The Fear of Falling Behind: Product Market Rivalry and Talent Competition in China*

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Abstract

We examine how Chinese firms compete for high-skilled talent using novel text-based product market competitor networks and job posting data. We document strong strategic complementarity: a one unit increase in rivals' high-skilled postings raises a firm's own postings by 0.6, generating a multiplier of 2.5. This competition is product-market driven, national in scope, and absent for low-skilled workers. Crucially, the strength of strategic complementarity increases with the downside risk of falling behind. A theoretical model shows complementarity arises when the fear of falling behind outweighs the gain from leading. Our results indicate that talent competition amplifies labor demand and is a central channel for product-market rivalry.

Keywords: strategic complementarity, DMP, peer effects, competition network.

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1 Introduction

Talent is widely regarded as one of the most critical resources for modern firms (e.g., Fedyk and Hodson, 2023; Prato, 2025). Skilled workers are the engines of technological innovation, the architects of new business lines, and the drivers of organizational adjustments, collectively shaping a firm's core competitive advantages. Consequently, the ability to compete for such talent is central to a firm's sustained performance and its marketplace rivalry. This competition could be especially intense in China, where a relative scarcity of high-skilled workers compared to developed economies coincides with highly competitive product markets. In this paper, we examine the following questions: how do Chinese firms strategically compete for high-skilled workers, and what are the implications of this competition for labor market and product market equilibrium?

To provide a foundation for our empirical analysis, we construct a parsimonious Diamond-Mortensen-Pissarides (DMP) search and matching model. We use this framework to examine how product market competition and labor market frictions jointly shape firms' strategic hiring decisions and to derive testable empirical predictions. The model features two initially symmetric, competing firms that hire high-skilled workers (for innovation) and low-skilled workers (for production) in separate frictional labor markets. Stochastic innovations lead to either a tie or a leader–follower product market outcome. Firm value is rank-dependent—the leader earns a premium, while the follower incurs a penalty—implying that the marginal return to innovation depends critically on whether the rival also innovates.

The model generates two main insights. First, *strategic complementarity* in high-skilled hiring arises from innovation competition only when the penalty of falling behind outweighs the gain from pulling ahead. This asymmetry is crucial because a rival's increased hiring simultaneously reduces a firm's chance of becoming the leader and raises its risk of becoming a follower. If the cost of falling behind is sufficiently large, the defensive motive prevails, prompting the firm to recruit additional high-skilled workers to avoid losing ground. Conversely, when the prospect of gaining an advantage is stronger, a rival's increased hiring can instead reduce a firm's own hiring incentives. In contrast, low-skilled hiring lacks this innovation-driven strategic channel.

Second, the model demonstrates that this strategic complementarity can be attenuated or even reversed by labor-market congestion when firms operate in the same local market. In that case, a rival's increased hiring raises the labor-market tightness ratio, which drives up the marginal cost of hiring through the standard *congestion effect* (Mercan et al., 2024) and creates *strategic substitutability*. Consequently, the net effect of a rival's hiring becomes ambiguous when firms share a labor market. By contrast, when firms locate in different separate labor markets, congestion effects are absent, leaving only the strategic complementarity in high-skilled hiring.

Guided by these theoretical insights, we develop a novel empirical strategy by integrating job postings from China's largest online recruitment platform (51job) with granular financial reports of listed firms. We first construct a dynamic, text-based measure of product market competition network by analyzing the Management Discussion and Analysis (MD&A) sections of corporate filings, following the method of Hoberg and Phillips (2016). This yields a yearly, intransitive network that identifies each firm's principal product market competitors. We then estimate spatial autoregressive (SAR) models on this network to test for strategic complementarity in hiring of high-skilled workers. The SAR framework is well-suited to our goal as it directly quantifies the degree to which a firm's high-skilled job postings respond to the average postings of its network-defined competitors.

The primary empirical challenge in identifying strategic interactions is the reflection problem (Manski, 1993): the simultaneity between a firm's actions and its peers' actions makes it difficult to separate true strategic responses from spurious correlation driven by common shocks. To overcome this, we control a comprehensive set of fixed effects to address common shocks at different levels, such as firm and industry-by-year fixed effects. Furthermore, we employ an instrumental variable (IV) strategy that exploits the structure of our competition network. Following the network econometric literature (Bramoullé et al., 2009; Lin, 2010), we use the characteristics of a firm's direct competitors and, critically, the characteristics of its second-order competitors as instruments. The identification strategy relies on the partial (not necessarily full) intransitivity of our text-based network, in which not all of a firm's second-order competitors are its direct competitors. Under this structure, those intransitive second-order competitors can influence the focal firm's hiring only indirectly by affecting the hiring behavior of direct competitors—not directly or through shared contemporaneous labor demand shocks—after controlling for direct competitors' hiring, fixed effects and the focal firm's characteristics. This network-based IV design isolates strategic hiring responses and remains robust to common industry-level or aggregate shocks. Diagnostic tests confirm that our instruments satisfy relevance and exclusion restrictions and are plausibly exogenous.

Our analysis reveals four novel facts. Fact 1 is that there is strong strategic complementarity in the hiring of high-skilled workers: a one unit increase in a firm's rivals' high-skilled job postings leads to a 0.6 increase in the firm's own postings. This interdependence triggers a multiplier effect; the initial competitive response induces further rounds of reaction from competitors. The resulting multiplier is 1/(1-0.6) = 2.5, indicating that competitive dynamics cause firms to post, on average, 2.5 times the vacancies they would in a non-strategic setting. This demonstrates that localized labor demand shocks can be strongly amplified through strategic interactions across firms. This complementarity is not driven by learning or imitation, as firms do not respond more strongly to hiring by industry leaders—presumably better informed about future market conditions—or to supply-chain partners, who might facilitate information sharing. Moreover, we find that this complementarity holds for high-skilled workers, but not for low-skilled workers.

Fact 2 establishes that this competition operates at the product market level and is national in scope. Firms respond to the aggregate high-skilled job posting of their competitors across the entire country, with no significant reaction to geographically localized hiring activity, consistent with the dampening of complementarity by local labor market congestion. Furthermore, the competition is specific to product market rivals: firms adjust their behavior based on the actions of firms with similar business operations but show no significant response to non-competitors in the same local labor market. This pattern indicates that strategic competition for high-skilled labor among listed firms is driven predominantly by the pursuit of competitive advantage in national product markets, rather than by localized labor market dynamics.

Fact 3 is that the intensity of strategic complementarity varies with the downside risk of falling behind. Consistent with our model's mechanism, we find that firms in product market competition networks with a fatter left tail of the firm-value distribution –where the penalty for lagging is more severe– exhibit a stronger hiring response to rivals' moves. This pattern underscores that the fear of becoming a follower, rather than the ambition to become a leader, is a primary driver of aggressive hiring behavior in high-skilled labor markets.

Fact 4 documents that high-skilled hiring has significant effect on firms' performance. A firm's own hiring of high-skilled workers boosts its market share, market capitalization share, and patent output. In contrast, rivals' hiring reduces the firm's market share and market capitalization, though it does not significantly affect its innovation output. The findings confirm the model setting that high-skilled hiring shapes not only innovation potential but also market leadership and firm value.

This paper contributes to three strands of literature. First, it connects to research on the role of skilled workers in economic growth and firm dynamics (Hsieh et al., 2019; Chang and Hong, 2019; Martellini, 2022; Fedyk and Hodson, 2023; Babina et al., 2024; Akcigit et al., 2025). While prior work focuses on the returns to talent, we examine the strategic process of talent acquisition itself, offering evidence on how firms compete to secure this critical resource.

Second, the paper relates to the macroeconomic literature on strategic interactions in labor markets (Diamond, 1982; Diamond and Fudenberg, 1989; Kaplan and Menzio, 2016; Schaal and Taschereau-Dumouchel, 2016; Eeckhout and Lindenlaub, 2019; Mercan and Schoefer, 2020; Fernández-Villaverde et al., 2025a). Our contribution is twofold: we introduce a new mechanism based on product-market competition, and we address the long-standing scarcity of firm-level empirical evidence on strategic complementarities by applying established spatial econometric techniques.

Finally, this paper speaks to two related strands of research. The first examines the consequences of competition for skilled workers, often taking such competition as given (Marinovic and Povel, 2017; He, 2018; Bessen et al., 2024; Indriawan et al., 2024; Chen et al., 2025). The second explores firm-level recruitment and retention strategies (De Bettignies and Chemla, 2008; Damiano et al., 2012; Abebe et al., 2021; Kim, 2022; Black et al., 2024; Huang et al., 2024; Board et al., 2025; Fernández-Villaverde et al., 2025b; Benkert et al., 2025). We connect these perspectives by directly testing for strategic interactions in hiring. Our empirical analysis documents strong strategic complementarity in the acquisition of skilled workers, while our theoretical framework characterizes the conditions under which such complementarity emerges.

The paper is structured as follows. Section 2 introduces a parsimonious model examining the interplay between product market competition and labor market friction. Section 3 presents four novel facts on strategic complementarity in firms' high-skilled hiring. Section 4 concludes.

2 A Model of Talent Competition

In this section, we develop a DMP search and matching framework to analyze how product market competition and labor market frictions jointly shape firms' strategic hiring decisions. The model delivers predictions about when firms' hiring decisions are strategic complements, which will guide our empirical analysis.

2.1 Baseline Environment

Consider two firms, a and b, that compete in a product market. Both firms start with the same technology level L. Innovation outcomes determine the market structure.[1] Successful research and development (R&D) allows a firm to advance its technology by one level. If

[1] The model's focus on R&D serves as a representative channel for how talent drives firm value; the underlying logic of strategic complementarity remains invariant to other high-skilled roles, such as business development, which our empirical evidence includes are equally subject to product-market rivalry.

both firms innovate or both fail to innovate, they remain tied in technology. If only one firm innovates, it becomes the technological leader, while the other becomes the follower, creating a leader–follower market structure.

The market structure is crucial because firm value depends on product market ranking. When firms are tied—that is, when they have the same technology level—each earns a baseline payoff π. When they differ in technology, the leader earns more $(\pi + \Delta^+)$, capturing the benefits of higher output, greater market power, and a lower risk of displacement. The follower earns less $(\pi - \Delta^-)$, reflecting reduced markups due to a smaller market share and a higher risk of displacement. For analytical tractability, these value functions are expressed in reduced form, but they can be microfounded in a richer environment with monopolistic competition and endogenous firm exit.

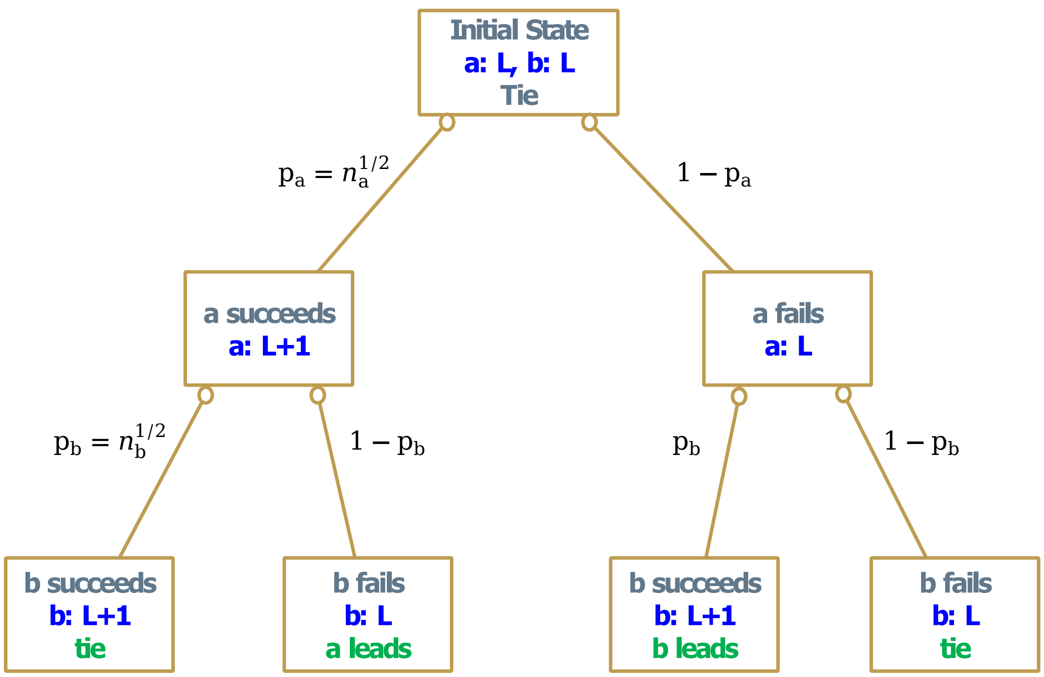

Figure 1: Innovation Outcomes and Technology Levels

The payoff to innovation. Firms hire high-skilled workers to conduct R&D. The innovation probability for firm k is:

$$p_k = n_k^{1/2}, \quad k \in \{a, b\},$$

where $n_k \in [0, 1]$ is the measure of high-skilled workers employed. The concave probability function captures diminishing returns in research production. Firms move simultaneously in the labor market.

Figure 1 illustrates the stochastic innovation process. Both firms begin at level L. With probability $p_a p_b$, both advance to $L+1$ and remain tied. With probability $p_a(1-p_b)$, only firm a advances, becoming the leader. With probability $(1-p_a)p_b$, only firm b advances, becoming the leader. With probability $(1-p_a)(1-p_b)$, neither innovates, and both remain tied at L.

Next, we derive the incremental value of successful innovation for firm a, denoted Δ_a, depends on firm b's innovation outcome. Consider two scenarios.

First, suppose firm b innovates successfully (with probability p_b). If firm a also innovates, they remain tied and firm a's value is π. If firm a fails, it becomes the follower with value $\pi - \Delta^-$. Thus, conditional on firm b's success, innovation is worth Δ^- to firm a.

Second, suppose firm b fails to innovate (probability $1-p_b$). If firm a innovates, it becomes the leader with value $\pi + \Delta^+$. If it fails, they remain tied at value π. Thus, conditional on firm b's failure, innovation is worth Δ^+ to firm a.

Therefore, the expected value of innovation for firm a is

$$\Delta_a = p_b \Delta^- + (1-p_b)\,\Delta^+ = n_b^{1/2}\Delta^- + \left(1 - n_b^{1/2}\right)\Delta^+, \tag{1}$$

which depends on firm b's employment of high-skilled workers. Firm b's innovation value is symmetric.

2.2 Labor Market Frictions

Both high-skilled and low-skilled labor markets are frictional. Firms must post vacancies to search for and match with workers. Let u_i and $\widetilde{u}_i$ denote the measures of high-skilled and low-skilled workers searching for jobs in location i, respectively. Similarly, let v_i and $\widetilde{v}_i$ denote the measures of vacancies for high-skilled and low-skilled workers in location i, which equal the sums of vacancies posted by all firms in that location. Posting a vacancy incurs a unit cost κ for either type.

Matches are determined by standard constant-returns-to-scale matching functions: $M_i = M(u_i, v_i)$ for high-skilled workers and $\widetilde{M}_i = M(\widetilde{u}_i, \widetilde{v}_i)$ for low-skilled workers. The labor market tightness ratios are defined as $\theta_i = v_i/u_i$ and $\widetilde{\theta}_i = \widetilde{v}_i/\widetilde{u}_i$. The job finding rates for workers are $\mu(\theta_i) = M_i/u_i = M(1, \theta_i)$ and $\widetilde{\mu}(\widetilde{\theta}_i) = \widetilde{M}_i/\widetilde{u}_i = M(1, \widetilde{\theta}_i)$, while the vacancy filling rates for firms are $q(\theta_i) = M_i/v_i = M(1/\theta_i, 1)$ and $\widetilde{q}(\widetilde{\theta}_i) = \widetilde{M}_i/\widetilde{v}_i = M(1/\widetilde{\theta}_i, 1)$. The functions $\mu(\theta_i)$ and $\widetilde{\mu}(\widetilde{\theta}_i)$ are increasing in their arguments, while $q(\theta_i)$ and $\widetilde{q}(\widetilde{\theta}_i)$ are decreasing. For analytical tractability, we assume that matches last only one period and dissolve at the end of each period.

We assume firm a is located in area i; the location of firm b will be specified later. Under the law of large numbers, to hire n_a high-skilled workers and $\widetilde{n}_a$ low-skilled workers in location

i, firm a need to post $v_a = n_a/q(\theta_i)$ and $\widetilde{v}_a = \widetilde{n}_a/\widetilde{q}(\widetilde{\theta}_i)$ vacancies, respectively. Tighter labor markets (higher θ_i or $\widetilde{\theta}_i$) imply lower vacancy filling rates, requiring the firm to post more vacancies to achieve a given hiring target. The economy also contains other firms beyond firms a and b. While these firms do not compete with a or b in the product market, they may affect labor market tightness in the labor markets where a or b hire. Following standard practice in business-cycle models, we assume firms begin with zero employment of each worker type. This assumption is made without loss of generality: while initial employment would influence the total cost of vacancy posting, it does not affect the optimal employment decision. This is because the vacancy cost function is linear, rendering the marginal cost of posting a vacancy—and thus the first-order condition for target employment—independent of initial employment levels.[2]

2.3 Firms' Optimal Hiring Decision

Firm a chooses high-skilled employment n_a and low-skilled employment $\widetilde{n}_a$ to maximize expected value, which comprises the expected benefit from innovation (depending on high-skilled workers) and the output from production (depending on low-skilled workers), net of total wage and vacancy costs for both types of labor.

Formally, taking firm b's employment as given, firm a solves:

$$\max_{n_a,\widetilde{n}_a} \underbrace{p_a(n_a)\Delta_a}_{\text{R\&D benefit}} + \underbrace{z_a\widetilde{n}_a^{\alpha}}_{\text{Production output}} - \underbrace{[n_a w_a + \widetilde{n}_a \widetilde{w}_a]}_{\text{Total wage cost}} - \underbrace{\left[\kappa n_a/q(\theta_i) + \kappa \widetilde{n}_a/\widetilde{q}(\widetilde{\theta}_i)\right]}_{\text{Total vacancy cost}}, \tag{2}$$

where $p_a(n_a) = n_a^{1/2}$, Δ_a denotes the expected value of innovation given by equation (1). z_a is the predetermined productivity of low-skilled workers, and $\alpha \in (0,1)$ is the output elasticity with respect to low-skilled labor. The term $z_a\widetilde{n}_a^{\alpha}$ represents the output produced by low-skilled workers. w_a and $\widetilde{w}_a$ are the wage rates for high- and low-skilled workers, respectively, determined through Nash bargaining as discussed below. The vacancy costs in the high- and low-skilled labor markets are given by $\kappa n_a/q(\theta_i)$ and $\kappa\widetilde{n}_a/\widetilde{q}(\widetilde{\theta}_i)$, respectively.

For simplicity, our benchmark model assumes that low-skilled productivity, z_a, is predetermined and contemporaneously unaffected by the outcome of R&D; productivity gains from innovation materialize only with a lag. This assumption yields a clean analytical separation between high-skilled hiring (which is strategic due to rank-dependent innovation payoffs) and low-skilled hiring (which is not). In Appendix A, we relax this assumption and allow current

[2]Formally, with initial employment levels $n_{a,0}$ and $\widetilde{n}_{a,0}$ in equation (2), the total vacancy cost becomes $\kappa(n_a - n_{a,0})/q(\theta_i) + \kappa(\widetilde{n}_a - \widetilde{n}_{a,0})/\widetilde{q}(\widetilde{\theta}_i)$. The marginal costs with respect to n_a and $\widetilde{n}_a$ are $\kappa/q(\theta_i)$ and $\kappa/\widetilde{q}(\widetilde{\theta}_i)$, respectively, which do not depend on $n_{a,0}$ or $\widetilde{n}_{a,0}$.

low-skilled productivity to depend on current innovation outcomes. This modification generates strategic cross-effects in the hiring of both skill types, at the cost of greater analytical complexity.

Match value and wage determination. For high-skilled workers, the firm's value from the match is

$$J_a = p_a'(n_a)\Delta_a - w_a,$$

where $p_a'(n_a)\Delta_a$ is the marginal product of labor (MPL) for high-skilled workers. The worker's value is

$$W_a = w_a - h,$$

where h denotes the worker's outside option, such as the expected value of finding a job elsewhere, home production, or leisure. The total surplus is

$$TS_a = J_a + W_a = p_a'(n_a)\Delta_a - h,$$

which is the sum of the firm and the worker's gain from the match.

Wages are determined by Nash bargaining between firm and worker. Once a match is formed, the wage splits the total surplus according to fixed bargaining shares. Assuming the firm's bargaining share is τ and the worker's is $1-\tau$, Nash bargaining yields:

$$w_a = (1-\tau)p_a'(n_a)\Delta_a + \tau h, \tag{3}$$

which shows that the high-skilled wage is the weighted average of high-skilled worker's MPL and outside option value.

The wage determination for low-skilled workers is similar to the high-skilled case. The firm's value is $\widetilde{J}_a = z_a\alpha\widetilde{n}_a^{\alpha-1} - \widetilde{w}_a$, where $z_a\alpha\widetilde{n}_a^{\alpha-1}$ is the MPL of the low-skilled worker. The worker's value is $\widetilde{W}_a = \widetilde{w}_a - \widetilde{h}$, where $\widetilde{h}$ is the low-skilled worker's outside option. The total surplus is determined by the sum of these two values: $\widetilde{TS}_a = z_a\alpha\widetilde{n}_a^{\alpha-1} - \widetilde{h}$. With bargaining share $\widetilde{\tau}$ for the firm and $1-\widetilde{\tau}$ for the low-skilled worker, the wage is:

$$\widetilde{w}_a = (1-\widetilde{\tau})z_a\alpha\widetilde{n}_a^{\alpha-1} + \widetilde{\tau}\widetilde{h}, \tag{4}$$

which shows that the low-skilled wage is the weighted average of low-skilled worker's MPL and outside option value.

Optimality conditions. Substituting the wage equations (3) and (4) into equation (2), the firm's optimization problem becomes:

$$\max_{n_a, \widetilde{n}_a} \Big[p_a(n_a) - (1-\tau) n_a p'_a(n_a)\Big] \Delta_a - \Big[\tau h + \kappa / q(\theta_i)\Big] n_a$$
$$+ \Big[1 - (1-\alpha)(1-\widetilde{\tau})\Big] z_a \widetilde{n}_a^{\alpha} - \Big[\widetilde{\tau}\widetilde{h} + \kappa / \widetilde{q}(\widetilde{\theta}_i)\Big] \widetilde{n}_a.$$

The first-order conditions with respect to n_a and $\widetilde{n}_a$ are:

$$\left[p'_a(n_a) - (1-\tau)\big(p'_a(n_a) + n_a p''_a(n_a)\big)\right] \Delta_a - \tau h = \kappa / q(\theta_i), \tag{5}$$

for the high-skilled worker, and

$$\alpha \Big[1 - (1-\alpha)(1-\widetilde{\tau})\Big] z_a \widetilde{n}_a^{\alpha-1} - \widetilde{\tau}\widetilde{h} = \kappa / \widetilde{q}(\widetilde{\theta}_i), \tag{6}$$

for the low-skilled worker, respectively. Equations (5) and (6) reflect the standard equilibrium condition that the expected marginal value generated by a match equals the marginal cost of forming that match.

Using $p_a(n_a) = n_a^{1/2}$, we have $p'_a(n_a) = \frac{1}{2} n_a^{-1/2}$ and $p''_a(n_a) = -\frac{1}{4} n_a^{-3/2}$. Substituting these into equation (5) yields:

$$\left(\frac{1+\tau}{4}\right) n_a^{-1/2} \Delta_a = \tau h + \kappa / q(\theta_i),$$

which further implies

$$n_a^* = \left\{ \frac{(1+\tau)\Delta_a}{4\left[\tau h + \kappa / q(\theta_i)\right]} \right\}^2. \tag{7}$$

Equation (7) shows that high-skilled hiring n_a^* increases with the expected value of innovation Δ_a and decreases with the high-skilled labor market tightness θ_i, since $q'(\theta_i) < 0$. Intuitively, a higher Δ_a raises the marginal benefit of R&D, incentivizing the firm to hire more high-skilled workers. Conversely, a higher θ_i reflects a tighter labor market, which lowers the vacancy-filling rate $q(\theta_i)$ and raises effective hiring costs, thereby reducing optimal employment.

Similarly, equation (6) implies

$$\widetilde{n}_a^* = \left\{ \frac{\big[1 - (1-\alpha)(1-\widetilde{\tau})\big] z_a \alpha}{\widetilde{\tau}\widetilde{h} + \kappa / \widetilde{q}(\widetilde{\theta}_i)} \right\}^{1/(1-\alpha)}, \tag{8}$$

which shows that the hiring of low-skilled worker increases with the productivity z_a, while decreases with the low-skilled tightness ratio $\widetilde{\theta}_i$.

The corresponding optimal vacancy postings are $v_a^* = n_a^* / q(\theta_i)$ and $\widetilde{v}_a^* = \widetilde{n}_a^* / \widetilde{q}(\widetilde{\theta}_i)$ for high- and low-skilled workers, respectively.

Firm b's problem is symmetric: taking firm a's employment as given, its optimal employment levels are determined by

$$n_b^* = \left\{ \frac{(1+\tau)\Delta_b}{4\left[\tau h + \kappa/q(\theta_j)\right]} \right\}^2, \quad \text{and} \quad \widetilde{n}_b^* = \left\{ \frac{\left[1-(1-\alpha)(1-\widetilde{\tau})\right] z_b \alpha}{\widetilde{\tau}\widetilde{h} + \kappa/\widetilde{q}(\widetilde{\theta}_j)} \right\}^{1/(1-\alpha)}$$

for high-skilled and low-skilled workers, respectively, where j denotes firm b's location, which may be the same as or different from i. The corresponding optimal vacancy postings are then given by $v_b^* = n_b^*/q(\theta_j)$ and $\widetilde{v}_b^* = \widetilde{n}_b^*/\widetilde{q}(\widetilde{\theta}_j)$.

2.4 Strategic Interactions in Vacancy Posting

In this section, we examine the central question: How does firm a's vacancy postings depend on firm b's vacancy postings. We distinguish between two geographic scenarios: when both firms operate in the same local labor market and when they operate in separate markets.

2.4.1 High-skilled hiring

For high-skilled hiring, the optimal vacancy posting $v_a^* = n_a^*/q(\theta_i)$ depends on firm b's actions through two channels: (i) the innovation value Δ_a, which is a function of n_b (equation (1)), and (ii) the labor market tightness θ_i when firms are in the same market.

Case 1: Firms locate in different labor markets. When firm b is located in area $j \neq i$, its high-skilled vacancy posting v_b does not affect the high-skilled labor market tightness ratio in area i, θ_i. However, it influences firm a's expected innovation value, Δ_a, because $n_b = v_b q(\theta_j)$, while n_b affects firm a's expected technological rank as in equation (1). Substituting $n_b = v_b q(\theta_j)$ and equation (1) into equation (7) and using $v_a^* = n_a^*/q(\theta_i)$ yields:

$$v_a^* = \underbrace{\frac{(1+\tau)^2}{16\left[\tau h + \kappa/q(\theta_i)\right]^2}}_{\text{Empl response to innovation value}} \times \underbrace{\frac{1}{q(\theta_i)}}_{\text{Vacancy-empl ratio}} \times \underbrace{\left[v_b^{1/2} q(\theta_j)^{1/2}(\Delta^- - \Delta^+) + \Delta^+\right]^2}_{\text{Innovation value}}. \tag{9}$$

From equation (9), it entails that firm a's high-skilled vacancy, v_a^*, increases with firm b's high-skilled vacancy, v_b, if and only if

$$\Delta^- - \Delta^+ > 0. \tag{10}$$

Condition (10) holds whenever Δ^- (the loss to the follower) is larger than Δ^+ (the benefit to the leader).[3] This leads to the following characterization of strategic interactions between the two firms.

Proposition 1. *When the two firms locate in different areas, vacancy postings in high-skilled labor*

[3] Note that $\partial v_a^*/\partial v_b \propto \left[v_b^{1/2} q(\theta_j)^{1/2}(\Delta^- - \Delta^+) + \Delta^+\right](\Delta^- - \Delta^+)$, and $v_b^{1/2} q(\theta_j)^{1/2}(\Delta^- - \Delta^+) + \Delta^+ = \Delta_a > 0$.

markets are:

(i) If $\Delta^- > \Delta^+$, then $\partial v_a^* / \partial v_b > 0$. Vacancy postings are strategic complements: firms respond to increased hiring by a rival by increasing their own hiring.

(ii) If $\Delta^- < \Delta^+$, then $\partial v_a^* / \partial v_b < 0$. Vacancy postings are strategic substitutes: firms respond to increased hiring by a rival by decreasing their own hiring.

The intuition of Proposition 1 is as follows. When $\Delta^- > \Delta^+$, the primary motive is to avoid the follower's penalty. An increase in v_b (and hence in p_b) raises firm a's probability of becoming the follower, which occurs with probability $p_b(1-p_a)$. In response, firm a scales up its own hiring effort, leading to strategic complementarity.

Conversely, when $\Delta^- < \Delta^+$, the primary motive is to capture the leader's reward. An increase in v_b reduces firm a's probability of becoming the leader, which occurs with probability $(1-p_b)p_a$. As the expected return from trying to overtake the rival diminishes, firm a scales back its own effort, resulting in strategic substitutability.

Case 2: Firms locate in the same labor market. Now suppose both firms post high-skilled vacancies in the same area i. Then v_b not only affects the expected innovation value v_a as in the previous case, but also affects area i's labor market tightness ratio $\theta_i = (v_b + v_{-b})/u_i$, where v_{-b} denotes vacancies posted by other firms (including firm a). A higher v_b raises θ_i, which reduces vacancy filling rate $q(\theta_i)$ and makes firm a's hiring more costly because $q'(\theta_i) < 0$.

The reduction in $q(\theta_i)$, which reflects a pure labor-market channel, exerts two countervailing forces on v_a^*, as shown in equation (9). First, a lower $q(\theta_i)$ raises the effective marginal hiring cost $\kappa/q(\theta_i)$, dampening the desired employment level n_a^*—this is the standard *congestion effect* common to DMP settings. Second, the same reduction in $q(\theta_i)$ increases the vacancy-employment ratio $1/q(\theta_i)$, compelling the firm to post more vacancies for any given target n_a^*. This second channel arises because our model allows firms to choose a continuous employment level, unlike the canonical one-worker-per-firm DMP formulation. The net impact on equilibrium vacancies v_a^* depends on which of these two forces dominates, a condition that varies with the model's parameters.

To illustrate, consider the limiting case where the worker's outside option is negligible, $h \approx 0$. The first two multiplicative terms in (9) then reduce to $(1+\tau)^2 q(\theta_i)/(16\kappa)$, which rises with $q(\theta_i)$ and thus falls as v_b increases. Here, the conventional congestion channel dominates: higher rival hiring tightens the market, lowers the vacancy-filling rate, and discourages the firm's own vacancy posting. Consequently, for a fixed innovation value Δ_a, v_a^* decreases with v_b, implying that vacancies become strategic substitutes—consistent with the standard DMP intuition. If, however, h is sufficiently large, the hiring-cost component $\tau h + \kappa / q(\theta_i)$ becomes less sensitive to $q(\theta_i)$, and the sign of the relationship may flip, potentially restoring strategic complementarity.[4]

Finally, as in Case 1, the innovation value term in (9) increases with v_b whenever condition (10) holds.[5] In summary, when firms operate in the same labor market, the effect of v_b on v_a^* is more ambiguous than when they operate in separate markets, reflecting the tension between strategic complementarity in innovation incentives and potential strategic substitutability due to labor market congestion.

The above results are summarized by the following proposition.

Proposition 2. *Suppose firms a and b compete for high-skilled workers in the same labor market i. The net effect of v_b on v_a^* is the sum of three channels:*

(i) The innovation incentive (as in Proposition 1), which is positive if $\Delta^- > \Delta^+$ and negative if $\Delta^- < \Delta^+$;

(ii) The congestion effect, whereby a rise in v_b raises θ_i, lowers $q(\theta_i)$, and increases the effective marginal hiring cost, tending to reduce v_a^*;

(iii) The vacancy requirement effect, whereby a lower $q(\theta_i)$ forces the firm to post more vacancies to achieve a given employment target, tending to increase v_a^*.

The overall sign of $\partial v_a^* / \partial v_b$ is ambiguous and depends on parameters.

Proposition 2 shows that when firms compete in the same labor market, the impact of a rival's hiring on a firm's own vacancy posting reflects the interplay of three distinct channels – innovation incentives, labor market congestion, and vacancy requirements– leading to parameter-dependent strategic interactions that may be either complementary or substitutive.

Amplification of idiosyncratic shocks. Strategic complementarity amplifies labor demand shocks: an initial shock to one firm's hiring propagates through the product market competition as rival responds, generating a total effect larger than the initial impulse.

Let λ denote the slope of a firm's best response function—the change in its high-skilled vacancies resulting from a one-unit change in its competitor's vacancies:

$$\lambda = \frac{\partial v_a^*}{\partial v_b} = \frac{\partial v_b^*}{\partial v_a}. \tag{11}$$

[4] However, h cannot exceed the marginal product of labor for the match to be viable.

[5] Note that $v_b^{1/2} q(\theta_j)^{1/2}$ increases with v_b when $v_{-b} > 0$.

When the condition for strategic complementarity holds, we have $\lambda > 0$.

Consider a small exogenous shock to firm b's innovation productivity that directly increases its high-skilled vacancies by δ. Firm a responds by increasing its own vacancies by $\lambda\delta$, which induces a further reaction from firm b of $\lambda^2\delta$, prompting another round of adjustment by firm a, and so on. This iterative process continues indefinitely.

Summing across all rounds, the total change in firm b's vacancies is:

$$\Delta v_b^{\text{total}} = \delta + \lambda^2\delta + \lambda^4\delta + \cdots = \delta \sum_{k=0}^{\infty} \lambda^{2k} = \frac{\delta}{1-\lambda^2}.$$

Similarly, the total change in firm a's vacancies is:

$$\Delta v_a^{\text{total}} = \lambda\delta + \lambda^3\delta + \lambda^5\delta + \cdots = \lambda\delta \sum_{k=0}^{\infty} \lambda^{2k} = \frac{\lambda\delta}{1-\lambda^2}.$$

The aggregate change in total vacancies ($v_a + v_b$) is therefore:

$$\Delta V^{\text{total}} = \Delta v_a^{\text{total}} + \Delta v_b^{\text{total}} = \frac{(1+\lambda)\delta}{1-\lambda^2} = \frac{\delta}{1-\lambda}.$$

Thus, the initial shock δ is amplified by a factor of $1/(1-\lambda)$ at the aggregate level—a direct consequence of iterative strategic interaction.

2.4.2 Low-skilled hiring

For low-skilled hiring, the optimal vacancy posting $\widetilde{v}_a^* = \widetilde{n}_a^*/\widetilde{q}(\widetilde{\theta}_i)$ does not depend on innovation outcomes.

Case 1: Firm b locates in a different area. When firm b is in a different area $j \neq i$, its low-skilled vacancy posting $\widetilde{v}_b$ does not affect $\widetilde{\theta}_i$. Moreover, $\widetilde{v}_a^*$ is independent of $\widetilde{v}_b$ because z_a is exogenous. This contrasts with the high-skilled case, where strategic complementarities arise through Δ_a.

Case 2: Firm b locates in the same area. If both firms post low-skilled vacancies in the same area i, then $\widetilde{v}_b$ affects $\widetilde{\theta}_i = (\widetilde{v}_b + \widetilde{v}_{-b})/\widetilde{u}_i$, where $\widetilde{v}_{-b}$ denotes low-skilled vacancies posted by other firms. A higher $\widetilde{v}_b$ raises $\widetilde{\theta}_i$, reducing $\widetilde{q}(\widetilde{\theta}_i)$.

Similar to the high-skilled market, this change in $\widetilde{q}(\widetilde{\theta}_i)$ has two opposing effects on $\widetilde{v}_a^*$. The first is the congestion effect: a lower $\widetilde{q}(\widetilde{\theta}_i)$ increases the effective hiring cost $\kappa/\widetilde{q}(\widetilde{\theta}_i)$, discouraging employment and reducing $\widetilde{n}_a^*$. The second effect is that a lower $\widetilde{q}(\widetilde{\theta}_i)$ raises the vacancy-employment ratio $1/\widetilde{q}(\widetilde{\theta}_i)$, meaning the firm must post more vacancies to achieve a given employment level. The net effect depends on parameter values.

To illustrate, consider again the limiting case where $\widetilde{h} \approx 0$. Equation (8) and $\widetilde{v}_a^* = \widetilde{n}_a^*/\widetilde{q}(\widetilde{\theta}_i)$ imply:

$$\widetilde{v}_a^* = \left\{ \frac{\left[1-(1-\alpha)(1-\widetilde{\tau})\right] z_a \alpha}{\kappa} \right\}^{1/(1-\alpha)} \left[\widetilde{q}(\widetilde{\theta}_i)\right]^{\alpha/(1-\alpha)},$$

which is increasing in $\widetilde{q}(\widetilde{\theta}_i)$ and therefore decreasing in $\widetilde{v}_b$. In this case, the congestion effect dominates, and $\widetilde{v}_a^*$ decreases with $\widetilde{v}_b$. However, if $\widetilde{h}$ is sufficiently large, the sign of the relationship may reverse. Hence, when firms operate in the same low-skilled labor market, the effect of $\widetilde{v}_b$ on $\widetilde{v}_a^*$ is ambiguous, reflecting the same tension between congestion and hiring incentives present in the high-skilled market, but without the additional strategic complementarity channel through innovation value. The results are summarized by the following proposition.

Proposition 3. *For low-skilled hiring,*

(a) If firms a and b locate in different labor markets ($j \neq i$), $\widetilde{v}_b$ does not affect $\widetilde{v}_a^*$; vacancy decisions are independent.

(b) If firms a and b locate in the same labor market i, $\widetilde{v}_b$ affects $\widetilde{v}_a^*$ through two countervailing channels:

(i) a congestion effect that lowers $\widetilde{q}(\widetilde{\theta}_i)$ and raises hiring costs, reducing $\widetilde{v}_a^*$, and

(ii) a vacancy-requirement effect that increases $\widetilde{v}_a^*$ for a given employment target.

The overall sign of $\partial \widetilde{v}_a^* / \partial \widetilde{v}_b$ is ambiguous and depends on parameters.

Proposition 3 shows that low-skilled hiring lacks innovation-driven strategic complementarities, so any strategic interaction stems solely from labor-market congestion and vacancy-requirement effects, leading to parameter-dependent labor market strategic interaction or independence across markets.

2.5 Taking Stock

Our model yields four testable predictions. Prediction 1 establishes that strategic complementarity in hiring, driven by product market competition, is specific to high-skilled job postings (Proposition 1), while its effect on low-skilled postings is ambiguous (Proposition 3). Prediction 2 states that this complementarity is stronger when competitors are located in separate labor markets or in a larger labor market with lower congestion (Proposition 2). Prediction 3 indicates that the strength of complementarity increases with the penalty for falling behind in competition (Proposition 1). Prediction 4 indicates that a firm's high-skilled hiring enhances its own innovation and market leadership while diminishing the market leadership of its rivals, a result derived from our specification of the innovation probability functions. The following section documents four empirical facts that directly correspond to these predictions.

3 Empirical Analysis of Hiring Competition

Motivated by the theoretical model, this section documents four key facts about hiring competition among Chinese listed firms.

3.1 Data and Product-Market Networks

We integrates multiple data sources to analyze firms' competition in the hiring of high-skilled workers.

Job posting data. We utilize job posting data from 51job, China's largest online recruitment platform, spanning the period from 2015 to 2021.[6] This granular dataset, structured at the job advertisement level, includes detailed information on firm identity, posting time, job location, title, description, educational and experience requirements, and the number of positions available.[7]

Based on job characteristics, we differentiate between high-skilled and low-skilled positions. Specifically, as outlined in Table 1, we classify a job advertisement as targeting high-skilled workers if it meets the two following criteria: (1) the job title or description contains keywords associated with specialized or managerial roles (e.g., director, senior, engineer, manager) and (2) the position requires at least three years of work experience, at least a bachelor's degree, or proficiency in at least one foreign language.[8] Using this definition, approximately 38% of the 1.6 million job postings by listed firms are classified as high-skilled positions. Our findings remain robust when applying alternative, more restrictive or broader definitions of high-skilled workers.

A non-negligible share of postings (12–25%) do not report the number of positions or use the vague descriptor "several."[9] To ensure robustness, we adopt several alternative imputations. In

[6]51job was listed on NASDAQ in 2004 (ticker: JOBS) and privatized in 2022. In 2020, it held a market share of approximately 34%, well ahead of its nearest competitor (18%). Firms post vacancies for a fee, while job seekers access listings freely.

[7]Wage information is notoriously scarce in online job postings (Kuhn and Shen, 2013; Deming and Kahn, 2018). In our data, only a small fraction of advertisements report wage details; we therefore exclude wage variables from the main analysis to preserve sample size. The results on wages are available upon request.

[8]Although prior research frequently uses educational attainment as a proxy for skill (Chen et al., 2025), education alone may not fully capture the heterogeneous competency requirements of specific roles. Our main definition therefore incorporates multiple dimensions, such as experience, job title, and language proficiency, which better align with the economic concept of skill relevant to firms' hiring decisions. We confirm, however, that our results remain robust when skill is defined using educational attainment only.

[9]Figure B1 in Appendix B plots the nationwide annual trend in the share of advertisements containing this

Table 1: Criteria for Defining High-Skilled Workers

Criteria	Field	Requirement
(1)	Job Title/Description	Contains at least one of the following keywords: director, senior, chief, head, specialist, analyst, architect, engineer, manager
(2)	Work Experience	Minimum of 3 years
(3)	Education	Bachelor's degree or higher
(4)	Language Skills	Proficiency in at least one foreign language

Notes: Because few advertisements simultaneously report information for criteria (2)–(4), we first take the union of these three criteria, and then intersect the result with criterion (1). The Original Chinese keywords in job titles/descriptions are reported in Table B1 in Appendix B.

our baseline specification, we assign the value 3 to advertisements that list "several" openings. For sensitivity checks, we recode "several" as 0, 1, or 5, confirming that our results remain consistent across these alternative definitions.

We then aggregate the number of positions across all job advertisements at the firm-year level to construct our primary outcome variable: the total number of high-skilled workers that firms intend to hire each year.[10]

Firm characteristics data. We obtain listed firms' characteristics data from the China Stock Market & Accounting Research Database (CSMAR), which serves as the primary source of control variables in our analysis.[11] We include five firm-level characteristics: the debt-to-assets ratio (D/A), return on total assets (RoA), total assets, total employment, and the share of employees holding a bachelor's degree or higher. The first two variables capture firms' financial leverage and profitability, while the remaining three account for scale and workforce composition. All control variables are lagged by one period to mitigate potential endogeneity concerns.

Management Discussion and Analysis (MD&A) Data. We obtain textual data from the Management Discussion and Analysis (MD&A) sections of listed firms' annual financial reports, as provided by the China Research Data Service (CNRDS).[12] In China, every listed firm's financial report contains an MD&A section, in which managers summarize the firm's operations over the past year. While the structure of these sections varies across firms, they typically cover key

ambiguous term. The declining trend suggests that firms have progressively disclosed more precise hiring figures. The time-varying prevalence of vague postings also reinforces the need to control for year fixed effects whenever a non-zero value is assigned to "several."

[10]Trends in average firm-level job postings of high- and low-skilled workers, as well as the nationwide annual evolution of the high-skilled position ratio and the high-skilled advertisement ratio, are provided in Figures B2 and B3 in Appendix B.

[11]Link: https://data.csmar.com

[12]Link: https://www.cnrds.com

business characteristics, an overview of main products or business segments, discussions of relevant macroeconomic and market conditions, and strategic priorities for both the previous and upcoming years. The content and role of the MD&A are analogous to those found in the 10-K filings of U.S. listed firms.

Constructing Product-Market Competitor Networks. We follow Hoberg and Phillips (2016) to build text-based product-market competitor networks using the MD&A data. For each pair of firms, we compute the cosine similarity between their MD&A texts based on TF-IDF (term frequency–inverse document frequency) weighted word vectors. TF-IDF balances the frequency of a word in a given document against its prevalence across the entire corpus, thereby highlighting words that are distinctive to a particular firm's discussion. The resulting similarity scores form a pairwise matrix that translates high-dimensional text data into a tractable measure of business-profile proximity.

We define a firm's set of potential competitors as the 30 firms whose MD&A texts are most similar to its own.[13] This text-based competitor network is represented by matrix $G_t = \{g_{ijt}\}$, where

$$g_{ijt} = \begin{cases} 1 & \text{if firm } j \text{ is among the 30 most textually similar firms to firm } i, \\ 0 & \text{otherwise.} \end{cases}$$

To ensure that the measurement of competitors' hiring is not affected by the number of competitors,[14] we row-normalize G_t to get $W_t = \{w_{ijt}\}$, where $w_{ijt} = g_{ijt} / \sum_j g_{ijt}$; therefore, competitors' hiring is measured at the average level.[15]

Our text-based approach offers several advantages comparing to traditional industry classifications such as the China Association for Public Companies (CAPCO). Traditional industry classifications impose rigid, time-invariant boundaries and assume competition occurs only within predefined groups. In contrast, the text-based network evolves annually, captures cross-industry competitive linkages, and does not impose transitivity, i.e., a firm's competitors' competitors need not be its own direct competitors. This flexible, data-driven representation of competitive relationships has been widely adopted in recent studies of firm networks (e.g., Runge et al., 2022; Grieser et al., 2022a,b).[16]

Benchmark sample. We merge firm-level characteristics with MD&A disclosures using ticker

[13] We test alternative thresholds in robustness checks; results remain qualitatively unchanged.

[14] Not all firms have a complete set of 30 competitors in our matched sample. For instance, some identified competitors lack job posting data. As a result, the average number of competitors per firm-year is approximately 18.

[15] Figure B4 in Appendix B illustrates the product-market competition network in 2021.

[16] We illustrate the advantages of the text-based approach with a concrete example in Appendix C.

symbols, and then link these data to job posting records through the unique business registration code assigned to each listed firm and its subsidiaries. This yields 13,949 firm-year observations from 3,186 unique firms, with 1,400-2,400 firms observed each year.

Panel A of Table 2 presents summary statistics for firms' high-skilled and low-skilled job postings used for our benchmark sample. Panel B of Table 2 presents summary statistics for the five firm-level characteristics.

Table 2: Summary Statistics of Main Variables

	Mean	Median	St. dev	Obs	Unit
	(1)	(2)	(3)	(4)	(5)
Panel A: Number of Job Postings, Firm-year Level					
High-skilled worker	0.890	0.220	3.174	13,949	Hundred person
Low-skilled worker	1.862	0.540	8.704	13,949	Hundred person
Panel B: Firm Financial Characteristics					
Lagged D/A	0.446	0.432	0.220	13,949	1
Lagged RoA	0.031	0.037	0.142	13,949	1
Lagged assets	52.556	4.680	640.761	13,949	Billion CNY
Lagged no. of employees	73.411	24.310	238.178	13,949	Hundred person
Lagged bachelor's degree ratio	0.151	0.074	0.318	13,949	100%

Notes: The number of job openings is calculated by coding "several" = 3.

3.2 Econometric Framework

In this section, we present our econometric strategy for estimating competition among firms for high-skilled workers. We adopt a spatial autoregressive (SAR) model, a well-established framework for analyzing strategic interactions, network effects, and competitive dynamics in interconnected markets (e.g., König et al., 2019; Guo and Qu, 2022; Grieser et al., 2022a,b).

Our baseline specification is

$$v_{it} = \lambda \sum_{j \neq i} w_{ijt} v_{jt} \; + \; \boldsymbol{x}_{i,t-1}\boldsymbol{\beta} \; + \; \text{FE} \; + \; u_{it}, \tag{12}$$

where v_{it} denotes the number of high-skilled positions posted by firm i in year t, and w_{ijt} is the row-normalized weight that captures the competitive linkage from firm j to firm i based on text-similarity of their management disclosures. The vector $\boldsymbol{x}_{i,t-1}$ contains lagged firm-level characteristics as controls. Fixed effects (FE) include firm, 3-digit CAPCO industry $\times$ year, and headquarters city $\times$ year effects, which help to control different levels of common shocks.[17] The error term u_{it} captures idiosyncratic shocks.

[17] In estimation, these are handled following the approach of Grieser et al. (2022a).

The spatial coefficient λ is the key parameter of interest: it measures the average responsiveness of a firm's high-skilled hiring to the hiring of its text-based competitors, thus quantifying the intensity of strategic interactions in the market for high-skilled labor.

This model can be expressed in vector form as

$$V_t = \lambda W_t V_t + X_{t-1}\beta + \text{FE} + U_t, \tag{13}$$

which constitutes a simultaneous system: the spatial lag $W_t V_t$, the average hiring of a firm's text-based competitors, and the dependent variable V_t are jointly determined; therefore, the spatial lag is endogenous, requiring IV estimation. Following Bramoullé et al. (2009) and Lin (2010), if the network is intransitive (i.e., a firm's competitors' competitors are not necessarily its own direct competitors), then $W_t X_{t-1}$ and $W_t^2 X_{t-1}$, the average characteristics of a firm's first- and second-order competitors, serve as valid instruments for $W_t V_t$.[18]

Our text-based network inherently satisfies this intransitivity condition, as listed firms often operate across multiple, non-overlapping product markets. To formally assess the degree of intransitivity, we calculate the global clustering coefficient, a standard network metric bounded between 0 and 1. A value closer to 0 indicates strong intransitivity, that is, if firm A competes with B and B competes with C, it is unlikely that A also competes with C. In our constructed network, the global clustering coefficient is below 0.1, confirming a high degree of intransitivity and supporting the validity of our IV design.

The exclusion restriction of $W_t X_{t-1}$ is based on the following logic: conditional on a firm's own characteristics (X_{t-1}) and direct competitors' hiring ($W_t V_t$), the characteristics of its direct competitors influence its hiring decisions solely through the hiring activity of those competitors (i.e., through $W_t V_t$). Similarly, $W_t^2 X_{t-1}$, the characteristics of second-order competitors, affect a firm's hiring only indirectly via the hiring of second-order competitors and then of first-order competitors.[19] For instance, Firm A competes with Firm B (both in market a), and Firm B competes with Firm C (both in market c), but Firms A and C do not directly compete. This intransitive structure allows the lagged characteristics of Firm C to serve as a valid instrumental variable when estimating the effect of Firm B's hiring on Firm A's hiring.

The relevance of these instruments follows directly: if X_{t-1} is correlated with V_t, then $W_t X_{t-1}$

[18] Using multiple instruments allows for over-identification tests, which help assess the validity of IVs, and improves efficiency by better approximating the theoretically optimal instrument $W_t(I - \lambda W_t)^{-1} X_{t-1}$.

[19] Because the text-based network is intransitive, $W_t X_{t-1}$ and $W_t^2 X_{t-1}$ remain linearly independent. We further reduce potential collinearity by removing from the second-order set any firms that are already included as first-order competitors, i.e., remaining those intransitive second-order competitors. This approach resembles the strategy of De Giorgi et al. (2010), which relies on partially overlapping peer groups.

is correlated with $W_t V_t$, and $W_t^2 X_{t-1}$ is correlated with $W_t^2 V_t$, which in turn influences the hiring of direct competitors $W_t V_t$ through network spillovers.

A potential concern is that firms operating in multiple product markets could be subject to common labor demand shocks. For instance, growth in the electric vehicle sector may increase demand for software engineers from downstream and upstream industries. If unaccounted for, such common factors could create a direct correlation between second-order competitor characteristics and the focal firm's hiring, violating the exclusion restriction. Our identification strategy, however, does not require the absence of these common shocks, rather, it require that they operate at a level we can control for. Specifically, our identifying assumption is conditional: after controlling for firm and industry-year fixed effects, and focal firm characteristics, the attributes of second-order competitors influence a firm's hiring decisions only through their impact on the strategic responses of its direct competitors. This weaker, more realistic assumption allows our network-based IV to isolate strategic hiring even in the presence of cross-industry demand shocks.

3.3 Empirical Results

In this section, we present the core empirical results regarding the strategic interaction between firms in high-skilled hiring. First, there is strong strategic complementarity in the hiring of high-skilled workers, a pattern not observed for low-skilled workers. Second, this competition occurs at the national level among product market rivals. Third, the complementarity is most pronounced when the competitive penalty for falling behind is highest. Fourth, a firm's high-skilled hiring increases its market share and innovation, whereas competitors' hiring reduces its market share.

Fact 1: There is strategic complementarity in firms' high-skilled hiring between product market competitors.

We begin by examining whether firms' high-skilled hiring decisions are influenced by those of their rivals, a phenomenon known as strategic complementarity in labor demand. Table 3 reports the results of estimating equation (13), which provide strong evidence of strategic complementarity in high-skilled hiring. As shown by Column (1), for each additional high-skilled job posted by a firm's competitors, the firm posts approximately 0.6 more high-skilled positions itself. This strategic interaction generates a substantial multiplier effect, the initial strategic response induces further rounds of competitive reactions. With a competition coefficient $(\hat{\lambda})$ of 0.6, the multiplier $1/(1-0.6) \approx 2.5$ implies that strategic rivalry causes firms to ultimately post about 2.5 times more high-skilled job openings than they would in a non-competitive environment. Columns (2)-(4) show that the result is insensitive to alternative codings of the imprecise term "several" in job advertisements (0, 1, 3, or 5), with the coefficient consistently stable around 0.6.

Notably, the IV strategy is well-supported by standard diagnostics. The high Cragg–Donald and Kleibergen-Paap F-statistics reject concerns of weak instruments, while the Hansen J-test fails to reject the null of valid over-identifying restrictions. Together, these tests support a causal interpretation of the competition effect.

A series of additional robustness checks, detailed in Appendix B, confirms that the finding of strategic complementarity is robust across a wide range of specifications and measurement choices. For example, when we refine the analysis to the firm-occupation level (Table B2), the estimated complementarity strengthens to 0.73. The effect remains statistically similar across different talent categories (science/technology versus management/marketing), is stable over time (pre- and post-2018), and does not vary significantly by ownership structure (state-owned versus non-state-owned enterprises). Furthermore, the result holds under stricter/broader definitions of high-skilled workers –such as requiring a master's degree or at least five years of experience– and is insensitive to alternative competitor network thresholds (top 10, 20, 40, or top 1% most similar firms). We also address concerns related to lagged effects, advertisement duration, outliers, functional form, unequal weighted (by text similarity scores) average of competitors' hiring, using second-order competitors' characteristics as the only IVs, and potential network endogeneity. Taken together, these extensive tests confirm that the documented strategic complementarity is not an artifact of particular measurement or modeling choices.

Finally, as shown by Table B3 in Appendix B, a placebo test using dissimilar firms as artificial "non-competitors" –defined as those with the least similar MD&A texts– shows no significant response in hiring. The absence of a reaction to these unrelated firms confirms that strategic complementarity is specific to product market competitors.

Absence of strategic complementarity in low-skilled hiring. Having established significant strategic complementarity in high-skilled hiring, we now ask whether a similar pattern exists for low-skilled workers. To test this, we redefine v_{it} as firm i's low-skilled job postings in year t. As Table B4 shows, the estimated coefficients are statistically insignificant across all specifications, consistent with theoretical expectation. This result also helps rule out an important alternative explanation: unobserved common shocks at the product market level. If such product market shocks were driving our main results, we would expect positive coefficients for both high- and

Table 3: Competition in the Hiring of High-Skilled Workers

	(1)	(2)	(3)	(4)
	Benchmark	Alternative Specifications		
	Several=3	Several=0	Several=1	Several=5
Competitors' High-Skilled Posting	0.593***	0.605***	0.598***	0.591***
	(0.127)	(0.139)	(0.131)	(0.130)
Multiplier effects	2.454	2.531	2.488	2.446
Cragg-Donald F-statistic	66.846	35.744	46.710	82.209
Kleibergen-Paap F-statistic	25.047	18.027	21.507	26.153
Hansen J-test (p-value)	0.502	0.429	0.453	0.498
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
Observations	13,949	13,949	13,949	13,949

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parentheses are clustered at the 3-digit CAPCO industry level. Firm fixed effects, 3-digit CAPCO industry×year fixed effects, and headquarter city×year fixed effects are controlled in all columns. Controls include lagged firm-level characteristics. Weak identification tests are based on Cragg-Donald and Kleibergen-Paap F-statistics. Over-identification tests are based on Hansen J-statistics, and p-values are reported. Multiplier effects are calculated as $1/(1-\hat{\lambda})$.

low-skilled hiring. The absence of any effect for low-skilled workers suggests our findings for high-skilled workers are not driven by shared external shocks, but rather by strategic competition.

Absence of a learning channel. An alternative explanation for the positive correlation in hiring is social learning: if firms rely on competitors' actions to infer future market conditions, they may imitate hiring decisions perceived as informative.

To distinguish between strategic rivalry and alternative explanations based on social learning, we test whether firms respond more strongly to competitors whose actions are likely to convey superior information. We define two types of "informative" peers: (1) superior competitors—firms ranked among the top five in RoA within their industry or whose RoA exceeds the focal firm by at least one standard deviation—whose hiring may signal strong future prospects; and (2) supply-chain partners, identified from disclosed top-five customers and suppliers, who may share private demand or operational information (e.g., Alfaro-Urena et al., 2022; Amiti et al., 2024).

Table 4 displays the estimation results. While the baseline strategic complementarity remains strong (coefficients around 0.61–0.64), the additional effect from superior competitors is statistically insignificant, implying that neither measure of superiority elicits a significant incremental hiring response. Similarly, column (1) of Table 5 show that there is no significant reaction to hiring by supply-chain partners. Together, these findings provide little support for imitation or learning as the mechanism behind strategic complementarity. Instead, the evidence reinforces that hiring responses are driven by product-market rivalry rather than informational spillovers.

Table 4: Testing the Imitation or Learning Mechanism from Superior Competitors

	(1)	(2)
Competitors' High-Skilled Posting	0.614***	0.643***
	(0.160)	(0.134)
Superior Competitors' Posting (top 5 in RoA)	0.026	
	(0.322)	
Superior Competitors' Posting (RoA exceeds by 1 s.d.)		−0.605
		(0.571)
Cragg-Donald F-statistic	12.237	18.548
Kleibergen-Paap F-statistic	15.751	7.534
Hansen J-test (p-value)	0.586	0.488
Controls	Yes	Yes
Fixed Effects	Yes	Yes
Observations	13,949	13,949

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parentheses are clustered at the 3-digit CAPCO industry level. Fixed effects include firm fixed effects, 3-digit CAPCO industry×year fixed effects, and headquarter city×year fixed effects. Controls include lagged firm-level characteristics.

Fact 2: High-skilled labor competition operates at a national scale among product market rivals.

No significant competition at the local level. To test for local labor market competition, we disaggregate our data to the firm-city level. The dependent variable, v_{it}^c, is now firm i's high-skilled job postings in city c. We estimate:

$$v_{it}^c = \lambda \sum_{j \neq i} w_{ijt} \, v_{jt}^c \; + \; \boldsymbol{x}_{i,t-1}\boldsymbol{\beta} \; + \; \text{FE} \; + \; u_{it}^c. \tag{14}$$

Table 6 reports the results. Column (1) shows an insignificant coefficient, indicating no evidence of strategic hiring competition within regional labor markets. This null result holds when focusing on the top 10% of cities by GDP (column (2)) and China's four major metropolitan areas (column (3)), suggesting competition is not localized even in large, high-skilled labor markets. These findings are consistent with the prediction of our theoretical model that if firms compete for high-skilled workers in the same local labor market, the estimated effect may be insignificant since it combines three countervailing forces, a positive competition effect, a positive vacancy requirement effect, and a negative congestion effect.

To confirm the national scope of competition, we focus on a firm's "hiring anchor city"—the city where it posts the most job openings. We estimate whether a firm responds to its competitor's hiring in the competitor's anchor city by hiring in its own anchor city. Our specification becomes:

$$v_{it}^{anchor(i)} = \lambda \sum_{j \neq i} w_{ijt} \, v_{jt}^{anchor(j)} \; + \; \boldsymbol{x}_{i,t-1}\boldsymbol{\beta} \; + \; \text{FE} \; + \; u_{it}, \tag{15}$$

where $v_{it}^{anchor(i)}$ is firm i's high-skilled job posting in its hiring anchor city $anchor(i)$, and $v_{it}^{anchor(j)}$ is firm j's high-skilled job posting in its hiring anchor city $anchor(j)$. Here, unlike Equation (14), $anchor(i)$ and $anchor(j)$ are not necessarily equal.

Column (4) reports a significant and substantial coefficient of approximately 0.6, closely mirroring our national-level estimate. This indicates that strategic competition for talent is not geographically bounded: firms respond to rivals' hiring even when it occurs in different cities, reinforcing that the rivalry operates at the level of aggregate talent acquisition rather than local labor-market overlap.

To illustrate, consider the case of two major product-market competitors in China's new energy vehicle sector: BYD and BAIC BluePark. In 2021, BYD's hiring anchor city was Shenzhen, while BAIC BluePark's was Beijing. The estimated coefficient implies that if BYD were to increase its high-skilled hiring in Shenzhen, BAIC BluePark would respond by raising its own high-skilled hiring in Beijing, despite the geographic separation. This example underscores that what matters for competitive hiring is the rival's total talent intake, not where that hiring takes place. Firms thus treat high-skilled hiring as a strategic, nationally-scoped move in product-market competition, consistent with the model's prediction that local congestion effects are absent when firms operate in distinct labor markets.

Competition occurs in product markets, not labor markets. We next test whether direct labor market overlap—rather than product market rivalry—drives strategic complementarity. We construct a "labor market competitor" network based on the textual similarity of firms' job descriptions, which reflect the skills and tasks they seek.[20]

The results in column (2) of Table 5 show that the coefficient of labor market competitors' high-skilled hiring is statistically insignificant. This confirms that strategic complementarity in high-skilled hiring is driven by product market competition, not by competition for similar worker profiles in the labor market.

[20] For instance, one of BYD's top labor market competitors is KOTL (300032.SZ), an electrical machinery manufacturer. While both firms seek similar high-skilled profiles (e.g., engineers), they operate in different industries and are not product market competitors. This illustrates how labor market overlap can exist without product market rivalry.

Table 5: Alternative Competitor Networks: Supply Chain and Labor Market

	(1) Supply Chain Partners	(2) Labor Market Competitors
Competitors' High-Skilled Posting	−0.030	−0.037
	(0.154)	(0.064)
Cragg-Donald F-statistic	17.824	129.021
Kleibergen-Paap F-statistic	3.971	42.215
Hansen J-test (p-value)	0.272	0.203
Controls	Yes	Yes
Fixed Effects	Yes	Yes
Observations	13,949	13,949

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors in parentheses are clustered at the 3-digit CAPCO industry level. The key explanatory variable is instrumented in both specifications. Fixed effects include firm fixed effects, 3-digit CAPCO industry×year fixed effects, and headquarter city×year fixed effects. Controls include lagged firm-level characteristics.

Table 6: Absence of Competition at Firm-City Levels

	(1) All cities	(2) Top 10% cities	(3) Top 4 cities	(4) Hiring anchor cities
Competitors' High-Skilled Posting	0.227	0.298	0.102	0.595***
	(0.242)	(0.202)	(0.271)	(0.129)
Cragg-Donald F-statistic	8.864	9.458	4.000	59.490
Kleibergen-Paap F-statistic	4.117	4.199	2.995	29.578
Hansen J-test (p-value)	0.377	0.24069	0.487	0.503
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
Observations	110,615	62,145	17,543	13,034

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors in parentheses are clustered at the 3-digit CAPCO industry level. Firm fixed effects, 3-digit CAPCO industry×year fixed effects, headquarter city×year fixed effects, and hiring city×year fixed effects are controlled in all columns. Controls include lagged firm-level characteristics.

Fact 3: Strategic complementarity strengthens when the penalty for falling behind is larger.

Product market competition can motivate firms to hire high-skilled workers for two distinct reasons: to overtake rivals and become the market leader, or to avoid falling behind. As shown by our theoretical model, while a race for leadership induces strategic substitutability, the fear of lagging induces strategic complementarity. This is because a competitor's hiring reduces a firm's chance of becoming a leader but raises its risk of becoming a loser. Formally, a more concave (less convex) firm value function—where losses at the lower tail are more severe—amplifies the incentive for aggressive hiring responses, leading to stronger complementarity.

To test this mechanism, we construct a measure of the concavity of the firm value distribution within each text-based product market competition network:

$$\text{Concavity} = \frac{(Q_{50\%} - Q_{5\%}) - (Q_{95\%} - Q_{50\%})}{Q_{50\%}},$$

where $Q_{\alpha\%}$ is the α%-percentile of firm value. A higher concavity index indicates a distribution with a fatter left tail, i.e., a high downside risk from falling behind ($Q_{50\%} - Q_{5\%}$) and a low upward benefit from pulling ahead ($Q_{95\%} - Q_{50\%}$). We define a *HC* (short for high concavity) dummy that equals one for networks in the top three quartiles of this index, and zero for those in the bottom quartile.

To test whether strategic complementarity is moderated by the risk of falling behind, we examine whether the hiring response to competitors' vacancies varies with the concavity of the firm-value distribution within each product-market network. Networks with higher concavity exhibit a fatter left tail—implying a larger penalty for becoming a follower—which may strengthen firms' willingness to escalate hiring in response to rivals. We estimate the following model:

$$v_{it} = a_1 \sum_{j \neq i} w_{ijt} \, v_{jt} \; + \; a_2 \, \text{HC}_{i,t-1} \times \sum_{j \neq i} w_{ijt} \, v_{jt} \; + \; a_3 \, \text{HC}_{i,t-1} \; + \; \boldsymbol{x}_{i,t-1} \boldsymbol{\beta} \; + \; \text{FE} \; + \; u_{it},$$

where $\text{HC}_{i,t-1}$ is a measure of the concavity (or "hazard of falling behind") of the value distribution in firm i's product-market network, and the interaction term a_2 captures how the strength of strategic complementarity varies with this concavity. We employ the lagged concavity measure to mitigate potential endogeneity arising from simultaneous effects between competition and the shape of the value distribution. A positive estimate of a_2 would indicate that firms in networks with a higher downside risk respond more aggressively to rivals' hiring.

Table 7 reports the results. Importantly, the interaction term between competitors' hiring and an indicator for the top quartiles of concavity is positive. This pattern indicates that firms in networks with higher concavity—where downside losses are larger—respond more aggressively to competitors' hiring, consistent with the model's prediction that heightened risk of falling behind increases strategic complementarity in high-skilled hiring.

Fact 4: A firm's high-skilled hiring increases its market share and innovation, whereas competitors' hiring reduces its market share.

Finally, we examine how competition for high-skilled workers influences firm performance and innovation. To assess these dynamics, we focus on firms' relative market position—captured

Table 7: Competition is Stronger with More Concave Firm Value

Competitors' High-Skilled Posting	0.282***
	(0.100)
Competitors' High-Skilled Posting × HC	0.500**
	(0.194)
Cragg-Donald F-statistic	36.321
Kleibergen-Paap F-statistic	24.691
Hansen J-test (p-value)	0.678
Controls	Yes
Fixed Effects	Yes
Observations	13,949

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parentheses are clustered at the 3-digit CAPCO industry level. Firm value is measured by market capitalization. High concavity is a dummy variable that equals one if the concavity measure of the product market is in the top three quartiles. Fixed effects include firm fixed effects, 3-digit CAPCO industry×year fixed effects, and headquarter city×year fixed effects. Controls include lagged firm characteristics.

through market share and market capitalization share—along with innovation output measured by patent applications and estimate the following equation:

$$\pi_{it} = a_1 v_{i,t-1} + a_2 \sum_{j \neq i} w_{ij,t-1} \, v_{j,t-1} \; + \; \boldsymbol{x}_{i,t-1} \boldsymbol{\beta} \; + \; \text{FE} \; + \; \epsilon_{it},$$

where $\pi \in \{$market share, market cap share, patent applications$\}$.

The estimation results are displayed in Table 8. As shown in the first row, a firm's own high-skilled hiring has a positive and statistically significant effect on its market share, market capitalization share, and patenting activity. This underscores the strategic value of talent accumulation in strengthening competitive positioning and fostering innovation.

In contrast, the second row reveals that competitors' high-skilled hiring significantly reduces a firm's market share and market capitalization share. Interestingly, competitor hiring does not exhibit a statistically significant impact on a firm's patent applications. This finding aligns with the model's prediction: while a rival's talent acquisition erodes a firm's market position, it does not directly diminish its innovation output—though the market value of that innovation is attenuated.

3.4 Discussion

Our findings yield several implications for labor economics and policy design. First, the documented strategic complementarity in high-skilled hiring generates a multiplier effect that amplifies labor demand shocks. This suggests a promising extension for labor-macroeconomic

Table 8: The Effect of High-Skilled Hiring on Firms' Performance

	(1) Market Share	(2) Market Capitalization Share	(3) Patent Applications
Lagged Own Posting	0.051**	0.053***	0.099***
	(0.023)	(0.016)	(0.030)
Lagged Competitors' Posting	−1.044***	−1.743***	0.253
	(0.397)	(0.574)	(0.187)
Hansen J-test (p-value)	0.326	0.056	0.470
Controls	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes
Observations	10,198	10,198	10,198

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors in parentheses are clustered at the 3-digit CAPCO industry level. Fixed effects include firm fixed effects, 3-digit CAPCO industry×year fixed effects, and headquarter city×year fixed effects. Cragg-Donald and Kleibergen-Paap F-statistics are 21.718 and 10.066, respectively. Controls include lagged firm characteristics.

models: incorporating product-market rivalry into business-cycle frameworks could help explain the high volatility of vacancies, a feature that is considered challenging for standard search-and-matching models (Shimer, 2005).

Second, because a portion of job postings is driven by strategic competition rather than immediate hiring needs, vacancy data may overstate the true extent of labor shortages in some markets.[21] Policymakers and researchers should therefore interpret vacancy data with caution, taking into account that observed openings reflect not only underlying demand but also competitive interactions among firms.

Finally, our analysis highlights how the effect of labor-market policies depends on the geographic scope of product-market competition. In local labor markets, congestion externalities may dampen the effectiveness of policies that lower hiring costs, such as vacancy subsidies (Mercan et al., 2024); whereas when product market competition is national, the same policies may more effectively stimulate hiring by reinforcing strategic complementarity. These insights underscore that policy design should account for the structure of product-market competition, as interventions may yield divergent outcomes across different market settings.

4 Conclusion

This paper examines how firms compete for high-skilled talent and how this competition affects firm outcomes and market dynamics. Using job-posting data and text-based product-market networks for Chinese listed firms, we establish four key facts: (1) there exists strong

[21] See Mandelman et al. (2024).

strategic complementarity in high-skilled hiring; (2) competition is national in scope and driven by product-market rivalry, not by local labor markets; (3) the intensity of strategic complementarity is stronger when the penalty for falling behind is larger; and (4) high-skilled hiring boosts a firm's market share and innovation while rivals' hiring erodes its market position.

These findings are consistent with a model in which talent rivalry arises primarily from the fear of falling behind in product-market competition. Our results indicate that strategic hiring amplifies labor demand and serves as a key channel of product-market rivalry.

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Online Appendix

A A Model with Low- and High-skilled Interaction

A.1 Baseline Environment

Consider two firms, a and b, that hire both high-skilled (n_h) and low-skilled (n_l) workers. The profit function for firm a is:

$$\Pi = An_l^{\alpha} - n_h w_h - n_l w_l - \frac{\kappa n_h}{f(\theta_h)} - \frac{\kappa n_l}{f(\theta_l)},$$

where A is total factor productivity (TFP), w_h and w_l are wages, and the last two terms represent vacancy-posting costs. The matching rates $f(\theta_h)$ and $f(\theta_l)$ are decreasing in market tightness.

A.2 Innovation and Rank-Dependent Productivity

Innovation outcomes affect TFP in a rank-dependent manner. Let p_a and p_b denote the innovation probabilities of firms a and b. The TFP of firm a is:

$$A_a = \begin{cases} A + \Delta^+, & \text{if } a \text{ innovates and } b \text{ does not,} \\ A - \Delta^-, & \text{if } a \text{ does not innovate and } b \text{ does,} \\ A, & \text{otherwise.} \end{cases}$$

Thus, expected TFP for firm a is:

$$\mathbb{E}[A_a] = A + \Delta^+ p_a(1 - p_b) - \Delta^-(1 - p_a)p_b.$$

A.3 Wage Determination

Wages are determined by Nash bargaining. Let τ_h and τ_l be the firm's bargaining shares for high- and low-skilled workers, and let h and ℓ denote the outside options of the two worker types. The wages are:

$$w_h = (1 - \tau_h)\left[\Delta^+ p_a'(1 - p_b) + \Delta^- p_a' p_b\right] n_l^{\alpha} + \tau_h h,$$

$$w_l = (1-\tau_l)\alpha\left[A + \Delta^+ p_a(1-p_b) - \Delta^-(1-p_a)p_b\right] n_l^{\alpha-1} + \tau_l \ell.$$

A.4 Expected Profit and First-Order Conditions

Substituting wages into the profit function gives expected profit:

$$\begin{aligned}
\mathbb{E}\Pi = &\left[A + \Delta^+ p_a(1-p_b) - \Delta^-(1-p_a)p_b\right] n_l^{\alpha} \\
&- n_h \left\{ (1-\tau_h)\left[\Delta^+ p_a'(1-p_b) + \Delta^- p_a' p_b\right] n_l^{\alpha} + \tau_h h + \frac{\kappa}{f(\theta_h)} \right\} \\
&- \alpha(1-\tau_l)\left[A + \Delta^+ p_a(1-p_b) - \Delta^-(1-p_a)p_b\right] n_l^{\alpha} \\
&- n_l \left(\tau_l \ell + \frac{\kappa}{f(\theta_l)} \right).
\end{aligned}$$

Assume $p_a = n_h^{1/2}$ and $p_a' = \frac{1}{2} n_h^{-1/2}$. The first-order conditions with respect to n_h and n_l are:

$$\begin{cases}
\frac{1}{2} N n_l^{\alpha} n_h^{-1/2} = H, \\
\alpha n_l^{\alpha-1}\left(M + N n_h^{1/2}\right) = L,
\end{cases}$$

where

$$\begin{aligned}
M &= \left[1 - \alpha(1-\tau_l)\right](A - \Delta^- p_b), \\
N &= \Delta_a \left[1 - \alpha(1-\tau_l) - \frac{1}{2}(1-\tau_h)\right], \\
\Delta_a &= \Delta^+(1-p_b) + \Delta^- p_b, \\
H &= \tau_h h + \kappa / f(\theta_h), \\
L &= \tau_l \ell + \kappa / f(\theta_l).
\end{aligned}$$

Here, Δ_a is the expected marginal value of innovation for firm a, and H and L represent the effective marginal hiring costs.

A.5 Closed-Form Solution for $\alpha = 1/2$

When $\alpha = 1/2$, the system admits explicit solutions:

$$\begin{cases}
n_h^* = \left(\frac{NM}{4LH - N^2}\right)^2, \\
n_l^* = \left(\frac{2HM}{4LH - N^2}\right)^2.
\end{cases}$$

A.6 Strategic Interactions

Let $n_{h,b}$ and $n_{l,b}$ denote the employment levels of firm b. The strategic derivatives are derived as follows.

A.6.1 High-Skilled Hiring Response

$$\frac{\partial n_h^*}{\partial n_{h,b}} = \frac{NM}{2p_b(4LH - N^2)^3}\Big[-(1+\tau_l)\Delta^- N(4LH - N^2) + (\tau_l + \tau_h)(\Delta^- - \Delta^+)M(4LH + N^2)\Big].$$

Assuming $4LH - N^2 > 0$, two cases emerge:

1. **Case 1:** $\Delta^- < \Delta^+$. Then $\frac{\partial n_h^*}{\partial n_{h,b}} < 0$; hiring is strategically substitutive.
2. **Case 2:** $\Delta^- > \Delta^+$. Strategic complementarity ($\frac{\partial n_h^*}{\partial n_{h,b}} > 0$) requires

$$\frac{(\Delta^- - \Delta^+)(A - \Delta^- p_b)}{\Delta^- [\Delta^+ + (\Delta^- - \Delta^+)p_b]} > \frac{4LH - N^2}{4LH + N^2}.$$

This inequality is more likely to hold when:

- Baseline productivity A is high,
- Hiring costs H and L are low,
- The innovation value Δ_a (captured by N) is large,
- Firms' bargaining shares τ_h, τ_l are large.

A.6.2 Low-Skilled Hiring and Cross-Type Responses

Low-skilled hiring does not respond to rival's low-skilled hiring:

$$\frac{\partial n_l^*}{\partial n_{l,b}} = 0.$$

Cross-type responses are given by:

$$\frac{\partial n_l^*}{\partial n_{h,b}} = \frac{2H^2 M}{\sqrt{n_{h,b}}(4LH - N^2)^3}\Big[-(1+\tau_l)\Delta^-(4LH - N^2) + 2MN(\tau_l + \tau_h)(\Delta^- - \Delta^+)\Big].$$

Again, if $\Delta^- < \Delta^+$, then $\frac{\partial n_l^*}{\partial n_{h,b}} < 0$. If $\Delta^- > \Delta^+$, complementarity requires

$$2MN(\tau_l + \tau_h)(\Delta^- - \Delta^+) > (1 + \tau_l)\Delta^-(4LH - N^2).$$

Finally,

$$\frac{\partial n_h^*}{\partial n_{l,b}} = 0.$$

This alternative model extends the baseline by allowing innovation to affect the productivity of both high- and low-skilled workers. The key insights remain: strategic complementarity in high-skilled hiring arises when the penalty for falling behind (Δ^-) outweighs the gain from leading (Δ^+), and is reinforced by high baseline productivity, low hiring costs, and strong firm bargaining power. Low-skilled hiring shows no direct strategic interaction with rival's low-skilled employment, but can be indirectly influenced through innovation spillovers when $\Delta^- > \Delta^+$. These results further underscore the central role of rank-dependent competition in shaping hiring dynamics across skill types.

B Additional Tables and Figures

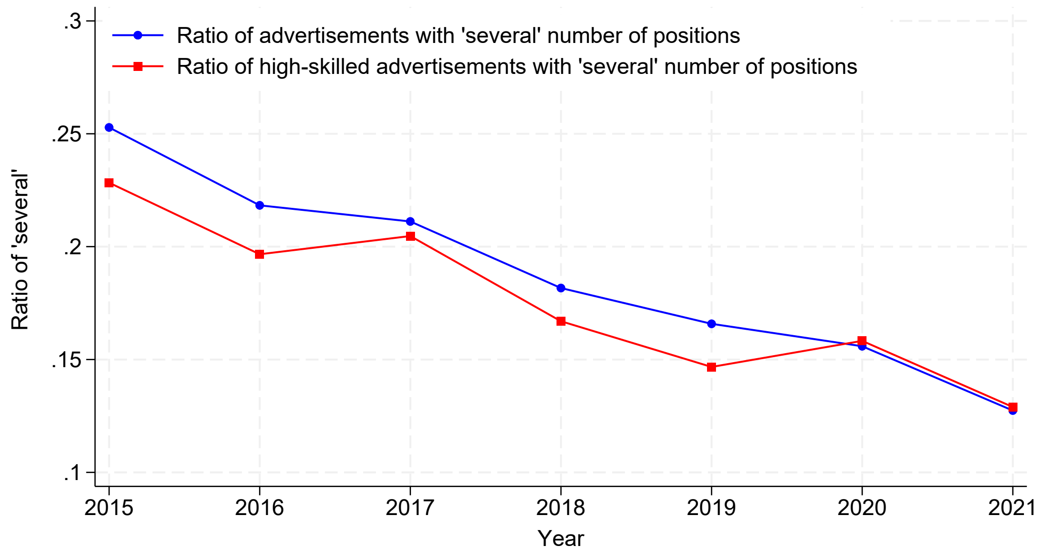

Figure B1: Annual Trends in the Ratio of Advertisements with “several” Number of Positions

Trends in average firm-level job postings of high- and low-skilled positions, as well as the nationwide annual evolution of the high-skilled position ratio and the high-skilled advertisement ratio, are provided in Figures B2 and B3. The patterns revealed in these figures show a steady annual increase in the hiring of high-skilled workers after 2018, accompanied by a decline in low-skilled hiring—a shift that coincides with China’s marked economic slowdown from 2019 onward.[22] This suggests that firms may have reoriented their strategies from expansion toward efficiency gains. Moreover, the consistent gap between the high-skilled advertisement ratio and the high-skilled position ratio indicates that, on average, each high-skilled advertisement offers fewer positions than other ads—a pattern consistent with the more specialized and selective nature of high-skilled recruitment.

Figure B4 illustrates the product-market competition network in 2021, the final year of our sample period. Nodes represent listed firms, and edges denote competitive relationships between them.

[22]China’s annual GDP growth fell to 6.1% in 2019, down from the 6.8–7% range in 2015–2018, and continued to decline thereafter.

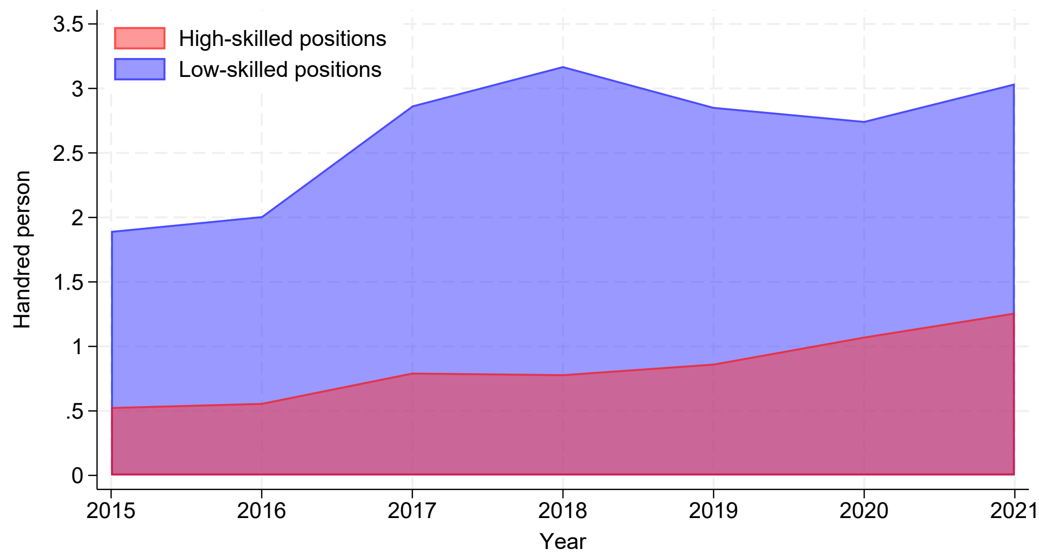

Figure B2: Annual Trends in the Average Number of Job Openings
Notes: The average number of high/low-skilled positions per firm is calculated by setting "several"=3.

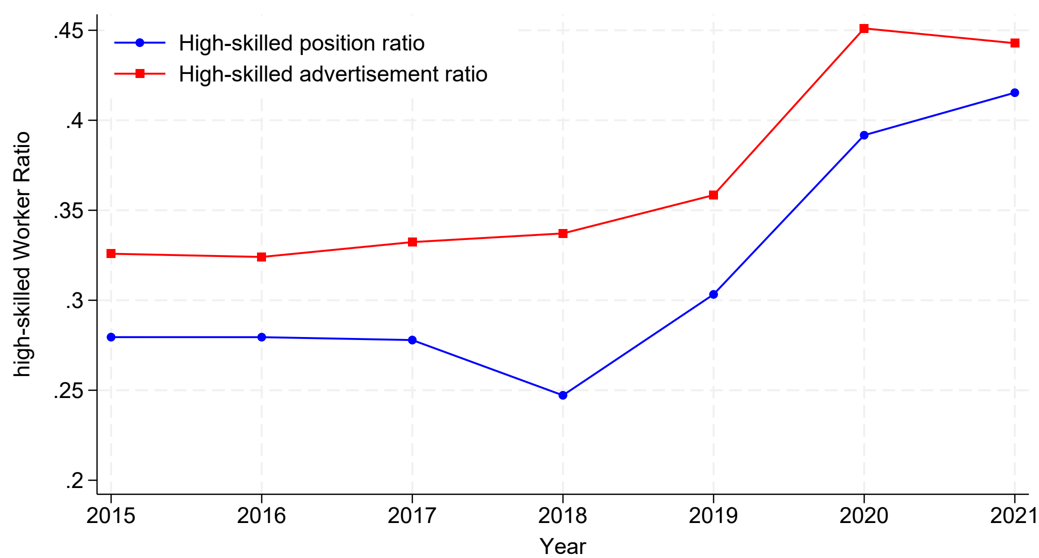

Figure B3: Annual Trends in High-skilled Job Postings Ratio
Notes: The *high-skilled position ratio* is defined as the total number of high-skilled positions divided by the total number of positions for all firms ("several"=3). Similarly, the *high-skilled worker advertisement ratio* is calculated as the total number of high-skilled worker job advertisements divided by the total number of job advertisements.

Table B1: Chinese Keywords in Job Title and Description

Keywords
总监，资深，主管，总管，高级，主任，专家，负责人
工程师，分析师，架构师，开发经理，部门经理，项目经理，区域经理，省区经理

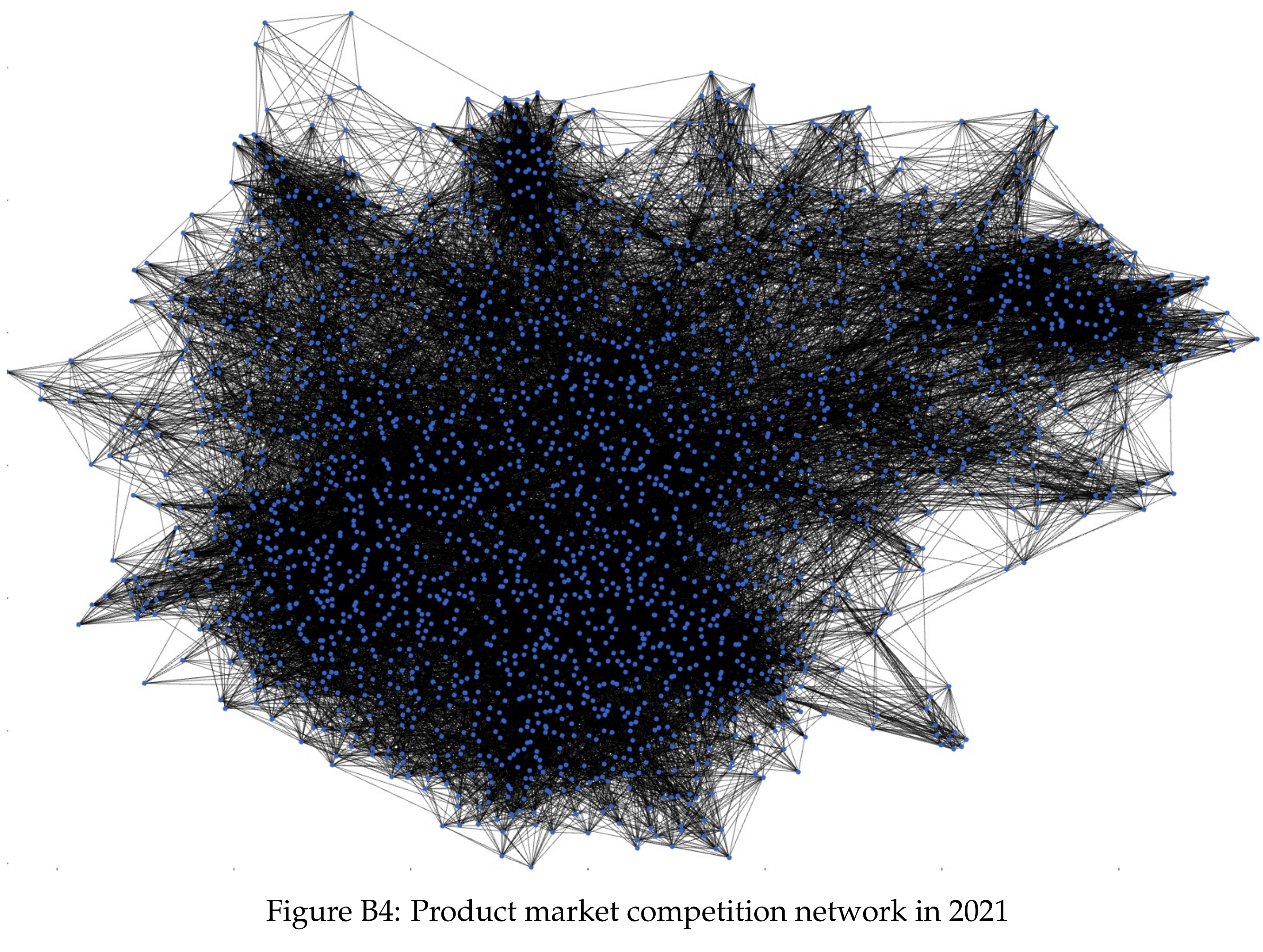

Figure B4: Product market competition network in 2021

Table B2: Explore Potential Competition at Firm-Occupation Levels

	(1)	(2)	(3)	(4)
	Benchmark	Alternative Specifications		
	Several=3	Several=0	Several=1	Several=5
Competitors' High-Skilled Posting	0.730***	0.751***	0.744***	0.720***
	(0.240)	(0.198)	(0.219)	(0.247)
Cragg-Donald F-statistic	7.789	5.187	5.963	9.518
Kleibergen-Paap F-statistic	8.875	5.167	6.531	10.107
Hansen J-test (p-value)	0.571	0.647	0.609	0.559
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
Observations	119,869	119,869	119,869	119,869

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parentheses are clustered at the 3-digit CAPCO industry level. The regression model is $v^o_{it} = \lambda \sum_{j \neq i} w_{ijt} v^o_{jt} + \boldsymbol{x}_{i,t-1}\boldsymbol{\beta} + \text{FE} + u^o_{it}$, where v^o_{it} firm i's high-skilled job postings for occupation o. Firm fixed effects, 3-digit CAPCO industry×year fixed effects, headquarter city×year fixed effects and occupation×year fixed effects are controlled in all columns. Controls include lagged firm-level characteristics.

Table B3: Define Least Textually Similar Firms as Non-Competitors

	(1)	(2)	(3)	(4)
	Benchmark	Alternative Specifications		
	Several=3	Several=0	Several=1	Several=5
Non-Competitors' High-Skilled Posting	-0.051	-0.034	-0.042	-0.056
	(0.060)	(0.081)	(0.073)	(0.052)
Cragg-Donald F-statistic	230.936	254.892	246.171	221.073
Kleibergen-Paap F-statistic	99.536	101.711	90.611	123.957
Hansen J-test (p-value)	0.864	0.874	0.886	0.804
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
Observations	13,949	13,949	13,949	13,949

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parentheses are clustered at the 3-digit CAPCO industry level. Firm fixed effects, 3-digit CAPCO industry×year fixed effects and headquarter city×year fixed effects are controlled in all columns. Controls include lagged firm-level characteristics.

Table B4: Absence of Strategic Complementarity in Low-Skilled Hiring

	(1)	(2)	(3)	(4)
	Benchmark	Alternative Specifications		
	Several=3	Several=0	Several=1	Several=5
Competitors' Low-Skilled Posting	-0.018	0.003	-0.017	0.017
	(0.382)	(0.480)	(0.445)	(0.329)
Cragg-Donald F-statistic	5.078	4.278	4.478	5.909
Kleibergen-Paap F-statistic	8.611	7.665	8.100	8.754
Hansen J-test (p-value)	0.328	0.197	0.239	0.404
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
Observations	13,949	13,949	13,949	13,949

Notes: This table reports 2SLS estimates of strategic complementarity in low-skilled hiring under different specifications. In contrast to high-skilled hiring, all coefficients are statistically insignificant, indicating no evidence of strategic interaction for low-skilled workers. Column (1) presents the benchmark specification (several=3); columns (2)–(4) show alternative coding of "several". Standard errors (in parentheses) are clustered at the 3-digit CAPCO industry level. Firm fixed effects, 3-digit CAPCO industry×year fixed effects and headquarter city×year fixed effects are controlled in all columns. Controls include lagged firm-level characteristics.

B.1 Heterogeneity Analyses

We further conduct additional heterogeneity analyses to examine how the competition varies across different types of high-skilled workers, changes in competitive intensity over time, and differences across firms with different ownership structures.

First, we classify high-skilled workers based on job descriptions into two categories using keywords (See Table B5 for details. 11.7% of the positions belong to both categories.): science or technology high-skilled workers, and management or marketing high-skilled workers. We then re-estimate Equation (12) by specifying v_{it} as the number of job postings in each high-skilled worker category, respectively. The results, presented in Table B6, show that the intensity of competition for science or technology talent is similar to that for management or marketing talent. This suggests that firms place almost comparable importance on both types of talent.

In Figures B2 and B3, we observe that while firms' overall hiring scale contracted after 2018, high-skilled worker hiring continued to grow. To investigate whether the intensity of the competition for high-skilled workers changed following this period, we examine this shift in Column (1) of Table B7. The results suggest a decline in competition intensity after 2018; however, the change is not statistically significant.

We further explore whether the intensity of competition varies across firms with different ownership structures. Column (2) of Table B7 shows that the competitive response of state-owned enterprises is not significantly different from that of non-state-owned firms.

Table B5: Chinese Keywords to Distinguish Two Types of High-skilled Workers

High-Skilled Worker Types	Keywords
Science or technology	资深，高级，工程师，分析师， 架构师，开发经理，专家
Management or marketing	总监，主管，总管，负责人，部门经理， 项目经理，区域经理，省区经理，主任

Notes: We use keywords to classify high-skilled workers into two categories based on job descriptions, namely science or technology high-skilled workers and management or marketing high-skilled workers. If a job description contains "senior, specialist, analyst, architect or engineer", then it will be categorized as a job posting for science or technology high-skilled workers. Similarly, if a job description contains "director, chief, head or manager', then it will be categorized as a job posting for management or marketing high-skilled workers. This table reports the original Chinese version of these keywords since the English translation may be vague.

Table B6: Heterogeneity in Different Types of High-Skilled Workers

	(1)	(2)
High-Skilled Worker Types	Science or Technology	Management or Marketing
Competitors' High-Skilled Posting	0.610***	0.608***
	(0.150)	(0.091)
Cragg-Donald F-statistic	53.715	83.243
Kleibergen-Paap F-statistic	23.773	23.118
Hansen J-test (*p*-value)	0.299	0.280
Controls	Yes	Yes
Fixed Effects	Yes	Yes
Observations	13,949	13,949

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parentheses are clustered at the 3-digit CAPCO industry level. Firm fixed effects, 3-digit CAPCO industry×year fixed effects and headquarter city×year fixed effects are controlled in all columns. Controls include lagged firm-level characteristics.

Table B7: Heterogeneity in Time and Ownership Types

	(1)	(2)
	Heterogeneity in Time	Heterogeneity in Ownership
Competitors' High-Skilled Posting	0.739***	0.466***
	(0.260)	(0.150)
Competitors' High-Skilled Posting	-0.167	
× Year>2018	(0.305)	
Competitors' High-Skilled Posting		0.375
× State-Owned		(0.256)
Cragg-Donald F-statistic	24.914	21.111
Kleibergen-Paap F-statistic	42.055	12.338
Hansen J-test (*p*-value)	0.430	0.839
Controls	Yes	Yes
Fixed Effects	Yes	Yes
Observations	13,949	13,949

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parentheses are clustered at the 3-digit CAPCO industry level. Firm fixed effects, 3-digit CAPCO industry×year fixed effects and headquarter city×year fixed effects are controlled in all columns. Controls include lagged firm-level characteristics.

B.2 Robustness Checks

In the main regressions, we define high-skilled workers as individuals with at least three years of work experience and a bachelor's degree or higher, as specified in Table 1. To test the robustness of our results, we tighten these criteria to require a minimum of five years of experience and a master's degree or higher. Columns (1)-(3) of Table B8 presents the results when these thresholds are raised individually and together. As shown, the coefficient on competitors' high-skilled job postings remains consistent. In column (4), following the tradition of the definition of high-skilled workers (e.g., Buera and Kaboski, 2012; Diamond, 2016; Guo et al., 2025), we only consider the education criterion, i.e., with a bachelor's degree or higher. We find the coefficient is similar. These results imply that our findings are robust to the definitions of high-skilled workers.

We also explore alternative thresholds in definitions of competitors to test the robustness of our results. In the main specification, a firm's competitors are identified as the 30 firms whose MD&A texts are most similar to its own. For robustness checks, we vary this threshold by redefining competitors as the top 10, 20, and 40 most textually similar firms. The corresponding results, reported in Table B9 columns (1) through (3), remain consistent, suggesting stable estimates of competition intensity. In column (4), we adopt a quantile-based approach instead of a fixed numerical threshold. Specifically, we rank all firm-pair textual similarities within a year and define competitors as those whose similarity scores fall within the top 1% quantile. This alternative definition also yields robust results, further reinforcing the reliability of our findings.

One potential concern is that a firm's response to competitors' actions may occur with a delay, reacting to competitors' hiring activities in the previous period rather than the current one. Table B10 reports the effects of lagged competitors' high-skilled worker job postings. As shown, the coefficients in the second row are insignificant, suggesting that the competition operates contemporaneously and does not exhibit a lagged effect.

In the previous analyses, when counting job positions, we only considered the year in which the job advertisements were posted, implicitly assuming that they were valid only for that year. In practice, however, a firm may keep an advertisement active for multiple years and use it to recruit on an ongoing basis. To account for this possibility, we incorporate the duration of each advertisement's active period. Our data source provides the last modification date for each posting, allowing us to define an advertisement's lifetime as the interval from its initial publication date to its most recent modification. During this lifetime, the associated number of positions is counted on an annual basis. The results, presented in column (1) of Table B11, confirm that the coefficients of competitors' high-skilled job postings remain robust.

Given the unusually high number of high-skilled worker job postings in certain observations, we trim the top 1% of outliers in column (2), and the results remained robust. We further apply a logarithmic transformation to the number of job postings and remove firm-specific effects via first differencing rather than demeaning. The results are robust to both modifications, as reported in columns (3) and (4). Different from the main specifications which using equally weighted average of competitors' high-skilled hiring, we also try unequally weighted average, weighted by text similarity scores. The results are reported in column (1) of Table B12, which are robust. In column (2), we also only use second-order competitors' characteristics ($W_t^2 X_{t-1}$) as IVs to better satisfy the exclusion restriction (but at the cost of weaker correlation), and the results still robust.

In our main specifications, we use the text of each firm's MD&A to construct text-based product market competition networks. However, these time-varying networks may be endogenous, as unobservable factors could simultaneously influence both network formation and firms' hiring practices. To address this concern, we apply the method of Jochmans (2023) , which mitigates potential endogeneity by constructing IVs through transformations of the existing network structure, without the need to search for external instruments. The results are presented in column (3) of Table B12. Although the estimated coefficients become smaller, they remain positive and statistically significant. This suggests that our main findings are unlikely to be driven by the endogeneity of product market competition networks.

Table B8: Alternative Definitions of High-Skilled Workers

Changed Criterion	(1) Raise Education	(2) Raise Experience	(3) Raise Both	(4) Only Education
Competitors' High-Skilled Posting	0.533***	0.621***	0.551***	0.640***
	(0.137)	(0.136)	(0.190)	(0.140)
Cragg-Donald F-statistic	83.285	53.194	58.968	47.091
Kleibergen-Paap F-statistic	16.231	28.026	18.236	23.529
Hansen J-test (p-value)	0.474	0.503	0.277	0.172
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
Observations	13,949	13,949	13,949	13,949

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parentheses are clustered at the 3-digit CAPCO industry level.Firm fixed effects, 3-digit CAPCO industry×year fixed effects and headquarter city×year fixed effects are controlled in all columns. Controls include lagged firm-level characteristics.

Table B9: Alternative Thresholds in Constructing Competitors

	(1) Top 10	(2) Top 20	(3) Top 40	(4) Top 1%
Competitors' High-Skilled Posting	0.392***	0.464***	0.570***	0.464***
	(0.100)	(0.097)	(0.124)	(0.164)
Cragg-Donald F-statistic	32.680	58.896	69.321	21.858
Kleibergen-Paap F-statistic	9.096	20.191	26.296	7.621
Hansen J-test (p-value)	0.763	0.302	0.710	0.195
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
Observations	13,949	13,949	13,949	13,949

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parentheses are clustered at the 3-digit CAPCO industry level. Firm fixed effects, 3-digit CAPCO industry×year fixed effects and headquarter city×year fixed effects are controlled in all columns. Controls include lagged firm-level characteristics.

Table B10: Introduce the Lagged Term

	(1)	(2)
Competitors' High-Skilled Posting		0.621***
		(0.173)
Lagged Competitors' High-Skilled Posting	0.337	0.039
	(0.229)	(0.241)
Cragg-Donald F-statistic	26.984	10.620
Kleibergen-Paap F-statistic	19.412	20.862
Hansen J-test (p-value)	0.678	0.648
Controls	Yes	Yes
Fixed Effects	Yes	Yes
Observations	13,949	13,949

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parentheses are clustered at the 3-digit CAPCO industry level. Firm fixed effects, 3-digit CAPCO industry×year fixed effects and headquarter city×year fixed effects are controlled in all columns. Controls include lagged firm-level characteristics.

Table B11: Other Robustness Checks: Alternative Specifications on sample or models

	(1) Consider Duration	(2) Trim Top 1%	(3) $\ln(1+v)$	(4) First Difference
Competitors' High-Skilled Posting	0.553***	0.458***	0.382**	0.787**
	(0.130)	(0.104)	(0.193)	(0.310)
Cragg-Donald F-statistic	78.112	133.287	82.121	11.757
Kleibergen-Paap F-statistic	28.451	73.686	45.086	6.842
Hansen J-test (p-value)	0.503	0.493	0.016	0.425
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
Observations	15,636	13,084	13,949	11,365

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parentheses are clustered at the 3-digit CAPCO industry level. Firm fixed effects, 3-digit CAPCO industry×year fixed effects and headquarter city×year fixed effects are controlled in all columns. Controls include lagged firm-level characteristics.

Table B12: Other Robustness Checks: Alternative Specifications on networks or IVs

	(1) Unequal Weights	(2) Only second-order competitors as IVs	(3) Endogenous Networks
Competitors' High-Skilled Posting	0.613***	0.646***	0.146**
	(0.149)	(0.185)	(0.062)
Cragg-Donald F-statistic	56.844	26.889	11.137
Kleibergen-Paap F-statistic	30.580	13.454	13.103
Hansen J-test (*p*-value)	0.503	0.284	0.064
Controls	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes
Observations	13,949	13,949	13,949

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parentheses are clustered at the 3-digit CAPCO industry level. Firm fixed effects, 3-digit CAPCO industry$\times$year fixed effects and headquarter city$\times$year fixed effects are controlled in all columns. Controls include lagged firm-level characteristics.

C The Advantage of Text-Based Product Market Competition Networks

The text-based product market competition networks derived from MD&A disclosures offer two principal advantages over traditional industry code classifications in capturing inter-firm linkages.

First, they allow for a more precise identification of business-content similarity. Conventional industry codes constrain firms to predefined categories, often failing to capture meaningful cross-sector relationships. In contrast, textual similarity analysis, which compares the content of firms' business descriptions directly, identifies both intra-industry and cross-industry competitive ties. This is illustrated in Figure C1(a), where 28 of the top 30 most textually similar firms to Yonghui Superstores in 2015 belong to the retail sector—confirming that the text-based approach preserves strong within-sector consistency. At the same time, it also captures economically relevant cross-industry linkages: for example, HLA, a clothing manufacturer and retailer classified under textiles and apparel, appears among Yonghui's top text-based competitors. Such connections, though spanning different code-based sectors, reflect genuine business overlap. Furthermore, the text-based method avoids misclassification in cases of reverse mergers, which can distort industry codes based on shell firms' legacy classifications. As shown in Figure C2(a), firms such as Times Media Oriental and Yinji Entertainment & Media, both involved in reverse mergers, are correctly linked to TCL based on their actual business content rather than their nominal industry codes.

Second, text-based networks capture the dynamic evolution of inter-firm linkages, a feature that static industry codes inherently lack. By recomputing textual similarity annually from updated MD&A disclosures, the method reveals how competitive relationships shift over time. For instance, comparing Figure C1(a) (2015) and Figure C1(b) (2021), we observe both stability—e.g., persistent connections to Inzone Group, New Hua Du Supercenter, and Rainbow Department Store—and change, such as the emergence of new competitors like Bestore and the fading of former ties such as Hangzhou Jiebai. A similar evolution is also visible for TCL. In 2015 (Figure C2(a)), its closest text-based competitors were largely telecommunications and broadcasting firms (e.g., Oriental Pearl, Jishi Media). By 2021 (Figure C2(b)), the network had shifted toward special-equipment manufacturers such as Linton Technologies and PNC Process Systems, mirroring TCL's strategic pivot from media-related operations toward advanced equipment manufacturing.

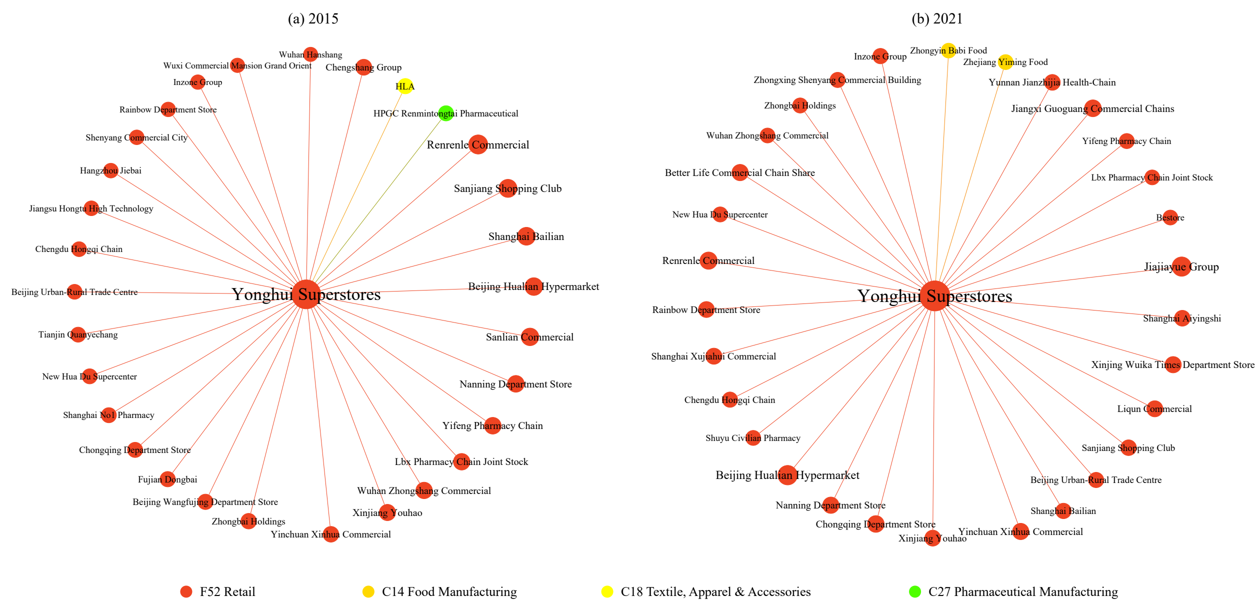

Figure C1: Text-based product market competition network of *Yonghui Superstores* in 2015 and 2021

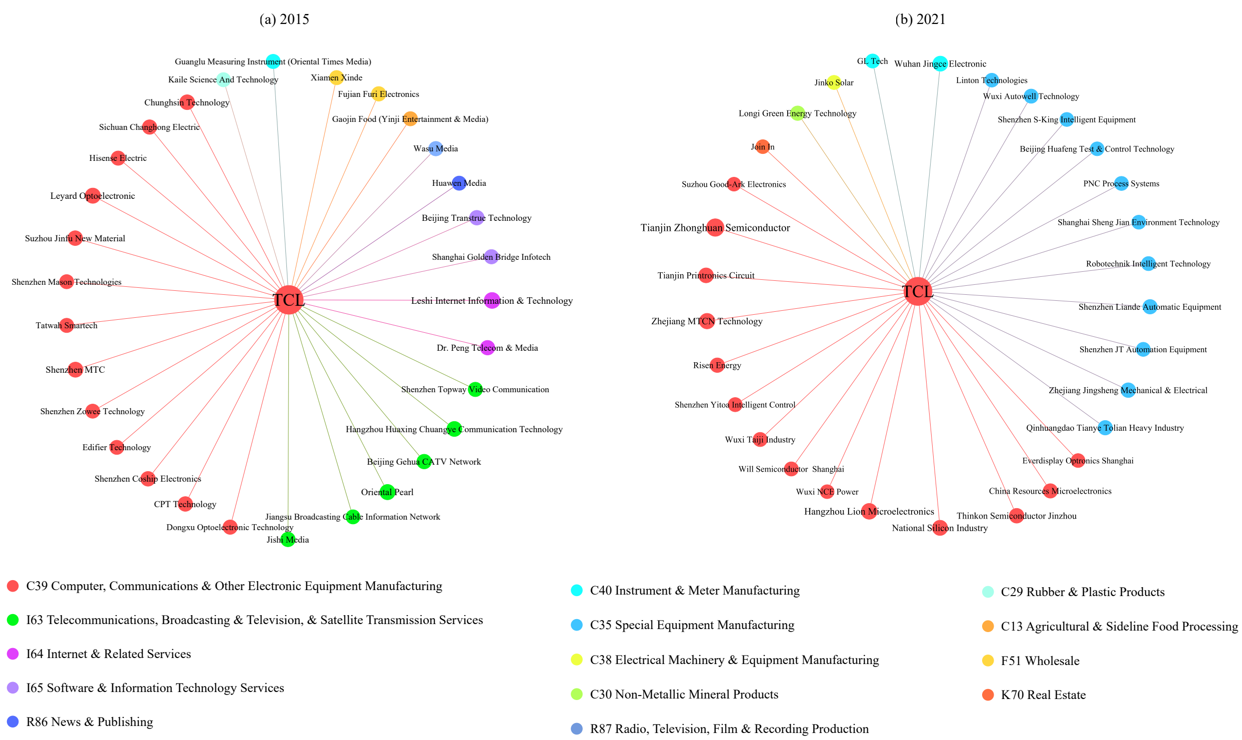

Figure C2: Text-based product market competition network of *TCL* in 2015 and 2021