Talent Market Competition and Firm Growth

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Abstract

How does competition for talent affect firm growth? Combining establishment-level occupational employment microdata with job posting data, we measure a firm's talent retention pressure (TRP) based on other firms' job postings for talent in the local market. Our TRP captures CFOs' subjective talent retention concerns and predicts firms' talent outflows. We show that (i) TRP substantially dampens firms' capital investment; (ii) firms do not elastically retain talent when TRP is higher, yielding lower subsequent talent productivity; and (iii) TRP dampens primarily laggard firms' growth but not superstars', leading to a limited impact on aggregate U.S. investment but increased industry concentration.

Keywords: *talent market competition, talent retention, corporate investment, superstar firms, investment-Q gap, industry concentration*

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Competition for talent is central for firms in the 21st century. Recent executive surveys repeatedly highlight that "attracting and retaining talent" is the most pressing internal concern of firms.[1] The competitive talent market that firms face likely affects their growth, as multiple CFO surveys show that talent constraints are the dominant reason for firms to forgo otherwise profitable investment projects (see Graham and Harvey (2011), Jagannathan et al. (2016) and a summary in Appendix A). Yet, how to characterize the *intensity* of talent market competition, to what extent firms address talent market competition in practice, and how talent market competition shapes firm growth are not well understood, largely due to measurement challenges.

In this paper, we construct a novel measure of firms' retention pressure from talent market competition. Talent retention pressure varies by firms' talent occupation and geographic location and has increased substantially over time. We quantify a sizeable negative impact of firms' talent retention pressure on their investment via panel regressions and also an instrumental variable approach, and we examine the underlying mechanism. Our firm-level analyses uncover an important heterogeneity that talent market competition only dampens the investment of laggard firms but not superstar firms (Gutierrez and Philippon (2020)). Consistent with this heterogeneity, we show that rising talent retention pressure has a limited impact on aggregate U.S. investment (Gutiérrez and Philippon (2017))—making the firm-level effect difficult to detect in the aggregate data, but fosters industry concentration in the recent decade (Gutiérrez and Philippon (2018) and Autor et al. (2020)).

Our measurement of firms' talent retention pressure utilizes two comprehensive datasets that overcome some major empirical challenges. First, firms' exposure to talent markets is difficult to measure as talent concerns a small group of highly skilled labor in the firms (Baghai et al. (2021)). We overcome this challenge by obtaining firms' establishments' *occupational* employment and wage rates from the U.S. Bureau of Labor Statistics (BLS) OEWS microdata, which covers 1.2 million establishments representing the U.S. economy. Second, talent moves primarily from job to job across firms, making the traditional labor market tightness measure (vacancy-to-unemployment ratio) unfit to capture talent market competition (Abraham et al. (2020)).[2] We combine the Lightcast's near-universe of job postings with the BLS microdata, and we measure the competition of local talent markets, defined at the MSA-occupation level, as the vacancy-to-employment ratio based on the *on-the-job search* model (Pissarides (1994)).

[1] See Appendix A for evidence from the Duke CFO Survey, Deloitte CFO Signals Survey, and PwC Family Business Survey.

[2] We show in the Internet Appendix Table IA.1 that more than 75% of new hires of our defined talent were job-to-job moves rather than from the non-employment pool in the Census Current Population Survey (CPS) data.

Using the two massive datasets, we construct our firm-level talent retention pressure as follows. First, we define a 5-digit SOC occupation as talent of a firm if its analytical and interpersonal skills rank in the top decile within the firm's industry a la Baghai et al. (2021).[3] Second, we measure the competition of a local talent market (MSA-occupation) as the ratio of vacancy, v, and the total employment, e. Third, we obtain each firm's employment exposure to each local talent market by merging Compustat firms with the BLS establishments. A firm's talent retention pressure (TRP) is the exposure-weighted average v-e ratio across talent markets, where we exclude the firm's own job postings in each market. TRP thereby captures the average abundance of outside options for the firm's talent stemming from local talent market competition. Intuitively, increases in job postings by other firms in a local talent market can expand the outside options of a focal firm's talent and raise the firm's talent retention pressure.[4]

We validate our TRP measure by answering the following two questions: First, does the TRP measure capture corporate executives' subjective talent retention concerns? We access the firm-year-level microdata of the Duke CFO Survey and show that firms' TRP is highly positively associated with their CFOs' election of talent retention as their most pressing concerns. Second, does TRP predict ex-post talent departure from the firm? We use the Revelio Lab Workforce Dynamics microdata (assembled from individuals' online profiles and resumes) and show that firms' TRP strongly and positively predicts their talent outflows in the next year. Hence, our TRP measure represents a credible threat of losing talent to firms.

After validating our measure, we present our main findings about talent retention pressure and firm investment. In our baseline OLS regressions, we find that TRP significantly reduces the next-period capital investment after controlling for common investment predictors (such as Tobin's Q) and fixed effects by firm and year. Firms with top-tercile TRP invest 22% less than firms with bottom-tercile TRP in the same year. This magnitude parallels the magnitude of major investment predictors such as Tobin's Q in explaining firm investment. The effect persists when we measure firm growth using the total investment from Peters and Taylor (2017) which accounts for intangible investment. Highlighting the importance of *talent* for firm growth, we do

[3]Defining firms' talent is challenging. We follow the procedure of Baghai et al. (2021) who discuss the advantages of using skills to measure talent over using education and other individual characteristics. We conduct extensive validation tests to support this skill-based measure of talent using the Duke CFO survey microdata (see Section III).

[4]Our TRP measure focuses on the abundance of outside options but not the attractiveness of the options. We discuss later that numerous studies on voluntary turnover suggest employees leave their firms for various reasons, making it difficult to characterize the attractiveness of outside options via a limited number of variables. Nevertheless, we validate that our TRP, based on the abundance of outside options, captures a significant part of firms' talent retention concerns and strongly predicts ex-post talent departure in Section III.

not find similar results when examining firms' retention pressure of non-talent which accounts for the majority of firms' employees. Highlighting the *retention* channel for firm growth, we do not find similar results when inspecting firms' talent hiring pressure, i.e., the attracting channel from talent market competition.[5]

Although our TRP measure is based on other firms' job postings that are not directly controlled by the focal firm, three remaining endogeneity concerns may bias our OLS estimates. First, omitted variables of local talent markets may drive both firms' TRP and their investment. Second, firms may endogenously reallocate labor across local markets, and the reallocation may change firms' TRP and at the same time be associated with firms' investment decisions. Third, a firm's product market competitors may post jobs relying on their expectations of the focal firm's investment. We address these concerns by constructing a shift-share instrument for TRP. Specifically, to address the omitted variable concern, we discard time-series variations of the v-e ratio at the local level but use the *national* growth of each occupation's v-e ratio instead. To address firms' endogenous reallocation, we fix firms' talent exposure across MSA-occupations at the levels observed at the beginning of our sample period in 2010 (see also in Card (2001) and Tabellini (2020)). Finally, we use only non-peer firms' job postings to mitigate the product market competition channel. Our instrumented TRP strongly and negatively predicts firm investment, consistent with our baseline results.

Our instrumental variable design relies on the identifying assumption that firms with higher initial talent retention pressure must not be on different investment trajectories in subsequent years (see Goldsmith-Pinkham et al. (2020) and Borusyak et al. (2022)). We support this assumption in several ways. First, we examine pre-sample period investment following Tabellini (2020) and rule out the confounding effects from persistent and unobservable firm characteristics that drove firms' initial share. Second, we show that our findings are unlikely to be driven by observable firm initial characteristics that may have prolonged effects on the instrument and firm investment. Third, we follow the diagnosis suggested by Goldsmith-Pinkham et al. (2020) and inspect the top five occupations that drive the instrument's sensitivity-to-misspecification. We show that firms' exposure to these occupations is not related to other firm characteristics that predict investment, and our results are robust if we exclude these occupations from the construction of our instrument. In sum, while the assumption underlying our research design is fundamentally untestable, our empirical strategies and robustness checks significantly mitigate concerns that our findings are driven by a spurious relation.

[5] Talent hiring pressure is the negative of the average job filling rate for the firm's job postings (see Section II).

We next propose a mechanism to understand our main findings by nesting an on-the-job search model into an investment setting. The intuition is the following: Due to a limited supply of talent, as suggested by the CFO surveys, firms compete by hiring talent from each other. As documented by numerous studies on voluntary employee turnover (see reviews by Hom et al. (2017) and Holtom et al. (2008)), we assume that firms cannot fully avoid losing talent when talent's outside options arise.[6] Firms respond to talent retention pressure by posting more jobs, resulting in higher talent turnover. Since new hires tend to be less productive than incumbents during the onboarding period (Silva and Toledo (2009)), firms proactively adopt a conservative investment policy when facing higher talent retention pressure.

We find support for this mechanism in the data. First, we examine the Glassdoor microdata of individual employee ratings of their firms, and we show that talent's job satisfaction does not increase when firms face higher talent retention pressure. When further examining employees' pecuniary compensation using the BLS microdata, we find that firms raise talent's compensation in response to talent retention pressure but only to match the average compensation increase in the local talent market. The absence of significant retention responses to TRP by firms, in conjunction with the previous validation finding that TRP effectively predicts talent departure from firms, supports our model's central premise that the average firm cannot prevent talent losses when outside options arise.[7] Second, consistent with our equilibrium model, we observe that firms increase job postings in response to talent retention pressure, which feeds back to the local talent market competition. Third, firms exhibit lower talent productivity in the subsequent year after facing higher talent retention pressure, consistent with our assumption that talent is less productive during onboarding.

We complete our analyses by exploring the implications of our firm-level findings for the aggregate U.S. economy. We first document an important heterogeneity from the data: Talent retention pressure dampens investment only in small and midsized "laggard" firms but not in large "superstar" firms.[8] This finding can be due to institutional resilience, i.e., superstar firms' investment is less affected by talent departure, or talent resilience, i.e., talent does not leave superstar firms when talent retention pressure rises.

[6] A salient finding in the voluntary employee turnover literature is that employees' voluntary departure from their firms can be driven by multitudes of pecuniary and non-pecuniary reasons, making it difficult for firms to address in the short run when their employees' outside options arise (see more discussions in Section I).

[7] While we do not observe firms' specific expenses on talent retention, we show in Section V that firms' SG&A expenses, for example, do not significantly respond to talent retention pressure. Overall, it is unlikely that our findings are purely driven by firms' direct expenses on talent retention crowding out their capital investment.

[8] We define superstar firms as the top 4 firms with the highest sales in the industry-year following Gutierrez and Philippon (2020) and Autor et al. (2020), but our findings are robust to other definitions.

We support the latter channel as talent retention pressure does not predict talent outflows for superstar firms. Additional analyses show that superstar firms exhibit greater retention elasticity to talent retention pressure in terms of raising talent compensation and improving satisfaction, which contributes to their talent resilience.

The heterogeneous effects on laggard and superstar firms have important implications for the aggregate economy. In particular, given that superstar firms dominate the nationwide investment, our estimation of the aggregate investment-Q gap following Gutiérrez and Philippon (2017) suggests that rising talent retention pressure did not significantly contribute to the lackluster *aggregate* U.S. investment. However, as talent retention pressure dampens the growth of laggard firms but not superstar firms, we observe that rising talent retention pressure positively contributed to the recent rise in industry concentration in the U.S. economy (Gutiérrez and Philippon (2018) and Autor et al. (2020)).

Our study contributes to the growing literature explaining new patterns of U.S. firm investment in the 21st century. An important work is Gutiérrez and Philippon (2017) which shows a lackluster capital investment for firms and the aggregate economy in the U.S. after the early 2000s. Several recent studies shed light on this issue via the rise of intangible capital (Gutiérrez and Philippon (2017) and Crouzet and Eberly (2023)), increases in market power (Barkai (2020), Syverson (2019), Gutiérrez and Philippon (2018)), measurement issues in discount rates (Gormsen and Huber (2022)), etc. While prior investigations on intangible capital focused on measurement issues and the stock of firms' intangibles, our study examines a key feature of intangible capital—it is partially controlled by talent (Black and Lynch (2009), Eisfeldt and Papanikolaou (2013) and Eisfeldt and Papanikolaou (2014)). We show that the pressure to retain talent has significantly contributed to the average firm's lackluster investment in the recent decade.

Our findings also contribute to the literature on superstar firms and business dynamism.[9] Prior studies have examined superstar firms in the context of declining product market competition (Gutiérrez and Philippon (2018)), fallen labor share (Autor et al. (2020)), slowed knowledge diffusion (Akcigit and Ates (2023)), etc. Our findings suggest a new area in which superstar firms maintain an advantage over laggard firms—the area of retaining talent from talent market competition. We show that this heterogeneity has important implications for the aggregate economy, as rising talent retention pressure had a limited impact on the U.S. aggregate investment (Gutiérrez and

[9]See Andrews et al. (2016), Gutiérrez and Philippon (2017), Gutiérrez and Philippon (2018), Syverson (2019), Liu et al. (2021), Kroen et al. (2021), among others.

Philippon (2017)) but a positive impact on rising industry concentration (Gutiérrez and Philippon (2018), Autor et al. (2020), and Grullon et al. (2019)) in the recent decade.

Finally, our work is also related to recent studies on the economic impact of labor mobility. These studies explored policy shocks on employees' job-to-job move costs, e.g., non-complete enforcement, and developed many novel insights into how labor mobility causally affects firm outcomes in the local treatment group.[10] We extend the prior studies by comprehensively measuring the *intensity* of firms' talent retention pressure, which can be driven by factors beyond job-to-job move costs, such as job posting costs and the degree of talent supply shortage. Our measure allows us to study firm investment beyond the local treatment group and examine longer-period patterns in U.S. firm investment. In particular, while Jeffers (2023) identifies a positive treatment effect of state non-compete enforcement on firms' physical investment within the narrowly-defined event window, studies using the state non-compete enforcement index over longer periods do not find significant results (e.g., Shi (2023) and Johnson et al. (2023)).[11] A potential justification for this discrepancy is that other drivers, such as declining online job posting costs and rising shortage of talent supply relative to demand, are quantitatively important for firms' talent retention pressure outside the event window.[12] Indeed, our study using a comprehensive measure supports Jeffers (2023) and shows a significant dampening effect of talent retention pressure on firm investment.

This paper is organized as follows: Section I presents a conceptual framework conveying the intuition of how talent retention pressure affects firm investment. Section II constructs our firm-level measure of talent retention pressure, and Section III validates the measure. Section IV presents our main results of talent retention pressure's effects on firm investment. Section V examines our model mechanism. Section VI explores the implications of the rising talent retention pressure for the aggregate U.S. economy, and Section VII concludes.

[10] Examples of some important policy shocks are state enforcement of non-compete agreements (Garmaise (2011), Jeffers (2023), Chen et al. (2023), Shi (2023), Johnson et al. (2023), among others) and allocation shocks from the U.S. immigration system (Chen et al. (2021), Shen (2021), Jiang et al. (2023), among others).

[11] The prior findings on intangible investment are also mixed: Shi (2023) and Johnson et al. (2023) find a positive effect of state non-compete enforcement on intangible investment (although Johnson et al. (2023) find a negative effect on patenting), Chen et al. (2023) find mixed effects, and Jeffers (2023) finds no effect.

[12] A salient observation is that while states increasingly enforced non-compete agreements in the past decades (see Internet Appendix Figure IA.1) and employees are increasingly subject to non-compete agreements (Shi (2023)), both CFOs' subjective talent retention concerns and our talent retention pressure measure increased substantially rather than decreased in the past decade (see Figures 3 and 4).

I. Conceptual Framework

In this section, we provide a simple conceptual framework to serve two purposes. First, it defines a firm's retention pressure from talent market competition to guide our empirical measurement. Second, it conveys the intuition for talent retention pressure to affect firm investment. Importantly, it shows how challenges for a firm to retain talent enable talent retention pressure to dampen the firm's investment.

Consider a two-period investment model with convex adjustment costs. The firm is risk-neutral, maximizes shareholder value at $t = 0$, and discounts future cash flows with a rate of r. At $t = 0$, the firm is endowed with k_0 capital and chooses investment I_0 subject to adjustment costs $C(I_0, k_0) = \frac{\beta}{2}\left(\frac{I_0}{k_0}\right)^2 k_0$. Capital accumulates as follows:

$$k_1 = (1 - \delta)k_0 + I_0, \tag{1}$$

where δ is the depreciation rate. The firm's production requires both capital and key talent employees ("talent") following a Cobb-Douglas production function, $y_0 = k_0^{\alpha}(a_0 n_0)^{1-\alpha}$, where n_0 is the number of talent and a_0 is the labor-augmented productivity. The firm pays a spot wage to talent each period, w_t. Both the firm and talent are wage takers.

We add a parsimonious on-the-job search (OJS) labor market to this investment model: There is a large number m of identical firms in the economy, and there are $N_0 = n_0 m$ talent employees in total. There is no entry and exit of firms and talent in the labor market. Importantly, we assume that firms are always constrained by the limited supply of talent, as suggested by the evidence from several CFO surveys (Graham and Harvey (2011) and Jagannathan et al. (2016)). Specifically, we assume that a_t is so high that the marginal product of labor is always greater than w_t.[13] This talent constraint assumption incentivizes the firm to post vacancies for talent in our model.

Talent employees are risk-neutral and have heterogeneous satisfactions with their matching to their current firms.[14] Motivated by numerous prior micro-level findings

[13]Recent findings support that firms have monopsony power. Seegmiller (2021) estimates that productive firms with skilled labor pay 62% of the marginal product of labor. Yeh et al. (2022) show a similar estimate of 65% for U.S. manufacturing firms. We assume the wage rate follows an exogenous and known process for simplicity and to focus our model on the firm's hiring and investment decisions. See Shi (2023) for a recent theoretical treatment of dynamic wage determination in a labor market with job-to-job move frictions.

[14]We use the term "satisfaction" to broadly capture employees' non-wage-related preference for working in the firm. See Sorkin (2018) for estimating the preference using the Census microdata.

on voluntary employee turnover, we assume that the firm cannot change employee satisfaction in the short run for simplicity.[15] Without loss of generality, we assume talent satisfaction is uniformly distributed between 0 and 1.

The talent market works as follows. At $t = 0$, firms post in total V_0 job vacancies. We adopt the setting of Jovanovic (1979) and assume that employees have no information about their matching satisfaction to the new firms before they work there for a while.[16] Hence, searching for an outside opportunity is similar to drawing a lottery of job satisfaction. Thus, the expected matching satisfaction of OJS is always $\frac{1}{2}$, and only the employees with low satisfaction will engage in OJS. OJS incurs a search cost of c to a job seeker.

Assume s share of employed talent in the firm engages in OJS. Given firms are identical, i.e., similar to the representative firm in the classic DMP search model, there are in total sN_0 job seekers in the talent market and V_0 total vacancies. The number of successful matches follows a Cobb-Douglas matching function as $x(V_0, sN_0) = (V_0)^\gamma (sN_0)^{1-\gamma}$, with $\gamma \in (0, 1)$. The probability for each job seeker to land a new job (job finding rate) is $\frac{x(V_0, sN_0)}{sN_0} = \left(\frac{V_0}{sN_0}\right)^\gamma$. The equilibrium share of employed talent searching for jobs can be computed by equalizing the marginal benefit of OJS and the marginal cost of OJS:

$$\underbrace{\left(\frac{V_0}{sN_0}\right)^\gamma \left(\frac{1}{2} - s\right)}_{\text{marginal benefit of OJS}} = \underbrace{c}_{\text{marginal cost of OJS}}. \tag{2}$$

From the above equation, we know that the equilibrium s is between 0 and $\frac{1}{2}$ and an increasing function of $\frac{V_0}{N_0}$ and a decreasing function of c. Denote $s = g(\frac{V_0}{N_0}, c)$.

We define the degree of *talent market competition* as the ratio of job vacancies for talent and the number of employed talent $\theta = \frac{V_0}{N_0}$. This measure (*vacancy-to-employment* ratio) is similar to the traditional definition of labor market tightness (*vacancy-to-unemployment* ratio) but focuses on the OJS market (see also in Pissarides

[15] A large body of literature has studied the drivers for voluntary employee turnover (see recent reviews from Hom et al. (2017) and Holtom et al. (2008)). This literature discovers several key drivers, as summarized by Holtom et al. (2008), that include (i) employee personality, (ii) employees' relationship with coworkers and leaders in the firm (e.g., Bauer et al. (2006)), (iii) corporate culture and commitment to job embeddedness (e.g., Harrison et al. (2006)), and (iv) shocks to employees' job satisfaction (e.g., the unfolding model of Lee and Mitchell (1994)). These drivers are arguably difficult for firms to control and change in the short run when their talent's outside job options emerge. We encapsulate all these drivers to the talent's matching "satisfaction" with their current firms. In Section V, we empirically inspect firms' labor-related reactions when their talent's outside job options expand.

[16] Recent empirical studies show substantial imperfect information and beliefs for employees about their future job offers at outside firms (see Conlon et al. (2018) and Jäger et al. (2021)). Belot et al. (2019) show that unemployed job seekers also possess substantial imperfect information about prospective firms.

(1994) and Abraham et al. (2020)).

We next define a firm's *talent retention pressure*, ψ, as the average probability for each of its talent to find a job in other firms. Given that $\psi = s \times \left(\frac{V_0}{sN_0}\right)^{\gamma} + (1-s) \times 0 = \theta^{\gamma} \left[g(\theta, c)\right]^{1-\gamma}$, and $g(\theta, c)$ increases in talent market competition θ, we have the following proposition.

Proposition 1 (Talent Market Competition and Talent Retention Pressure): *A firm's talent retention pressure is an increasing function of talent market competition.*

At $t = 0$, the firm takes the labor market condition as given and posts job vacancies $v_0^{'}$ by paying a posting cost of κ for each vacancy. Hence, the firm expects to lose ψn_0 talent due to its talent's OJS but also gain $\frac{\psi N_0}{V_0} v_0^{'}$ new talent from its job postings.[17] The firm's number of talent thus evolves as follows:

$$n_1 = (1-\psi) n_0 + \frac{\psi N_0}{V_0} v_0^{'}. \tag{3}$$

Labor turnover is costly for the firm. In particular, many studies have shown that new hires need time and training to onboard a firm, during which the new hires are less productive than the incumbent talent.[18] We assume that a new hire's productivity is $\rho < 1$ times the productivity of an existing employee (Silva and Toledo (2009)). As a result,

$$y_1 = k_1^{\alpha} \left[a_1 (1-\psi) n_0 + \rho a_1 \frac{\psi N_0}{V_0} v_0^{'} \right]^{1-\alpha} \tag{4}$$

At $t = 0$, the firm chooses optimal $v_0^{'}$ and I_0 to maximize firm value at $t = 0$:

$$\max_{v_0^{'}, I_0} \ \mathcal{V}_0 = y_0 - w_0 n_0 - I_0 - \frac{\beta}{2} \left(\frac{I_0}{k_0}\right)^2 k_0 - \kappa v_0^{'} + r E_0[y_1 - w_1 n_1], \tag{5}$$

subject to equations (1), (3), and (4).

With these settings, we can now deliver the core intuition for how talent market competition affects firm investment: Due to talent shortage in the economy, firms have an incentive to post job vacancies (i.e., *talent constraint assumption*). Firms cannot fully avoid losing talent to competition (i.e., *imperfect retainability assumption*). There-

[17] In equilibrium, because firms are identical, the firm posts vacancies $v_0^{'} = \frac{V_0}{m}$ and $n_1 = n_0$.

[18] For instance, Silva and Toledo (2009) argue that new hires take about 1 year to become fully productive. Hansen (1997) estimates that the direct cost of hiring and training a new worker equals 150–175% of her annual pay while the indirect costs are also high.

fore, by poaching talent from each other, firms end up worse off ex-post, because they also lose existing productive talent to other firms and the new hires are less productive than their lost talent during the onboarding period (i.e., *costly onboarding assumption*). The reduced talent productivity dampens the marginal product of capital. Hence, talent retention pressure (ψ) driven by talent market competition (θ) dampens the firm's investment (I_0). The following proposition conveys this intuition formally.

Proposition 2 (Talent Retention Pressure and Firm Investment): *A firm's investment is negatively related to its talent retention pressure,*

$$\frac{\partial I_0}{\partial \psi} < 0.$$

Proof: See Appendix B.1.

II. Data and Measurement

In this section, we corroborate multiple microdata sets to measure each firm's talent retention pressure based on its exposure to talent market competition. As specified in our conceptual framework, two important components of this measure are the firm's exposure to local talent markets and each talent market's v-e ratio.

A. Firms' labor market distribution

Throughout our study, we define firms' perceived local labor market at the MSA-occupation level.[19] To obtain a firm's employment distribution across MSA-occupations, we access the administrative OEWS microdata from the Bureau of Labor Statistics

[19]Labor economic studies typically characterize the labor market as being local, such as within commuting zones or MSAs. Recent studies examine this characterization and find strong support that job search is highly local. Marinescu and Rathelot (2018) examine job searching behavior on CareerBuilder.com and show that workers strongly dislike applying to distant jobs. In particular, the application probability for job searchers, regardless of their skills, drops to near zero if the jobs are 50 miles away from their current location (see their Figure 3). Workers may sometimes change occupations before and after job-to-job moves, making it difficult for their firms to gauge the scope of their outside options. To account for this flexibility, we use the broader 5-digit Standard Occupational Classification (SOC) codes when defining the local labor market, though the results are similar if we use the more granular 6-digit SOC codes. Overall, despite that some workers may move across MSAs or change occupations (Schubert et al. (2022)), we view MSA-occupation as an appropriate scope for firms to form their ex-ante perceptions of local talent market competition. Our validation results in Section III support this view.

(BLS).[20] The data track occupational employment and wage rates in approximately 1.2 million establishments stratified to represent the U.S. economy from 2010 to 2018, representing about 62% of the nonfarm employment in the U.S. For each establishment, we obtain the number of employees and average hourly wage rate for each 6-digit SOC occupation in the establishment. In addition to occupational information, we also have the establishment's sampling weight, industry code, county code, and its parent firm's name and employer identification number (EIN). We merge OEWS establishments to Compustat firms using a combination of EIN matching and fuzzy name matching (see more details in Zhang (2019)). Merging the data sets generates a firm i's employment in each MSA(m)-occupation(o) each year.

B. *Defining talent*

Defining and measuring talent is known to be challenging, as human capital can be multidimensional, and whether an occupation is a talent can vary substantially across industries. An important recent advancement is Baghai et al. (2021) which uses Swedish individual-level data and defines talent by male employees' scores on analytical and interpersonal skills in their military records.[21] These two skills closely mirror the cognitive-analytical skills and cognitive-interpersonal skills defined by Acemoglu and Autor (2011) using the O*Net data in the U.S.

We construct from the O*Net V23.0 database the average importance scale for cognitive-analytical skills and cognitive-interpersonal skills for each 6-digit SOC occupation and aggregate the measure to the 5-digit level.[22] We then follow Baghai et al. (2021) and sort occupations' employment share within each 4-digit NAICS industry by their skill measure in each year, where the industry's occupational employment is aggregated from the OEWS microdata. An occupation o is considered a **talent** for industry i in the year if the occupation ranks within the top 10th percentile of the skill

[20]OEWS refers to the Occupational Employment and Wage Statistics program at the BLS. See Zhang (2019) and Tuzel and Zhang (2021) for more detailed descriptions of the microdata.

[21]Baghai et al. (2021) discuss in detail the advantages of measuring talent by skill over education. In particular, Philippon and Reshef (2012) point out that there is significant variation in human capital within similar educational groups. We validate in the Internet Appendix Table IA.2 that this skill-based definition of talent captures CFOs' perception of talent better than other definitions of talent such as education-based.

[22]Following Acemoglu and Autor (2011), we extract three cognitive-analytical skills from O*Net, including 4.A.2.a.4 Analyzing data/information, 4.A.2.b.2 Thinking creatively, and 4.A.4.a.1 Interpreting information for each occupation, and three cognitive-interpersonal skills, including 4.A.4.a.4 Establishing and maintaining personal relationships, 4.A.4.b.4 Guiding, directing and motivating subordinates, and 4.A.4.b.5 Coaching/developing others for each occupation. We standardize the importance scale of each skill to have a mean of 0 and a standard deviation of 1 across occupations, and we average the six standardized scales to obtain our skill measure for each occupation.

distribution.[23] Finally, an occupation is a talent for a firm if it is a talent for the firm's Compustat industry. We treat all other occupations as non-talent for the firm.

Figure 1 summarizes the composition of talent at the broad 2-digit SOC level, showing that talent includes many management occupations (35%) but also other skilled occupations, such as computer and mathematical (e.g., computer programmers), business and finance (e.g., accountants), office and administrative support (e.g., supervisors of office and administrative support workers), transportation (e.g., supervisors of transportation and material moving workers) and sales occupations.

— Figure 1 about here —

C. Measuring talent market competition

Guided by our on-the-job search framework in Section I, we measure local talent market competition as the vacancy-to-employment (V/E) ratio for each MSA-occupation. A necessary condition for the V/E ratio to capture local talent market competition in practice is that most talent hires are via job-to-job rather than from the non-employment pool. We validate this condition in the Internet Appendix Table IA.1. First, by mapping our definition of talent occupations to the Census Current Population Survey (CPS) data, we observe that 76% of the newly hired talent were employed by another firm in the previous quarter.[24] Second, we observe that 81% talent occupations require at least one year of work experience on the job, suggesting that talents are unlikely to be hired directly out of schools but are internally promoted or poached from another firm.

We obtain the employment (E) information for each MSA-occupation from the OEWS microdata. We obtain job posting information (V) from the widely used Lightcast database (formerly Burning Glass Technologies), which provides the near-universe US online job posting data from 2010 to 2018.[25] Combining the two datasets, we

[23]Using alternative cutoffs to define talent generates qualitatively similar results (see the Internet Appendix Table IA.3).

[24]Job-to-job moves are identified based on changes in employer's name in CPS surveys (Fallick and Fleischman (2004)) and within-quarter job-to-job switch as (Hyatt et al. (2014)). See more details in the Internet Appendix Table IA.1.

[25]Lightcast collects more than 3.4 million job postings daily from over 50,000 sources, such as job boards, company websites, newspapers, and public agencies. It then uses a sophisticated system to deduplicate job posting ads and extract detailed information from the ads, including the job's 6-digit SOC code, employer name, industry code, county code, and many other features. Lightcast data have been widely used in economic studies, see Hershbein and Kahn (2018), Deming and Kahn (2018), Blair and Deming (2020), Deming and Noray (2020), Bloom et al. (2021), Acemoglu et al. (2022), among others. The raw data provide new job postings at a monthly frequency. We aggregate all new job

measure each MSA-occupation's local talent market competition as its vacancy-to-employment ratio (V/E). Figure 2 provides a visual illustration of the aggregate V/E ratio for all talents in each MSA in 2018, where MSAs such as Denver, San Francesco, Seattle, Austin, San Jose, and Dallas have high overall talent market competition, and Cleveland, Atlanta, Miami, Sacramento, and Houston have low overall talent market competition.

— Figure 2 about here —

D. Measuring firms' talent retention pressure (TRP)

Let $s_{i,m,o,t}$ be the fraction of firm i's talent in MSA(m)-occupation(o) over the firm's total talent employment in year t, and $\frac{V_{-i,m,o,t}}{E_{m,o,t}}$ be the measure of the local talent market competition for firm i, where we exclude firm's own job postings to capture the firm's talent's *outside* options.[26] A firm's *talent retention pressure (TRP)* is the average V/E ratio in the local talent market based on *other firms'* job postings, weighted by the firm's exposure to the local talent market:

$$TRP_{i,t} = \sum_{m,o} s_{i,m,o,t} \times \frac{V_{-i,m,o,t}}{E_{m,o,t}}. \tag{6}$$

We further define two firm-level control variables to help clarify the talent retention mechanism in our empirical analyses. The first control variable is a firm's non-talent retention pressure ($NonTRP$), which is defined based on the same formula as in equation 6 but using only the firm's non-talent occupations. This variable will help us gauge whether our findings are specific to talent employees or derive from the overall labor market conditions. The second control variable is a firm's talent hiring pressure (THP) imposed by talent market competition. We measure a firm's THP as the negative of the average E/V ratio across the local talent market, capturing job filling rate, weighted by the firm's number of job postings in each MSA-occupation in the year. When constructing the E/V ratio for THP, we exclude the firm's own employment. This variable will help us dissect whether talent market competition affects firm investment

postings within a calendar year to represent the stock of vacancies in that year. As a robustness check, we construct an alternative measure of the stock of vacancies in each month by applying a 1% per day job filling rate on prior job postings following Forsythe et al. (2020b) and average the monthly stock of vacancies within each calendar year. This alternative measure is over 98% correlated with our simple aggregation measure.

[26]That is, $V_{-i,m,o,t} = V_{m,o,t} - V_{i,m,o,t}$. We identify each firm's job postings in each local talent market by merging the Lightcast job posting microdata with Compustat firms using a crosswalk provided by Lightcast, which we further enhance using a fuzzy name-matching algorithm.

via firms' talent retention concerns or their talent attraction concerns in the data.

E. *Summary statistics*

Our final sample includes Compustat firms with the TRP measure from 2010 to 2018, where 2010 is the first year when the Lightcast job posting data are mainly available. We further require that the Compustat firm is established in the U.S., has total assets greater than $1 million, has more than 50 employees, and has at least 10% total employment covered in the OEWS data. Our final sample includes 13,502 firm-year observations with all variables winsorized at the 1% and 99% levels in each year.

Table I reports the summary statistics of our final Compustat sample which has many accounting variables comparable to those from the Compustat universe. This alignment suggests that our final sample is a reasonable representation of publicly traded firms in the U.S. The average firm in our sample has a TRP of 0.239, yet there are substantial variations, with the 10th percentile TRP as 0.086 and the 90th percentile TRP as 0.427. Moreover, consistent with the public notion that firms are increasingly concerned about talent retention, we observe in Figure 3 that the cross-sectional median TRP for our final sample firms doubled from 2010 to 2018.[27] Corroborating the rising TRP, Figure 4 uses the Duke CFO Survey microdata and shows CFOs' talent retention concerns also rose similarly in this period (see more details about the Duke CFO Survey microdata and measures in Section III.A below).

— Table I about here —

— Figure 3 about here —

— Figure 4 about here —

III. Validation

In this section, we conduct tests to validate our measure in two aspects. First, does our talent retention pressure measure based on employees' outside options relate to

[27] One may be concerned that the rising TRP measure over time is driven by the expanding coverage of job postings in the Lightcast database or employers' increasing use of online job postings compared to traditional job postings. This is unlikely: Hershbein and Kahn (2018) conduct extensive validations showing that the Lightcast vacancy data exhibit trends closely tracking the BLS Job Openings and Labor Market Turnover Survey (JOLTS) vacancy data over time, especially for highly skilled occupations. See similar validations in Forsythe et al. (2020a) and Carnevale et al. (2014). Lancaster et al. (2019) provide a review of academic efforts and findings in validating the Lightcast job posting data.

corporate executives' subjective talent retention concerns? Second, can talent retention pressure predict actual talent departure from the firm?

A. TRP and CFOs' talent retention concerns

Our first validation test compares our TRP measure with CFOs' talent retention concerns using the Duke CFO Survey microdata (Graham and Harvey (2001)). The survey obtained responses from an average of 460 firms on this topic each quarter from 2008 to 2019. Importantly, the survey asked CFOs to elect their internal company-specific concerns in nearly every quarter. The survey underwent a minor change in regime in 2014Q2. For the quarters before 2014Q2, the survey asked CFOs to elect the top three concerns from about ten options. Beginning in 2015Q1, the survey asked CFOs to elect the company's top four most pressing concerns from about eighteen options (see the survey questions in the Internet Appendix Figure IA.2). Throughout the surveys, "attracting and retaining qualified employees" is always an option.

We constructed an indicator measure of *CFO talent concerns* if "difficulty attracting and retaining qualified employees" was elected in the top three concerns in the earlier regime from 2008 to 2014 or was elected as the top four concerns in the later regime from 2015 to 2019 which has a slightly different survey design. We merge the survey microdata with our Compustat sample and compare CFOs' talent concerns with our talent-market-competition-based TRP measure by running the following regression:

$$\text{TalentConcern}_{i,t}^{CFO} = \beta \cdot \text{TRP}_{i,t} + X_{i,t} + \text{Firm-Regime FE} + \text{Year FE} + \epsilon_{i,t},$$

where $X_{i,t}$ is an array of firm-level control variables, and all standard errors are clustered at the firm level.

Table II reports the results. Columns (1)-(3) show that TRP positively and significantly relates to CFOs' talent concerns without and with controlling for firm fixed effects and firm characteristics such as firms' Tobin's Q, cash flows, size, and age. Column (4) conducts a placebo test by including a similarly constructed measure of firms' non-talent retention pressure (NonTRP). We observe a sharp contrast that NonTRP is negatively related to CFOs' talent concerns, indicating that our definition of talent captures the talent that CFOs have in mind. In the Internet Appendix Table IA.2, we further show that TRP constructed using other definitions of talent, such as the education-based definition, appear not as related to CFOs' talent concerns as our task-based TRP.

We next examine whether the positive association between TRP and CFOs' talent concerns is due to talent retention or attraction pressure. This test is particularly helpful because the Duke CFO survey did not differentiate talent attraction from talent retention in their survey question. In Column (5) of Table II, we add the talent hiring pressure (THP) measure into the regression. THP is defined in Section II.D and captures the negative of the firm's each vacancy posting's job filling rate. We observe that the THP is not significantly related to CFOs' talent concerns, and THP does not absorb the significance of TRP. Hence, CFOs' talent concerns are more associated with talent retention pressure in our setting. Given this finding, we refer to CFOs' talent concerns as talent retention concerns in the rest of this article. Given the importance of executive expectations and beliefs for firm investment decisions (Gennaioli et al. (2016)), it is plausible that our TRP can affect firm investment.

— Table II about here —

B. TRP and future talent outflows

Our second validation test examines whether the TRP measure derived from talent market competition can effectively lead to firms' talent departure in the future. We obtain workforce moves into and out of Compustat firms yearly from the Revelio Lab Workforce Dynamics database. Revelio Lab collects individual online resumes and profiles, such as those from LinkedIn, and aggregates the information to the firm-occupation level. For each Compustat firm in each year, we obtain the total number of employees by 6-digit SOC occupations, the total number of employees joining the firm by occupation (inflow), and the total number of employees leaving the firm by occupation (outflow). We construct a firm's talent job-to-job outflow rate as the number of talent leaving the firm in year t divided by the total number of talent at the beginning of year t. We also measure the firm's job-to-job inflow rate in a similar way.

In Panel A of Table III, we regress talent job-to-job outflow rate in year t, $t+1$, and $t+2$ on the firm's TRP in year t:

$$\text{Talent Outflow Rate}_{i,t+k} = \beta \cdot \text{TRP}_{i,t} + X_{i,t} + \text{Firm FE} + \text{Year FE} + \epsilon_{i,t}.$$

We observe that firms experience relatively more talent outflows in the next year when facing higher TRP this year. A one-standard-deviation increase in TRP is associated with roughly a 1% increase in talent outflow rate (while the sample standard deviation of talent outflow rate is 12%). The predictive power decreases as we examine the outflow rate in year $t + 2$. In contrast, Panel B shows that TRP does not significantly reduce current or future talent inflows.

In summary, the validation evidence suggests that our TRP measure represents a credible threat to talent retention that can cause firms to lose talent next year, and such a threat is not driven by firms' financial and operational characteristics. These findings are consistent with numerous previous studies showing that employee departure can be driven by multitudes of individual factors (see reviews by Hom et al. (2017) and Holtom et al. (2008)), and firms in practice cannot fully avoid their talent leaving the firm when they face more outside options.

— Table III about here —

IV. Talent Retention Pressure and Investment

In this section, we present our main findings about TRP's effect on firms' capital investment. We first present our baseline results. Then, we strengthen the identification of the causal relationship using an instrument for TRP.

A. *Main findings*

We define a firm's physical investment as capital expenditure (CAPX) normalized by the beginning of year total assets (AT). Our main focus is to examine how talent retention pressure affects corporate investment using the following regression specification:

$$\text{Inv}_{i,t+1} = \beta \cdot \text{TRP}_{i,t} + X_{i,t} + \text{Firm FE} + \text{Year FE} + \epsilon_{i,t}, \tag{7}$$

where $X_{i,t}$ controls common investment predictors proposed in the prior literature, including the firm's Tobin's Q, cash flows, firm size proxied by the natural logarithm of total assets, and the natural logarithm of firm age. We cluster standard errors at the firm level.

Table IV shows the results. Columns (1)-(3) show that firms significantly reduce physical investment when the pressure for talent retention is high. Column (1) shows the results of our baseline model. Column (2) adds non-talent retention pressure (NonTRP) as an additional control. Consistent with our earlier validation results that NonTRP is not aligned with CFOs talent retention concerns, we observe that NonTRP does not negatively relate to firms' physical investment. The contrast between TRP and NonTRP delivers an important message that not all types of employee retention pressure can dampen firm growth.[28]

Our TRP measure is based on local talent market competition. A more competitive talent market, i.e., more job postings for talent, can impose greater pressure on firms' retention of existing talent and also their attraction of new talent. Can the negative relation between TRP and firm investment be driven primarily by the talent attraction channel rather than the retention channel? To answer this question, Column (3) reports results that include firms' talent job postings and talent hiring pressure (THP) as controls. Job posting for talent captures the quantity of firms' demand for talent, and THP captures the difficulty in filling each job posting. We observe that the effect of talent retention pressure on physical investment is robust to including the controls, whereas the coefficient of THP is insignificant. Hence, talent market competition dampens firm growth primarily via firms' talent retention pressure rather than talent hiring pressure.[29]

The economic magnitude of TRP's effect on physical investment is also sizeable. Following Hoberg and Maksimovic (2022), we sort firms into three tercile portfolios based on the distribution of TRP in the cross-section and report the portfolio's average investment rates in the Internet Appendix Table IA.4. The average inter-tercile range for investment rate is 1.22%, suggesting that high-TRP firms invest 22% less than low-TRP firms. This difference represents a sizable magnitude as the mean and standard deviation of firms' physical investment rate in our sample are 5% and 6.4% (see Table I), respectively.

In recent decades, investment in intangible capital such as knowledge capital and organizational capital also account for a large part of firm investment and growth (e.g., Peters and Taylor (2017), Eisfeldt and Papanikolaou (2014), Crouzet and Eberly (2023), Belo et al. (2021)). In particular, Peters and Taylor (2017) propose a measure of total investment to account for firms' investment in both physical capital and intangible capital and a measure of total Q to account for the replacement value of the firm's physical capital and intangible capital. Although intangible capital is not clearly defined

[28]There can be many reasons for NonTRP to have a positive significant impact on firm investment. One potential explanation is that physical capital may substitute non-talent employees such as routine-task workers, and thus the departure of non-talent employees may foster firms to invest in physical capital to replace labor (Autor et al. (2003)). Tuzel and Zhang (2021) use state adoption of investment tax incentives to estimate the elasticity of substitution between capital and skilled labor and between capital and routine-task labor.

[29]Conceptually, the talent retention and attraction channels may also entangle and reinforce each other, as difficulty in hiring new talent can reinforce firms' pressure of retaining existing talent. We do not explore the interaction of these two channels in this study.

in our model, we examine total investment for robustness of inference.[30]

In Columns (4)-(6) of Table IV, we show a robustness check that incorporating firms' intangible capital does not change the inference. In particular, we observe a similar dampening effect of TRP on investment when using total investment and total Q following Peters and Taylor (2017). Column (5) shows a similar result to Column (2) that there is a stark contrast between talent and non-talent in affecting firms' total investment. Column (6) shows that the talent retention channel is a primary driver for TRP to dampen firms' total investment rather than the talent attraction channel.[31]

— Table IV about here —

B. *Instrument for TRP*

A priori, we may expect firms to reallocate labor across local markets, and the reallocation decisions may be endogenously related to firm investment decisions. It is also possible that omitted characteristics of the local labor markets may drive both firms' TRP and their investment. In either case, OLS estimates in equation (7) will likely be biased. To address the endogeneity concerns, we construct a modified version of the shift-share instrument (Card (2001)).

Note that our TRP measure is defined as $TRP_{i,t} = \sum_{m,o} s_{i,m,o,t} \times \frac{V_{-i,m,o,t}}{E_{m,o,t}}$ (see equation (6)). To address the endogenous reallocation problem, we fix firms' exposure to talent markets as their initial exposure at the beginning of our sample period, $s_{i,m,o,2010}$.[32] To address the omitted local variable problem, we use the shift-share technique and replace $\frac{V_{-i,m,o,t}}{E_{m,o,t}}$ with the local talent market's initial V/E ratio in 2010 multiplied by the *national* growth rate of the V/E ratio for the occupation from 2010 to t. Formally, $TRP_{i,t}$ in equation (7) is instrumented with

$$\text{IV}_{i,t} = \sum_{m,o} s_{i,m,o,2010} \times \frac{V_{-i,m,o,2010}}{E_{m,o,2010}} \times G_{o,t} = \sum_{o} \underbrace{\left[\sum_{m} s_{i,m,o,2010} \times \frac{V_{-i,m,o,2010}}{E_{m,o,2010}} \right]}_{\text{share}} \times \underbrace{G_{o,t}}_{\text{shift}}, \tag{8}$$

[30]Our simple model has only one type of capital and thus does not separate physical and intangible capital. We view the results on total investment as a robustness check for most of our analyses

[31]We also check for reversals in the Internet Appendix Table IA.5 by regressing firms' investment in $t+2$ and $t+3$ on their TRP at t. We observe the negative effects diminish as we inspect future investments but do not reserve to be positive significant. Hence, we do not detect the reversal.

[32]This lagged-exposure technique is frequently used in the immigration literature for identification, see, for example, Card (2001).

where $G_{o,t}$ is the cumulative growth rate of occupation o's V/E ratio from 2010 to t.[33]

The instrument constructed in equation (8) exploits two sources of variation: First, cross-sectional variation in each occupation's retention pressure on the firm in 2010, expressed as the weighted sum of the V/E ratio for MSAs within the occupation, i.e., $\sum_m s_{i,m,o,2010} \times \frac{V_{-i,m,o,2010}}{E_{m,o,2010}}$. Second, time-series variation induced by changes in the competition for the occupation at the national level from 2010 to t, i.e., $G_{o,t}$.

Identifying assumptions and instrument validity The key identifying assumption behind this instrument is that firms with higher talent retention pressure in 2010 (from each occupation) must not be on different investment trajectories in subsequent years (see Goldsmith-Pinkham et al. (2020) and Borusyak et al. (2022)). In the words of Goldsmith-Pinkham et al. (2020), it means that the 2010 firm "shares" cannot be endogenous to changes in firms' subsequent investment.

This assumption can be violated when characteristics of firms that drove their 2010 retention pressure from each occupation (via the interplay between firms' employment distribution across MSA-occupations and the MSA-occupation's V/E ratio) have persistent and confounding effects on both firms' retention pressure and investment in later years. We address this concern in three different ways. First, we conduct a standard check for lagged-exposure instruments (e.g., Tabellini (2020)) and show that pre-2010 changes in firm investment are uncorrelated with subsequent changes in TRP predicted by the instrument, mitigating the concerns about such persistent unobservable firm characteristics. Second, we augment our baseline specification by including interactions between year dummies and 2010 firm characteristics that may have prolonged effects on TRP and investment. Third, we follow the diagnosis procedure by Goldsmith-Pinkham et al. (2020) and inspect firms' exposure to the top 5 occupations that drive the instrument's sensitivity-to-misspecification (i.e., occupations with the highest Rotemberg weights). In particular, we show that firms' exposures to the top 5 occupations are not related to other firm characteristics that predict investment, and we also show that our results are robust if we exclude the top occupations from the construction of our instrument.[34]

[33]Ideally, one would also leave the firm's own job postings and employment out from the calculation of $G_{o,t}$. We do not impose this leave-one-out requirement as it is unlikely that a single firm drives the occupation's aggregate V/E dynamics.

[34]We thank Paul Pinkham-Goldsmith for suggesting the robustness check of excluding the top occupations with the highest Rotemberg weights.

2SLS results Table V presents the second stage results of the 2SLS estimation. Column (1) shows that the TRP instrumented by the IV significantly dampens firms' physical investment. Column (3) shows a similar finding that TRP instrumented by the IV also significantly dampens firms' total investment. The F-statistics are 131.4 and 126.9 for the samples in Columns (1) and (3), respectively, strongly rejecting the null hypothesis that our shift-share instrument is a weak instrument for TRP.[35]

Inspecting the magnitude of instrument estimates Jiang (2017) surveys 255 published papers in the big three finance journals and finds that the average magnitude of β_{IV} is 3.3 to 9.2 times that of β_{OLS} depending on the nature of endogeneity concerns. The large magnitude of the instrument estimates alarms concerns about the instrument's strength, even if the F-statistics of the instrument pass the weak instrument test. Comparing Table V with Table IV, our β_{IV} is 3.6 (= 5.352/1.472) times greater than β_{OLS} in magnitude for physical investment, which is at the lower end of the range from prior studies but still worthy of a careful inspection. We thus conduct two diagnostic checks suggested by Jiang (2017) to improve the transparency of the instrument estimates. First, we enhance the transparency of our instrument's potency by reporting the partial R^2 of the instrument on TRP. Internet Appendix Table IA.6 reports the first-stage results and shows that the instrument explains 2% of the variation in TRP after partialling out various controls and fixed effects, suggesting a meaningful strength of our instrument.[36]

Our second check following Jiang (2017) inspects the economics for why β_{IV} exhibits a greater magnitude than β_{OLS}. One difference between our instrument and TRP is that the instrument discards local economic dynamics by using the national growth of occupational v-e ratio. Note that local economic dynamics may have attenuated the TRP's effect on firm investment in the baseline tests, resulting in a lower β_{OLS} than β_{IV}. For example, local economic factors that drive other firms' job postings for talent may represent a greater growth potential in the local area, countering the negative effects of TRP on firm investment. In the Internet Appendix Table IA.7, we conduct a diagnostic "mid-step" instrument, which differs from our instrument in that it allows for local economic dynamics. We observe the 2SLS coefficient for the diagnostic instrument to be only 1.7 (= 2.495/1.472) times greater than β_{OLS}. Hence, local omitted variables likely have led to an underestimation of TRP's dampening effects on firm investment in the baseline analyses.

[35] The rule of thumb threshold for F-statistics to pass the Stock and Yogo (2005) weak instrument test is about 10 (see Jiang (2017)).

[36] Jiang (2017) regards 2% partial R^2 as a "respectable number if considered as the incremental explanatory power of the instrument on top of other exogenous regressors" (page 136).

Inspecting the validity of the instrument As mentioned earlier, we conduct a battery of robustness checks to inspect the validity of the instrument. Internet Appendix Table IA.8 shows that firm investment before 2010 is unrelated to the 2010 TRP predicted by the instrument. Hence, confounding firm characteristics that drove firm investment and TRP prior to 2010 are unlikely to persistently affect firm TRP in subsequent years. Internet Appendix Table IA.9 shows that our results are robust to controlling for interactions between year dummies and 2010 firm characteristics that may have prolonged effects on TRP and investment. Internet Appendix Table IA.10 regresses firms' 2010 retention pressure ("share") from each of the top 5 occupations with the highest Robemberg weights on 2010 firm-level investment predictors and shows the shares are not driven by investment predictors. Internet Appendix Table IA.11 further constructs instruments excluding the top 5 occupations that drive the instrument's sensitivity-to-misspecification and shows that our results are robust.

C. Distinguishing from product market competition

A remaining interpretation concern is that our main findings on firm investment may be driven by the product market competition (e.g., Hoberg et al. (2014), Hoberg and Phillips (2022)). In particular, a firm may infer job postings from its competitors as signals for increased level or uncertainty about the production market competition, which can also dampen the focal firm's investment. To rule out this concern, we construct another instrument for TRP using only job postings from *non-competitor firms* of the focal firm, where we identify a competitor firm if its 4-digit NAICS industry code belongs to one of the top three industries of the focal firm in the Compustat Segment data. We label this instrument *NonPeer IV*.

Columns (2) and (4) of Table V show that TRP instrumented by the NonPeer IV also significantly dampens firm investment. Hence, talent retention pressure derived from job postings from non-competitor firms can dampen a firm's capital investment.[37] These results draw distinctions between our TRP and the non-compete policies which focus mainly on the pressure of employees joining competitors or becoming competitors.

— Table V about here —

[37]In the Internet Appendix Table IA.12, we show similar results where we construct the TRP, not the instrument, using only non-competitor firms's job postings and employment. These findings are unlikely to be explained by product market competition.

V. Testing Model Mechanism

Having tested and supported our model's predictions on firm investment, in this section, we establish our model's mechanism by testing several core building blocks of the mechanism. First, our model relies on the inability of firms to fully avoid losing talent when talent's outside options become more abundant. Second, in our model, firms increase their current job postings when facing higher TRP so as to fill in the slots due to potential talent loss. Third, our model assumes that talent turnover reduces average talent productivity as newly hired talent takes time to become productive.

A. Limited retention responses

Our model features that firms cannot immediately improve employee satisfaction in response to increased talent retention pressure. In practice, such limited ability to immediately meet employee satisfaction can be due to many reasons. For instance, firms may not have enough resources and capacity to learn the particular dissatisfaction of each talent, given that numerous micro-studies on voluntary employee turnover suggest that the reasons for employee departure are highly multi-dimensional (Hom et al. (2017) and Holtom et al. (2008)). Even if firms learn talent's dissatisfaction, some of the factors for such dissatisfaction cannot be changed immediately, such as corporate culture, past events that led to employee dissatisfaction, management style, location of their businesses, etc.

While addressing non-pecuniary aspects of employee dissatisfaction is difficult, changing pecuniary compensation for certain employees may also be complex and ineffective. For instance, the firm may need to maintain similar pay for employees in the same rank due to inequality aversion of employees (Green and Zhou (2023)) and investors (Pan et al. (2022)). Hence, the firm may increase compensation for many other employees in order to increase the compensation for certain employees. More problematically, if all firms in the local labor market increase their compensation when local talent market competition intensifies, then, increasing compensation would not increase the firm's competitive edge over others.

Our validation tests in Section III.B have shown that TRP significantly predicts talent outflows, suggesting that firms cannot fully avoid losing talent when the talent market becomes more competitive. Below, we directly inspect firms' compensation responses and employee satisfaction responses to talent retention pressure.

Ineffective compensation responses We obtain the wage rate for each occupation in the firm from the BLS microdata. Importantly, this wage rate includes not only base salary but also several sources of incentive pay such as bonuses.[38] We compute the natural logarithm of the average wage rate for each firm's talent in the current year and future years. Then, we run the following regression of the talent wage rates on TRP:

$$\text{Talent Wage}_{i,t+k} = \beta \cdot \text{TRP}_{i,t} + X_{i,t} + \text{FirmFE} + \text{YearFE} + \epsilon_{i,t}. \quad (9)$$

Panel A of Table VI reports the results. In Columns (1)-(3), we observe that TRP is significantly associated with the firm's concurrent talent wage rate but not with future talent wage rates. A one-standard-deviation increase in TRP is associated with a 1.3% increase in the firm's average talent wage rate.

How effective does the firm's increase in talent wage rate boost the firm's competitive advantage in the local talent market? In particular, if all firms increase their wage rate when the MSA-occupation-level talent market becomes more competitive, then, increasing the talent wage rate would not effectively boost each firm's competitive edge in terms of pecuniary compensation. To answer this question, we construct each firm's talent wage premium, where we subtract from the firm's actual talent wage rate a benchmark talent wage rate. To construct the benchmark rate, we first replace the actual hourly wage rate of each talent with its corresponding MSA-occupation's average hourly wage rate in the year, and then we compute the average rate within the firm and take the natural logarithm of the average. This wage premium thus captures the firm's average over or underpay relative to the talent market. We then run the same regression as in equation (9) using firms' talent wage premium.

Columns (4)-(6) in Panel A of Table VI show that talent wage premium is not significantly associated with TRP across the board. Hence, while firms facing higher talent retention pressure appear to increase their wage rate more, they do not increase their wage rate more than other firms in the talent market. As a result, increasing wages does not appear to be an effective way to retain talent if other firms in the local talent market all increase their talent's wages. This intuition is analogous to a price war where reducing prices does not bring more customers if all competitors also reduce prices in the same product market.

[38] Wage rate in the BLS OEWS survey includes "*base rate pay, cost-of-living allowances, guaranteed pay, hazardous-duty pay, incentive pay such as commissions and production bonuses, and tips are included in a wage. Back pay, jury duty pay, overtime pay, severance pay, shift differentials, non-production bonuses, employer costs for supplementary benefits, and tuition reimbursements are excluded.*" See details on the technical notes of the OEWS at https://www.bls.gov/oes/oes_doc_arch.htm.

Lack of employee satisfaction responses While pecuniary retention efforts may be ineffective because other firms can equally increase compensation, prior studies have shown that non-pecuniary factors also play a crucial role in employee satisfaction and voluntary turnover. If firms can effectively boost employee satisfaction, they may increase their chance of retaining their talent. We thus measure firms' employee job satisfaction using the Glassdoor microdata, which provides employees' ratings based on their pecuniary and nonpecuniary satisfactions including career opportunity, compensation and benefits, leadership, work-life balance, and corporate culture.[39] We first adopt the overall job satisfaction rating based on all employees' reviews. To further capture the firm's talent's satisfaction, we use the review-level microdata and reconstruct the average job satisfaction rating based only on the firm's talent employees in the year. Then, we run the following regression:

$$\text{Satisfaction}_{i,t+k} = \beta \cdot \text{TRP}_{i,t} + X_{i,t} + \text{FirmFE} + \text{YearFE} + \epsilon_{i,t}. \qquad (10)$$

Panel B of Table VI shows that neither the overall-employee-rated satisfaction nor the talent-rated satisfaction responded to TRP at t, $t+1$ or $t+2$.[40] The lack of employee satisfaction is consistent with the prior findings on voluntary employee turnover that firms may need to pay substantial costs to address each dissatisfied employee's needs.

In summary, these findings on employee compensation and satisfaction support our model assumption that firms cannot easily address employees' needs and thus cannot fully avoid losing talent when outside options become more abundant. This inability to directly address talent retention pressure makes TRP a concern for firms' other decision-making such as on their capital investment.

— Table VI about here —

[39]Glassdoor is a website that collects employee ratings and reviews of their firms. We obtain the proprietary microdata from Glassdoor and match the firms to Compustat firms via a fuzzy name matching. Recent studies show that Glassdoor reviews capture important information about firms' employee satisfaction, which leads to predictions about firms business outlook (Huang et al. (2020)) and market valuation (Green et al. (2019)). Teoh (2018) describes the Glassdoor database as "potentially a rich source for private or qualitative information about the working condition for employees or of employee mood."

[40]Some Glassdoor reviews may be written by employees who have left the firm rather than the firm's current employees. This delay may cause our satisfaction measures at $t+1$ representing the firm's actual employee satisfaction at t. Yet, the fact that we do not find positive responses of satisfaction across the board at t, $t+1$, and $t+2$ mitigates this timing concern.

B. *Job postings*

Given that firms cannot fully avoid losing talent when talent market competition intensifies, in our model, firms will post jobs for talent to prepare for filling in the positions after their talent leaves. We thus test firms' job postings on their talent retention pressure. We thus compute from the Lightcast database the natural logarithm of one plus the number of the firm's job postings for talent in the year. We then run the following regression:

$$\text{Job Postings for Talent}_{i,t+k} = \beta \cdot \text{TRP}_{i,t} + X_{i,t} + \text{FirmFE} + \text{YearFE} + \epsilon_{i,t}. \tag{11}$$

Table VII confirms that firms indeed post significantly more jobs when TRP is higher. The job posting response is swift and short-lived as we do not observe significant job posting responses at $t+1$ or $t+2$. This finding is consistent with our model mechanism that firms post more jobs in response to the concurrent year's TRP because they want to prepare for losing talent in the near future.

— Table VII about here —

C. *Talent productivity*

We test the final assumption of our model that talent turnover lowers the average productivity of talent. This is an important assumption because reduced talent productivity lowers the marginal product of capital and reduces firm investment. We thus examine whether firms' talent productivity is indeed lower in the aftermath of high TRP.

We measure a firm's average talent productivity as the firm's total sales divided by its total number of talent.[41] We again run a regression similar to equation (9):

$$\text{Talent Productivity}_{i,t+k} = \beta \cdot \text{TRP}_{i,t} + X_{i,t} + \text{FirmFE} + \text{YearFE} + \epsilon_{i,t}. \tag{12}$$

Table VIII shows that talent productivity is significantly lower in the year following a higher TRP. We do not observe talent productivity to be significantly lower at t or $t+2$. This finding brings two reassuring messages. First, the finding suits nicely with

[41] To calculate firms' total number of talent that is consistent with firms' scale in the Compustat database, we first compute the share of talent out of each Compustat firm's BLS-merged total employment. The firm's total number of talent is thus the product of the talent share and the firm's total number of employees in the Compustat database.

our model mechanism that newly hired talent is less productive than incumbent talent during the onboarding period, which averages about one year in the literature (see, for example, Silva and Toledo (2009)).[42] As talent complements capital, the decline in talent productivity dampens the marginal product of capital and firm investment.[43] Second, this finding rules out a selection story that only low-productivity employees self-select to leave the firm when TRP is high. If this self-selection mechanism is true, then one may be concerned that this mechanism explains firms' limited talent retention responses to TRP in Section V.A. Our finding that the firm's average talent productivity declines (instead of increases) after TRP suggests that this self-selection mechanism is unlikely and thus cannot drive our prior results.

— Table VIII about here —

VI. Implications for the Aggregate Economy

In this section, we venture out of our conceptual framework and explore the implications of our investment findings for the aggregate U.S. economy. We begin by documenting an important heterogeneity between superstar firms and laggard firms in their investment response to talent retention pressure. Guided by this heterogeneity, we provide suggestive evidence of the contribution of the rising talent market competition to the recent patterns in aggregate investment and industry concentration in the U.S.

A. *Superstar vs. laggard firms*

A key heterogeneity that prior theoretical work on labor mobility has focused on is the firm size (e.g., Burdett and Mortensen (1998) and Moscarini and Postel-Vinay (2013)).[44] In this section, we examine the implications of talent retention pressure on superstar and laggard firms' growth. We follow Gutierrez and Philippon (2020) and many prior

[42]Different from the effects from talent productivity, talent retention pressure negatively associates with firms' labor productivity at $t + 2$ but not at t or $t + 1$ (see the Internet Appendix Table IA.13).

[43]It is also possible that talent retention pressure causes firms to spend more on wages, job postings, and other related expenses, which crowds out their capital investment. While firms' specific expenses on talent retention are extremely difficult to quantify, in the Internet Appendix Table IA.14, we inspect firms' SG&A expenses and show that such expenses do not significantly respond to talent retention pressure, mitigating the crowd-out channel.

[44]While the theoretical work by Burdett and Mortensen (1998) and Moscarini and Postel-Vinay (2013) predicts that workers move up the ladder of firm size, recent empirical work by Haltiwanger et al. (2018) shows that workers also move from large firms to young and small firms.

studies and define superstar firms as the top 4 firms with the highest sales within each 4-digit NAICS industry. We regard the other firms as the laggard firms.[45]

Heterogeneous investment To explore the heterogeneous investment effects between superstar and laggard firms, we interact a dummy variable of the firm's superstar status with TRP in the following panel regression:

$$\begin{aligned}\text{Inv}_{i,t+1} =& \beta \cdot \text{TRP}_{i,t} \times \text{Superstar}_{i,t} + \gamma \cdot \text{TRP}_{i,t} + \eta \cdot \text{Superstar}_{i,t} \\ &+ X_{i,t} + \text{FirmFE} + \text{YearFE} + \epsilon_{i,t},\end{aligned} \tag{13}$$

where γ represents TRP's impact on laggard firms' investment and the sum of γ, β, and η represents TRP's impact on superstar firms' investment.

Table IX reports the results. We observe that while laggard firms' investment is significantly dampened by TRP, superstar firms' investment is completely immune to TRP. That is, when summing up the three reported coefficients in each column, we obtain a mildly positive number.

— Table IX about here —

Institutional resilience vs. talent resilience Conceptually, there can be at least two camps of explanations for superstar firms' investment to be less susceptible to talent market competition than laggard firms. First, superstar firms' capital investment may be less susceptible to talent outflows despite TRP increasing superstar and laggard firms' talent outflows equally. For instance, superstar firms may see their organizational knowledge less concentrated among a few employees, making turnover less damaging (Li et al. (2022). Superstar firms may also be more efficient at transferring organizational knowledge to new hires due to their greater experience, more developed production procedures, and larger human resource capacity (Hancock et al. (2013) and Baron et al. (2001)). We label this explanation as "institutional resilience" to talent market competition.

The second explanation is that superstar firms' talent may find outside options less appealing. For example, superstar firms may provide employees with better compensation and non-pecuniary benefits, making talent more satisfied with working in

[45]Our results are robust to using other definitions of superstar versus laggard firms, such as within-industry ranking by total assets or employment, or full sample ranking by sales, total assets, or employment. We define superstar versus laggard firms based on within-industry sales ranking because it helps us explore implications for both aggregate investment and industry concentration.

these firms than laggard firms. This argument is consistent with the job ladder model of Burdett and Mortensen (1998) and Moscarini and Postel-Vinay (2013). Superstar firms may also have more financial slack to retain talent when TRP is higher than laggard firms (Hadlock and Pierce (2010)). We label this explanation as "talent resilience" to talent market competition.

Note that the two explanations are not mutually exclusive. We thus design the following test: If talent leaves superstar firms just like the case in the rest of the firms, then, we reject the talent resilience explanation, and our heterogeneous investment results are more likely to be explained by the institutional resilience mechanism. If talent does not leave superstar firms, then, we support the talent resilience explanation but do not necessarily reject the institutional resilience explanation. Below, we test the susceptibility of talent outflows to TRP for superstar and laggard firms.

Panel A of Table X reports the regressions of talent outflow rates on the interaction term between TRP and superstar status dummy similar to equation (13). The outflow rates are computed from the Revelio Labs Workforce Dynamism database and used in our earlier validation tests in Section III.B. We observe that superstar firms' talent outflow exhibits an inelastic response to TRP at t, $t+1$, and $t+2$: Unlike the case in laggard firms, talent does not leave superstar firms when TRP arises. This finding supports the talent resilience explanation.

Elastic retention vs. job ladder We next shed light on whether superstar firms' immutability to talent retention pressure is due to their elastic retention efforts or due to their superior status in the job ladder making their talent uninterested in leaving the firms even if the firms make no additional retention efforts.

In Panel B Table X, we examine whether superstar firms' talent's wage premium and satisfaction respond to TRP differently from laggard firms. Columns (1)-(3) show that talent's wage premiums in superstar firms are significantly more elastic to TRP than those in laggard firms at t and $t+1$. Columns (4)-(6) show that talent's job satisfaction (reported in Glassdoor reviews) in superstar firms is significantly more elastic to TRP than in laggard firms at $t+1$. These results provide suggestive evidence that superstar firms can more elastically retain talent when talent retention pressure is higher than laggard firms.[46] This finding expands the traditional job ladder theory based on wages

[46]There can be many reasons explaining superstar firms' differential retention elasticity from laggard firms. For instance, superstar firms may be more financially slack than laggard firms (Hadlock and Pierce (2010)), the marginal costs for superstar firms to retain talent are lower than laggard firms as their talent is closer to being satisfied to start with as in the job ladder theory, workers in superstar firms may possess more firm-specific human capital making them less productive when taking outside

(Burdett and Mortensen (1998) and Moscarini and Postel-Vinay (2013)).

Overall, the findings in this section deliver an important message that talent retention pressure leads to talent outflows and dampens investment only in laggard firms but not in the top superstar firms. In what follows, we explore the aggregate implications of this heterogeneity.

— Table X about here —

B. *Implications for aggregate investment*

Gutiérrez and Philippon (2017) seminally study recent trends of the U.S. aggregate investment by decomposing the investment as those explained by Tobin's Q and those that cannot be explained by Tobin's Q. They argue that despite the market valuation and Q are rising after 2000, U.S. aggregate investment is lackluster. Their findings show a widening investment-Q gap in recent decades and inspire researchers to explain the gap.[47]

In this section, we conduct a reduced-form estimation to gauge the extent to which talent market competition contributes to the lackluster U.S. aggregate investment. To motivate our empirical estimates, we extend our theoretical framework and show in Appendix B.2 that increasing talent retention pressure widens the investment-Q gap for an average firm. The intuition is that a firm's valuation is the weighted average of capital q_k and talent q_n. While firm investment is driven by q_k, the average Q that we can measure in the data reflects both q_k and q_n. Increasing TRP increases q_n and thus widens the investment-Q gap, making an average firm's investment low as compared to what average Tobin's Q predicts.

Whether TRP has contributed to the lackluster *aggregate* investment in the past decade is a quantitative question. On the one hand, we have shown in Figure 3 that firms' TRP steadily increased from 2010 to 2018, which can lead to a widening investment-Q gap for an *average* firm according to our model. On the other hand,

options (although Gao et al. (2021) find the opposite in the banking industry), and so on. Further explorations on the root causes are outside the scope of our research. Instead, we focus on exploring this heterogeneity's aggregate implications in the next section.

[47]For instance, Gutiérrez and Philippon (2017) show that the rising industry concentration and intangible capital contribute significantly to the investment-Q gap. Crouzet and Eberly (2023) decomposes the investment-Q gap into intangible capital, rent, and an interaction term between the two and advocates the explanation from intangible capital. Gormsen and Huber (2022) show that firms' discount rates did not rise as their market valuation and Q, resulting in an inflated Q and a widening investment-Q gap.

our findings in Section VI.A show that large superstar firms' investment is inelastic to TRP. Since superstar firms dominate the aggregate investment, the rising TRP may not contribute to the *aggregate* investment.

We answer this question using a reduced-form estimation proposed by Gutiérrez and Philippon (2017) as follows. We first run a panel regression of firm investment on Tobin's Q and dummies for each year while controlling for firm fixed effects, i.e.,

$$\text{Inv}_{i,t+1} = \sum_s \beta_s \cdot \text{YearDummy}_s + \alpha \text{Q}_{i,t} + \text{FirmFE} + \epsilon_{i,t}. \tag{14}$$

The coefficients for the year dummies, β_s represent the trend of the investment-Q gap without the impact of TRP. We call this estimation the baseline Q model. We next run the same regression but control for TRP, i.e.,

$$\text{Inv}_{i,t+1} = \sum_s \zeta_s \cdot \text{YearDummy}_s + \alpha \text{Q}_{i,t} + \gamma \text{TRP}_{i,t} + \text{FirmFE} + \epsilon_{i,t}. \tag{15}$$

The coefficients for the year dummies in this model, ζ_s represent the trend of the investment-Q gap with the impact of TRP. We call this estimation the Q+TRP model. The difference between the β_s and ζ_s represents the contribution of TRP for the widening investment-Q gap.

Figure 5 shows the results. Panel A plots the estimates of β_s and ζ_s and the standard error bars for average firms, and Panels B and C plot the estimates for superstar firms and laggard firms, respectively. Consistent with our model prediction and also the findings in Section VI.A, we observe that (i) TRP explains 31.5% of the widening investment-Q gap from 2010 to 2018 for laggard firms;[48] and (ii) TRP contributes little to the investment-Q gap for superstar firms.

We next pool all firms together and run the two estimation models while weighting each firm-year observation by total assets. The difference between β_s and ζ_s from this estimation captures the impact of TRP on the *aggregate* investment-Q gap. Consistent with superstar firms dominating aggregate investment, Panel D of Figure 5 shows that TRP has a small and insignificant contribution to the aggregate investment-Q gap.

In summary, these findings suggest that while talent market competition significantly dampens the growth of laggard firms, such effects may not be detectable from the aggregate U.S. investment data. To gauge the impact of talent market competition

[48] In particular, without controlling for TRP, the estimated investment-Q gap in 2018 for laggard firms is $\beta_{2018} = -1.295$. After controlling for TRP, the estimated investment-Q gap in 2018 for laggard firms becomes $\zeta_{2018} = -0.887$. The rising TRP thus explains 31.5% of the investment-Q gap between 2010 and 2018.

on firms, one needs to look into the granular firm-level data.

— Figure 5 about here —

C. *Implications for industry concentration*

Finally, we explore the implication of our heterogeneity findings for industry concentration. Our findings in Section VI.A suggest that the rising talent retention pressure dampens the growth of laggard firms but not the top 4 largest firms in the industry, i.e., superstar firms. Hence, we hypothesize that industries that see a rise in TRP can become more concentrated.

To test this hypothesis, we measure each 4-digit NAICS industry's top 4 concentration ratio (CR4) as the sales share of the top 4 firms in the industry.[49] We next compute the median value of firms' TRP and other firm control variables within each 4-digit NAICS industry in the year.[50] We then run the following regression at the industry-year level:

$$\text{CR4}_{i,t+1} = \beta \cdot \text{TRP}_{i,t} + X_{i,t} + \text{IndFE} + \text{YearFE} + \epsilon_{i,t}. \tag{16}$$

Supporting our hypothesis, we observe in Table XI a positive relation between industries' concentration in the next year and their median TRP in this year. This suggestive evidence brings a cautionary note that talent market competition could potentially contribute to the rising industry concentration because it dampens the growth of laggard firms but not superstar firms'. Yet, whether concentration fostered by talent market competition is "good" or "bad" a la Covarrubias et al. (2020) is out of the scope of this research and remains an open question.

— Table XI about here —

[49]Concentration ratio is commonly used to measure industry concentration in both academic research (see Opler and Titman (1994), Hou and Robinson (2006), Bustamante and Donangelo (2017), Gutiérrez and Philippon (2018) and many others) and in the Census Bureau (see https://data.census.gov/all?q=Concentration+Ratio).

[50]We choose median over mean value to represent industry' TRP because the largest firms dominate the mean value. On the other hand, the unweighted median captures mainly small firms with volatile TRP and control variables. We thus use firms' total assets to weight the median calculation to reach a balance.

VII. Conclusion

Recent executive surveys repeatedly highlight talent market competition as a top internal concern of firms in the 21st century. The economic implications of firms' retention pressure from talent market competition are underexplored, largely due to challenges in quantifying the pressure. We construct the first measure of firms' talent retention pressure by combining two comprehensive microdata sets. We show that talent retention pressure substantially dampens firm capital investment. To address endogeneity concerns, we construct a shift-share instrument for talent retention pressure, examine the identifying assumption, and show strong support for our OLS results.

We uncover a key underlying mechanism that many firms do not elastically retain talent in practice. In particular, we emphasize the challenges of using pecuniary compensation in retaining talent for an average firm, as the outside firms also make similar raises when talent market competition is fierce. Firms instead post more jobs in response to talent retention pressure. The resulting talent turnover reduces talent productivity and firm investment.

Finally, we show an important heterogeneity that talent market competition dampens the growth of small and midsized firms (laggard firms) but not superstar firms. Consistent with this heterogeneity, we show suggestive evidence that the rising talent market competition has contributed to the recent rise in industry concentration but not the decline in *aggregate* U.S. investment. Future research exploring the root causes for superstar firms' immunity to talent market competition remains fruitful.

We note that one must exercise caution when drawing policy implications from our study. First, our study focusing on firms' growth does not assess the full benefits of job-to-job moves for talent. Hence, our study does not tell whether talent market competition is excessive or is damaging the overall welfare. Estimating the overall welfare effects of talent market competition remains a fruitful research agenda. Second, while increasing talent market competition has affected laggard firms more than superstar firms and contributed to the industry concentration, this finding does not deduce an overall positive or negative effect on the health of the U.S. economy. Assessing whether talent market competition contributed to the good or bad concentration a la Covarrubias et al. (2020) is beyond the scope of this study and can be an important extension for future research.

Appendix

A. Survey of Firms on Talent

Subsection 1 summarizes four different surveys highlighting talent retention in firms' most pressing concerns. Subsection 2 provides the results from two CFO surveys showing that talent constraint is the dominating reason for firms to forgo investment opportunities.

1. Firms' most pressing concerns

Duke CFO Survey Duke CFO Survey asks corporate executives about their most pressing internal firm-specific concerns since 2008Q4.[51] The survey reports responses from an average of 460 firms on this topic each quarter. This survey question changed minorly in 2014 (see survey questions in the Internet Appendix Figure IA.2), yet the surveys consistently included the option "attracting and retaining qualified employees" in every quarter. We plot in the Internet Appendix Figure IA.3 the yearly-averaged ranking of the talent retention/attraction option among all other options in each year. We observe that talent retention/attraction concern increased in the ranking from 2008 to 2018 and is among the top 3 concerns in each year from 2012 to 2018.

Deloitte CFO Signals™ Survey The Deloitte CFO Signals™ Survey provides insights into the thinking and expectations of CFOs from large North American companies since 2010Q2. In particular, the survey asks CFOs "*What external and internal risk worries you the most?*" Deloitte then consolidates the CFOs' free-form answers into common themes and quantifies the top themes in some quarters' reports.[52] For instance, in the 2016Q2 report, out of 121 responses (with about 72% from public companies), the most frequently listed internal risk concern is talent retention concerns, expressed 42 times, followed by corporate execution concerns (34 times) and growth concerns (17 times). Similar findings can be obtained in many other quarters when the reports quantify the answers.

[51] The Duke CFO Survey reports can be downloaded at https://cfosurvey.fuqua.duke.edu/release/.

[52] The Deloitte CFO Signals™ Survey reports can be downloaded at https://www2.deloitte.com/us/en/pages/finance/articles/cfo-signals-quarterly-survey.html.

PwC Family Business Survey PricewaterhouseCoopers has conducted surveys on thousands of family businesses since 2002. The 2016 survey covers 2,802 interviews with senior executives from family businesses across 50 countries. 58% of family businesses rate "ability to attract and retain the right talent" as the key challenge over the next five years, making talent retention concerns the second most-chosen challenge following innovation concerns.

2. *Firms' reasons for forgoing capital investments*

Kellogg CFO Survey Jagannathan et al. (2016) analyzes the 2003 Kellogg CFO survey about firms' investment and cost of capital. A focal question (question 20) asks the CFOs the reasons for forgoing otherwise profitable projects by requesting the CFOs to scale the importance of the following three drivers. **Talent constraint:** *We cannot take all (otherwise) profitable projects due to limited resources in the form of limited qualified management and manpower.* **Financial constraint:** *"There are some (otherwise) good projects we cannot take due to limited access to capital markets."* **Optimism:** *We need a higher hurdle rate to account for optimism in cash flow forecasts."* As shown in Figure 2 of Jagannathan et al. (2016), 55% CFOs attribute forgoing otherwise profitable projects to talent constraint (i.e., those choose strongly agree or agree), 39% to financial concerns, and 39% to optimistic cashflow forecasts.[53]

Duke CFO Survey The 2011 Q3 Duke CFO Survey included a question (question 12) asking CFOs reasons to forgot otherwise positive NPV investment projects. In particular, the question asks *"During normal economic times, does your company pursue all investment projects that you estimate will have positive net present value? [If No], what prevents you from pursuing all positive net present value projects?"* Again, 58% CFOs viewed the lack of "management time and expertise" as the reason for bypassing otherwise valuable investment projects, making talent constraint the most-cited reason. 43% CFOs chose the lack of funding as the reason.

[53]Note that the percentages do not have to sum up to be one as CFOs can choose both options or neither of them.

B. Proofs

1. *Proof of Proposition 2*

The first order condition of equation (5) with respect to I_0 leads to:

$$1 + \beta \frac{I_0}{k_0} = r\alpha E_0[a_1^{1-\alpha}] k_1^{\alpha-1} \left[(1-\psi)n_0 + \rho \frac{\psi N_0}{V_0} v_0^{'} \right]^{1-\alpha}.$$

Note that in equilibrium, $v_0^{'} = \frac{V_0}{m}$. Hence, $\left[(1-\psi)n_0 + \rho \frac{\psi N_0}{V_0} v_0^{'} \right]^{1-\alpha} = [1 - \psi + \rho\psi]^{1-\alpha} n_0^{1-\alpha}$. Plugging into the above first order condition, we have

$$\left[1 + \beta \frac{I_0}{k_0} \right] [(1-\delta)k_0 + I_0]^{1-\alpha} = r\alpha E_0[a_1^{1-\alpha}][1 - (1-\rho)\psi]^{1-\alpha} n_0^{1-\alpha}. \tag{B.1}$$

In this equation, the LHS increases in I_0, and the RHS decreases in ψ. Hence,

$$\frac{\partial I_0}{\partial \psi} < 0.$$

Because ψ increases in θ (see Proposition 1), we have

$$\frac{\partial I_0}{\partial \theta} = \frac{\partial I_0}{\partial \psi} \cdot \frac{\partial \psi}{\partial \theta} < 0.$$

2. *Model Implications for Investment-Q Gap*

Here, we explore the implication of our model in Section I for the investment-Q gap documented by Gutiérrez and Philippon (2017). Costly adjustment in talent results in both capital q_k and talent q_n, where the firm value can be expressed as $V_0 = q_k k_1 + q_n n_1$. q_n can be viewed as a specific form of intangible q in Crouzet and Eberly (2023). Note that firm investment is governed only by q_k,[54] whereas the empirically measured Tobin's Q of the firm is $Q = V_0/k_1 = q_k + q_n \frac{n_1}{k_1}$. Hence, the observed investment-Q gap can be expressed as the wedge between Tobin's Q and q_k.

Intuitively, if the talent market becomes more competitive, q_n the marginal value for hiring an additional talent increases, k_1 decreases (as predicted by Proposition 2), and thus the wedge between Tobin's Q and q_k increases. We formalize this intuition in

[54] A general relationship between I_0 and q_k holds in investment models as $\frac{I_0}{k_0} = \frac{1}{\beta}(q_k - 1)$, where β is the quadratic adjustment cost parameter.

the following corollary.

Corollary 1 (Implication for the Investment-Q Gap): *Rising talent retention pressure widens the firm's investment-Q gap.*

Proof: In equilibrium, $n_1 = n_0$. Hence, the wedge between Tobin's Q and q_k is determined by $\frac{q_n}{k_1}$. To derive q_n, we include the law of motion for capital (equation (1)) and talent (equation (3)) into a Lagrangian function of firms' optimization problem.

$$L = \left[rE_0[a_1^{1-\alpha}]k_1^{\alpha}\left[(1-\psi)n_0 + \rho(n_1 - (1-\psi)n_0)\right]^{1-\alpha} - wn_1\right] - I_0 - \frac{\beta}{2}\left(\frac{I_0}{k_0}\right)^2 k_0 - \kappa v_0^{'}$$
$$- q_k\left[k_1 - k_0(1-\delta) - I_0)\right] - q_n\left[n_1 - n_0(1-\psi) - \frac{\psi N_0}{V_0}v_0^{'}\right].$$

The first order conditions with respect to k_1 and n_1 results in:

$$\left[\frac{q_n + w}{(1-\alpha)\rho}\right]^{\frac{1}{\alpha}} = \left(\frac{q_k}{\alpha}\right)^{\frac{1}{\alpha-1}}.$$

Hence, q_n decreases in q_k. We have shown in Proposition 2 that I_0 decreases in talent market competition θ. Thus, (i) q_n increases in θ because q_k decreases in θ, and (ii) k_1 decreases in θ. Therefore, $\frac{q_n}{k_1}$ increases in θ, and the investment-Q gap increases in θ. As shown in Proposition 2 that θ is a monotonic function of only one variable, talent retention pressure, ψ. Hence, the investment-Q gap increases in ψ.

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Figure 1: Composition of Talent

This figure illustrates the occupation distribution of talent employees in our final sample. Talent employees for each 4-digit NAICS industry are the top 10% 5-digit SOC occupations with the highest average score of cognitive analytical and cognitive inter-personal (Baghai et al. (2021)). Section II.B provides more details. We pool all talent in our final Compustat firm sample from 2010 to 2018 and present the shares at the 2-digit SOC broad occupation level.

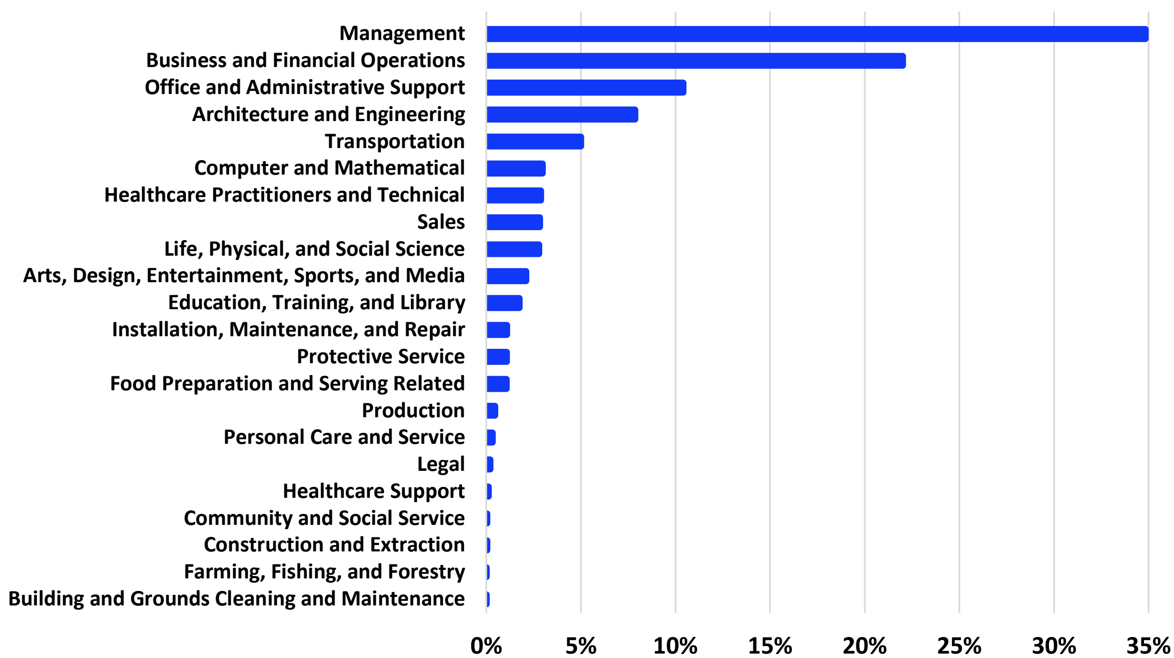


Figure 2: Average Talent Market Competition Across MSAs

This figure plots the average vacancy-to-employment ratio for talent employees for each Metropolitan Statistical Area (MSA) in 2018.

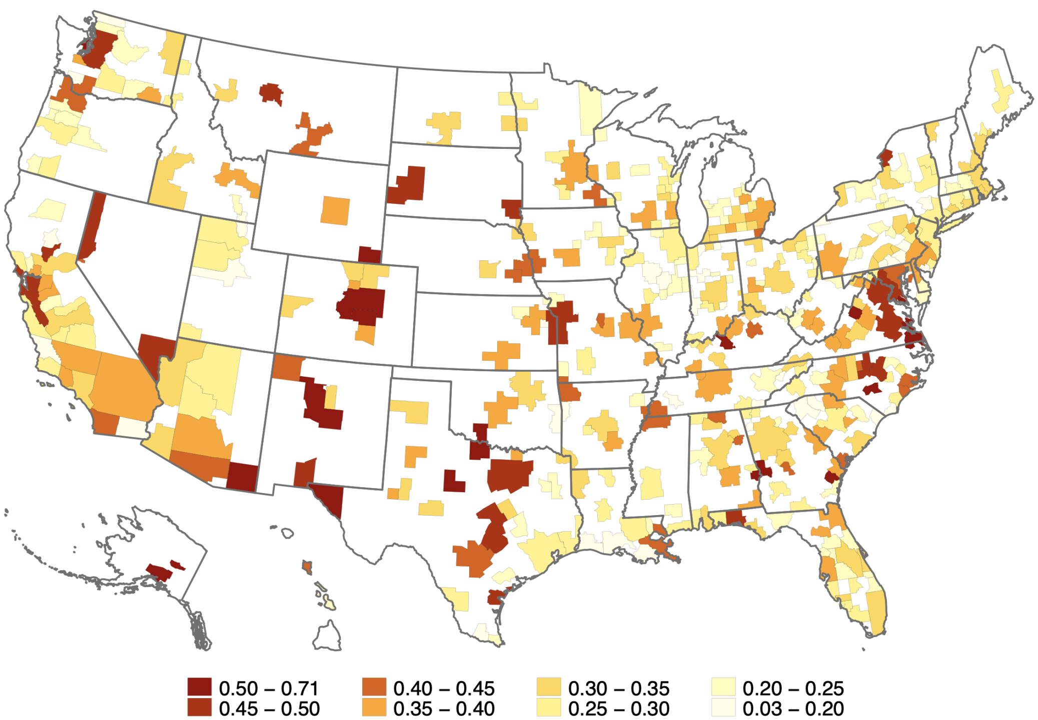


Figure 3: Talent Retention Pressure Across Firms

This figure plots the 10th percentile, median, and 90th percentile of talent retention pressure (TRP) across firms in our final sample from 2010 to 2018.

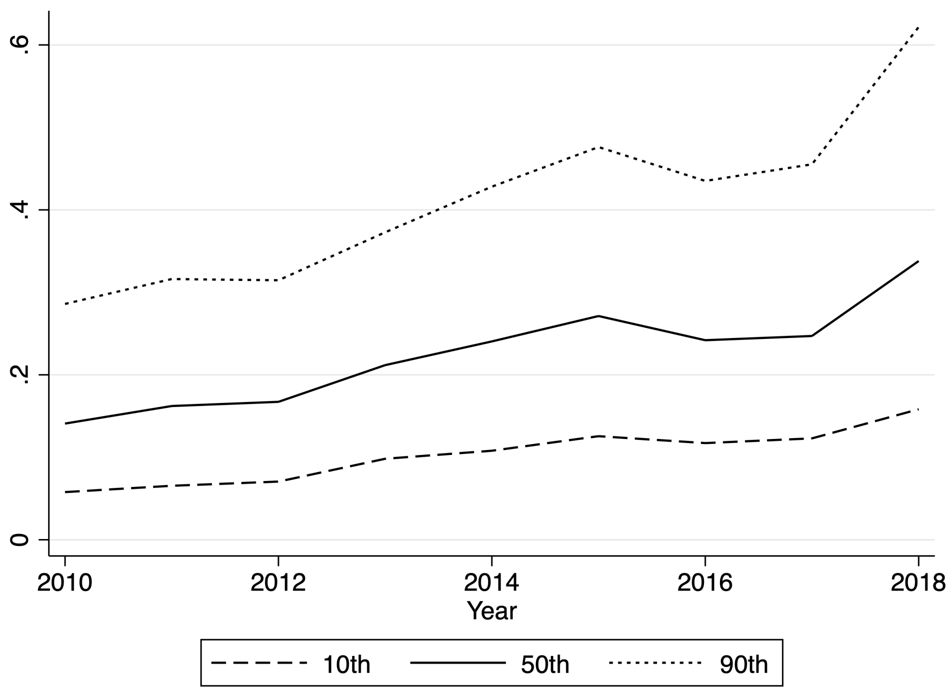


Figure 4: CFOs' Talent Retention Concerns

This figure plots the fraction of CFOs electing "attracting and retaining qualified employees" as the top firm-specific concerns using the microdata of the Duke CFO Survey. During 2008Q4-2014Q1 (early regime), the survey asked CFOs to elect from approximately 10 options to answer "*What are the top three internal, company-specific concerns for your corporation?*" During 2015Q1-2019Q4 (later regime), the survey asked CFOs to elect from approximately 18 options to answer "*During the past quarter, which items have been the most pressing concerns for your company's top management team? (Choose up to 4)*" Both waves of survey include the option "attracting and retaining qualified employees." See Section III and Appendix A for more details.

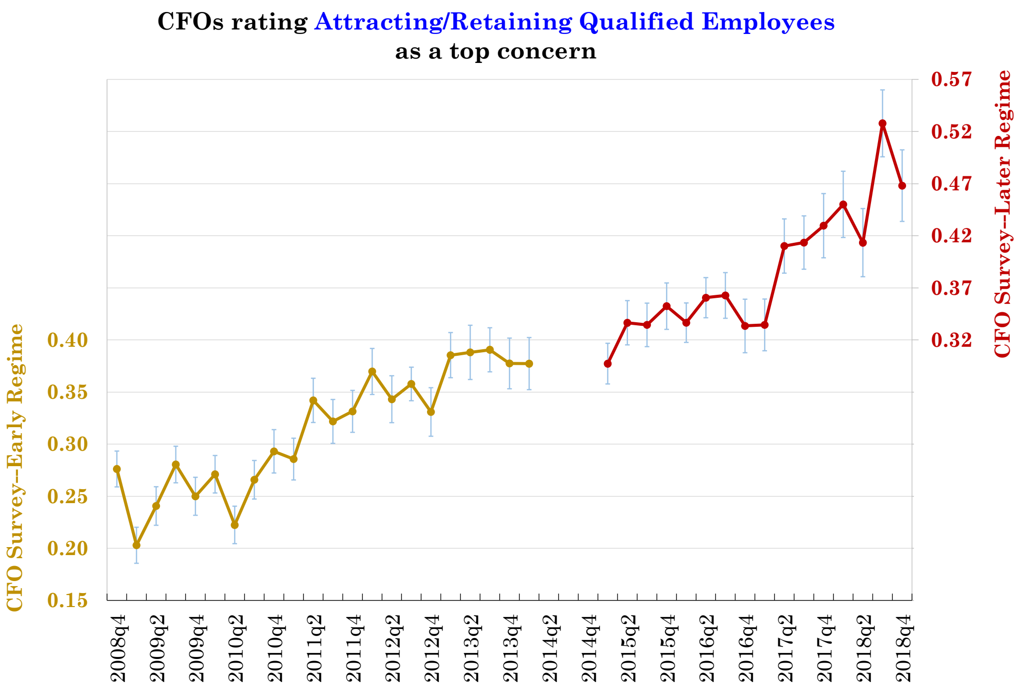
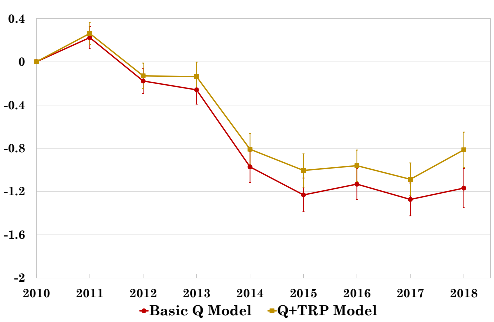


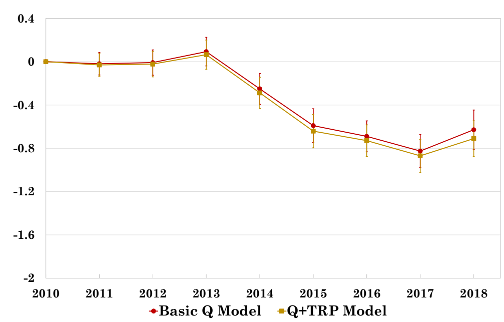
Figure 5: Talent Retention Pressure and Investment-Q Gap

This figure plots actual physical investment relative to what Tobin's Q predicts (*Investment-Q Gap*) for each year from 2010 to 2018. We follow Gutiérrez and Philippon (2017) and compute the investment-Q gap in each year as the coefficients of the year dummies in equations (14) and (15). The red line plots the coefficient and standard error bars without controlling for talent retention pressure in the regression (i.e., Basic Q Model in equation (14)) and the yellow line is based on a regression controlling for talent retention pressure (i.e., Q+TRP Model in equation (15)). See Section VI for the two models. Panel A estimates the two models using all firms while equally weighting firms, Panel B estimates the two models using only superstar firms while equally weighting firms, Panel C uses only laggard firms while equally weighting firms, and Panel D uses all firms while weighting firms with their total assets. Superstar firms are firms with sales ranking in the top 4 of the 4-digit NAICS industry category in the year, and laggard firms are the rest.

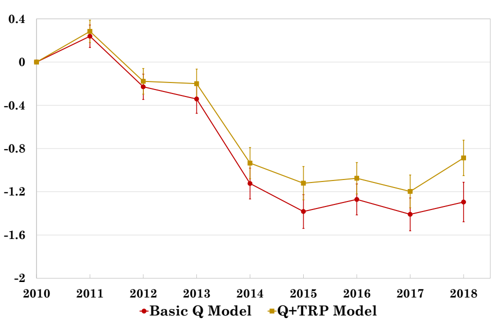
Panel A: Average Firms' Investment-Q Gap



Panel B: Superstar Firms' Investment-Q Gap



Panel C: Laggard Firms' Investment-Q Gap



Panel D: Aggregate Investment-Q Gap

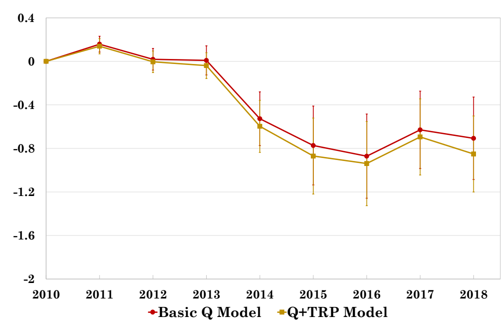


Table I
Summary Statistics

This table presents summary statistics of the variables in our Compustat firm sample from 2010 to 2018. Section II describes our sample selection. *TRP* is the talent retention pressure of the firm constructed as the average vacancy-to-employment ratio for MSA-occupations (excluding the firm's own vacancy) weighted by the firm's talent distribution in MSA-occupations in the year (see equation (6) and more details in Section II). *NonTRP* is the retention pressure for other non-talent employees of the firm constructed similarly. *THP* is the talent hiring pressure for the firm constructed as the average employment-to-vacancy ratio for MSA-occupations weighted by the firm's job postings distribution in MSA-occupations in the year. *Job Posting* is the natural logarithm of one plus the firm's number of job postings for talent in the year. *Physical Investment* is next year's capital expenditure (#CAPX) divided by this year's total assets (#AT). *Total Investment* is next year's physical and intangible expenditure (Peters and Taylor (2017)) divided by this year's total capital stock obtained from Peters and Taylor (2017). *Q* is Tobin's Q measured as the market value of the firm divided by book assets following Gutiérrez and Philippon (2017). *Total Q* adds intangible assets in the denominator of the Q calculation and is obtained from Peters and Taylor (2017). *Cashflow* is the sum of income before extraordinary items (#IB) and depreciation expense (#DP) normalized by total assets (#AT). *Size* is the natural logarithm of total assets (#AT). *Age* is the natural logarithm of firm age computed based on the first year the firm appears in the Compustat universe. The statistic $Median^{Compustat}_{Universe}$ presents the medians of the corresponding variables from the entire Compustat database from 2010 to 2018 to be compared with the medians of the variables from our sample.

Variable	Mean	SD	P10	Median	$\text{Median}^{Compustat}_{Universe}$	P90	# obs.
TRP	0.239	0.144	0.086	0.211	-	0.427	13,502
NonTRP	0.149	0.117	0.036	0.118	-	0.302	13,502
THP	-18.697	19.060	-44.843	-6.389	-	-2.120	13,502
Job Posting	2.936	2.289	0.000	2.890	-	6.050	13,502
Physical Investment	5.002	6.406	0.549	2.957	3.080	11.174	13,065
Total Investment	17.893	14.116	6.069	14.097	13.178	34.208	11,357
Q	1.908	1.657	0.650	1.351	1.230	3.885	12,399
Total Q	1.461	2.329	0.046	0.809	0.771	3.472	12,444
Cashflow	0.018	0.247	-0.214	0.072	0.066	0.190	13,077
Size (log)	6.570	2.109	3.805	6.533	6.543	9.373	13,502
Age (log)	1.975	0.475	1.609	2.079	1.946	2.484	13,502

Table II
Validation: Talent Retention Pressure and CFO Concerns

This table reports the results of regressing CFOs' talent retention concerns on our talent retention pressure (TRP) measure. The dependent variable is a dummy variable equal to one if the CFO elects "to attract and retain qualified employees" as the top firm-specific concern in the microdata of the Duke CFO Survey. *Regime* referees to two survey regimes from 2010 to 2014 and from 2015 to 2018 (see Section III and Appendix A for more details). *TRP* is the firm's average employment exposure to local talent market competition defined in equation (6). See Table I for the definitions of other variables. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 2010 to 2018.

	(1)	(2)	(3)	(4)	(5)
TRP	0.602***	1.629**	1.780**	1.588**	3.236***
	(0.126)	(0.608)	(0.564)	(0.544)	(0.469)
NonTRP				-1.582*	
				(0.790)	
THP					0.012
					(0.013)
Firm Control	N	N	Y	Y	Y
Firm-Regime FE	N	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Observations	275	146	144	144	108
Adjusted R^2	0.026	0.184	0.198	0.199	0.299

Table III
Validation: Talent Retention Pressure and Future Talent Outflows

This table reports the results of regressing firms' talent outflow and inflow rates on talent retention pressure (TRP). A firm's talent outflow (inflow) rate is the total number of talents leaving (joining) the firm in the year divided by the total number of talents at the beginning of the year using the Revelio Workforce Dynamics Database (see Section III for more details). *TRP* is the firm's average employment exposure to local talent market competition defined in equation (6). See Table I for the definitions of other variables. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 2010 to 2018.

Panel A: Talent Outflow Rate						
	t		$t+1$		$t+2$	
	(1)	(2)	(3)	(4)	(5)	(6)
TRP	1.097	0.336	6.035***	5.580***	4.896**	3.482
	(1.562)	(1.574)	(1.815)	(1.835)	(2.245)	(2.353)
Firm Control	N	Y	N	Y	N	Y
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	7,176	6,877	7,113	6,637	6,077	5,638
Adjusted R^2	0.429	0.441	0.426	0.440	0.422	0.439

Panel B: Talent Inflow Rate						
	t		$t+1$		$t+2$	
	(1)	(2)	(3)	(4)	(5)	(6)
TRP	0.383	-0.037	4.330	3.833	0.450	-1.173
	(2.820)	(2.808)	(3.065)	(3.132)	(3.217)	(3.396)
Firm Control	N	Y	N	Y	N	Y
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	7,176	6,877	7,113	6,637	6,077	5,638
Adjusted R-squared	0.433	0.434	0.437	0.423	0.419	0.402

Table IV
Talent Retention Pressure and Investment

This table reports the results of regressing firms' capital investment next year on their current talent retention pressure (TRP). *Physical Investment* is next year's capital expenditure (#CAPX) divided by this year's total assets (#AT). *Total Investment* is next year's physical and intangible expenditure divided by this year's total capital stock obtained from Peters and Taylor (2017). *TRP* is the firm's average employment exposure to local talent market competition defined in equation (6). See Section IV for regression specifications. See Table I for the definitions of other variables. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 2010 to 2018.

	Physical Investment			Total Investment		
	(1)	(2)	(3)	(4)	(5)	(6)
TRP	-1.472***	-1.717***	-1.605***	-2.044**	-2.358***	-2.203***
	(0.486)	(0.502)	(0.495)	(0.841)	(0.855)	(0.842)
NonTRP		1.609**			1.976	
		(0.654)			(1.389)	
THP			0.002			0.003
			(0.004)			(0.007)
Job Posting			0.125**			0.142
			(0.06)			(0.111)
Q	0.643***	0.636***	0.637***			
	(0.056)	(0.056)	(0.056)			
Total Q				2.221***	2.213***	2.220***
				(0.133)	(0.132)	(0.133)
Cashflow	1.917***	1.912***	1.917***	3.132***	3.131***	3.122***
	(0.401)	(0.401)	(0.401)	(0.889)	(0.888)	(0.888)
Size	-0.895***	-0.913***	-0.949***	-1.961***	-1.979***	-2.022***
	(0.183)	(0.183)	(0.182)	(0.431)	(0.431)	(0.429)
Age	-2.449**	-2.456**	-2.566**	-18.796***	-18.792***	-18.917***
	(1.116)	(1.119)	(1.116)	(2.327)	(2.323)	(2.332)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	11,985	11,985	11,985	10,581	10,581	10,581
Adjusted R^2	0.719	0.720	0.720	0.807	0.806	0.807

Table V
Instruments for Talent Retention Pressure

This table reports the second stage results of the 2SLS regressions of firms' capital investment on their talent retention pressure (TRP) instrumented by a shift-share instrumental variable. *IV* refers to a shift-share instrument where we use firms' 2010 retention pressure from each talent occupation as the share (i.e., cross-sectional variation) and the national growth rates of the vacancy-to-employment ratio of each talent occupation as the shift (i.e., time-series variation). *NonPeer IV* refers to a similar instrument by uses only job postings from non-competitor firms. Section IV.B details the construction of these instruments. *Physical Investment* is next year's capital expenditure (#CAPX) divided by this year's total assets (#AT). *Total Investment* is next year's physical and intangible expenditure divided by this year's total capital stock obtained from Peters and Taylor (2017). Table I describes the definitions of other variables. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 2010 to 2018.

	Physical Investment		Total Investment	
2SLS IV Type:	IV	NonPeer IV	IV	NonPeer IV
	(1)	(2)	(3)	(4)
2SLS(TRP)	-5.352**	-5.639***	-11.277***	-11.128***
	(2.091)	(2.180)	(3.567)	(3.661)
Q	0.654***	0.652***		
	(0.063)	(0.063)		
Total Q			2.159***	2.158***
			(0.144)	(0.144)
Cashflow	2.002***	2.012***	2.976***	3.006***
	(0.442)	(0.441)	(0.973)	(0.972)
Size	-0.878***	-0.879***	-2.044***	-2.051***
	(0.193)	(0.193)	(0.458)	(0.457)
Age	-2.656**	-2.637**	-18.106***	-18.125***
	(1.253)	(1.254)	(2.508)	(2.508)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	11,110	11,110	9,863	9,863
Adjusted R^2	0.040	0.040	0.206	0.208
F stat.	131.414	142.313	126.929	136.581

Table VI
Talent Retention Pressure and Retention Responses

This table reports the results of regressing firms' employee retention proxies on their talent retention pressure (TRP). Panel A shows the responses of firms' talent compensation from the OEWS microdata. *Talent Wage* is the natural logarithm of the average hourly wage rate of the firm's talent. *Talent Wage Premium* the firm's talent wage (in logarithm) subtracted by the natural logarithm of a benchmark hourly wage rate of the firm's talent which replaces each talent's actual hourly wage rate with the MSA-occupation-year average hourly wage rate. Panel B shows the responses of firms' employee job satisfaction using the Glassdoor review data. *Satisfaction of All Employees* is the overall job satisfaction rating of the firm on Glassdoor by employees in that year. *Satisfaction of Talent* the reconstructed average job satisfaction ratings by talent employees in the firm, where talent is defined using our definition in Section II.B. *TRP* is the firm's average employment exposure to local talent market competition defined in equation (6). See Section V.A for more details and Table I for the definitions of other variables. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 2010 to 2018.

Panel A: Responses of Compensation to TRP

	Talent Wage			Talent Wage Premium		
	t	$t+1$	$t+2$	t	$t+1$	$t+2$
	(1)	(2)	(3)	(4)	(5)	(6)
TRP	0.088**	0.052	0.010	0.003	0.023	0.002
	(0.036)	(0.036)	(0.035)	(0.026)	(0.027)	(0.027)
Firm Control	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	12,354	9,544	7,458	12,288	9,492	7,417
Adjusted R^2	0.796	0.812	0.813	0.556	0.578	0.580

Panel B: Responses of Job Satisfaction to TRP

	Satisfaction of All Employees			Satisfaction of Talent		
	t	$t+1$	$t+2$	t	$t+1$	$t+2$
	(1)	(2)	(3)	(4)	(5)	(6)
TRP	-0.093	-0.234**	0.128	0.016	-0.285	0.062
	(0.098)	(0.109)	(0.133)	(0.203)	(0.260)	(0.272)
Firm Control	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	6,403	5,739	5,307	3,821	3,474	3,250
Adjusted R^2	0.401	0.398	0.396	0.266	0.258	0.257

Table VII
Talent Retention Pressure and Job Posting for Talent

This table reports the results of regressing firms' job postings for talent on their talent retention pressure (TRP). *Job Posting* is the natural logarithm of one plus the firm's number of job postings for talent in the year. *TRP* is the firm's average employment exposure to local talent market competition defined in equation (6). See Section V.B for more details and Table I for the definitions of other variables. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 2010 to 2018.

	Job Posting		
	t	$t+1$	$t+2$
	(1)	(2)	(3)
TRP	0.445***	0.228	-0.019
	(0.123)	(0.158)	(0.160)
Firm Control	Y	Y	Y
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	12,799	9,864	7,668
Adjusted R^2	0.857	0.857	0.862

Table VIII
Talent Retention Pressure and Talent Productivity

This table reports the results of regressing firms' talent productivity on their talent retention pressure (TRP). *Talent Productivity* is the firm's annual sales divided by the firm's total number of talent in the year. The firm's total number of talent is the firm's total number of employees from the Compustat database multiplied by the firm's talent employment share computed from the BLS-Compustat merged sample. *TRP* is the firm's average employment exposure to local talent market competition defined in equation (6). See Section V.C for more details and Table I for the definitions of other variables. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 2010 to 2018.

	Talent Productivity		
	t	$t+1$	$t+2$
	(1)	(2)	(3)
TRP	-0.800	-3.192**	-2.083
	(1.919)	(1.386)	(1.421)
Firm Control	Y	Y	Y
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	12,643	9,751	7,601
Adjusted R^2	0.674	0.678	0.676

Table IX
Heterogeneous Investment Effects: Superstar vs. Laggard Firms

This table reports the results of regressing firms' capital investment next year on the interaction between their current talent retention pressure (TRP) and their superstar status. *Superstar* is a dummy variable equal to one if the firm's sales rank in the top 4 of the 4-digit NAICS industry category in the year. *TRP* is the firm's average employment exposure to local talent market competition defined in equation (6). See Section VI.A for more details and Table I for the definitions of other variables. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 2010 to 2018.

	Physical Investment (1)	Total Investment (2)
TRP × Superstar	3.319***	5.614***
	(0.818)	(1.542)
TRP	-1.821***	-2.684***
	(0.518)	(0.893)
Superstar	-0.811*	-0.714
	(0.426)	(0.610)
Firm Control	Y	Y
Firm FE	Y	Y
Year FE	Y	Y
Observations	11,985	10,581
Adjusted R^2	0.720	0.807

Table X
Heterogeneous Talent Effects: Superstar vs. Laggard Firms

This table reports the results of regressing firms' talent outflow/inflow rate (in Panel A) and retention responses (in Panel B) on the interaction between their talent retention pressure (TRP) and their superstar status. *Superstar* is a dummy variable equal to one if the firm's sales rank in the top 4 of the 4-digit NAICS industry category in the year. *Talent Outflow Rate* (*Talent Inflow Rate*) is a firm's total number of talent leaving (joining) the firm in the year divided by the total number of talent at the beginning of the year using the Revelio Workforce Dynamics Database. *Talent Wage Premium* the natural logarithm of the hourly wage rate of the firm's talent subtracted by the natural logarithm of a benchmark hourly wage rate of the firm's talent which replaces each talent's actual hourly wage rate with the MSA-occupation-year average hourly wage rate. *Satisfaction of Talent* the reconstructed average job satisfaction ratings by talent employees in the firm, where talent is defined using our definition in Section II.B. See Section VI.A for more details and Table I for the definitions of other variables. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 2010 to 2018.

Panel A: Heterogeneous Talent Flows

	Talent Outflow Rate			Talent Inflow Rate		
	t	$t+1$	$t+2$	t	$t+1$	$t+2$
	(1)	(2)	(3)	(4)	(5)	(6)
TRP × Superstar	-0.111	-8.711***	-7.643**	8.223*	-6.045	-5.483
	(2.927)	(2.838)	(3.703)	(4.319)	(4.187)	(5.661)
TRP	0.189	6.585***	4.337*	-1.384	4.474	-0.405
	(1.680)	(1.982)	(2.522)	(2.965)	(3.334)	(3.656)
Superstar	-0.283	2.130**	2.014*	-2.898**	3.025***	3.137**
	(0.897)	(0.830)	(1.110)	(1.379)	(1.167)	(1.495)
Firm Control	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	6,877	6,637	5,638	6,877	6,637	5,638
Adjusted R^2	0.441	0.441	0.440	0.434	0.423	0.402

Panel B: Heterogeneous Talent Retention Responses

	Talent Wage Premium			Satisfaction of Talent		
	t	$t+1$	$t+2$	t	$t+1$	$t+2$
	(1)	(2)	(3)	(4)	(5)	(6)
TRP × Superstar	0.110***	0.099**	0.062	0.061	1.484***	-0.162
	(0.041)	(0.042)	(0.043)	(0.404)	(0.508)	(0.533)
TRP	-0.009	0.013	-0.005	0.178	-0.258	-0.061
	(0.027)	(0.029)	(0.027)	(0.217)	(0.274)	(0.305)
Superstar	-0.029**	-0.023**	-0.018	-0.010	-0.418***	0.199
	(0.014)	(0.012)	(0.012)	(0.157)	(0.160)	(0.182)
Firm Control	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	12,354	9,544	7,458	3,714	3,379	3,157
Adjusted R^2	0.558	0.580	0.582	0.264	0.257	0.254

Table XI
Talent Retention Pressure and Industry Concentration

This table reports the results of regressing 4-digit NAICS industries' future top 4 concentration ratio (CR4) on the within-industry median talent retention pressure (TRP). The dependent variable is the industry's sales share of the top 4 firms with the highest sales within the industry in the next year. The independent variables are a series of within-industry median values of firms' TRP and other characteristics, weighted by firm total assets. See Section VI.C for more details. Standard errors are clustered at the industry level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 2010 to 2018.

	CR4 of Industry_{t+1}	
	(1)	(2)
TRP	1.169**	0.962**
	(0.521)	(0.480)
Q		-0.120
		(0.088)
Cashflow		-0.424
		(0.601)
Size		0.169
		(0.234)
Age		-0.579***
		(0.205)
Industry FE	Y	Y
Year FE	Y	Y
Observations	1,773	1,751
Adjusted R^2	0.917	0.921

Internet Appendix for

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Table IA.1
Pervasiveness of Job-to-Job Moves for Talent Occupations

This table reports two labor market characteristics of key talent (see Section II.D for the definition of industry-specific key talent). The second column reports the percentage of talent occupations that require over 1-year of working experience using O*Net data. The third column reports the percentage of newly hired key talent between 21-65 years old from job-to-job moves last quarter. Job-to-job moves are identified based on changes in the employer's name in CPS surveys (Fallick and Fleischman (2004)) and within-quarter job-to-job switches as in Hyatt et al. (2014). Conditional on having a job, three groups of employees are considered as job-to-job movers in month t, 1) those who explicitly indicated that he/she is not employed by the same same employer and the same job he/she reported working as his/her main job in the previous month's survey, 2) those who was in unemployment or not in labor force in month $t-1$ but was employed in month $t-2$, and 3) those who was in unemployment or not in labor force both in month $t-1$ and $t-2$ but was employed in month $t-3$. Conditional on having a job, employees are considered as movers from non-employment in month t if he/she was in unemployment or not in labor force for three consecutive months in $t-1$, $t-2$, and $t-3$. The % talent hires that are job-to-job is the ratio of job-to-job movers and the sum of job-to-job movers and movers from non-employment. The sample period is 2010 to 2018.

Sectors	% talent jobs requiring over 1 year work experience	% talent hires are job-to-job in CPS data
All	81%	76%
Manufacturing	88%	79%
Trade, Transportation, and Utilities	82%	74%
Information	94%	76%
Financial Activities	93%	83%
Professional and Business Services	87%	74%
Educational Services	81%	76%
Health Care	85%	79%
Leisure and Hospitality	58%	80%
Other	84%	78%

Table IA.2
CFO Perception and TRP using Other Definitions of Talent

This table examines the association between CFOs' talent retention concerns and talent retention pressure (TRP) measures where talent is defined in other ways from our main text in Section II. The dependent variable, CFOs' talent retention concerns, is a dummy variable equal to one if the CFO elects "to attract and retain qualified employees" as the top firm-specific concern in the microdata of the Duke CFO Survey. *Regime* referees to two survey regimes from 2010 to 2014 and from 2015 to 2018 (see Section III and Appendix A for more details). *TRP* is the firm's average employment exposure to local talent market competition defined in equation (6). In Columns (1), (2), and (3), occupations are considered talent if ranked in the top 10% within an industry based on the average wage, requirements for a college degree, and requirements for 4 year working experiences, respectively. In Column (4), occupations are considered talent is ranked in the top 10% nationally (instead of within-industry in our baseline TRP measure) based on the average cognitive skill requirements. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 2010 to 2018.

	Within-Industry Ranking by			National Ranking by
	Wage	College Degree	Work Experience	Cognitive Skill
	(1)	(2)	(3)	(4)
TRP	0.364	-0.789	1.034*	0.745
	(0.504)	(0.867)	(0.548)	(0.414)
Q	0.0672	0.111	0.067	0.077
	(0.111)	(0.129)	(0.113)	(0.110)
Cashflow	1.184*	1.250**	1.174*	1.151*
	(0.538)	(0.526)	(0.583)	(0.561)
Size	0.320	0.106	0.336	0.351
	(0.257)	(0.196)	(0.258)	(0.237)
Age	-2.509	-2.001	-2.921	-3.010
	(2.171)	(1.898)	(2.284)	(2.213)
Firm-Regime FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	147	142	147	147
Adjusted R^2	0.135	0.187	0.160	0.166

Table IA.3
Robustness Checks Using Alternative Cutoffs in Talent Definition

This table reports the results of regressing firms' next year's capital investment on their current talent retention pressure (TRP). The dependent variable is next year's capital expenditure (#CAPX) divided by this year's total assets (#AT). *TRP* is the firm's average employment exposure to local talent market competition defined in equation (6). Columns (1), (2), and (3) report the results when talent is defined as the top 7.5%, 10%, 20% within an industry based on cognitive skill requirements, respectively, where the 10% version is our baseline TRP used in the main text. See Section IV for regression specifications. See Table I for the definitions of other variables. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 2010 to 2018.

	Top 7.5%	Top 10% (Baseline)	Top 20%
	(1)	(2)	(3)
TRP	-1.056**	-1.472***	-1.091**
	(0.425)	(0.486)	(0.547)
Q	0.649***	0.643***	0.643***
	(0.057)	(0.056)	(0.059)
Cashflow	2.044***	1.917***	1.640***
	(0.426)	(0.401)	(0.425)
Size	-0.882***	-0.895***	-0.891***
	(0.185)	(0.183)	(0.187)
Age	-2.300**	-2.449**	-2.333**
	(1.163)	(1.116)	(1.118)
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	11,908	11,985	12,156
Adjusted R^2	0.718	0.719	0.719

Table IA.4
Economic Magnitude of Talent Retention Pressure on Investment

This table reports the economic magnitudes of the relationship between talent retention pressure (TRP) and investment policies. We sort firms into terciles based on their TRP and report the average value of investment rate for each of the three bins. *TRP* is the firm's average employment exposure to local talent market competition defined in equation (6). *IV(TRP)* and *NonPeer IV(TRP)* are the shift-share instrument for TRP and the non-peer based instrument for TRP, respectively. Section IV.B details the construction of these instruments. *Investment* is next year's capital expenditure (#CAPX) divided by this year's total assets (#AT). The sample period is 2010 to 2018.

Sorting Var.:	TRP (1)	IV(TRP) (2)	NonPeer IV(TRP) (3)
Tercile 1 (L)	5.56	5.77	5.68
Tercile 2 (M)	4.71	4.57	4.63
Tercile 3 (H)	4.34	4.39	4.41
H−L	-1.22	-1.38	-1.27
(H−L)/L	-22%	-24%	-22%

Table IA.5
Talent Retention Pressure and Long-Term Investment

This table reports the regression of firms' next period and also the longer-term investment rate on their talent retention pressure (TRP). See Table IV in the main text for details. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 2010 to 2018.

Panel A: Physical Investment					
	$t+1$	$t+2$		$t+3$	
	(1)	(2)	(3)	(4)	(5)
TRP_t	-1.472***	-1.245**	-1.092*	-0.278	0.103
	(0.486)	(0.488)	(0.615)	(0.517)	(0.621)
TRP_{t+1}			-0.867**		-1.348**
			(0.442)		(0.526)
TRP_{t+2}					-0.304
					(0.484)
Firm Control	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Observations	11,985	11,288	9,748	10,634	7,702
Adjusted R^2	0.719	0.695	0.723	0.679	0.736
Panel B: Total Investment					
	$t+1$	$t+2$		$t+3$	
	(1)	(2)	(3)	(4)	(5)
TRP_t	-2.042**	-1.423*	0.370	-0.449	1.481
	(0.901)	(0.849)	(1.102)	(1.014)	(1.039)
TRP_{t+1}			-2.277***		-1.448
			(0.824)		(0.997)
TRP_{t+2}					-0.651
					(0.887)
Firm Control	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Observations	10,508	9,869	8,549	8,429	6,769
Adjusted R^2	0.789	0.772	0.786	0.765	0.785

Table IA.6
Inspecting IV Magnitude: First Stage with Diagnostic IV

This table presents first-stage results for the relationship between actual talent retention pressure (TRP) and the instrument (IV), after partialling out time-varying firm controls and also firm and year fixed effects. In Column (1), we regress the actual TRP on firm-level control variables, firm fixed effects, and year fixed effects. In Column (2), we regress the actual TRP on the instrument, alongside the firm-level control variables, firm fixed effects, and year fixed effects. This is the first-stage result for Column (1) of Table V. In Column (3), we construct a diagnostic "mid-step" instrument, which differs from our instrument in that it allows MSA-occupation's v-e ratio to evolve locally instead of being replaced by the national growth at the occupation level. See Table I for the definitions of other variables. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 2010 to 2018.

	Dependent Variable = TRP		
	No IV	IV	Diagnostic IV
	(1)	(2)	(3)
IV		0.426***	0.561***
		(0.037)	(0.033)
Q	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)
Cashflow	-0.021*	-0.018	-0.011
	(0.011)	(0.012)	(0.010)
Size	0.007*	0.008*	0.008**
	(0.004)	(0.004)	(0.004)
Age	0.041	0.028	0.046
	(0.034)	(0.033)	(0.031)
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	11,110	11,110	11,110
Adjusted R^2	0.619	0.640	0.676

Table IA.7
Inspecting IV Magnitude: Second Stage with Diagnostic IV

This table presents second-stage results of the 2SLS regressions of firms' physical investment on their talent retention pressure (TRP) where TRP is instrumented. Column (1) displays the results in our main text (Table V) based on the shift-share instrument. In Column (2), we construct a diagnostic "mid-step" instrument, which differs from our instrument in that it allows MSA-occupation's v-e ratio to evolve locally instead of being replaced by the national growth at the occupation level. See Table I for the definitions of other variables. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 2010 to 2018.

	IV (1)	Diagnostic IV (2)
2SLS(TRP)	-5.352**	-2.495**
	(2.091)	(1.247)
Q	0.654***	0.651***
	(0.063)	(0.06190)
Cashflow	2.002***	2.062***
	(0.442)	(0.43537)
Size	-0.878***	-0.899***
	(0.193)	(0.19579)
Age	-2.656**	-2.773**
	(1.253)	(1.24733)
Firm FE	Y	Y
Year FE	Y	Y
Observations	11,110	11,110
Adjusted R^2	0.040	0.051

Table IA.8
Inspecting IV Validity: Pre-sample Investment and In-sample IV

This table examines the validity of our instrument for firms' talent retention pressure by regressing firms' investment before 2010 on their instrumented TRP after 2010 following Tabellini (2020). We report the results of regressing firms' capital investment 10 years before on their current instrumented talent retention pressure (TRP IV). See Table I for the definitions of variables. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period concerns firm investment from 2001 to 2009.

	Physical Investment$_t$		Total Investment$_t$	
	(1)	(2)	(3)	(4)
TRP IV$_{t+9}$	0.001	0.018	0.018	0.032
	(0.012)	(0.012)	(0.032)	(0.028)
Q$_{t-1}$		0.007***		
		(0.001)		
Total Q$_{t-1}$				0.001*
				(0.000)
Cashflow$_{t-1}$		0.024***		0.108***
		(0.005)		(0.015)
Size$_{t-1}$		-0.015***		-0.017***
		(0.002)		(0.006)
Age$_{t-1}$		-0.017		-0.183***
		(0.015)		(0.035)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	9,801	8,098	8,405	7,082
Adjusted R^2	0.647	0.707	0.609	0.669

Table IA.9
Inspecting IV Validity: Controlling for Firms' Initial Characteristics

This table reports the second stage results of the 2SLS regressions of firms' capital investment on their talent retention pressure (TRP) instrumented by a shift-share instrumental variable while controlling for additional variables to examine the validity of the IV following Tabellini (2020). The dependent variable is next year's capital expenditure (#CAPX) divided by this year's total assets (#AT). *TRP IV* is the shift-share instrumented firm's average employment exposure to local talent market competition defined in equation (6). Column (1) reports the baseline results in Table V. Columns (2)-(6) report the results with additional controls of firms' 2010 characteristics interacted with year dummy variables. See Section IV for regression specifications. See Table I for the definitions of other variables. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 2010 to 2018.

Firm 2010 Char	None	Q	Cashflow	Size	Age	All
	(1)	(2)	(3)	(4)	(5)	(6)
2SLS(TRP)	-5.352**	-6.857***	-7.077***	-6.669***	-7.011***	-6.703***
	(2.091)	(2.383)	(2.378)	(2.354)	(2.379)	(2.476)
Firm 2010 Char×Year Dummies	N	Y	Y	Y	Y	Y
Firm Control	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	11,110	8,998	9,184	9,329	9,329	8,980
Adjusted R^2	0.040	0.034	0.033	0.036	0.032	0.037

Table IA.10
Inspecting IV Validity: Occupation Shares and Firm Characteristic

Panel A lists the five occupations with the highest sensitivity-to-misspecification elasticity (Rotemberg weight) in our shift-share instrument following Goldsmith-Pinkham et al. (2020). Panel B conducts a key diagnose test suggested by Goldsmith-Pinkham et al. (2020) where we regress firms' 2010 share in each occupation on their 2010 characteristics. The shares are defined in equation (8). We show the variations in these occupation shares cannot be explained by firm characteristics in 2010, as suggested by small R^2s in cross-sectional regressions. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Top 5 Occupations with High Rotemberg Weights

Occupation	SOC-5	Rotemberg Weight
Marketing and Sales Managers	11-202	0.603
Miscellaneous Managers	11-919	0.147
First-Line Supervisors of Sales Workers	41-101	0.144
Market Research Analysts and Marketing Specialists	13-116	0.070
Management Analysts	13-111	0.068

Panel B: Relation between Occupation Shares and Firm Characteristics

SOC-5	11-202	11-919	41-101	13-116	13-111
	(1)	(2)	(3)	(4)	(5)
Q	0.715***	-0.086	0.101**	0.182***	0.013
	(0.154)	(0.065)	(0.049)	(0.059)	(0.089)
Cashflow	0.209	0.100	0.025	-0.287	-0.007
	(0.991)	(0.454)	(0.289)	(0.374)	(0.535)
Size	-0.262***	0.154***	0.126***	-0.062**	-0.116**
	(0.078)	(0.052)	(0.032)	(0.030)	(0.050)
Age	-0.854	-0.521	-0.588	-0.013	2.146
	(1.775)	(0.788)	(0.533)	(0.616)	(1.433)
Observations	1,377	1,377	1,377	1,377	1,377
Adjusted R^2	0.033	0.006	0.014	0.014	0.005

Table IA.11
Inspecting IV Validity: Instrument without Selected Occupations

This table examines the robustness of our instrument for firms' talent retention pressure by excluding each of the top five occupations with the highest sensitivity-to-misspecification elasticity (Rotemberg weight) following Goldsmith-Pinkham et al. (2020). We report the second stage results of the 2SLS regressions of firms' capital investment on their instrumented talent retention pressure where the instrument is constructed without the selected occupation. Investment is next year's capital expenditure (#CAPX) divided by this year's total assets (#AT). *TRP IV* is the shift-share instrumented firm's average employment exposure to local talent market competition defined in equation (6). Column (1) reports the result when constructing shift-share IV using all occupations. Columns (2)-(6) report the results where we increasingly exclude occupations with the highest Rotemberg weight from the top 1st to the 5th in Table IA.10: 11-202, 11-919, 41-101, 13-116, and 13-111. See Section IV for regression specifications. See Table I for the definitions of other variables. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 2010 to 2018.

Excluded Occupations	None	Top 1	Top 2	Top 3	Top 4	Top 5
	(1)	(2)	(3)	(4)	(5)	(6)
2SLS(TRP)	-5.639***	-9.063***	-6.477**	-7.581**	-6.194*	-4.653
	(2.180)	(2.649)	(2.558)	(3.143)	(3.255)	(3.131)
Q	0.652***	0.658***	0.655***	0.656***	0.655***	0.653***
	(0.063)	(0.064)	(0.063)	(0.064)	(0.063)	(0.063)
Cashflow	2.012***	1.924***	1.978***	1.955***	1.984***	2.017***
	(0.441)	(0.444)	(0.444)	(0.446)	(0.447)	(0.445)
Size	-0.879***	-0.850***	-0.869***	-0.861***	-0.872***	-0.883***
	(0.193)	(0.196)	(0.194)	(0.193)	(0.191)	(0.191)
Age	-2.637**	-2.504**	-2.610**	-2.565**	-2.622**	-2.685**
	(1.254)	(1.276)	(1.255)	(1.262)	(1.248)	(1.241)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	11,110	11,110	11,110	11,110	11,110	11,110
Adjusted R^2	0.719	0.726	0.726	0.726	0.725	0.725

Table IA.12
Robustness Check: Talent Retention Pressure from NonPeers

This table reports the results of regressing firms' next year's capital investment on their current talent retention pressure from other industries (*TRP NonPeer*). See Section IV for the definition of firms' non-peers. *Physical Investment* is next year's capital expenditure (#CAPX) divided by this year's total assets (#AT). *Total Investment* is next year's physical and intangible expenditure (Peters and Taylor (2017)) divided by this year's total capital stock obtained from Peters and Taylor (2017). See Section IV for regression specifications. See Table I for the definitions of other variables. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 2010 to 2018.

	Physical Investment	Total Investment
	(1)	(2)
TRP NonPeer	-1.540***	-2.081**
	(0.498)	(0.841)
Q	0.642***	
	(0.056)	
Total Q		2.220***
		(0.133)
Cashflow	1.919***	3.135***
	(0.401)	(0.889)
Size	-0.896***	-1.962***
	(0.183)	(0.431)
Age	-2.444**	-18.796***
	(1.117)	(2.327)
Firm FE	Y	Y
Year FE	Y	Y
Observations	11,985	10,581
Adjusted R^2	0.719	0.807

Table IA.13
Talent Retention Pressure and Labor Productivity

This table reports the results of regressing firms' labor productivity on their talent retention pressure (TRP). *Labor Productivity* is the firm's annual sales divided by the firm's total number of employees in the year. *TRP* is the firm's average employment exposure to local talent market competition defined in equation (6). See Section V.C for more details and Table I for the definitions of other variables. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 2010 to 2018.

	Labor Productivity		
	t	$t+1$	$t+2$
	(1)	(2)	(3)
TRP	0.053*	-0.006	-0.073*
	(0.030)	(0.038)	(0.043)
Firm Control	Y	Y	Y
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	12,643	9,751	7,601
Adjusted R^2	0.908	0.911	0.914

Table IA.14
Talent Retention Pressure and SG&A Expense

This table reports the results of regressing firms' next year's selling, general and administrative expenses on their current talent retention pressure. *SG&A* is next year's selling, general and administrative expense (#XSGA) divided by this year's total assets (#AT). *TRP* is the firm's average employment exposure to local talent market competition defined in equation (6). Column (1) reports the OLS result using our baseline TRP measure, and Column (2) reports the 2SLS result using our instrument for TRP (see Section IV.B). See Table I for the definitions of other variables. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 2010 to 2018.

	SG&A	
	OLS	2SLS
	(1)	(2)
TRP	1.799	-1.564
	(1.589)	(5.768)
Q	2.422	2.299
	(0.246)	(0.252)
Cashflow	-5.651	-4.979
	(1.914)	(1.967)
Size	-16.660	-15.812
	(0.915)	(0.922)
Age	11.099	8.490
	(4.603)	(5.040)
Firm FE	Y	Y
Year FE	Y	Y
Observations	10,520	9,809
Adjusted R^2	0.920	0.312

Figure IA.1: Average State Non-Compete Enforcement Index

This figure plots the average of state covenants-not-to-compete enforcement index for 50 states and D.C. in each year. The index was constructed by Garmaise (2011) and extended to 2018 by Bai et al. (2023). The index can be downloaded at Matthew Serfling's website at: https://docs.google.com/spreadsheets/d/1JaRjhu4Ic3mRlspzhB0YRoMb6p6B3D1W/edit?usp=sharing&ouid=104446980150550029667&rtpof=true&sd=true.

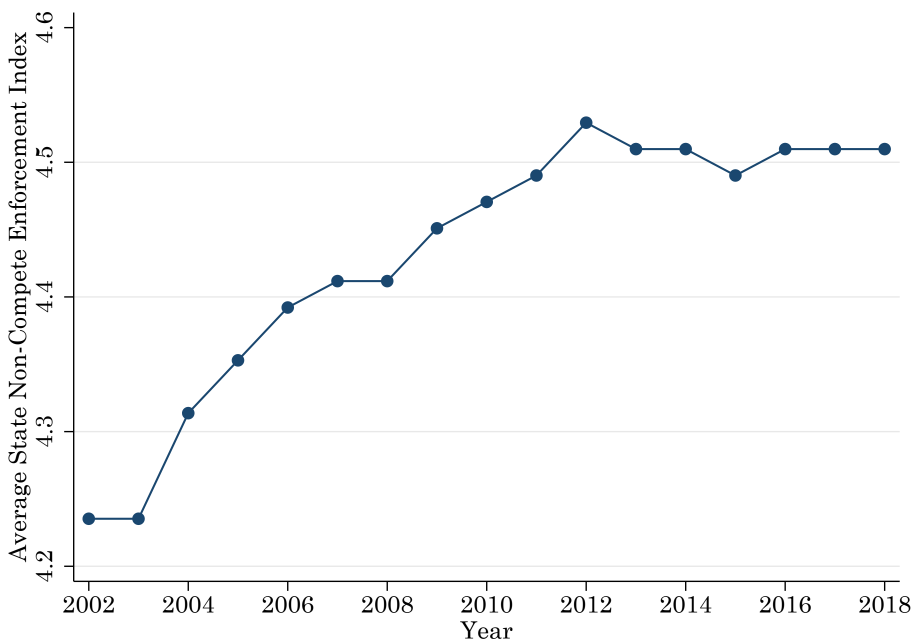

Figure IA.2: Duke CFO Survey Questions on CFOs' Talent Retention Concerns

This figure shows the screenshots of the Duke CFO Survey questions regarding CFOs' talent retention concerns. Panel A represents the question from 2008Q4-2014Q1 (early regime), and Panel B represents the question in 2015Q1-2019Q4 (later regime). The survey questions can be accessed at https://cfosurvey.fuqua.duke.edu/release/.

Panel A: Duke CFO Survey Q4 for 2014Q1 (Early Regime)

4. What are the top three internal, company-specific concerns for your corporation? (rank #1, #2, #3)

Ability to forecast results	Maintaining morale/productivity
Ability to maintain margins	Managing IT systems
Attracting and retaining qualified employees	Pension obligations
Balance sheet weakness	Protection of intellectual property
Cost of health care	Supply chain risk
Counterparty risk	Working capital management
Data security	Other:

Panel B: Duke CFO Survey Q3 for 2015Q1 (Later Regime)

3a. During the past quarter, which items have been the most pressing concerns for your company's top management team? (Choose up to 4)

Access to capital	Employee productivity
Corporate tax code (domestic)	Geopolitical / health crises
Cost of benefits	Government policies
Cost of borrowing	Inflation
Currency risk	Regulatory requirements
Data security	Rising input or commodity costs
Deflation	Rising wages and salaries
Difficulty attracting / retaining qualified employees	Weak demand for your products/services
Economic uncertainty	Other
Employee morale	

Figure IA.3: Ranking of Talent Retention/Attraction in Duke CFO Survey

This figure plots the the yearly-averaged ranking of the talent retention/attraction option among all other options in each year. During 2008Q4-2014Q1 (early regime), the survey asked CFOs to elect from approximately 10 options to answer "*What are the top three internal, company-specific concerns for your corporation?*" During 2015Q1-2019Q4 (later regime), the survey asked CFOs to elect from approximately 18 options to answer "*During the past quarter, which items have been the most pressing concerns for your company's top management team? (Choose up to 4)*" Both waves of survey include the option "attracting and retaining qualified employees." See Section III and Appendix A for more details.