
B1. On-the-job training



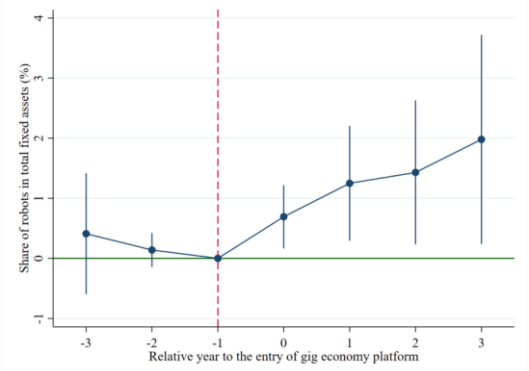
B2. Log form of training duration

B. Firm-level panel dataset

Figure 5. Dynamic effects of gig economy platform on robot deployment



A. Robot adoption



B. Share of robots in total fixed assets

Tables:

Table 1. Descriptive statistics

Variables	Obs.	Mean	S.D.
A. Employee characteristics			
Employment contract (dummy)	85,860	0.879	0.326
Term of employment contract (months)	60,671	27.449	14.175
Employee leasing (dummy)	75,465	0.195	0.396
Long-term employment contract (dummy)	75,465	0.196	0.397
Training (dummy)	85,860	0.262	0.440
Training duration (days)	85,860	4.735	10.540
Monthly income (yuan)	85,860	4,753	5,443
Age	85,860	36.260	9.364
Female (dummy)	85,860	0.459	0.498
Years of schooling	85,860	11.926	3.114
Rural *hukou* (dummy)	85,860	0.559	0.497
Migrant (dummy)	85,860	0.366	0.482
Married (dummy)	85,860	0.800	0.400
Property owner (dummy)	85,860	0.574	0.494
Non-managerial and non-skilled worker (dummy)	85,860	0.474	0.499
B. Firm characteristics			
Robot deployment (dummy)	8,909	0.162	0.368
Share of robot capital in total fixed assets (%)	8,909	1.920	7.603
On-the-job training (dummy)	8,909	0.900	0.301
Training duration (days)	8,909	9.801	16.960
State-owned enterprise (dummy, initial value)	2,501	0.098	0.298
Foreign enterprise (dummy, initial value)	2,501	0.184	0.388
Firm age (initial value)	2,501	8.543	7.132
Employment size (initial value)	2,501	584	1,335
Fixed capital (million yuan, initial value)	2,501	133.552	416.746
C. City characteristics			
Disposable income per capita (yuan, 2010)	60	52,384	8,842
Road area per capita (m^2, 2010)	60	11.166	6.801
Share of workers in catering service industry (%, 2010)	60	0.589	0.450
Share of secondary industry in GDP (%, 2010)	60	50.993	6.765
Internet penetration rate (%, 2010)	60	32.474	15.562

Notes: Firm characteristics such as ownership, firm age, employment size, and fixed capital are initial values that are first observed in CEES. City characteristics are all initial values in 2010.

Table 2. The effects of gig economy on employment contract

Variables	(1) Employment contract	(2) Long-term employment contract	(3) Log form employment contract term
Gig economy platform	-0.093***	-0.149***	-0.129***
	(0.040)	(0.024)	(0.029)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Adj R-squared	0.2727	0.2486	0.2778
Observations	85,860	75,465	60,671

Notes: Standard errors are clustered at city level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Controls include individual characteristics (i.e., age, age square, years of schooling, and dummies for rural hukou, migration, marriage, property owner, and non-managerial and non-skilled workers), interaction term between the initial values of firm characteristics (i.e., ownership types, firm age, log values of employment size and fixed capital) and year fixed effects, and interaction term between the initial values of city characteristics (i.e., log values of disposable income per capita and road density, share of workers in catering service industry, share of secondary industry in GDP, and internet penetration rate) and year fixed effects. City-specific time trends including both linear and quadratic terms are controlled.

Table 3. The heterogeneous effects of gig economy on employment contract (job sensitivity)

Variables	(1) Employment contract	(2) Long-term employment contract	(3) Log form employment contract term
Gig economy platform	-0.073*	-0.077**	-0.112***
	(0.041)	(0.030)	(0.030)
Gig platform × non-managerial and non-skilled workers	-0.045***	-0.149***	-0.033***
	(0.017)	(0.040)	(0.009)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Adj R-squared	0.2731	0.2514	0.2779
Observations	85,860	75,465	60,671

Notes: Standard errors are clustered at city level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4-1. The heterogeneous effects of gig economy on employment contract (risk-aversion)

Variables	(1)	(2)	(3)
	Employment contract	Long-term employment contract	Log form employment contract term
Gig economy platform	-0.128***	-0.174***	-0.147***
	(0.042)	(0.027)	(0.031)
Gig platform × risk aversion	0.059***	0.043***	0.031**
	(0.019)	(0.012)	(0.013)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Adj R-squared	0.2734	0.2488	0.2779
Observations	85,860	75,465	60,671

Notes: Standard errors are clustered at city level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4-2. The heterogeneous effects of gig economy on employment contract (consumption commitment)

Variables	(1)	(2)	(3)
	Employment contract	Long-term employment contract	Log form employment contract term
Gig economy platform	-0.135***	-0.171***	-0.154***
	(0.047)	(0.022)	(0.032)
Gig platform × property owners	0.074***	0.037**	0.043***
	(0.021)	(0.014)	(0.016)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Adj R-squared	0.2736	0.2487	0.2779
Observations	85,860	75,465	60,671

Notes: Standard errors are clustered at city level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5-1. The heterogeneous effects of gig economy on employment contract (time preference)

Variables	(1)	(2)	(3)
	Employment contract	Long-term employment contract	Log form employment contract term
Gig economy platform	-0.091*	0.075***	-0.153***
	(0.052)	(0.020)	(0.030)
Gig platform × patience	0.065***	0.037**	0.103***
	(0.023)	(0.014)	(0.036)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Adj R-squared	0.2867	0.2697	0.2708
Observations	58,827	51,694	41,756

Notes: Standard errors are clustered at city level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5-2. The heterogeneous effects of gig economy on employment contract (probability of promotion)

Variables	(1)	(2)	(3)
	Employment contract	Long-term employment contract	Log form employment contract term
Gig economy platform	-0.115***	-0.158***	-0.141***
	(0.040)	(0.024)	(0.027)
Gig platform × probability of promotion	0.130***	0.046***	0.067***
	(0.018)	(0.011)	(0.022)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Adj R-squared	0.2746	0.2487	0.2780
Observations	85,860	75,465	60,671

Notes: Standard errors are clustered at city level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6-1. The heterogeneous effects of gig economy on employment contract (high-tech firms)

Variables	(1)	(2)	(3)
	Employment contract	Long-term employment contract	Log form employment contract term
Gig economy platform	-0.122***	-0.177***	-0.146***
	(0.042)	(0.028)	(0.030)
Gig platform × high-tech firms	0.108***	0.072***	0.058**
	(0.017)	(0.019)	(0.028)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Adj R-squared	0.2753	0.2492	0.2783
Observations	85,860	75,465	60,671

Notes: Standard errors are clustered at city level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6-2. The heterogeneous effects of gig economy on employment contract (OEM manufacturing)

Variables	(1)	(2)	(3)
	Employment contract	Long-term employment contract	Log form employment contract term
Gig economy platform	-0.078**	-0.129***	-0.136***
	(0.039)	(0.025)	(0.033)
Gig platform × OEM manufacturing	-0.040**	-0.059***	0.015
	(0.018)	(0.021)	(0.026)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Adj R-squared	0.2732	0.2490	0.2781
Observations	85,860	75,465	60,671

Notes: Standard errors are clustered at city level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 7. The effects of gig economy on monthly income (log form, yuan)

Variables	(1)	(2)
	Long-term contracts	No contracts/Short-term contracts
A. For all workers		
Gig economy platform	0.183***	-0.146***
	(0.052)	(0.025)
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
Adj R-squared	0.4066	0.4798
Observations	52,871	32,989
B. For non-managerial and non-skilled workers		
Gig economy platform	0.215***	-0.138***
	(0.056)	(0.027)
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
Adj R-squared	0.3849	0.5380
Observations	23,676	17,024

Notes: Standard errors are clustered at city level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 8. The effects of gig economy on on-the-job training

Variables	(1)	(2)
	On-the-job training	Log form of training duration
A. Individual-level panel dataset		
Gig economy platform	-0.044**	-0.529***
	(0.019)	(0.089)
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
Adj R-squared	0.1561	0.3133
Observations	85,860	22,492
B. Firm-level panel dataset		
Gig economy platform	-0.016*	-0.517***
	(0.009)	(0.080)
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
Adj R-squared	0.8023	0.7439
Observations	8,909	8,014

Notes: Standard errors are clustered at city level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

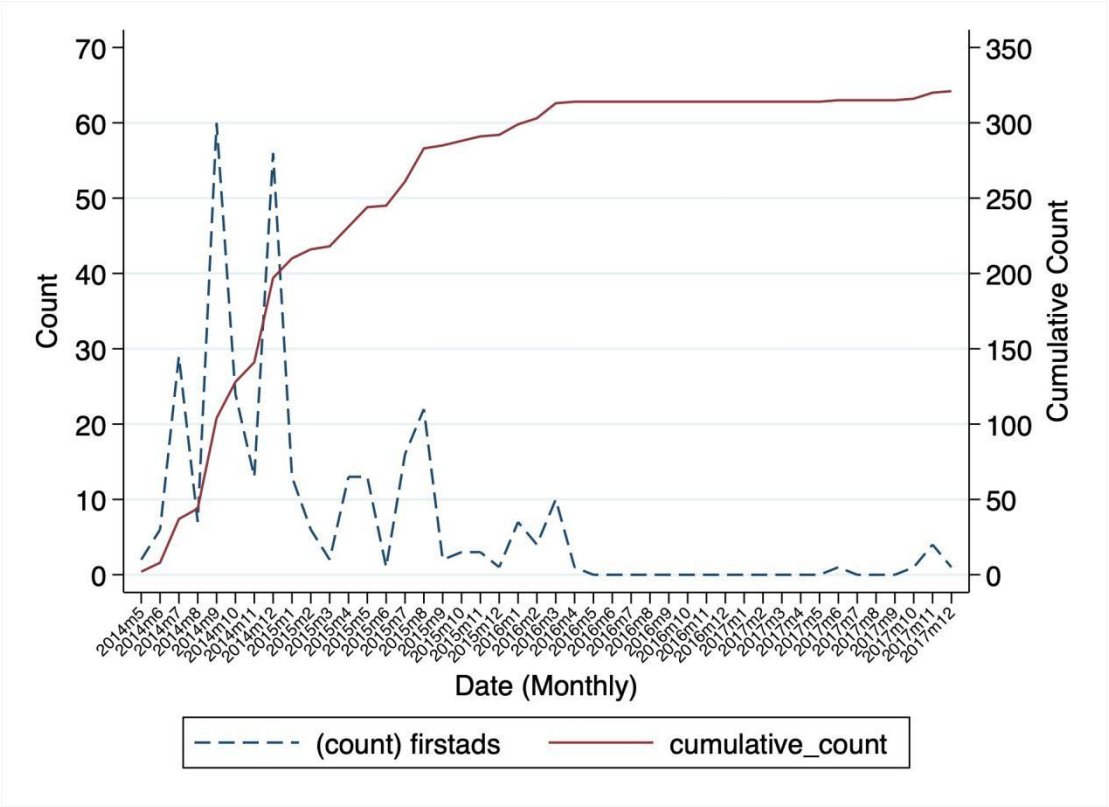
Table 9. The effects of gig economy on robot adoption

Variables	(1)	(2)
	Robot adoption	Share of robots in total fixed assets
Gig economy platform	0.033***	0.841**
	(0.006)	(0.343)
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
Adj R-squared	0.8785	0.7434
Observations	8,909	8,909

Notes: Standard errors are clustered at city level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

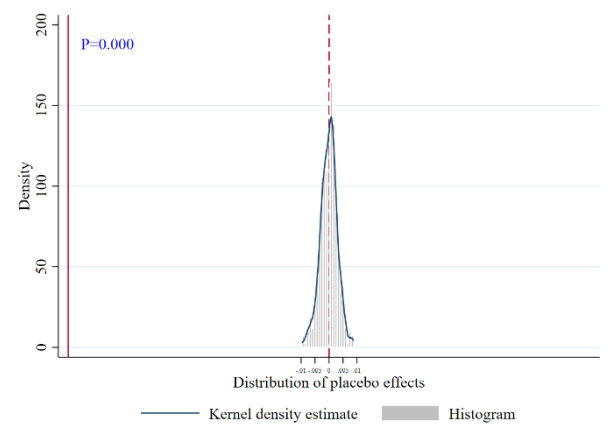
Appendix

Figure A1. Alternative Measure of Platform Entry Timing using Mo and Li (2022)'s Definition: Monthly New Entries and Cumulative Coverage

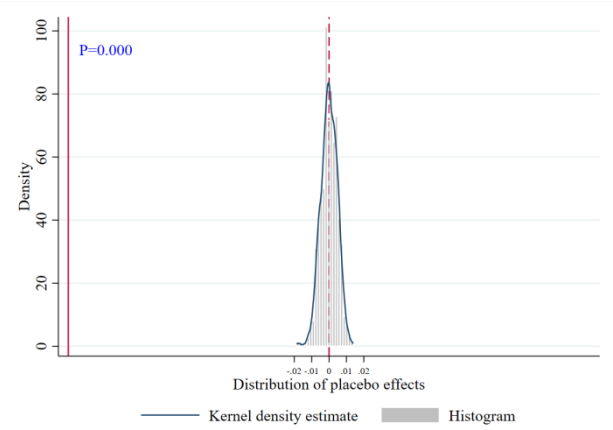


Notes: This figure replicates Figure 1 using an alternative definition of city-level platform entry based on Mo and Li (2022). The horizontal axis reports calendar months. The left y-axis measures the number of cities that experience their first platform entry in a given month (monthly new entries). The right y-axis measures the cumulative number of cities that have been entered by at least one platform up to and including that month (cumulative coverage). The blue dashed line plots monthly new entries, and the red solid line plots cumulative coverage. A city is defined as "entered" in the month when we first observe a food-delivery–related job posting according to the Mo and Li (2022)'s coding rule; we then aggregate the implied first-entry months across cities to construct the flow and cumulative series.

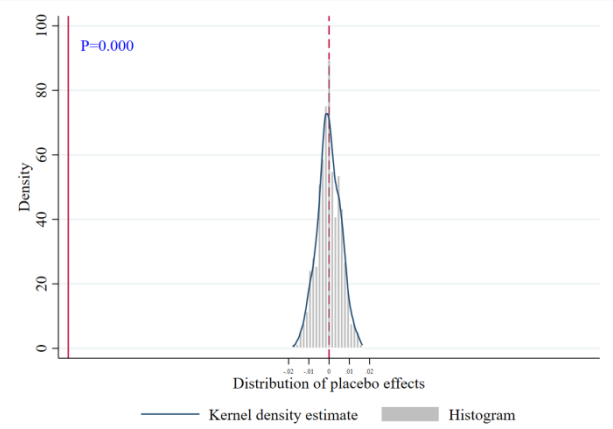
Figure A2. Placebo tests for the DID estimations (Employment contract measures)



A. Employment contract



B. Long-term employment contract



C. Log form employment contract term

Table A1-1. The effects of gig economy on employment contract (Wooldridge, 2025)

Variables	(1) Employment contract	(2) Long-term employment contract	(3) Log form employment contract term
Gig economy platform	-0.487***	-0.050	-0.407***
	(0.028)	(0.031)	(0.033)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Adj R-squared	0.3204	0.2137	0.3615
Observations	33,662	29,671	24,348

Notes: Standard errors are clustered at city level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A1-2. The effects of gig economy on employment contract (Wooldridge, 2025)

Variables	(1) Employment contract	(2) Long-term employment contract	(3) Log form employment contract term
Gig economy platform (0)	-0.285***	-0.097***	-0.320***
	(0.017)	(0.018)	(0.014)
Gig economy platform (1)	-0.559***	-0.050	-0.476***
	(0.028)	(0.035)	(0.037)
Gig economy platform (2)	-0.703***	0.036	-0.442***
	(0.050)	(0.051)	(0.065)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Adj R-squared	0.3204	0.2137	0.3615
Observations	33,662	29,671	24,348

Notes: Standard errors are clustered at city level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A2-1. The effects of gig economy on employment contract (alternative measure)

Variables	(1) Employment contract	(2) Long-term employment contract	(3) Log form employment contract term
Gig economy platform	-0.059**	-0.068**	-0.123***
	(0.029)	(0.027)	(0.020)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Adj R-squared	0.2723	0.2474	0.2781
Observations	85,860	75,465	60,671

Notes: Standard errors are clustered at city level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A2-2. The effects of gig economy on monthly income (log form, yuan, alternative measure)

Variables	(1) Long-term contracts	(2) No contracts/Short-term contracts
A. For all workers		
Gig economy platform	0.098**	-0.069***
	(0.038)	(0.016)
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
Adj R-squared	0.4053	0.4803
Observations	52,871	32,989
B. For non-managerial and non-skilled workers		
Gig economy platform	0.125***	-0.060***
	(0.044)	(0.021)
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
Adj R-squared	0.3828	0.5375
Observations	23,676	17,024

Notes: Standard errors are clustered at city level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A2-3. The effects of gig economy on on-the-job training (alternative measure)

Variables	(1)	(2)
	On-the-job training	Log form of training duration
A. Individual-level panel dataset		
Gig economy platform	-0.023*	-0.404***
	(0.013)	(0.076)
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
Adj R-squared	0.1560	0.3122
Observations	85,860	22,492
B. Firm-level panel dataset		
Gig economy platform	-0.014**	-0.309***
	(0.007)	(0.094)
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
Adj R-squared	0.8023	0.7413
Observations	8,909	8,014

Notes: Standard errors are clustered at city level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A2-4. The effects of gig economy on robot adoption (alternative measure)

Variables	(1)	(2)
	Robot adoption	Share of robots in total fixed assets
Gig economy platform	0.029***	0.802**
	(0.007)	(0.309)
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
Adj R-squared	0.8785	0.7435
Observations	8,909	8,909

Notes: Standard errors are clustered at city level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.