Talent Market Competition and Firm Growth

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Abstract

How does competition for talent affect firm growth? Using establishment-level occupational employment microdata and job postings, we measure local occupational market tightness and a firm's talent retention pressure (TRP) based on outside job postings in its talent markets. TRP strongly predicts job-to-job talent outflows and captures firms' talent-retention concerns. We find that higher TRP reduces capital investment, increases talent turnover, and raises talent retention costs. Notably, TRP dampens the growth of laggard firms but not superstars, as superstar firms retain talent more responsively to TRP and experience lower talent outflows, suggesting an uneven impact of TRP on the business landscape.

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 key employees" 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, how 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' talent retention pressure due to talent market competition. Talent retention pressure varies by firms' key employees' occupations and locations and has increased substantially over time. We quantify a sizable negative impact of firms' talent retention pressure on their investment via panel regressions and instrumental variable approaches, 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)). Aligned with this heterogeneity, we find that laggard firms spend less resources on talent retention than superstar firms when talent market competition intensifies and experience greater talent outflows, consistent with smaller firms being more resource-constrained as documented in the prior literature (Hadlock and Pierce (2010)).

Our measurement of firms' talent retention pressure leverages two comprehensive microdata sets that overcome several major empirical challenges. First, a firm's exposure to talent markets is difficult to measure as talent typically concerns a small group of highly skilled labor within the firm (Baghai et al. (2021)). We address this challenge by obtaining granular *occupational* employment of firms from the U.S. Bureau of Labor Statistics (BLS) OEWS microdata, which covers 1.2 million establishments representative of the U.S. economy. Second, talent moves primarily from job to job across firms, making the traditional labor market tightness measure (i.e., vacancy-to-unemployment ratio) inadequate for capturing talent's outside options and firms' retention pressure (Abraham et al. (2020)).[2] To address this challenge, we combine Lightcast's near-universe of job postings with the confidential BLS microdata, and we measure the competition of local talent markets as the vacancy-to-employment ratio motivated by the *on-the-job search* model (Pissarides (1994)). Finally, the ambiguity in

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

[2]For instance, Trevor (2001) shows that changes in the unemployment rate have little effect on the turnover of workers with high cognitive skills. 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 using the Census Current Population Survey (CPS) data.

defining and measuring a firm's talent poses additional challenges for empirical analysis. We leverage detailed OEWS data on firms' occupational composition and show that our results are robust under different talent definitions.

Using the two granular datasets, we construct our firm-level talent retention pressure through three steps. First, we conceptualize a firm's talent (or key employees) as a small group of skilled occupations that strongly *complement its capital* to capture key employees' critical role in driving firm growth. This conceptualization allows the definitions of talent to vary across firms, reflecting heterogeneity in their capital composition and the complementary skills required. Following a large body of labor economics literature highlighting the complementarity between cognitive skills and capital (e.g., Autor and Acemoglu (2011)), we classify a SOC 5-digit occupation as a firm's talent if its cognitive skills rank within the top decile in the firm's industry. This within-industry definition of key employees captures firms' retention concerns in the data, especially for firms in conventionally low-skilled industries.[3] Second, a firm's talent employees can search for outside opportunities and move to other firms or industries. We measure the competition of the firm's local talent market, defined at the MSA-occupation level, as its vacancy-to-employment ratio (V/E), where we exclude the firm's own job postings. Third, we obtain each firm's employment exposure to local talent markets by merging Compustat firms with the BLS establishment microdata. A firm's talent retention pressure (TRP) is the employment-weighted average V/E ratio across its talent markets. TRP thereby captures the average abundance of outside options for the firm's talent due to 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 thus raise the firm's TRP.

We conduct three tests to validate our TRP measure. First, using 26 million individual-year observations from Revelio Labs microdata (compiled from individuals' LinkedIn and other online profiles), we show that the local V/E ratio strongly predicts job-to-job transitions among individual talent employees. This result is robust after controlling for various fixed effects that account for known turnover predictors, thereby validating the inner workings of our firm-level TRP measure. Second, at the firm level, TRP strongly predicts firms' talent outflows, further validating it as a measure of firms' concerns about losing talent. Third, we construct textual measures of firms' talent retention concerns from 10-K annual reports and show that our TRP measure is strongly and positively associated with firms' expressed concerns about talent competition and retention.

[3] Our main findings are robust to classifying key employees uniformly across industries. Relative to our baseline measure, the uniform definition of talent does not capture talent-retention concerns as effectively for firms in low-skilled industries (see Section II.A for details).

After validating the measure, we present our main findings on talent retention pressure and firm investment. In our baseline panel regressions, we find that TRP significantly reduces the next-period capital investment after controlling for common investment predictors and fixed effects by firm and year. The effect persists when we further control for industry-year fixed effects and measure firm growth using the total investment following Peters and Taylor (2017) to account for intangible investment. Finally, the effect is also robust to alternative definitions of talent used to construct TRP (see Internet Appendix IA.1).

While our TRP measure is constructed based on other firms' job postings, which are beyond the control of the focal firm, three remaining endogeneity concerns may still affect the interpretation of our panel regression estimates. First, omitted variables related to local talent markets could simultaneously influence both TRP and firm investment. Second, firms may strategically reallocate labor across local markets, and these relocation decisions could be endogenously related to both TRP and investment decisions. Third, a firm's product market competitors may post jobs based on their expectations of the focal firm's investment, raising a concern about reverse causation.

To address these concerns, we construct a shift-share instrument for TRP: To mitigate the omitted variable concern, we discard time-series variations of the V/E ratio at the local level and use the *national* growth of each occupation's V/E ratio instead. To account for firms' endogenous labor reallocation, we fix firms' talent exposure across MSA-occupations at the beginning of our sample period in 2010, as in Card (2001b) and Tabellini (2020). Finally, we consider only non-industry-peer firms' job postings to mitigate the influence of the product market competition channel. 2SLS analyses using this instrument indicate that TRP has a strong, negative, and causal effect on firm investment, reinforcing our baseline findings.

We further bolster the causal inference by conducting two additional sets of tests. First, our shift-share instrument relies on the identifying assumption that firms with higher initial talent retention pressure are not on different investment trajectories in subsequent years (see Goldsmith-Pinkham et al. (2020) and Borusyak et al. (2022)). We show that our instrument passes a comprehensive set of diagnostic tests following Tabellini (2020) and Goldsmith-Pinkham et al. (2020), which significantly alleviate concerns that our IV results are driven by spurious correlations. Second, we corroborate our shift-share IV results by constructing an alternative instrument based on quasi-exogenous shocks from local defense-related industries winning government military procurement contracts. These shocks can raise demand for relevant occupations in the local labor market, thereby increasing talent retention pressure for neighboring firms. Importantly, for firms in unrelated industries that rely on similar talent, their investment is unlikely to be affected by this TRP instrument through other channels. Consistent with our baseline findings, we show that TRP driven solely by local military procurement spending significantly reduces investment by unrelated firms.

The economic magnitude of TRP's effect on firm investment is sizable. Our panel regressions suggest that a one-standard-deviation increase in TRP reduces firms' physical investment rate by 0.21 percentage points, or 4.2% of the sample mean. To assess the plausibility of this effect, we compare it with evidence from seven related studies and find that our estimate lies well within the range of labor-related effects on firm investment documented in the literature (see Section IV.E). The magnitude implied by the shift-share IV estimation is 3.6 times that from our panel regressions. Jiang (2017) shows that $\beta_{IV} > \beta_{OLS}$ is a common phenomenon in the literature and cautions against interpreting IV estimates as economic magnitudes, as they tend to overstate economic significance.[4] Consistent with this view, we decompose the IV–OLS gap following Ishimaru (2024) and find supporting evidence that the IV estimates are likely substantially amplified, as they capture local average treatment effects (LATE) among compliers rather than average treatment effects (ATE) across all firms (see Section IV.E). Overall, we view the magnitude of TRP's dampening effect on firm investment likely lies between the OLS and the shift-share IV estimates, while cautioning that the upper bound is likely substantially overstated due to the IV amplification.

After establishing the effect of TRP on firm investment, we next examine firms' labor responses to TRP to better understand the investment findings. On the one hand, it is natural to expect that firms make efforts to retain and replace employees when TRP rises. On the other hand, mounting evidence from prior studies highlights that fully retaining talent is challenging due to costs and constraints (e.g., Sorkin (2018) and Caldwell and Danieli (2024)).[5] As a result, whether and how firms retain and replace their key employees in response to rising TRP is an empirical question.

We find that both firms' average talent wage rates and talent promotion propensities are significantly higher when TRP is elevated, consistent with the common prior that firms actively respond to TRP through labor policies. While quantifying the total retention cost is unfeasible in our data, the additional wage expenses associated with mitigating talent loss appear roughly comparable in magnitude to the foregone investment returns. Beyond retention, we also find that firms post more job openings for talent positions when TRP is higher. While these efforts help offset some of the net losses, average talent productivity

[4] Jiang (2017) survey the literature and find that β_{IV} averages 3.3 to 9.2 times β_{OLS}, depending on the nature of endogeneity concerns, cautioning that IV estimates tend to amplify economic significance due to factors such as the "complier" effect. In our setting, the magnitude implied by the military-procurement IV estimation is 1.8 times that from the panel regression.

[5] For example, raising wages to retain an employee can potentially increase other employees' wage demands, resulting in substantial retention costs (Breza et al. (2018) and Mueller et al. (2017)); employees may also leave for nonpecuniary reasons such as cultural fit or work-life balance, which are difficult for firms to address in the short run (Allen et al. (2010)).

declines significantly in the year following a TRP increase. This pattern echoes prior findings that labor turnover reduces productivity (Bishop (1996); Silva and Toledo (2009)). Taken together, the results suggest that firms incur substantial costs and face meaningful constraints in retaining and replacing talent under high TRP, which in turn contributes to the negative effect of TRP on capital investment.

The effect of TRP on firm investment can be heterogeneous across firms, depending on the costs and constraints firms face. Consistent with this notion, we uncover that TRP dampens investment in small and midsized "laggard" firms, which are shown to be more constrained (Hadlock and Pierce (2010)), but barely in large "superstar" firms.[6] We further observe a similar heterogeneity in talent outflows, suggesting that key employees in laggard firms are much more susceptible to the impact of TRP than those in superstar firms. Finally, laggard firms appear to raise wages less and post fewer jobs for talent when TRP rises, as compared to superstar firms. Collectively, these results on heterogeneous effects reinforce the mechanism that costs and constraints play an important role in our main investment effects.

Our study contributes to the growing literature explaining new observations 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 in the U.S. after the early 2000s. Several recent studies have shed light on this phenomenon through 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 (2025)), 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)). Complementing this literature, our research provides micro-level evidence that the pressure to retain talent significantly reduced firm investment in the recent decade.

Our findings also contribute to the literature on superstar firms and business dynamism.[7] 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 ability to retain talent from talent market competition. This heterogeneity has important potential implications for

[6] We define superstar firms as the top four firms with the highest sales in an industry-year, following Gutierrez and Philippon (2020) and Autor et al. (2020). Our findings are robust to using alternative definitions.

[7] 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.

understanding the rise of superstar firms and the increase in industry concentration (Gutiérrez and Philippon (2018); Autor et al. (2020); Grullon et al. (2019)).

Finally, our work connects to recent studies on the economic impact of labor mobility. These studies have explored policy shocks on employees' job-to-job move costs, e.g., non-compete enforcement, and developed many novel insights into how labor mobility causally affects firm outcomes in the local treatment group.[8] We extend the prior studies by comprehensively measuring the *intensity* of firms' talent retention pressure, which can be driven by factors beyond policy-driven shifts in job-to-job move costs. 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)).[9] 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.[10] Indeed, our study using a comprehensive measure supports Jeffers (2023) and shows a significant dampening effect of talent retention pressure on firm investment. In addition, from a methodological perspective, our study adds to the literature by introducing a novel measure of labor market competition customized to firms' talent, which can be relevant to both academia and policymakers.

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. Section III validates the measure. Section IV presents our main results of talent retention pressure's effects on firm investment. Section V examines responses of firms' labor policies to talent retention pressure. Section VI shows important heterogeneous responses between superstar and laggard firms to talent retention pressure, and Section VII concludes.

[8] Examples of important policy shocks include 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).

[9] 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.

[10] 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 Figure 3).

I. Conceptual Framework

We consider a conceptual framework in which firms produce outputs by investing in capital and hiring employees with various skills. Skills are grouped by occupations.

A firm's key employees (i.e., talent) have two main features. First, they are a small number of occupations with skills *complementing* the firm's capital. This complementarity naturally captures key employees' critical role in the firm's growth. It also implies that different firms may define their key employees differently, depending on the nature of their capital. Second, due to the high demand, key employees transit primarily from job to job rather than in and out of the unemployment pool.[11]

For each occupation and location, there exists a labor market where firms can post job vacancies and workers can search for outside options. In a perfectly competitive labor market, an exogenous increase in talent's outside options attracts employees to transition immediately and compels the firm to swiftly adjust wages to match the outside options. In practice, the labor market does not adjust instantaneously as workers and firms face search frictions. Under the on-the-job search framework (e.g., Pissarides (1994)), we can characterize the abundance of a talent's outside options as its occupation's vacancy-to-employment ratio (V/E) in the labor market (Abraham et al. (2020)). The firm's *talent retention pressure* (TRP) can thus be measured as the average V/E ratios of the labor markets, weighted by the firm's talent employment in each market.

Our key prediction is that the firm reduces capital investment when TRP is high. This effect arises because TRP increases the firm's costs of retaining and replacing talent, thereby lowering the net present value (NPV) of its investment. TRP can also trigger constraints in the firm's ability to retain or replace talent, leading the firm to scale back capital budgeting in anticipation of talent and productivity losses. For instance, recent studies show that employees may leave the firm for numerous pecuniary and also nonpecuniary reasons such as dissatisfaction with the corporate culture that the firm can hardly adjust in the short run (Sorkin (2018) and Caldwell and Danieli (2024)), making full retention impractical.[12] The firm's efforts in posting job vacancies to replace departing talent may also fall short in maintaining the scale and possibly productivity of its talent workforce, as high market

[11] Abraham et al. (2020) point out that the traditional vacancy-to-unemployment ratio (V/U) fails to capture the pervasive on-the-job searchers in the modern economy. For skilled workers, accounting for on-the-job search appears particularly important, as Trevor (2001) shows that changes in the unemployment rate have little impact on skilled workers' turnover.

[12] Allen et al. (2010) note that many managers believe that "*there is little managers can do to affect individual turnover decisions.*" See reviews from Hom et al. (2017) and Holtom et al. (2008) on empirical findings on employee voluntary turnovers.

competition for the talent occupation can lead to low job-filling rates, and new hires typically face an unproductive onboarding period (Bishop (1996) and Silva and Toledo (2009)).[13] These costs and constraints associated with talent retention and replacement ultimately drive TRP's negative effect on firms' capital investment.

Discussions on empirical implementation: We complete this section by discussing a few specific considerations for implementing this framework to measure firms' talent retention pressure. We relegate the detailed supporting evidence in the later sections.

First, our framework suggests that, from the *firm's perspective*, whether an occupation is a key talent for the firm depends on the firm's line of business and capital type. This definition allows us to empirically explore the possibility that firms across industries may hire the same occupation but can hold different views of whether the occupation is key to their business. For instance, while top executives can be key for all firms, occupations like software developers could be more crucial for IT firms, and financial managers could be more central to investment firms. In Section II.A, we classified talent both uniformly and within the industry. While our main results are robust under both classifications of a firm's talent, we show that the within-industry classification of talent appears to capture firms' talent better in practice. Therefore, we adopt the within-industry talent definition to construct our main TRP measure.

Second, following a large body of labor economic literature, we characterize the occupational labor markets in our framework at the occupation-MSA level in the empirical analysis to reflect both the aggregate demand shifts for an occupation and also the heterogeneity across local labor markets (e.g., Beaudry et al. (2010) and Autor and Dorn (2013)). Indeed, evidence from Section III.A shows that an occupation's V/E defined at the local level subsumes the effect of V/E defined at the national level in predicting talent employees' job-to-job transitions. Hence, while the tightness at the national level is certainly relevant, it tends to affect workers and firms through the local labor markets. This is also consistent with recent studies reinforcing the importance of the local labor market for job searches even among the very skilled workers (Marinescu and Rathelot (2016) and Manning and Petrongolo (2017)). Marinescu and Rathelot (2016), for example, examine detailed job application data on a leading platform and show that job seekers, regardless of skills, dislike applying for distant jobs.[14]

[13] Silva and Toledo (2009) argue that new hires take about 1 year to become fully productive.

[14] In particular, Figure 3 of Marinescu and Rathelot (2016) shows that the job application probabilities drop to below 10% when the jobs are 50 miles away from job seekers' current residence and to almost 0% when the jobs are 100 miles away.

Third, our framework and methodology may not be well-suited for analyzing non-talent occupations. First, low-skilled workers often transition in and out of unemployment, making the V/E ratio a noisy measure of their labor market tightness. Second, non-talent workers may have various elasticity of substitution with capital (e.g., routine-task occupations may be substitutes rather than complements to automation capital), leading to ambiguous predictions on firm investment. We thus focus on firms' talent employees throughout this study.

II. Data and Measurement

In this section, we gather multiple microdata to measure each firm's talent retention pressure based on the firm's exposure to talent market competition.

A. *Measuring a firm's key employees*

Methodology Our conceptual framework defines key employees (talent) as a small group of occupations whose skills complement a firm's capital (Section I). While firms frequently cite the retention of "key employees" as a central concern in annual reports and survey responses, their definition of key employees is usually ambiguous and likely heterogeneous across firms and industries in practice. This measurement challenge poses a major hurdle for research on firms' talent.[15] We make progress on this issue based on a well-established literature that classifies skills into cognitive, routine, and manual, and shows that cognitive skills are the most complementary to capital in the modern economy (Autor et al. (2003) and Acemoglu and Autor (2011)). In particular, we follow Acemoglu and Autor (2011) and select occupations with high cognitive skills as talent in our main analyses. We validate that the TRP measure based on this talent definition captures firms' concerns about retaining key employees in their annual reports. Additionally, our main findings are robust to alternative measures of talent based on wages (Juhn et al. (1993)) and work experience (Tuzel and Zhang (2021)) as shown in Internet Appendix IA.1.[16]

[15] For example, Baghai et al. (2021) highlight that the empirical challenge in studying firms' talent is "*further compounded by the measurement question of how to define and measure talent.*"

[16] Earlier studies have also attempted to measure skilled workers based on education level (Krusell et al. (2000)). However, Philippon and Reshef (2012) point out significant variations in human capital within similar educational groups. Baghai et al. (2021) discuss in detail the advantages of measuring talent by cognitive skill over education. In addition, we uncover a practical limitation of ranking by education: it can overly emphasize occupations with post-graduate degrees and fail to classify certain occupations that are naturally core to firms as talent. For example, when ranking occupations by the requirement of college degree using the O*Net data, we observe that Chief Executives rank behind many specialists in various industries,

We next rank occupations based on their cognitive skills *within* each 4-digit NAICS industry to help identify occupations that most complement the specific industry's capital. We note that this approach to capturing firms' view of key employees differs slightly from the conventional approach, which classifies skilled labor by uniformly ranking occupations across the entire economy (i.e., *uniform classification* hereafter). While the two approaches yield highly overlapping results and our main findings are robust under both (see Internet Appendix IA.1), the within-industry classification appears to better capture firms' concerns about retaining key employees in the data, particularly in low-skill industries such as restaurants, retail, mining, and construction. For example, in these industries, our within-industry TRP measure captures firms' self-disclosed key-employee concerns in 10-K filings, whereas the uniform classification does not.[17] This pattern aligns with our observation that the uniform classification is less effective in identifying key occupations for low-skill firms,[18] resulting in a noisier TRP measure for those firms. Because our research aims at constructing a comprehensive measure for *all firms* and studying key-employee retention concerns across them, we use the within-industry classification as our baseline measure.

Finally, we define key employees of a firm as occupations in the top decile of cognitive skill intensity within the firm's industry. We show that our results are robust to alternative cutoffs (5%–20%) and to the uniform classification.[19] While our choice of the top decile cutoff is necessarily arbitrary, we note that our methodology requires a cutoff that should be neither too stringent nor too lenient: overly stringent cutoffs yield too few key employees per firm, introducing noise and attenuation effects, while overly lenient cutoffs include non-talent occupations that are not complementary to firms' capital.

Overall, our methodology of measuring firms' key employees preserves occupations universally viewed as high-skill (e.g., executives) while recognizing industry-specific key employees (e.g., head chefs in food service), as we discuss later in Figure 1. To ensure that cross-industry differences in the definition of talent do not drive our results, we conduct our main tests with and without industry-year fixed effects for robustness.

Data To implement the above methodology, we exploit the confidential Occupational Employment and Wage Statistics (OEWS) microdata from the Bureau of Labor Statistics

such as Surgeons, Psychiatrists, Scientists, Teachers, Audiologists, Lawyers, and Engineers, resulting in Chief Executives classified as non-talent in many industries. See more discussions in the Internet Appendix IA.1.

[17] In contrast, both approaches perform similarly for high-skill industries (Internet Appendix Table IA.2).

[18] For instance, Internet Appendix Table IA.3 lists examples of firms' self-disclosed key-employee occupations from 10-K filings but missed by the uniform classification, such as head chefs, store supervisors, and pharmacists. Moreover, occupations classified as talent under the baseline within-industry ranking but not under the uniform ranking are equally likely to transition from job to job (as opposed to from nonemployment) as occupations identified as talent under both classifications (see Internet Appendix Figure IA.2).

[19] Internet Appendix Figure IA.3 and Table IA.4.

(BLS).[20] This microdata provides detailed information on occupational employment and wage rates across approximately 1.2 million establishments, stratified to represent the U.S. economy from 2010 to 2018, covering roughly 62% of nonfarm employment in the United States. 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, county code, industry code, and the establishment's parent firm's name and employer identification number (EIN).

We prepare two datasets from this highly granular microdata. First, we aggregate occupational employment from establishments to the NAICS 4-digit industry level each year, where we weigh establishments using their sampling weights. This industry-occupation level employment data facilitates our within-industry classification of talent in the baseline analyses. Second, we obtain each Compustat firm's occupational employment in each MSA by merging OEWS establishments with Compustat firms using a combination of EIN matching and fuzzy name matching following Zhang (2019). This data allows us to compute each Compustat firm's talent market exposure and talent retention pressure in Section II.C below.

Measure We construct our baseline measure of a firm's talent as follows: First, following Acemoglu and Autor (2011), we compute the average importance scale of six cognitive skills for each SOC 5-digit occupation using the O*Net V23.0 database.[21] Second, using the industry-level occupational employment data, we rank occupations by their cognitive skills within each NAICS 4-digit industry, and we classify an occupation as **talent** for the industry if the occupation ranks within the top decile of the distribution in the year. Finally, an occupation is a talent for a firm if it is a talent for the firm's industry. We treat all other occupations as non-talent for the firm.

Figure 1 illustrates the composition of talent in our Compustat firm sample at the broad

[20] This study draws on several datasets across different analyses. We introduce each dataset when it is first used in the paper. Appendix B provides an overview of all the main datasets and summarizes their uses.

[21] Following Acemoglu and Autor (2011), we extract three cognitive-analytical skills from O*Net, i.e., *4.A.2.a.4 Analyzing data/information, 4.A.2.b.2 Thinking creatively, and 4.A.4.a.1 Interpreting information*, and three cognitive-interpersonal skills, i.e., *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. O*Net provides an importance scale of each skill for each SOC 8-digit occupation. We standardize each skill's importance scale to have a mean of 0 and a standard deviation of 1 across occupations, and we average the six standardized scales to obtain an average cognitive skill measure for each occupation. Finally, we aggregate the cognitive skill score from the 8-digit occupation level to the 5-digit level to facilitate a harmonized talent measure over time. The SOC classification system embodies a hierarchy of non-military occupations with 22 major groups at the 2-digit level, 94 minor groups at the 3-digit level, 458 broad groups at the 5-digit level, and 820 detailed groups at the 6-digit level. The BLS adopted different versions of the SOC system over time with slight updates on the detailed 6-digit codes. The SOC 5-digit classification maintains the granularity of occupations while facilitating a harmonized measure over time (e.g., Gallipoli and Makridis (2018)).

SOC 2-digit level. Management and business occupations are by far the largest component of firm talent, accounting for 35% and 22%, respectively. Other skilled occupations that are classified as talent include computer and mathematical (e.g., computer programmers), office and administrative support (e.g., supervisors of office and administrative support workers), transportation (e.g., supervisors of transportation and material moving workers), etc.

— Figure 1 about here —

B. *Measuring talent market competition*

Throughout this study, we define labor markets for different skills at the occupation-MSA level. As mentioned in Section I above, our choice of defining talent markets at the local level is supported by recent findings in the literature that job seekers, regardless of skills, dislike applying for distant jobs (Marinescu and Rathelot (2016) and Manning and Petrongolo (2017)) and also by our own findings that talent employees primarily respond to local job postings, which we discuss in detail in Section III.A.

In line with our conceptual framework, we measure 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 transitions rather than from the non-employment pool. We validate this condition in the Internet Appendix Table IA.1. In particular, 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. Corroborating these findings, Trevor (2001) shows the unemployment rate has little effect on the turnover of high cognitive skill workers, suggesting that talented employees primarily compete primarily with other employed talents.

We obtain the employment (E) for each MSA-occupation from the OEWS microdata. We obtain job postings (V) for each MSA-occupation from the widely used Lightcast database (formerly Burning Glass Technologies), which provides the near-universe U.S. online job posting data from 2010 to 2018.[22] Combining the two datasets, we measure each MSA-

[22]Lightcast job posting 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. Lightcast collects more than 3.4 million job postings daily covering both public and private firms 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. The raw data provide new job postings at a monthly frequency, which we aggregate within a calendar year (Hershbein and Kahn (2018)). As a robustness check, we construct an alternative measure

occupation's local talent market competition as its vacancy-to-employment ratio (V/E), where we use both metropolitan and micropolitan statistical areas when referring to MSAs.

Figure 2 provides a visual illustration of the aggregate V/E ratio for all talents in each MSA in 2018. We observe that MSAs such as Denver, San Francisco, Seattle, Austin, San Jose, and Dallas have a high overall talent market competition, and Cleveland, Atlanta, Miami, Sacramento, and Houston show low overall talent market competition.

— Figure 2 about here —

C. *Measuring firms' talent retention pressure (TRP)*

We measure a firm's talent retention pressure as the average competition the firm faces across its local talent markets, weighted by the firm's exposure to each market.

Let $s_{f,m,o,t}$ denote the fraction of firm f's talent in MSA(m)-occupation(o) over the firm's total talent employment in year t.[23] The local talent market competition in MSA(m)-occupation(o) for the firm is given by $\frac{V_{-f,m,o,t}}{E_{m,o,t}}$, where we exclude firm's own job postings to capture the firm's talent's *outside* options.[24] A firm's *talent retention pressure (TRP)* is the average of $\frac{V_{-f,m,o,t}}{E_{m,o,t}}$, weighted by the firm's corresponding talent share in each market, $s_{f,m,o,t}$:

$$TRP_{f,t} = \sum_{m,o} s_{f,m,o,t} \times \frac{V_{-f,m,o,t}}{E_{m,o,t}}. \tag{1}$$

D. *Summary statistics*

Our final sample includes Compustat firms with the TRP measure from 2010 to 2018, where 2010 is the year when Lightcast job posting data became widely available. We further require the Compustat firms to be based in the U.S., have total assets exceeding \$1 million, employ

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 at the MSA-occupation-year level.

[23] BLS surveys establishments in a three-year cycle. We follow the methodology suggested by the BLS and use a firm's establishments surveyed from $t-2$ to t to represent the firm's employment distribution at t. This approach achieves a better coverage and reduces measurement errors, and the BLS adopts it to generate aggregate statistics for public use at https://www.bls.gov/oes/tables.htm.

[24] That is, $V_{-f,m,o,t} = V_{m,o,t} - V_{f,m,o,t}$. 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.

more than 50 workers, and have at least 10% of their total employment represented 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. Internet Appendix IA.2 details the match statistics throughout our sample construction.

We highlight three features of our data and measure. First, Panel A of Table I reports the summary statistics of our final firm sample, which has many accounting variables comparable to those from the Compustat universe.[25] This alignment suggests that our final sample is a reasonable representation of publicly traded firms in the U.S. Second, there are substantial variations in firms' TRP measure, with the 10th percentile as 0.086, the median as 0.211, and the 90th percentile as 0.427. Third, there is a reasonable within-firm variation in TRP, with a within-firm autocorrelation of 0.42. This within-firm variation in TRP is largely driven by time-series changes in the V/E ratio within the local talent market.[26]

Consistent with the public notion that firms are increasingly concerned about talent retention, Panel A of Figure 3 shows that the cross-sectional median TRP for firms doubled from 2010 to 2018.[27] Reinforcing this finding, we observe similar trends in other data. In Panel B, firms increasingly highlight talent retention and attraction in their SEC 10-K annual reports (see Section III.C). Similarly, in Panel C, a growing number of firms identify these issues as their top internal concerns in the Duke CFO Survey (see Appendix A).

— Table I about here —

— Figure 3 about here —

III. Validation

We report three validation test results in this section. First, at the individual level, we show that talent workers' job-to-job transitions respond strongly to the local V/E ratio even after controlling for various known predictors. This result supports the inner workings of our firm-level TRP measure. Second, we show a consistent finding that TRP predicts actual talent

[25]Internet Appendix Table IA.5 reports the correlation matrix of the variables.

[26]The MSA-occupation level V/E ratio varies substantially over time with a within-MSA-occupation autocorrelation of 0.27.

[27]This is unlikely 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. 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.

outflows at the firm level, underscoring TRP's ability to capture a credible risk of talent loss for firms. Third, we use firms' 10-K reports to show that TRP positively associates with firms' disclosed concerns about talent market competition.

A. *Individual job-to-job transitions and local V/E ratio*

To measure individual job-to-job transitions, we use LinkedIn individual position-level microdata provided by Revelio Labs. The raw data offer the start time and end time of individuals' job positions, along with the positions' SOC 8-digit occupation codes, MSA codes, parent firms' names and their Compustat identifiers (gvkey) if the parent firm is publicly traded.

We select individual positions in the U.S. and from parent firms with gvkey identifiers, and we convert the position-level data into an individual-year panel (see the Internet Appendix IA.3 for details). Following our baseline definition of talent, we select talent workers if their occupations (first 5 digits of the SOC 8-digit codes) have cognitive skills ranked in the top 10 percentiles within the parent firms' industry. Our final sample includes about 26.39 million individual-year observations of talent in Compustat firms.[28]

Our key measure is a dummy variable of whether a talent goes through a job-to-job transition in the next year, *J2J Transition*$_{i,t+1}$, where we identify a job-to-job transition if the individual's next year's parent firm is different this year's. Panel B of Table I shows that about 10.5% of talent workers have job-to-job transitions in a year from 2010 to 2018. We use the following regression specification for our validation test:

$$\text{J2J Transition}_{i,t+1} = \beta \cdot V/E_{m,o,t} + X_{i,t} + FEs + \epsilon_{i,t+1}, \tag{2}$$

where $V/E_{m,o,t}$ is the vacancy-to-employment ratio for MSA m and occupation o in year t, and $X_{i,t}$ and FEs are individual characteristics and various fixed effects that control for known predictors of employee turnovers. We cluster standard errors at the MSA-occupation level.

Talent J2J transitions and local V/E ratio Panel A of Table II reports the individual-level validation results. Column (1) presents our baseline specification with firm and year

[28] One caveat is that Revelio Labs mapped the job titles of all workers to a subset (rather than the universe) of the SOC 8-digit occupations, resulting in workers from occupations outside the subset being falsely assigned occupations in the subset and inflating the number of employees in each reported SOC occupation. This over-inclusion issue explains the large sample of talent employees and can bring attenuation bias to our analyses, as some workers are incorrectly assigned to MSA-occupation-level V/E ratios, potentially making significant results harder to detect. Internet Appendix IA.3 discusses this issue in more details.

fixed effects to mirror our firm-level analyses later. Talent workers' J2J transitions significantly respond to the local MSA-occupation level V/E ratio. The economic magnitude is meaningful: A one-standard-deviation increase in MSA-occupation level V/E predicts a 1.7% $=(0.547 \times 0.339/0.105)$ increase of the mean J2J transition probability. This magnitude is on par with the impact of a one-standard-deviation increase in the firm's talent wage premium, i.e., 2%, and a one-standard-deviation increase in the firm's talent employee satisfaction rating in Glassdoor, i.e., 1% (see more details in the Internet Appendix Table IA.6).

Local vs. Non-local V/E ratios We next examine the importance of *local* labor markets' V/E beyond an occupation's national-level tightness. To inspect our local characterization, we construct a V/E ratio for occupation o using all MSAs *except* for the worker's current MSA. Column (2) shows a positive significant coefficient of talent workers' J2J transitions to this "non-local" V/E ratio, while Column (3) shows that this positive association is completely subsumed by the "local" V/E ratio. Hence, the non-local V/E ratio predicts talent J2J transitions only through its association with the local V/E ratio. This finding brings two important messages. First, it is consistent with recent findings in the literature that employees dislike searching for distant jobs (Marinescu and Rathelot (2016) and Manning and Petrongolo (2017)) and supports our "local" characterization of the talent market in Section II.B. Second, it also motivates our shift-share instrumental variables for firms' talent retention pressure in Section IV.B below.[29]

V/E ratio vs. Other turnover predictors A massive literature has studied the drivers for employee voluntary turnovers ranging from worker characteristics (e.g., skills and perception of job hopping) and firm policies (e.g., promotion opportunities, work from home, compensation, and corporate culture) to worker-firm matches (e.g., work culture matches, skill matches, supervisor matches, and location matches).[30] While our data do not provide specific predictors, Columns (4)-(6) use different fixed effects to control for the known predictors as much as possible. In particular, Column (4) controls for firm-year fixed effects to address time-varying firm policies; Column (5) controls for firm-worker fixed effects to address time-invariant worker characteristics, firm policies, and worker-firm matching quality; and finally, Column (6) adds workers' years worked in their current positions to control for the linear impact of tenure on job-to-job transitions. Local V/E ratio robustly predicts talent J2J transitions in all specifications, suggesting that the effect of the local V/E ratio is

[29]In the Internet Appendix Table IA.7, we further show that the local talent market competition tends to be occupation specific, as $V/E_{m,o,t}$ also subsumes the effect of $V/E_{m,-o,t}$ on workers' J2J transitions.

[30]See reviews of the literature from Hom et al. (2017), Allen et al. (2010), and Holtom et al. (2008).

not subsumed by known turnover predictors.[31] Indeed, while most prior predictors focused internally on firms, their employees, and their matches, our V/E ratio explores the prediction power of talent turnover based on employees' external labor market environment.[32]

B. *Firms' talent outflows and TRP*

We next examine whether the TRP measure derived from local V/E ratios can predict *firms'* talent departure. We compute a proxy for a firm's *talent outflow rate* by averaging the firm's talent workers' next year J2J transition dummies, which is equivalent to the proportion of talents leaving for outside jobs next year.[33]

Panel B of Table II shows the estimates of the following regression specification that mirrors our individual J2J transition analyses above:

$$\text{Talent Outflow Rate}_{f,t+1} = \beta \cdot \text{TRP}_{f,t} + X_{f,t} + \text{Firm FE} + \text{Year FE} + \epsilon_{f,t}, \qquad (3)$$

where $TRP_{f,t}$ is defined in equation (1), and all standard errors are clustered at the firm level. Column (1) presents the results without additional controls, whereas Column (2) further controls for firm characteristics including Tobin's Q, cashflows, firm size, and firm age.

Consistent with our individual-level findings, firms' talent outflow rate significantly responds to their TRP. A one-standard-deviation increase in TRP predicts a 3% increase in the mean firm-level talent outflow rate.[34]

[31] In addition, Internet Appendix Table IA.6 shows that V/E robustly predicts talent J2J transitions after controlling for proxies for talent wage premium and talent satisfaction.

[32] Allen et al. (2010) relate the abundance of outside options with employee retention and note that "*When alternatives are plentiful and employees perceive many options, they tend to evaluate the work environment and their own attitudes against a higher standard than when options are sparse. Thus, plentiful opportunities become an especially difficult issue for retention: not only do employees have high ease of movement, but they may also be more difficult to keep satisfied.*"

[33] As mentioned earlier, one caveat for this firm-level measure is that the Revelio Labs microdata only covers a partial list of the SOC occupation codes. This lack of full coverage adds noise to our measure of firm-level talent outflow rate as it leads to missing talent occupations for certain industries in the Revelio Labs data, such as Social and Community Service Managers, Environmental Engineers, and Medical Scientists (see the Internet Appendix IA.3).

[34] The coefficient of TRP from the firm-level regression is about five times that of V/E from the individual-level regression (e.g., 2.562 in Panel B vs. 0.547 in Panel A). This discrepancy arises because the two analyses draw on different sources of variation: the individual-level analysis relies on talent workers' V/E, which vary both between and within firm-years, whereas the firm-level analysis relies only on variation between firm-years. In addition, Internet Appendix Table IA.7 shows that the discrepancy may also reflect the fact that the individual-level regression naturally over-weights larger firms, whose workers are less likely to leave in response to local talent market competition (we discuss this heterogeneity between large and small firms in detail in Section VI).

In summary, the support evidence from both the individual-level and firm-level validation tests suggests that our TRP measure and its underlying driver of talent market competition (i.e., the local V/E) represent a credible threat to firms' talent retention. This finding is consistent with numerous previous studies showing that employee departure can be driven by multitudes of individual factors, and firms in practice cannot fully avoid their talent leaving when outside options rise.

— Table II about here —

C. *Firms' talent concerns in 10-Ks and TRP*

Our third validation test compares the TRP measure with firms' concerns about talent competition mentioned in their 10-K annual reports. We extract the texts of all available 10-K filings between 2010 and 2018 from the SEC Electronic Data Gathering, Analysis and Retrieval (EDGAR) database. We quantify firms' discussions on talent retention in two steps.

First, we develop word lists on talent-related terms and competition-related terms. We regard a sentence in the 10-K texts as mentioning talent if the sentence directly mentions "talent" or "talents" or if it contains a combination of words between the following two lists:[35]

List 1: *"talented," "key," "core," "skilled," "skillful," "essential," "important," "trained," "experienced," "qualified," "quality," "effective," "professional," "best," "competent," "capable," "right," "top,"* and *"exceptional."* + **List 2:** *"worker," "employee," "personnel," "colleague," "team member," "individual," "people," "specialist," "labor," "staff," "professional,"* and *"workforce."*

We regard a sentence in the 10-K texts as mentioning competition/retention/attraction if the sentence contains one or more words in the following list:

List 3: *"competition," "competitive," "compete," "competes," "competing," "retain," "retains," "retention," "retaining," "attract," "attracts," "attraction," "attracting," "recruit," "recruits,"* and *"recruiting."*

Finally, we identify a sentence as discussing talent competition if it mentions both talent keywords and competition keywords. For each firm-year, we create two main measures:

[35] We define a *combination of words* as a word from List 1 that is either immediately followed by a word from List 2 or separated from a word in List 2 by a single intervening word (see more details in the Internet Appendix IA.4). We generate these two keyword lists through a combination of methods: applying a word2vec word-embedding model trained to identify talent-related unigrams and bigrams in 10-K filings and directly incorporating keywords from existing literature (e.g., Qiu and Wang (2021)). To ensure completeness, we include both the singular and plural forms of each word.

the number of sentences in the 10-K report discussing talent competition, and the share of sentences in the 10-K report discussing talent competition. The median firm has three sentences in the 10-K report discussing talent competition, accounting for 0.2% of the total number of sentences in the 10-K report.

A well-known issue about firms' disclosure in SEC filings is that the information tends to be sticky (Dyer et al. (2017) and He and Plumlee (2020)). Indeed, the autocorrelation of our two measures, i.e., the number and share of sentences discussing talent competition, are 90% and 87%, respectively. We thus view the 10-K measures as most informative about which firms in the cross-section are concerned about talent competition (Qiu and Wang (2021)). We validate our TRP's ability to capture this cross-sectional variation by running the following regression:[36]

$$\text{Talent Competition Mentions}_{f,t} = \beta \cdot \text{TRP}_{f,t} + X_{f,t} + \text{Year FE} + \epsilon_{f,t}. \tag{4}$$

Table III reports the results. Columns (1) and (2) show that TRP significantly captures the variation in firms' share of sentences mentioning talent competition in 10-Ks without and with controlling for firm characteristics (see Section III.B). It is possible that the 10-K texts for firms in different industries differ systematically. We control for industry-year fixed effects in Column (3) and show that TRP captures the within-industry variation in firms' discussions of talent competition. Columns (4)-(6) show that the results are similar if we use the raw number of sentences instead of the share of sentences mentioning talent competition.

We report a battery of robustness checks of the above findings in the Internet Appendix Table IA.8, including (a) using the total words of sentences to account for the intensive margin, (b) using paragraphs instead of sentences, (c) using only retention and competition keywords but not attraction keywords in List 3 to focus on firms' retention concerns, and (d) using more conservative keywords for talent by excluding from List 1 the keywords like "qualified," "experienced," "professional," "competent," "capable," etc. In all checks, we observe that TRP significantly relates to firms' concerns about talent competition in their 10-Ks.[37]

[36] Seminal studies in the 10-K literature also focus on the cross-sectional variations in their specifications, e.g., Li (2008), Hoberg et al. (2014), and Dyer et al. (2017).

[37] In unreported tests, we find that TRP is significantly associated with firms ranking "difficulty in attracting and retaining qualified employees" as their top internal concern in the Duke CFO Survey microdata (see Appendix A). However, the CFO Survey–BLS merged sample is small, with only 146 firm-year observations from 2010 to 2018, and the validation results are somewhat not robust under alternative TRP measures. By contrast, the 10-K based validation uses a much larger sample and remains robust to alternative skill-based TRP definitions (see Internet Appendix Table IA.9). Finally, we have also explored an alternative measure of firms' talent hiring pressure by using firms' job postings (rather than employment) as the exposure in equation (1). This measure is highly correlated with TRP and yields very similar results on firm investment.

— Table III about here —

IV. Talent Retention Pressure and Firm 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 through an instrumental variable approach for TRP. Lastly, we discuss the economic magnitude of the effect.

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 TRP affects corporate investment using the following regression specification:

$$\text{Inv}_{f,t+1} = \beta \cdot \text{TRP}_{f,t} + X_{f,t} + \text{Firm FE} + \text{Year FE} + \epsilon_{f,t}, \tag{5}$$

where $\text{Inv}_{f,t+1}$ represents the firm's investment in year $t+1$ and $X_{f,t}$ 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 univariate effect, and Column (2) assures that the effect of TRP on firm investment is not explained by known investment predictors. In Column (3), we further control for industry-year fixed effects to ensure that our results are not a manifest of industry-level trends. Across all three specifications, the coefficients of TRP are negative and statistically significant at the 1% level. In terms of economic magnitude, the coefficients in Column (2) indicate that a one-standard-deviation increase in TRP is associated with a $0.21 = 1.472 \times 0.144$ percentage point reduction in investment rate, or a 4.2% reduction relative to the sample mean of firm investment rate. We discuss the economic magnitudes in details in Section IV.E.

In recent decades, investments in intangible capital such as knowledge capital and organizational capital also account for a significant portion 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) introduce 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. However, it is possible that part of firms' spending on retaining and replacing talent also enters the intangible investment measure. In this case, the economic inference of TRP's impact on total investment is less clear than that on physical investment. With this caveat, we examine total investment for robustness.

In Columns (4)-(6) of Table IV, we present the robustness check results that incorporating firms' intangible capital does not alter 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). A one-standard-deviation increase in TRP is associated with a 1.3%-2.3% reduction in firms' total investment rate relative to the sample mean.

— Table IV about here —

B. *Shift-share instrument for TRP*

A priori, it is possible that omitted characteristics of the local labor markets may drive both firms' TRP and their investment. Moreover, firms may relocate their operations across local labor markets, and these relocation decisions could be endogenously related to both TRP and investment decisions. To address the endogeneity concerns, we construct a modified version of the shift-share instrument (Card (2001b)).

Note that our TRP measure is defined as $TRP_{f,t} = \sum_{m,o} s_{f,m,o,t} \times \frac{V_{-i,m,o,t}}{E_{m,o,t}}$ (see equation (1)). 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. To address the endogenous reallocation problem, we fix firms' exposure to talent markets as their initial exposure $s_{f,m,o,2010}$ at the beginning of our sample period,following Card (2001b). Formally, our shift-share instrumental variable for $TRP_{f,t}$ is:

$$\text{IV}_{f,t} = \sum_{m,o} s_{f,m,o,2010} \times \frac{V_{-i,m,o,2010}}{E_{m,o,2010}} \times G_{o,t} = \sum_{o} \underbrace{\left[\sum_{m} s_{f,m,o,2010} \times \frac{V_{-i,m,o,2010}}{E_{m,o,2010}} \right]}_{\text{share}} \times \underbrace{G_{o,t}}_{\text{shift}}, \quad (6)$$

where $G_{o,t}$ is the cumulative growth rate of occupation o's V/E ratio from 2010 to t.[38]

[38]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.

This instrumental variable exploits two sources of variation: First, it leverages 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., $\sum_m s_{f,m,o,2010} \times \frac{V_{-i,m,o,2010}}{E_{m,o,2010}}$. Second, it incorporates time-series variation induced by changes in the competition for the occupation at the national level from 2010 to t, i.e., $G_{o,t}$.

2SLS results Table V presents the second-stage results of the 2SLS estimation. Column (1) shows that the instrumented TRP significantly dampens firms' physical investment. Column (3) reveals a similar finding that the instrumented TRP also significantly dampens firms' total investment. The first-stage 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.[39]

Identifying assumptions and instrument validity The key identifying assumption behind the shift-share instrument is that firms with higher talent retention pressure in 2010 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 firms' "shares" in equation (6) 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 (through the interplay between firms' employment distribution across MSA-occupations and MSA-occupations' V/E ratios) 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 (see the Internet Appendix Table IA.11). Second, we show that our baseline results are robust to controlling for interactions between year dummies and 2010 firm characteristics that may have prolonged effects on TRP and investment (see the Internet Appendix Table IA.12). Third, we follow the diagnostic 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, as suggested

[39]The rule of thumb threshold for F-statistics to pass the Stock and Yogo (2005) weak instrument test is about 10 (see Jiang (2017)). Internet Appendix Table IA.10 reports the first-stage result.

by small R^2s in cross-sectional regressions (see the Internet Appendix Table IA.13), and we also show that our results are robust if we exclude the top occupations from the construction of our instrument (see the Internet Appendix Table IA.14).[40]

Addressing product market competition A remaining 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 intensified product 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 NAICS 4-digit industry code belongs to one of the top three sales-ranked industries of the focal firm in the Compustat Segment data. We label this instrument *NonPeer IV*.[41]

Columns (2) and (4) of Table V show the second stage results that TRP instrumented by the NonPeer IV also significantly dampens firm investment. Hence, our findings on firm investment are unlikely to be driven by product market competition. These results also distinguish the effect of our TRP from the non-compete policies, which primarily aim to mitigate the pressure of employees joining competitors or becoming competitors.[42]

— Table V about here —

C. *Quasi-exogenous variation based on government defense spending*

We further complement the shift-share instruments by constructing an additional instrument of firm TRP based on a clearly sourced (albeit narrowly scoped) quasi-exogenous driver for local talent market competition. Specifically, we explore quasi-exogenous variation in local V/E ratios driven by local military-related industries receiving federal military contracts (Barro and Redlick (2011) and Nakamura and Steinsson (2014)).

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

[41] NonPeerIV shows a strong association with TRP with a coefficient of 0.442 (t-stat.= 12.6) in the first stage regression, similar to that for the baseline IV.

[42] In the Internet Appendix Table IA.15, we further show that our results are not driven by the input-output channel—job postings from the firm's supplier and customer industries may be correlated with the firm's supply-chain shocks that can affect the firm's investment. To do so, we improve the NonPeer IV by further excluding job postings from the focal firm's input-output-connected industries identified as the top three supplier industries or the top three customer industries of the focal firm's peer industries, based on the BEA industry-by-industry total requirements table. We observe that TRP instrumented by this NonPeer&Non-I/O IV again significantly dampens firm investment.

It is well-known that government military procurement spending is massive and concentrated in a few military-related industries (Cox et al. (2024) and Barattieri et al. (2023)). The winning of the government military procurement contracts by the *military-related industries* in an MSA can quasi-exogenously increase the local demand for relevant talent occupations ($V/E_{m,o,t}$). The heightened demand can thus increase the TRP for *non-military-related firms* in the same area and dampen their investment. Therefore, our identifying assumption is that changes in $V/E_{m,o,t}$ due to local military-related industries winning government military contracts are unlikely to negatively affect the investment of non-military-related firms in the area through channels other than the local talent market competition channel.

Using detailed data on federal military procurement contracts from www.USAspending.gov, we construct an instrument for firms' TRP following the design outlined above. Internet Appendix Table IA.16 reports a significant negative effect of the instrumented TRP on firm investment. The result remains robust when defining military-related industries as the top 3, top 5, or top 10 recipients of government procurement spending. Taken together, these findings strengthen the inference that TRP's impact on firm investment is likely causal. Internet Appendix IA.5 provides additional details on the data, empirical design, and results.

D. Robustness

Our baseline findings remain robust when we use alternative TRP measures based on different definitions of talent in Section II.A. First, Internet Appendix Tables IA.17 and IA.18 show that our main investment results are robust to defining talent using wage rates or work experience requirements, instead of cognitive skill requirements. Second, Internet Appendix Table IA.4 shows that our results also hold when talent is defined using uniform occupation rankings, rather than within-industry rankings.

Third, Internet Appendix Figure IA.3 demonstrates that our results are generally robust to varying the cutoff for defining talent occupations around our baseline of the top 10% of the occupation ranking. However, we note that the effects become insignificant if the talent pool is expanded too broadly. For firms' physical investment (our preferred measure of investment), TRP's effects on physical investment are substantially weakened once the cutoff is expanded beyond the top 20% (and 15% for the effects on total investment). This sensitivity aligns with our conceptual characterization of key employees in Section I and the broader view in the literature that only a limited set of occupations are central to firms' "core competencies" (Song et al. (2018) and Goldschmidt and Schmieder (2017)). Hence, a contribution of our study is to provide an occupation-based framework that allows researchers to measure key employees and analyze their impact on firm decisions and outcomes. It is also aligned with the limitation of applying our framework for non-talent as discussed in Section I, e.g., lower-skilled occupations may transition more into and out of the nonemployment pool. Finally, prior studies indicate that Lightcast online job posting data may also have greater measurement and coverage issues for lower-skilled occupations.[43] In unreported tests, we find that a measure of non-talent retention pressure, constructed based on equation (1) but using occupations outside the top 10% skill cutoff, does not negatively predict firm investment.

Taken together, these robustness checks highlight that our findings are robust across different skill metrics and ranking methodologies, provided that talent is defined as a relatively small group of top-skilled employees.[44]

E. Economic magnitudes

Our baseline OLS estimates indicate that a one-standard-deviation increase in TRP reduces firms' physical investment rate by 0.21 percentage points, or 4.2% of the sample mean, with a smaller effect on total investment of 1.6% relative to the mean. The shift-share IV estimates imply that a one-standard-deviation increase in TRP reduces physical investment by 0.77 percentage points (15.4% of the mean) and 1.62 percentage points (9.1% of the mean) for total investment. Internet Appendix IA.7 details these estimates.

Magnitudes from IV estimation Comparing the magnitudes from the shift-share IV estimates and the OLS estimates, we observe that β_{IV} is 3.6 and 5.5 times that of β_{OLS} for physical and total investment, respectively.[45] An extensive literature has documented that amplification of IV estimates is a common feature in the data. Notably, Jiang (2017) surveys 255 published papers in the big three finance journals and finds that the 80%-94% papers have greater magnitudes for IV than OLS, and β_{IV} averages 3.3 to 9.2 times β_{OLS}, depending on the nature of endogeneity concerns. The amplification from IV estimates in our case sits within the range of those from the literature. The greater magnitudes from IV estimation than the OLS estimation can be due to several possible reasons.

[43] The Lightcast database may under-represent job postings for lower-skilled occupations due to, for example, the low usage of online job posting for these occupations or one posting for multiple openings (Rothwell (2014), Carnevale et al. (2014), Hershbein and Kahn (2018), Acemoglu et al. (2022), and Schubert et al. (2025)).

[44] In Internet Appendix IA.6, we also examine heterogeneity in firms' talent with respect to cross-occupation mobility. We find that the investment effects are highly significant among firms whose talent has lower cross-occupation mobility, consistent with our methodology based on occupation-specific labor markets (see Internet Appendix Table IA.19).

[45] I.e., comparing the coefficient of 2SLS(TRP) in Column (1) of Table V with the coefficient of TRP in Column (2) of Table IV yields a multiple of $5.352/1.472 = 3.6$.

First, instruments can be weakly correlated with TRP, therefore inflating the IV magnitudes in a finite sample.[46] This "weak instrument" issue is unlikely in our setting, as Table V shows that the first-stage F-statistic is well above the rule of thumb threshold of 10. Internet Appendix Table IA.10 further shows that our instrument explains 2% of the variation in TRP after partialling out controls and fixed effects, suggesting economically meaningful relevance.[47]

The second potential reason is based on a "measurement error" argument: OLS may be biased toward zero if TRP is measured with classical errors (Bound et al. (2001)). For instance, the growth rate of the local V/E ratio may include noise, and the shift-share IV purges the noise by using an occupation's national growth rate of V/E ratio (see equation (6)), resulting in a greater IV magnitude.

The third explanation relates to the"endogeneity bias": Omitted factors like local economic conditions may induce a positive association between firm investment and TRP, resulting in an underestimated OLS magnitude. As a result, the IV approach produces a greater magnitude by mitigating the endogeneity bias.

The fourth reason concerns the well-known "complier effect" in IV estimation: OLS identifies the population Average Treatment Effect (ATE) across all firms in the sample, while the IV approach identifies a Local Average Treatment Effect (LATE) among compliers whose TRP responds to the instrument. If compliers' investments are systematically more responsive to TRP, the IV magnitude will exceed OLS (Imbens and Angrist (1994)).[48]

If the difference between IV and OLS estimates is due to "measurement error" or "endogeneity bias" explanations, then the IV estimate should be viewed as closer to the true effect of TRP on firm investment. By contrast, if the difference reflects a "complier effect", then the OLS estimate may better represent the average treatment effect of interest, since our focus is on the effect across all firms rather than only the compliers. While disentangling these explanations is inherently difficult (see Jiang (2017)), we diagnose whether the "complier effect" explanation plays a major role in driving the gap.

[46] The intuition is that $\beta_{IV} = \frac{\widehat{Cov(z,y)}}{\widehat{Cov(z,x)}}$, where x is the independent variable, z is the instrument, and y is the dependent variable. Weak instrument implies a small dominator $\widehat{Cov(z,x)}$, which can inflate β_{IV}.

[47] Jiang (2017) argues that instruments may lack potency even though the F-statistic passes the threshold, therefore recommends inspecting the partial R^2 of the instrument, and 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).

[48] A related possibility is that the true relationship may be nonlinear. In this case, OLS gives the best linear approximation over the full support, but IV, focusing on compliers, might capture a steeper slope segment and yield a larger coefficient.

Decompose the IV-OLS gap We start by noting a distinction between the "complier effect" explanation and the other two: The "complier effect" explanation relies on heterogeneous investment responses to TRP across firms, i.e., the complier firms are more responsive to TRP than the average firm, whereas the "measurement error" and "endogeneity bias" explanations can arise even under homogeneous responses. Based on this distinction, we apply the recent econometric framework of Ishimaru (2024) to assess the role of "complier effects" in explaining the IV–OLS gap (i.e., $\beta_{IV} - \beta_{OLS}$). The key insight is that OLS and IV assign different weights to observations within the same sample: OLS places higher weights on units with greater variation in TRP, whereas IV disproportionately weights units where the instrument most effectively predicts TRP. When treatment effects vary across firms, years, or other dimensions, this difference in "weighting schemes" between OLS and IV can generate an IV–OLS gap even in the absence of endogeneity bias or measurement error.

Using this decomposition framework, we find that, for physical investment, 45% of the IV-OLS gap is attributable to the "complier effect", and 55% is attributable to the residual, which includes the potential effects from "endogeneity bias" and "measurement error." For total investment, the corresponding shares are 52% and 48%. Overall, this diagnostic exercise suggests that the "complier effect" is likely to play a sizable role in amplifying the IV estimates relative to the OLS. Internet Appendix IA.7 provides detailed discussions about the decomposition methodology, the results, and the economic interpretation.

Preferred range of magnitudes The above analyses suggest that the "complier effect" may have amplified the IV estimates, consistent with the findings of Jiang (2017), implying that the magnitudes from the shift-share IV approach may overstate the average effects across all firms.[49] Meanwhile, the remaining gap between the OLS and shift-share IV estimates unexplained by the "complier effect" may reflect genuine improvements from IV, such as correcting endogeneity bias in the OLS. Taken together, we view the true economic magnitudes as likely to be significantly lower than the estimates from the shift-share IV, but also possibly higher than the OLS estimates. We therefore continue to report headline magnitudes as a range between the two estimates—a one-standard-deviation increase in TRP reduces firms' physical investment rate by 0.21∼0.77 percentage points, or 4.2%∼15.4% relative to the sample mean, while cautioning that the upper bound is likely substantially overstated due to the IV amplification effect.

[49]Unlike the shift-share IV estimates, the alternative IV based on government military procurement spending produces a much smaller IV-OLS gap (see Internet Appendix Table IA.16).

Evaluation of the magnitudes We evaluate the economic magnitudes in two ways. First, we show that our estimated magnitudes align closely with prior findings in the literature. In Internet Appendix IA.7, we survey the magnitudes of the impact of labor variables on firm investment from previous studies, including labor mobility (Shen (2021), Sanati (2025), and Jeffers (2023)), labor protection and unionization (Bai et al. (2020) and Fallick and Hassett (1999)), and labor wage and health care cost pressure (Silva (2021) and Tong (2024)). Because definitions of firm investment differ across studies, we standardize their economic magnitudes relative to the sample means of their investment measures, based on a one-standard-deviation change in their independent variables. Internet Appendix IA.7 details the step-by-step calculation of the magnitudes using statistics reported in each paper. Internet Appendix Table IA.20 shows the magnitudes, showing that the baseline TRP effect on physical investment (4.2%) falls within the range of prior studies, while the effect on total investment (1.6%) is at the lower end. The shift-share IV estimates correspond to the higher end of the distribution in the literature, consistent with the discussions above that they are likely amplified by the "complier effects".

Second, the magnitudes of these investment effects also appear to be internally consistent with the talent retention costs. As shown in Section V.A, the dollar losses from foregone investment returns induced by TRP are of a similar order of magnitude to the additional costs associated with talent retention under higher TRP. This consistency holds under both the baseline OLS estimates and the shift-share IV estimates.

V. Talent Retention Pressure and Firm Labor Policies

This section inspects firms' labor responses to TRP to enhance our understanding of the investment findings. When TRP is higher, firms naturally have stronger incentives to retain and replace talent. In this section, we provide stylized facts regarding talent retention and replacement policies and the consequences on their average talent productivity. These labor responses manifest the costs and constraints firms face in directly addressing TRP as discussed in our conceptual framework, leading to a negative impact on firm investment.

A. Firms' talent retention policies

Comprehensively measuring firms' talent retention policies is challenging, as a large body of literature on voluntary turnovers has uncovered numerous reasons for employee departure. Some reasons are specific to the particular workers' situations, such as location preferences, responsibility for childcare, and relationship with coworkers. It is challenging for firms to identify these idiosyncratic reasons and systematically address them. Indeed, Allen et al. (2010) note that many managers in practice believe that "*there is little managers can do to affect individual turnover decisions.*" Other reasons can stem from firms' policies, such as compensation competitiveness and career advancement opportunities. These reasons are relatively easier for firms to identify but may still be costly to address. While we do not have data for all employee retention policies, we examine how two key dimensions—compensation and promotion opportunities—respond to talent retention pressure.[50]

Talent wages We obtain the wage rate for each occupation in each firm from the BLS microdata.[51] Importantly, this wage rate includes not only base salary but also several sources of incentive pay such as bonuses.[52] 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 firms' talent wage rates on their TRP:

$$\text{Talent Wage}_{f,t+k} = \beta \cdot \text{TRP}_{f,t} + X_{f,t} + \text{FirmFE} + \text{YearFE} + \epsilon_{f,t}. \tag{7}$$

Panel A of Table VI reports the results of firms' concurrent and next-year average talent wages. In Columns (1) and (2), we observe that TRP is positively and significantly associated with the firm's concurrent talent wage rate without and with controlling for firm characteristics. A one-standard-deviation increase in TRP is associated with a 1.3% = (0.088×0.144) increase in firms' average talent wage rate. In contrast, Columns (3) and (4) show a positive yet not statistically significant association between TRP and firms' future talent wage rate, indicating that firms tend to respond to TRP by immediately raising talent workers' wages. It is worth noting that our wage rate does not capture all forms of compensation for retaining talent. For example, Oyer (2004) argues that firms can address employees' varying outside opportunities by offering broad-based stock options plans, which are not covered by our wage data.

[50]For example, a recent Pew Research Center survey shows that low pay and no opportunities for career advancement are the two most cited firm policies that result in workers leaving their firms.

[51]The raw BLS microdata provides the number of employees at the establishment-occupation-wage-bin level (with 12 predefined wage bins). Following BLS's recommended procedure, we average the middle values of the wage bins provided by the BLS weighted by the number of employees in each bin to obtain the average wage rate for each establishment-occupation, which we further aggregate to the firm-occupation level.

[52]Wage rate 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 BLS OEWS at https://www.bls.gov/oes/oes_doc_arch.htm.

Back-of-the-envelope calculation: retention costs vs. investment losses The analyses above indicate that for an average publicly traded firm in our sample, a one-standard-deviation increase in TRP is associated with about $2 million additional wage bills paid to talent employees within a year. Below, we try to assess the compatibility of this magnitude with the investment effects through the lens of our simple conceptual framework. Intuitively, firms at the margin trade off between paying higher retention costs for talent and incurring losses from the foregone investment returns. Measuring either side of the trade-off is, however, challenging. For example, our wage effect does not fully capture TRP's impact on talent retention costs, as discussed above, and estimating the total losses from foregone investment is known to be difficult, e.g., we do not observe the marginal Q of a firm's investment.

Given the challenge, we focus on short-term cash flow effects and conduct a simple back-of-the-envelope calculation that compares firms' immediate wage increases and immediate losses in investment returns due to rising TRP. This calculation suggests that the magnitudes are reasonably compatible: for an average firm in our sample, a one-standard-deviation increase in TRP reduces physical investment by about $12 million in the following year. Applying the corporate required rate of return of 16% from Gormsen and Huber (2025), this translates into a loss of about $1.9 million in foregone investment returns—roughly in line with the wage effect.[53] The magnitudes also remain comparable when using the shift-share IV estimates, as Internet Appendix Table IA.21 shows that β_{IV} is amplified by similar multiples for wages and investment—3.2 and 3.6 times β_{OLS}, respectively.

Talent promotion Following Gupta et al. (2024), we construct a firm-level measure of the talent promotion rate using individuals' job seniority metrics from Revelio Labs microdata. We first identify a promotion if the talent worker's job seniority increases during the year.[54] We then average the promotion dummy for all talent workers in a firm to measure the firm's *talent promotion rate* in the year. For an average firm, about 4.2% of talent workers get promoted in a year (see Panel A of Table I).[55] Finally, we examine the association between firms' talent promotion rate and TRP using the same regression specification as in equation (7) above.

Panel B of Table VI reports that firms' concurrent talent promotion rate is significantly

[53] This calculation is intended only as a sanity check to gauge comparability of magnitudes. We caution that it relies on several simplifying assumptions and should not be interpreted as an exact quantification of the trade-off between retention costs and investment losses.

[54] Revelio Labs creates seven seniority categories based on raw job titles and other information. For instance, in the legal track, paralegal, legal adviser, attorney, lead lawyer, head of legal, attorney partner, and CEO are sequentially ranked from the lowest "entry level" to the highest "senior executive level". See details of the measure at https://www.data-dictionary.reveliolabs.com/methodology.html#seniority.

[55] This promotion rate is broadly consistent with the Society for Human Resource Management (SHRM)'s benchmarking report, which shows that the median and average promotion rate is 4% and 7%, respectively.

higher when TRP is higher, consistent with the wage results. A one-standard-deviation increase in TRP is associated with a 2.7% increase in firms' concurrent talent promotion rate relative to sample mean but not their future promotion rate. Moreover, our talent promotion results, which focus exclusively on the firm's continuing talent workers, suggest that the increase in talent wage is at least partially driven by firms' efforts to retain their existing talent. Finally, Internet Appendix Table IA.21 shows that the retention effects in terms of both wage and promotion remain robust when TRP is instrumented with the shift-share IV.

In summary, while we cannot comprehensively measure firms' talent retention policies, these findings on firms' talent wage and promotion policies support that firms have a greater incentive to retain talent when TRP is higher. Nonetheless, firms appear to face costs and constraints in fully retaining talent—talent workers still leave firms when TRP is high (see Section III), ultimately allowing TRP to dampen firms' capital investment.

B. Firms' talent replacement policies

Next, we examine firms' talent replacement policies. When TRP is higher, the firm may post more vacancies for talent positions to mitigate the impact of potential talent departures. However, in practice, the firm may not be able to fully replace its talent workforce as the job-filling rate can be low when the talent market competition is high. More importantly, even if a firm can quickly replace departing employees, such turnover may still reduce the productivity of its talent workforce, since new hires are generally less productive during the onboarding period.

In Panel C of Table VI, we examine firms' number of job postings for talent occupations using the Lightcast job posting data as described in Section II. We observe that firms immediately increase their job postings for talent when TRP increases. This result remain robust when we instrument TRP with the shift-share IV (see Internet Appendix Table IA.21). Next, we examine the efficacy of the replacement policies in terms of firms' net talent growth rate using Revelio Labs data. In Panel D, we observe that when facing higher TRP, firms, on average, experience greater net losses of talent next year (see Columns (3) and (4)). The magnitudes of TRP's effects on firms future net talent growth rate are generally smaller than those on future talent outflow rate (Panel B of Table II), indicating that firms' talent replacement policies partially mitigated their net talent losses.

— Table VI about here —

C. *Effects on firms' talent productivity*

In this section, we supplement our previous findings on firms' talent outflows by further showing the negative impact of TRP on firms' average talent *productivity*.

We measure a firm's average talent productivity as the firm's total revenue divided by its total number of talent.[56] Table VII suggests that firms' average talent productivity is significantly lower in the year following a higher TRP, both with and without controlling for industry-year fixed effects. This finding is consistent with the literature showing that newly hired employees are less productive during the onboarding period (Bishop (1996) and Silva and Toledo (2009)) and also with our framework. The potential loss in talent productivity constitutes a form of turnover costs beyond direct hiring costs, which again cautions the firm to resort to a lower capital investment when TRP is higher.[57]

— Table VII about here —

VI. Heterogeneous Effects: Superstar versus Laggard

Our analysis in Section IV indicates that the investment effect of talent retention pressure is likely heterogeneous across firms. In this section, we begin by documenting a key heterogeneity between superstar and laggard firms in their investment response to TRP. We then explore the underlying differences that may drive this heterogeneity, highlighting that laggard firms face greater constraints in addressing retention challenges compared to superstar firms. Finally, we discuss the potential broader implications of this heterogeneity for the aggregate U.S. economy.

[56]We construct our proxy for a firm's average talent productivity following the literature which typically measures a firm's average labor productivity using the ratio of total revenue to the number of employees (e.g., Haltiwanger et al. (1999)). 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.

[57]This finding on talent productivity also rules out a potential selection concern that only unproductive employees self-select to leave the firm when TRP is high. In this case, while firms are forced to experience high talent turnover when TRP is high, their average talent productivity may increase due to the selection. As a result, the turnover mechanism may not necessarily explain the negative effect of TRP on firm investment. Our finding does not support this selection argument, as we show that the firm's average talent productivity is lower instead of higher in the next year following a higher TRP.

A. Heterogeneous investment effects

Our conceptual framework in Section I emphasizes that TRP's dampening effect on firms' investment relies on the assumption that firms face high costs and constraints in retaining their key employees. This intuition motivates potential implications in the cross-section, as firms facing greater resource constraints may reduce investment more in response to a given increase in talent market competition. It is well established that small and mid-sized firms are financially more constrained than large firms (Hadlock and Pierce (2010)). Hence, we hypothesize that when TRP increases, laggard firms are less capable of exerting retention and replacement efforts than superstar firms, leading to larger losses of talent and a more pronounced dampening effect on their investment.

To test the hypothesis, we follow Gutierrez and Philippon (2020) and many prior 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.[58] To explore the heterogeneous investment effects, we interact a superstar indicator with TRP in the following panel regression:

$$\begin{aligned} \text{Inv}_{f,t+1} =& \beta \cdot \text{TRP}_{f,t} \times \text{Superstar}_{f,t} + \gamma \cdot \text{TRP}_{f,t} + \eta \cdot \text{Superstar}_{f,t} \\ &+ X_{f,t} + \text{FirmFE} + \text{YearFE} + \epsilon_{f,t}, \end{aligned} \tag{8}$$

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

Table VIII reports the results. In Columns (1) and (3), we observe that while laggard firms' investment is significantly dampened by TRP, as reflected in a negative γ estimation, superstar firms' investment is more immune to TRP, as reflected in a positive β estimation.[59] Columns (2) and (4) further show that the results are robust if we further restrict the comparison between superstar and laggard firms to be within industry by imposing industry-year fixed effects.

Robustness This heterogeneous effect is robust across a battery of checks. First, one may be concerned that superstar firms are more diversified across industries, making our baseline

[58]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.

[59]Note that this coefficient is a relative term due to the year fixed effects that demeans all variables in the cross-section. In untabulated tests that use only the subsample of superstar firms, we observe that the absolute investment effects from TRP on superstar firms are negative and insignificant.

TRP measure, which identifies a firm's talent based on its main industry, noisier. This is unlikely, as Internet Appendix Table IA.4 shows very similar findings when talent is defined based on the uniform classification rather than within-industry ranking. Second, Internet Appendix Table IA.22 shows that the results are also robust when using the 2SLS estimates based on the shift-share IV. Third, the findings are also robust when we alternatively define firm talent based on other skill metrics, as shown in Internet Appendix Tables IA.17 and IA.18.

— Table VIII about here —

B. *Heterogeneous effects on talent outflow*

Are the heterogeneous investment effects due to (i) TRP differently affecting talent outflows for superstar and laggard firms, or due to (ii) different pass-throughs of talent outflow on investment in superstar and laggard firms even though TRP affects talent outflow of all firms similarly? For instance, larger firms may be more resilient to talent departures because their organizational knowledge is less concentrated among a few employees (Li et al. (2022)) and is easier to transfer to new hires given more developed production procedures and larger human resource capacity (Hancock et al. (2013) and Baron et al. (2001)). This "institutional resilience" mechanism predicts that superstar firms' capital investment is less sensitive to talent departures, even if TRP does not differentially affect talent outflow rates between superstar and laggard firms.

In Columns (5) and (6) of Table VIII, we replace the dependent variable in equation (8) with firms' talent outflow rate at $t+1$, constructed from Revelio Labs microdata. We find that, mirroring the heterogeneous investment effects, talent outflows are much less responsive to TRP in superstar firms than in laggard firms. This suggests that the "institutional resilience" mechanism alone cannot fully explain the heterogeneous investment effects. Rather, the similarly heterogeneous effects on capital investment and talent outflow are consistent with our conceptual framework that key employees are highly complementary to capital and play a crucial role in firms' investment for all firms.

C. *Heterogeneous labor policies*

There remains a question of why key employees in superstar firms are less likely to leave than those in laggard firms when talent market competition intensifies. One possibility is that workers view larger (and potentially more productive) firms as being higher on the "job ladder" and more desirable workplaces than smaller firms, due to the prospect of higher labor productivity, more lucrative pecuniary compensation and greater amenity value (see Burdett and Mortensen (1998) and Moscarini and Postel-Vinay (2013)). Under this hypothesis, workers in superstar firms are less likely to leave than those in laggard firms even when facing the same intensity of talent market competition. Taken to the extreme, this argument predicts that superstar firms are insulated from the impact of TRP and can "passively" retain key employees even without exerting additional retention efforts, because their key employees are less inclined to depart given these firms' higher status on the job ladder.[60]

Compared to this extreme version of the job ladder mechanism, which emphasizes the superior status that superstar firms have achieved in passively retaining employees, the standard constraint-based mechanism highlights the responsiveness of retention efforts to TRP. That is, when TRP rises, laggard firms may be constrained to exert retention and replacement efforts as responsively as superstar firms.

To shed light on the above two potential explanations, we next analyze retention and replacement responses to TRP across superstar and laggard firms. In Columns (1) and (2) of Table IX, we examine firms' wage responses to TRP using the same specification as equation (8). Two results stand out. First, both superstar and laggard firms increase wages for talent when TRP rises. Second, superstar firms' wage response is 3.2 times as elastic as that of laggard firms, and 2.4 times when controlling for industry-year fixed effects. This finding supports the view that superstar firms are less constrained in raising wages to retain key employees. Interestingly, in Columns (3) and (4), we do not find statistically significant differences between superstar and laggard firms in their promotion responses to TRP. This may reflect differences in promotion environments between large and small firms (such as internal hierarchy and organizational structure), which contribute to the mixed evidence in the literature on firm size and promotion probability (Phillips (2001) and DeVaro (2006)). Further examining the different retention constraints faced by small versus large firms is beyond the scope of this study and is left for future research.

We also find suggestive evidence that superstar firms are less constrained in posting jobs for talent when TRP is high, as shown in Column (5) of Table IX. Similar to wages, their job postings are about three times as responsive to TRP as those of laggard firms. While results remain directionally similar when including industry-year fixed effects, they are not statistically significant. Finally, Columns (7) and (8) show that laggard firms experience a net loss of key employees in the following year, whereas superstar firms do not.

[60] The size-based job ladder framework has been challenged in recent data. For instance, Haltiwanger et al. (2018) document substantial worker flows from large firms to small firms in recent decades. Moreover, this hypothesis does not account for pressures from workers moving across superstar firms.

Taken together, these results suggest that superstar firms are more effective than laggard firms in retaining key employees. This advantage is unlikely to be fully explained by their elevated status in the job ladder, which would imply passive retention. Instead, their flexible use of resources—raising wages and posting jobs when TRP increases—appears to play a central role in sustaining retention and shielding them from scaling back growth. In contrast, laggard firms are more constrained in addressing retention pressures, leading to significant dampening effects of TRP on their investment. Overall, these findings between superstar and laggard firms reinforce the constraint-based mechanism described in our conceptual framework in Section I.[61]

— Table IX about here —

D. *Potential implications for aggregate economy*

Given that talent retention pressure significantly dampens the growth of laggard firms but not that of large superstar firms, it is tempting to consider the potential implications for the aggregate U.S. economy. Our framework, which focuses on the partial equilibrium effects on firm investment, is not fully equipped to capture general equilibrium effects in labor markets or to resolve the aggregation problem. Hence, one should exercise caution when directly extrapolating our findings to explain aggregate outcomes. With this caveat in mind, we illustrate how our results may help link talent retention pressure to industry concentration and the lackluster U.S. investment observed in recent decades.

In the Internet Appendix IA.8, we follow Gutiérrez and Philippon (2018) and construct the top-4 concentration ratio (CR4) for each NAICS 4-digit industry by year. We then show a positive association between an industry's median TRP (measured among Compustat firms within the industry) and its subsequent CR4. This suggestive evidence highlights the possibility that talent market competition contributes to rising industry concentration by constraining the growth of laggard firms, but not that of superstar firms. However, whether concentration driven by talent market competition is "good" or "bad," in the sense of Covarrubias et al. (2020), is beyond the scope of this study and remains an open question.

In the Internet Appendix IA.9, we also examine the implications of rising talent retention pressure for the slowdown in U.S. capital investment relative to what Q predicts, i.e., the widening investment-Q gap (Gutiérrez and Philippon (2017)). We show that because

[61] It is worth noting that the laggard firms in our sample are publicly-traded firms, which are still substantially larger than typical private firms. Therefore, TRP may have an even greater impact on private firms' investment, as they can be more constrained than publicly-traded firms.

talent market competition disproportionately dampens the growth of laggard firms while leaving large firms relatively unaffected—and since large firms dominate aggregate U.S. investment—the effect of TRP on an average firm's investment may not be easily detected in aggregate data. While these findings are mainly suggestive and intended to stimulate future research, we believe they underscore the potentially broader implications of our work.

VII. Conclusion

Recent executive surveys consistently highlight talent market competition as a top internal concern for firms in the 21st century. Yet the economic implications of firms' retention pressure from talent market competition remain underexplored, largely due to challenges in measurement. We develop the first measure of firms' talent retention pressure by combining two comprehensive microdata sets, and we provide extensive validation for this measure.

We document a robust finding that talent retention pressure substantially dampens firm capital investment. To address endogeneity concerns, we construct a shift-share instrument for talent retention pressure, examine its identifying assumptions, and find strong support for our OLS results. In addition, using firms that win government military procurement contracts as quasi-exogenous shocks to local talent market competition, we further reinforce the causal inference of TRP's effects on firm investment.

We shed light on these investment results by examining firms' talent retention and replacement responses to TRP. We find that firms offer higher wages and grant more promotions to their talent when TRP is higher. However, consistent with extensive prior studies highlighting the costs and constraints of fully retaining talent (Allen et al. (2010), Hom et al. (2017), and Holtom et al. (2008)), we observe that firms nonetheless lose more talent when TRP is higher. We also observe that firms post more jobs for talent under higher TRP, but net talent growth remains weak, and average talent productivity declines. Together, these findings underscore the challenges firms face in addressing TRP through labor policies, leaving firm growth adversely affected by talent retention pressure.

Finally, we uncover an important heterogeneity: talent market competition dampens the growth of small and mid-sized firms (laggard firms) much more than that of superstar firms. Analysis of the underlying mechanism reveals that the resource constraints faced by laggard firms hinder their ability to retain employees and safeguard investment, reinforcing the key mechanism highlighted in our conceptual framework. In contrast, superstar firms respond to TRP by offering higher wages and posting more jobs. Examining the aggregate implications of this heterogeneity remains a promising direction for future research.

We emphasize that one must exercise caution when drawing policy implications from our study. First, our analysis focuses on firm growth and does not assess the broader benefits of job-to-job moves for talent employees. As such, our findings do not imply whether talent market competition is excessive or detrimental to overall welfare. Estimating the welfare effects of talent market competition remains an important research agenda. Second, while increasing talent market competition disproportionately affects laggard firms relative to superstar firms and has contributed to rising industry concentration, this finding does not imply an overall positive or negative effect on the health of the U.S. economy. Assessing whether talent market competition has led to "good" or "bad" concentration in the sense of Covarrubias et al. (2020) is beyond the scope of this study and can be an important extension for future research.

Appendix

A. Survey Evidence of Firms on Their Talent

Subsection 1 summarizes results from three surveys highlighting talent concerns as firms' most pressing concerns. Subsection 2 provides the results from two CFO surveys showing that talent constraints are the primary reason firms 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.[62] The survey reports responses from an average of 460 firms on this topic each quarter. The survey question changed slightly in 2015Q1: 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 2015Q1-2018Q4 (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).*" The survey did not ask this question amid the transition period of the two regimes. Throughout the surveys, "difficulty in attracting and retaining qualified employees" is always an option.

Panel C of Figure 3 plots the fraction of firms electing talent concern as a top concern in each quarter: The left y-axis corresponds to the fraction of firms electing "difficulty in attracting and retaining qualified employees" as a top-three concern in the earlier regime, and the right y-axis corresponds to the fraction of firms electing the talent concern as a top-four concern in the later regime. During both regimes, we observe increasing fractions of firms are concerned about talent retention and attraction.

To compare "difficulty in attracting and retaining qualified employees" with other concerns in the survey, we rank each concern in the survey question based on the fraction of firms electing that concern as a top internal concern in the quarter. For instance, if "difficulty in attracting and retaining qualified employees" has the highest fraction of firms electing it as a top internal concern, the ranking will be one. We found that the talent concern increased in the ranking from 2008 to 2018. Importantly, the talent concern remained among the top 3 internal concerns each year from 2012 to 2018, while other competing concerns such as "government policies", "cost of benefits", and "data security" moved up and down the ranking

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

or in and out of the survey questions.

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.[63] 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.

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.[64]

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

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

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.

B. List of Data and Usage

The table below lists the main data sets used in this study and summarizes how we use them.

Dataset	Usage
BLS OEWS microdata	We use the establishment-occupation-level employment and wage data to measure local labor market's V/E ratio, firms' talent retention pressure, firms' talent wage, etc.
Lightcast job posting data	We use the individual job posting data to measure local labor markets' V/E ratio, firms' talent retention pressure, and firms' job postings for talent.
O*NET database	We use the occupational skill and task information to help categorize occupations as key talent.
Revelio Labs microdata	We use the individual-level panel data to measure workers job-to-job transitions, firms' talent outflow rate, and firms' talent promotion rate, etc.
10-K annual reports	We use the 10-K texts to measure firms' talent-retention concerns for validation tests.
Compustat database	We use the accounting information to measure firms' investment rate and various firm controls.
Peters and Taylor data	We use the total capital variable to measure firms' total investment rate and use total q as a firm control.
Duke CFO Survey data	We use the data to plot the trend of firms' concerns about key employee retention over time.

References

Abraham, Katharine G., John C. Haltiwanger, and Lea E. Rendell, 2020, How Tight Is the US Labor Market?, *Brookings Papers on Economic Activity* 2020, 97–165.

Acemoglu, Daron, David Autor, Jonathon Hazell, and Pascual Restrepo, 2022, Artificial intelligence and jobs: evidence from online vacancies, *Journal of Labor Economics* 40, S293–S340.

Acemoglu, Daron, and David H. Autor, 2011, Skills, tasks and technologies: Implications for employment and earnings, *Handbook of Labor Economics* 4, 1043–1171.

Akcigit, Ufuk, and Sina T Ates, 2023, What happened to us business dynamism?, *Journal of Political Economy* 131, 2059–2124.

Allen, David G., Phillip C. Bryant, and James M. Vardaman, 2010, Retaining Talent: Replacing Misconceptions With Evidence-Based Strategies, *Academy of Management Perspectives* 24, 48–64.

Andrews, Dan, Chiara Criscuolo, and Peter N. Gal, 2016, The Best versus the Rest: The Global Productivity Slowdown, Divergence across Firms and the Role of Public Policy .

Angrist, Joshua D, and Alan B Krueger, 1991, Does compulsory school attendance affect schooling and earnings?, *The quarterly journal of economics* 106, 979–1014.

Angrist, Joshua D, and Alan B Krueger, 1999, Empirical strategies in labor economics, in *Handbook of labor economics*, volume 3, 1277–1366 (Elsevier).

Autor, David, David Dorn, Lawrence F. Katz, Christina Patterson, and John Van Reenen, 2020, The Fall of the Labor Share and the Rise of Superstar Firms, *The Quarterly Journal of Economics* 135, 645–709.

Autor, David H., and Daron Acemoglu, 2011, Skills, tasks and technologies: Implications for employment and earnings, *Handbook of Labor Economics* 4, 1043–1171.

Autor, David H., and David Dorn, 2013, The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market, *American Economic Review* 103, 1553–1597.

Autor, David H., Frank Levy, and Richard J. Murnane, 2003, The Skill Content of Recent Technological Change: An Empirical Exploration, *Quarterly Journal of Economics* 118, 1279–1333.

Baghai, Ramin P., Rui C. Silva, Viktor Thell, and Vikrant Vig, 2021, Talent in Distressed Firms: Investigating the Labor Costs of Financial Distress, *The Journal of Finance* 76, 2907–2961.

Bai, John, Douglas Fairhurst, and Matthew Serfling, 2020, Employment protection, investment, and firm growth, *The Review of Financial Studies* 33, 644–688.

Bai, John Jianqiu, Ashleigh Eldemire, and Matthew Serfling, 2023, The Effect Of Labor Mobility On Corporate Investment And Performance Over The Business Cycle .

Barattieri, Alessandro, Matteo Cacciatore, and Nora Traum, 2023, Estimating the Effects of Government Spending Through the Production Network.

Barkai, Simcha, 2020, Declining Labor and Capital Shares, *The Journal of Finance* 75, 2421–2463.

Baron, James N., Michael T. Hannan, and M. Diane Burton, 2001, Labor Pains: Change in Organizational Models and Employee Turnover in Young, High-Tech Firms, *American Journal of*

Sociology 106, 960–1012.

Barro, Robert J., and Charles J. Redlick, 2011, Macroeconomic effects from government purchases and taxes, *The Quarterly Journal of Economics* 126, 51–102.

Bauer, Talya N., Berrin Erdogan, Robert C. Liden, and Sandy J. Wayne, 2006, A longitudinal study of the moderating role of extraversion: Leader-member exchange, performance, and turnover during new executive development, *Journal of Applied Psychology* 91, 298–310.

Beaudry, Paul, Mark Doms, and Ethan Lewis, 2010, Should the Personal Computer Be Considered a Technological Revolution? Evidence from U.S. Metropolitan Areas, *Journal of Political Economy* 118, 988–1036.

Belenzon, Sharon, and Larisa C. Cioaca, 2021, Guaranteed Markets and Corporate Scientific Research.

Belo, Frederico, Vito D. Gala, Juliana Salomao, and Maria Ana Vitorino, 2021, Decomposing firm value, *Journal of Financial Economics* 142, 619–639.

Belot, Michèle, Philipp Kircher, and Paul Muller, 2019, Providing Advice to Jobseekers at Low Cost: An Experimental Study on Online Advice, *The Review of Economic Studies* 86, 1411–1447.

Bishop, J. H., 1996, What We Know About Employer-Provided Training: A Review of Literature, *Center for Advanced Human Resource Studies Working Paper* .

Black, Sandra E., and Lisa M. Lynch, 2009, Measuring Organizational Capital in the New Economy, *Measuring Capital in the New Economy* 65, 205.

Blair, Peter Q, and David J Deming, 2020, Structural increases in skill demand after the great recession, Technical report, National Bureau of Economic Research.

Bloom, Nicholas, Tarek Alexander Hassan, Aakash Kalyani, Josh Lerner, and Ahmed Tahoun, 2021, The diffusion of disruptive technologies, Technical report, National Bureau of Economic Research.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel, 2022, Quasi-Experimental Shift-Share Research Designs, *The Review of Economic Studies* 89, 181–213.

Bound, John, Charles Brown, and Nancy Mathiowetz, 2001, Chapter 59 - Measurement Error in Survey Data, in James J. Heckman, and Edward Leamer, eds., *Handbook of Econometrics*, volume 5, 3705–3843 (Elsevier).

Breza, Emily, Supreet Kaur, and Yogita Shamdasani, 2018, The Morale Effects of Pay Inequality, *The Quarterly Journal of Economics* 133, 611–663.

Burdett, Kenneth, and Dale T. Mortensen, 1998, Wage Differentials, Employer Size, and Unemployment, *International Economic Review* 39, 257–273.

Bustamante, M. Cecilia, and Andres Donangelo, 2017, Product market competition and industry returns, *Review of Financial Studies* 30, 4216–4266.

Caldwell, Sydnee, and Oren Danieli, 2024, Outside Options in the Labour Market rdae006.

Card, David, 1999, The causal effect of education on earnings, *Handbook of labor economics* 3, 1801–1863.

Card, David, 2001a, Estimating the return to schooling: Progress on some persistent econometric problems, *Econometrica* 69, 1127–1160.

Card, David, 2001b, Immigrant Inflows, Native Outflows, and the Local Labor Market Impacts of Higher Immigration, *Journal of Labor Economics* 19, 22–64.

Carnevale, Anthony P., Tamara Jayasundera, and Dmitri Repnikov, 2014, Understanding online job ads data, Technical report, A technical report. MS o. PP Center on Education and the Workforce.

Chen, Jun, Shenje Hshieh, and Feng Zhang, 2021, The role of high-skilled foreign labor in startup performance: Evidence from two natural experiments, *Journal of Financial Economics* 142, 430–452.

Chen, Yuchen, Xuelin Li, Richard T. Thakor, and Colin Ward, 2023, Appropriated Growth.

Conlon, John J., Laura Pilossoph, Matthew Wiswall, and Basit Zafar, 2018, Labor Market Search With Imperfect Information and Learning.

Covarrubias, Matias, Germán Gutiérrez, and Thomas Philippon, 2020, From Good to Bad Concentration? US Industries over the past 30 years, *NBER Macroeconomics Annual* 34, 1–46.

Cox, Lydia, Gernot J. Müller, Ernesto Pastén, Raphael Schoenle, and Michael Weber, 2024, Big G, *Journal of Political Economy* 132, 3260–3297.

Crouzet, Nicolas, and Janice Eberly, 2023, Rents and Intangible Capital: A Q+ Framework, *The Journal of Finance* 78, 1873–1916.

Cummins, Jason G., Kevin A. Hassett, and R. Glenn Hubbard, 1994, A Reconsideration of Investment Behavior Using Tax Reforms as Natural Experiments, *Brookings Papers on Economic Activity* 1994, 1–74.

Deming, David, and Lisa B Kahn, 2018, Skill requirements across firms and labor markets: Evidence from job postings for professionals, *Journal of Labor Economics* 36, S337–S369.

Deming, David J, and Kadeem Noray, 2020, Earnings dynamics, changing job skills, and stem careers, *The Quarterly Journal of Economics* 135, 1965–2005.

DeVaro, Jed, 2006, Internal promotion competitions in firms, *The Rand Journal of Economics* 37, 521–542.

Dyer, Travis, Mark Lang, and Lorien Stice-Lawrence, 2017, The evolution of 10-K textual disclosure: Evidence from Latent Dirichlet Allocation, *Journal of Accounting and Economics* 64, 221–245.

Eisfeldt, Andrea L., and Dimitris Papanikolaou, 2013, Organization Capital and the Cross-Section of Expected Returns, *Journal of Finance* 68, 1365–1406.

Eisfeldt, Andrea L., and Dimitris Papanikolaou, 2014, The Value and Ownership of Intangible Capital, *American Economic Review* 104, 189–194.

Fallick, Bruce, and Charles A. Fleischman, 2004, Employer-to-Employer Flows in the U.S. Labor Market: The Complete Picture of Gross Worker Flows.

Fallick, C. Bruce, and A. Kevin Hassett, 1999, Investment and Union Certification, *Journal of Labor Economics* .

Forsythe, Eliza, Lisa B. Kahn, Fabian Lange, and David Wiczer, 2020a, Labor demand in the time of COVID-19: Evidence from vacancy postings and UI claims, *Journal of Public Economics* 189, 104238.

Forsythe, Eliza, Lisa B Kahn, Fabian Lange, and David G Wiczer, 2020b, Searching, recalls, and tightness: An interim report on the covid labor market, Technical report, NBER.

Gallipoli, Giovanni, and Christos A. Makridis, 2018, Structural transformation and the rise of information technology 97, 91–110.

Garmaise, Mark J., 2011, Ties that Truly Bind: Noncompetition Agreements, Executive Compensation, and Firm Investment, *The Journal of Law, Economics, and Organization* 27, 376–425.

Goldschmidt, Deborah, and Johannes F. Schmieder, 2017, The Rise of Domestic Outsourcing and the Evolution of the German Wage Structure, *The Quarterly Journal of Economics* 132, 1165–1217.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift, 2020, Bartik Instruments: What, When, Why, and How, *American Economic Review* 110, 2586–2624.

Gormsen, Niels Joachim, and Kilian Huber, 2025, Corporate Discount Rates, *American Economic Review* 115, 2001–2049.

Graham, John R., and Campbell R. Harvey, 2011, The Duke/CFO business outlook survey, *Duke CFO Global Business Outlook. http: www. cfosurvey. org* .

Grullon, Gustavo, Yelena Larkin, and Roni Michaely, 2019, Are US industries becoming more concentrated?, *Review of Finance* 23, 697–743.

Gupta, Abhinav, Naman Nishesh, and Elena Simintzi, 2024, Big Data and Bigger Firms: A Labor Market Channel, *UNC Working Paper* .

Gutiérrez, Germán, and Thomas Philippon, 2017, Investmentless Growth: An Empirical Investigation, *Brookings Papers on Economic Activity* 89–169.

Gutiérrez, Germán, and Thomas Philippon, 2018, Declining Competition and Investment in the U.S., Working Paper 23583, National Bureau of Economic Research.

Gutierrez, German, and Thomas Philippon, 2020, Some Facts About Dominant Firms, SSRN Scholarly Paper ID 3718897, Social Science Research Network, Rochester, NY.

Hadlock, Charles J., and Joshua R. Pierce, 2010, New evidence on measuring financial constraints: Moving beyond the KZ index, *The Review of Financial Studies* 23, 1909–1940.

Haltiwanger, John C., Henry R. Hyatt, Lisa B. Kahn, and Erika McEntarfer, 2018, Cyclical Job Ladders by Firm Size and Firm Wage, *American Economic Journal: Macroeconomics* 10, 52–85.

Haltiwanger, John C., Julia I. Lane, and James R. Spletzer, 1999, Productivity Differences across Employers: The Roles of Employer Size, Age, and Human Capital 89, 94–98.

Hancock, Julie I., David G. Allen, Frank A. Bosco, Karen R. McDaniel, and Charles A. Pierce, 2013, Meta-Analytic Review of Employee Turnover as a Predictor of Firm Performance, *Journal of Management* 39, 573–603.

Hansen, Fay, 1997, Currents in Compensation and Benefits, *Compensation & Benefits Review* 29, 6–18.

Harrison, David A., Daniel A. Newman, and Philip L. Roth, 2006, How Important are Job Attitudes? Meta-Analytic Comparisons of Integrative Behavioral Outcomes and Time Sequences, *Academy of Management Journal* 49, 305–325.

He, Jing, and Marlene A. Plumlee, 2020, Measuring disclosure using 8-K filings, *Review of Accounting Studies* 25, 903–962.

Hershbein, Brad, and Lisa B Kahn, 2018, Do recessions accelerate routine-biased technological change? evidence from vacancy postings, *American Economic Review* 108, 1737–72.

Hoberg, Gerard, Gordon Phillips, and Nagpurnanand Prabhala, 2014, Product Market Threats, Payouts, and Financial Flexibility, *The Journal of Finance* 69, 293–324.

Hoberg, Gerard, and Gordon M. Phillips, 2022, Scope, Scale and Concentration: The 21st Century Firm.

Holtom, Brooks C., Terence R. Mitchell, Thomas W. Lee, and Marion B. Eberly, 2008, Turnover and Retention Research: A Glance at the Past, a Closer Review of the Present, and a Venture into the Future, *Academy of Management Annals* 2, 231–274.

Hom, Peter W., Thomas W. Lee, Jason D. Shaw, and John P. Hausknecht, 2017, One hundred years of employee turnover theory and research, *Journal of Applied Psychology* 102, 530–545.

Hou, Kewei, and David T. Robinson, 2006, Industry concentration and average stock returns, *The Journal of Finance* 61, 1927–1956.

Hyatt, Henry R., Erika McEntarfer, Kevin L. McKinney, Stephen Tibbets, and Doug Walton, 2014, Job-to-Job (J2J) Flows: New Labor Market Statistics from Linked Employer-Employee Data.

Imbens, Guido W., and Joshua D. Angrist, 1994, Identification and Estimation of Local Average Treatment Effects, *Econometrica* 62, 467–475.

Ishimaru, Shoya, 2024, Empirical decomposition of the iv-ols gap with heterogeneous and nonlinear effects, *Review of Economics and Statistics* 106, 505–520.

Jagannathan, Ravi, David A. Matsa, Iwan Meier, and Vefa Tarhan, 2016, Why do firms use high discount rates?, *Journal of Financial Economics* 120, 445–463.

Jäger, Simon, Christopher Roth, Nina Roussille, and Benjamin Schoefer, 2021, Worker Beliefs About Outside Options, *NBER Working Paper No. 29623* .

Jeffers, Jessica, 2023, The impact of restricting labor mobility on corporate investment and entrepreneurship, *Review of Financial Studies* Forthcoming.

Jiang, Hao, Chris Parsons, Lin Sun, and Sheridan Titman, 2023, Skilled Foreign Labor, Urban Agglomeration, and Value Creation.

Jiang, Wei, 2017, Have Instrumental Variables Brought Us Closer to the Truth, *The Review of Corporate Finance Studies* 6, 127–140.

Johnson, Matthew S., Michael Lipsitz, and Alison Pei, 2023, Innovation and the Enforceability of Noncompete Agreements.

Jovanovic, Boyan, 1979, Job Matching and the Theory of Turnover, *Journal of Political Economy* 87, 972–990.

Juhn, Chinhui, Kevin M. Murphy, and Brooks Pierce, 1993, Wage Inequality and the Rise in Returns to Skill, *Journal of Political Economy* 101, 410–442.

Kroen, Thomas, Ernest Liu, Atif R Mian, and Amir Sufi, 2021, Falling rates and rising superstars, Technical report, National Bureau of Economic Research.

Krusell, Per, Lee E. Ohanian, Jose-Victor Rios-Rull, and Giovanni L. Violante, 2000, Capital-skill Complementarity and Inequality: A Macroeconomic Analysis, *Econometrica* 68, 1029–1053.

Kydland, Finn E., and Edward C. Prescott, 1982, Time to Build and Aggregate Fluctuations, *Econometrica* 50, 1345–1370.

Lancaster, Vicki, Devika Mahoney-Nair, and Nathaniel J. Ratcliff, 2019, Review of burning glass job-ad data, *Biocomplexity Institute and Initiative Social and Decision Analytics Division, University of Virginia* .

Lee, Thomas W., and Terence R. Mitchell, 1994, An Alternative Approach: The Unfolding Model of Voluntary Employee Turnover, *Academy of Management Review* 19, 51–89.

Li, Feng, 2008, Annual report readability, current earnings, and earnings persistence, *Journal of Accounting and economics* 45, 221–247.

Li, Qin, Ben Lourie, Alexander Nekrasov, and Terry Shevlin, 2022, Employee Turnover and Firm Performance: Large-Sample Archival Evidence, *Management Science* 68, 5667–5683.

Liu, Ernest, Atif Mian, and Amir Sufi, 2021, Low Interest Rates, Market Power, and Productivity Growth, *Econometrica* Forthcoming.

Manning, Alan, and Barbara Petrongolo, 2017, How Local Are Labor Markets? Evidence from a Spatial Job Search Model, *American Economic Review* 107, 2877–2907.

Marinescu, Ioana, and Roland Rathelot, 2016, Mismatch Unemployment and the Geography of Job Search, *NBER Working Paper* .

Mikolov, Tomas, 2013, Efficient estimation of word representations in vector space.

Mikolov, Tomas, Ilya Sutskever, Kai Chen, Greg S. Corrado, and Jeff Dean, 2013, Distributed representations of words and phrases and their compositionality, *Advances in neural information processing systems* 26.

Moscarini, Giuseppe, and Fabien Postel-Vinay, 2013, Stochastic Search Equilibrium, *The Review of Economic Studies* 80, 1545–1581.

Mueller, Holger M., Paige P. Ouimet, and Elena Simintzi, 2017, Within-Firm Pay Inequality, *The Review of Financial Studies* 30, 3605–3635.

Nakamura, Emi, and Jón Steinsson, 2014, Fiscal stimulus in a monetary union: Evidence from US regions, *American Economic Review* 104, 753–792.

Nekarda, Christopher J., and Valerie A. Ramey, 2011, Industry Evidence on the Effects of Government Spending, *American Economic Journal: Macroeconomics* 3, 36–59.

Opler, Tim C., and Sheridan Titman, 1994, Financial Distress and Corporate Performance, *The Journal of Finance* 49, 1015–1040.

Oyer, Paul, 2004, Why Do Firms Use Incentives That Have No Incentive Effects?, *The Journal of Finance* 59, 1619–1650.

Peters, Ryan H., and Lucian A. Taylor, 2017, Intangible capital and the investment-q relation, *Journal of Financial Economics* 123, 251–272.

Philippon, Thomas, and Ariell Reshef, 2012, Wages and Human Capital in the U.S. Finance Industry: 1909–2006*, *The Quarterly Journal of Economics* 127, 1551–1609.

Phillips, Damon Jeremy, 2001, The promotion paradox: Organizational mortality and employee promotion chances in silicon valley law firms, 1946–1996, *American Journal of Sociology* 106, 1058–1098.

Pissarides, Christopher A., 1994, Search Unemployment with On-the-job Search, *The Review of Economic Studies* 61, 457–475.

Qiu, Yue, and Tracy Yue Wang, 2021, Skilled Labor Risk and Corporate Policies, *The Review of Corporate Finance Studies* 10, 437–472.

Rothwell, Jonathan, 2014, Still searching: Job vacancies and STEM skills, *Metropolitan Policy Program at Brookings Institution* .

Sanati, Ali, 2025, How does labor mobility affect corporate leverage and investment?, *Journal of Financial and Quantitative Analysis* 60, 1146–1184.

Schubert, Gregor, Anna Stansbury, Bledi Taska, and Matthew Dey, 2025, Employer concentration and wages: Evidence from large firms' hiring shocks, *Available at SSRN 5374463* .

Seegmiller, Bryan, 2021, Valuing Labor Market Power: The Role of Productivity Advantages.

Shen, Mo, 2021, Skilled Labor Mobility and Firm Value: Evidence from Green Card Allocations, *The Review of Financial Studies* 34, 4663–4700.

Shi, Liyan, 2023, Optimal Regulation of Noncompete Contracts, *Econometrica* 91, 425–463.

Silva, José Ignacio, and Manuel Toledo, 2009, Labor turnover costs and the cyclical behavior of vacancies and unemployment, *Macroeconomic Dynamics* 13, 76–96.

Silva, Rui C., 2021, Internal Labor Markets, Wage Convergence, and Investment, *Journal of Financial and Quantitative Analysis* 56, 1192–1227.

Song, Jae, David J. Price, Fatih Guvenen, Nicholas Bloom, and Till Von Wachter, 2018, Firming up inequality, Technical report, National Bureau of Economic Research.

Sorkin, Isaac, 2018, Ranking Firms Using Revealed Preference*, *The Quarterly Journal of Economics* 133, 1331–1393.

Stock, James H., and Motohiro Yogo, 2005, Testing for Weak Instruments in Linear IV Regression, *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg* .

Syverson, Chad, 2019, Macroeconomics and Market Power: Context, Implications, and Open Questions, *Journal of Economic Perspectives* 33, 23–43.

Tabellini, Marco, 2020, Gifts of the Immigrants, Woes of the Natives: Lessons from the Age of Mass Migration, *The Review of Economic Studies* 87, 454–486.

Tong, Joy Tianjiao, 2024, Health care costs and corporate investment, *The Review of Financial Studies* 37, 1078–1117.

Trevor, Charlie O., 2001, Interactions Among Actual Ease-of-Movement Determinants and Job Satisfaction in the Prediction of Voluntary Turnover, *Academy of Management Journal* 44, 621–638.

Tuzel, Selale, and Miao Ben Zhang, 2021, Economic Stimulus at the Expense of Routine-Task Jobs, *Journal of Finance* 76, 3347–3399.

Yeh, Chen, Claudia Macaluso, and Brad Hershbein, 2022, Monopsony in the US Labor Market, *American Economic Review* 112, 2099–2138.

Zhang, Miao Ben, 2019, Labor-Technology Substitution: Implications for Asset Pricing, *Journal of Finance* 74, 1793–1839.

Figure 1: Composition of Talent

This figure illustrates the occupation distribution of talent employees in our final sample. Talent employees for each NAICS 4-digit industry are the top 10% SOC 5-digit occupations with the highest cognitive skills (Acemoglu and Autor (2011)). An occupation is a talent for a Compustat firm if the occupation is a talent for the firm's industry (see Section II.A for more details). We pool all talent in our final Compustat firm sample from 2010 to 2018 and present the employment distribution at the SOC 2-digit broad occupation level.

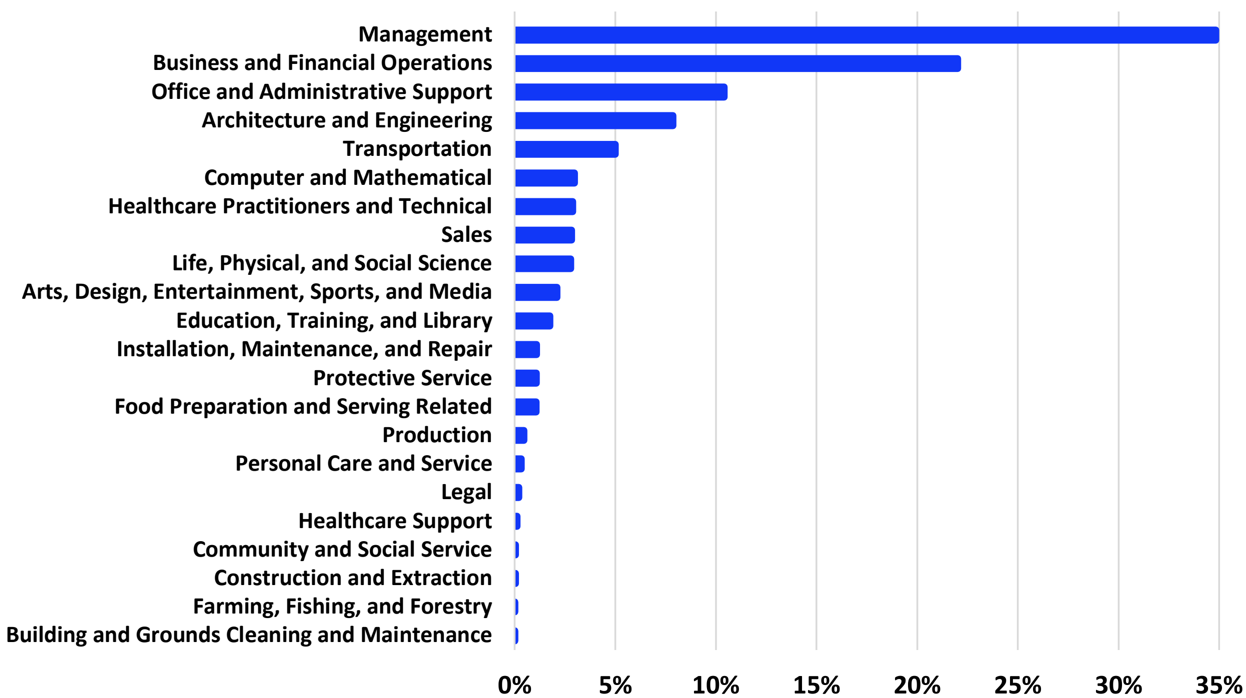


Figure 2: Average Talent Market Competition Across MSAs

This figure plots the average vacancy-to-employment (V/E) ratio for talent employees for each Metropolitan Statistical Area (MSA) in 2018 (see Section II.B).

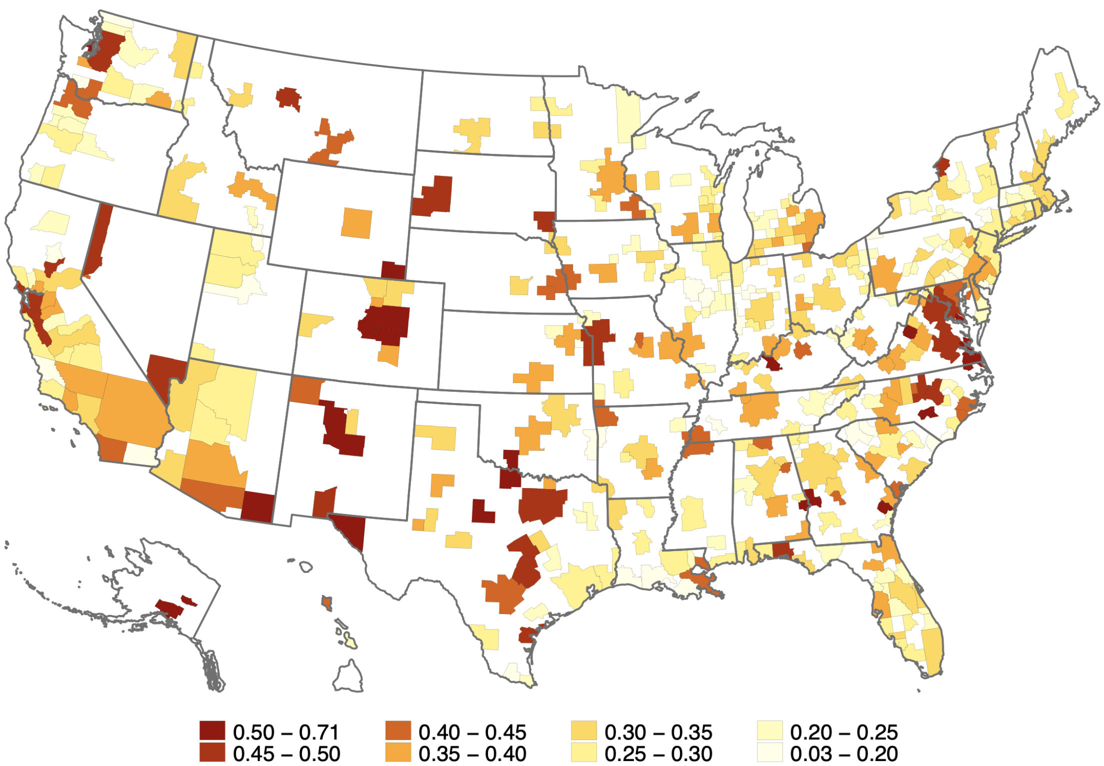
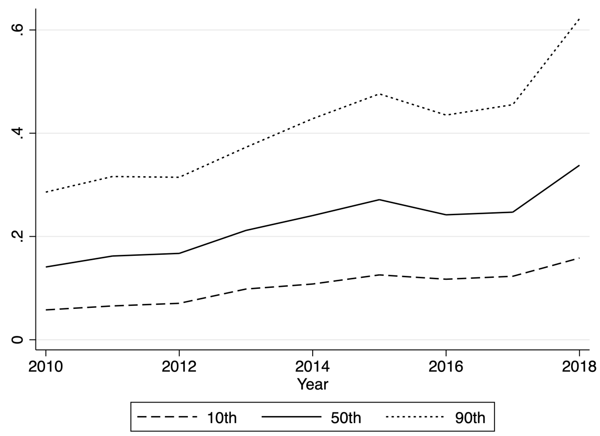


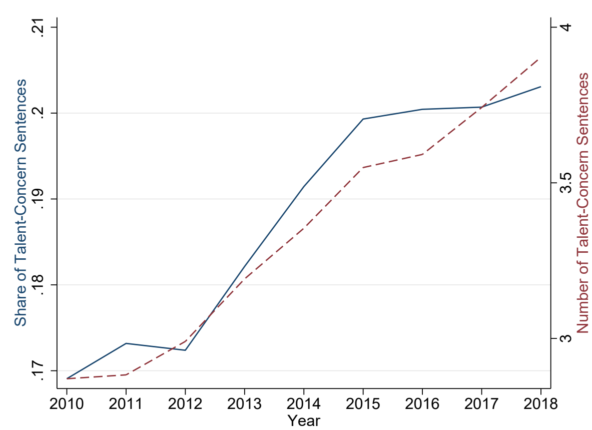
Figure 3: Time Series of Firms' Talent Retention Pressure and Concerns

Panel A plots the 10th percentile, median, and 90th percentile of our talent retention pressure (TRP) measure across firms in our final sample from 2010 to 2018 (see Section II.C). Panel B plots the average share in percentage (solid line) and number (dashed line) of sentences mentioning both talent and competition keywords in firms' 10-K annual reports filed to the SEC (see Section III.C). Panel C plots the fraction of firms rating "*difficulty in attracting/retaining qualified employees*" as a top internal concern in the Duke CFO Survey (see Appendix A).

Panel A: Talent Retention Pressure



Panel B: Talent Concerns in 10-K Annual Reports



Panel C: Talent Concerns in Duke CFO Survey

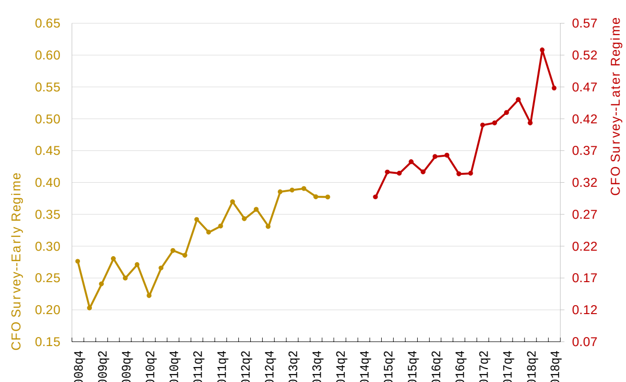


Table I
Summary Statistics

Panel A presents summary statistics of the variables in our Compustat firm sample from 2010 to 2018 described in Section II. *TRP* is the firm's talent retention pressure constructed as the average vacancy-to-employment ratio for MSA-occupations (excluding the firm's own vacancy) weighted by the firm's talent distribution across MSA-occupations in the year (see equation (1)). *Talent Outflow Rate* is the number of talent leaving the firm to join another firm next year divided by the total number of talent this year and multiplied by 100 using the Revelio Labs microdata. *Talent Growth Rate* is the net changes in the number of talent from this year to the next year divided by the firm's total number of talent this year and multiplied by 100. *Talent Wage Rate* is the natural logarithm of the average hourly wage rate of the firm's talent from the BLS OEWS microdata. *Talent Promotion Rate* is the percentage of talent employees in the firm experiencing an increase in seniority (promotion) in the Revelio Labs microdata. *Talent Job Posting* is the natural logarithm of one plus the firm's number of job postings for talent in the year from the Lightcast data. *Physical Investment* is next year's capital expenditure (#CAPX) divided by this year's total assets (#AT) and multiplied by 100. *Total Investment* is next year's physical and intangible expenditure divided by this year's total capital stock obtained from Peters and Taylor (2017) and multiplied by 100. *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 Tobin's Q calculation and is obtained from Peters and Taylor (2017). *Cash Flow* 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. Panel B presents the summary statistics of our talent employee sample from 2010 to 2018 based on the Revelio Labs microdata described in Section III.A. *Job-to-Job Transition* is a dummy variable that equals to one if the individual talent transits from one firm to another firm next year and is multiplied by 100. $V/E_{m,o,t}$ is the vacancy-to-employment ratio of the local talent market corresponding to the individual's MSA and occupation. $V/E_{-m,o,t}$ is the vacancy-to-employment ratio of the non-local talent market for the individual's occupation based on all MSAs except for the individual's own MSA.

Variable	Mean	SD	P10	Median	Median $^{Compustat}_{Universe}$	P90	# obs.
	Panel A: Firm-level Variables						
TRP	0.239	0.144	0.086	0.211	-	0.427	13,502
Talent Outflow Rate	11.649	7.755	4.255	10.204	-	20.388	9,207
Talent Growth Rate	4.528	13.829	-9.579	4.334	-	19.435	9,207
Talent Wage Rate	3.931	0.350	3.483	3.955	-	4.349	12,997
Talent Promotion Rate	4.212	3.218	0.660	3.636	-	8.219	8,447
Talent 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
Cash Flow	0.018	0.247	-0.214	0.072	0.066	0.190	13,077
Size	6.570	2.109	3.805	6.533	6.543	9.373	13,502
Age	1.975	0.475	1.609	2.079	1.946	2.484	13,502
	Panel B: Worker-level Variables						
Job-to-Job Transition	10.513	30.672	0.000	0.000	-	100.000	26,390,758
$V/E_{m,o,t}$	0.328	0.339	0.049	0.219	-	0.737	26,390,758
$V/E_{-m,o,t}$	0.269	0.223	0.051	0.199	-	0.637	26,390,758

Table II
Validation: Talent Market Competition and Talent Job-to-Job Transition

Panel A reports the results of regressing talent employees' job-to-job (J2J) transition indicator at year $t+1$ multiplied by 100 on the local talent market competition measure at t, i.e., vacancy-to-employment ratio ($V/E_{m,o,t}$), where a local talent market is defined at the MSA-occupation level. $V/E_{-m,o,t}$ is the vacancy-to-employment ratio of the individual's occupation from all MSAs except for the individual's MSA, representing the national talent market competition outside the local area. The sample includes a partial list of talent employees from Compustat firms with LinkedIn profiles from 2010 to 2018 in the Revelio Labs microdata. See more details about sample selection and the definition of firms' talent in Section III.A. A worker's tenure is defined as the years since the start of the worker's current position at the firm. Panel B reports the results of regressing Compustat firms' talent outflow rate next year on their current talent retention pressure. Firm controls include firms' Tobin's Q, cash flow, size, and age in the current year. Industry is classified at the NAICS 4-digit level. See Table I for definitions of all variables. Standard errors, reported in parentheses, are clustered at the MSA-occupation level in Panel A and the firm level in Panel B. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Panel A: Individual-Level Talent Job-to-Job Transition$_{t+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$V/E_{m,o,t}$	0.547***		0.581***	0.525***	0.622***	0.629***
	(0.154)		(0.161)	(0.155)	(0.230)	(0.231)
$V/E_{-m,o,t}$		0.618**	-0.071			
		(0.256)	(0.278)			
Year FE	Y	Y	Y	N	Y	Y
Firm FE	Y	Y	Y	N	N	N
Firm-Year FE	N	N	N	Y	N	N
Firm-Worker FE	N	N	N	N	Y	Y
Firm-Worker Tenure	N	N	N	N	N	Y
Observations	26,390,758	26,390,758	26,390,758	26,387,537	24,430,096	24,430,096
Adjusted R^2	0.022	0.022	0.022	0.026	0.150	0.150

	Panel B: Firm-Level Talent Outflow Rate$_{t+1}$		
	(1)	(2)	(3)
TRP	2.562***	2.487***	2.629**
	(0.930)	(0.943)	(1.100)
Firm Control	N	Y	Y
Firm FE	Y	Y	Y
Year FE	Y	Y	N
Year-Industry FE	N	N	Y
Observations	9,155	8,885	8,423
Adjusted R^2	0.439	0.445	0.404

Table III
Validation: Talent Retention Pressure and Firms' Talent Concern in 10-Ks

This table reports the results of regressing firms' concerns about talent competition mentioned in their 10-K annual reports on their contemporaneous talent retention pressure (TRP) measure. *Share of Talent-Concern Sentences in 10-K Report* is the percentage of sentences in the firm's 10-K report that mentions both talent keywords and competition/retention/attraction keywords (see Section III.C). *Number of Talent-Concern Sentences in 10-K Report* is the number of such sentences in the firm's 10-K report in the year. *TRP* is the firm's average employment exposure to local talent market competition defined in equation (1). Firm controls include firms' Tobin's Q, cash flow, size, and age in the current year. Industry is classified at the NAICS 4-digit level. See Table I for definitions of all 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.

	Share of Talent-Concern Sentences in 10-K Report$_t$			Number of Talent-Concern Sentences in 10-K Report$_t$		
	(1)	(2)	(3)	(4)	(5)	(6)
TRP	0.135***	0.129***	0.061***	3.590***	3.089***	1.673***
	(0.021)	(0.021)	(0.021)	(0.393)	(0.383)	(0.401)
Firm Control	N	Y	Y	N	Y	Y
Year FE	Y	Y	N	Y	Y	N
Year-Industry FE	N	N	Y	N	N	Y
Observations	12,343	11,979	11,407	12,343	11,979	11,407
Adjusted R^2	0.016	0.073	0.220	0.042	0.100	0.238

Table IV
Talent Retention Pressure and Firm 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 (1). Industry is classified at the NAICS 4-digit level. 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$_{t+1}$			Total Investment$_{t+1}$		
	(1)	(2)	(3)	(4)	(5)	(6)
TRP	-1.629***	-1.472***	-1.592***	-2.903***	-2.044**	-1.616**
	(0.494)	(0.486)	(0.434)	(1.078)	(0.841)	(0.750)
Q		0.643***	0.544***			
		(0.056)	(0.055)			
Total Q					2.221***	2.220***
					(0.133)	(0.131)
Cash Flow		1.917***	0.973***		3.132***	1.706*
		(0.401)	(0.373)		(0.889)	(0.915)
Size		-0.895***	-1.080***		-1.961***	-2.011***
		(0.183)	(0.180)		(0.431)	(0.458)
Age		-2.449**	-1.727		-18.796***	-17.011***
		(1.116)	(1.142)		(2.327)	(2.378)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	N	Y	Y	N
Year-Industry FE	N	N	Y	N	N	Y
Observations	11,985	11,985	11,396	10,581	10,581	10,009
Adjusted R^2	0.705	0.719	0.807	0.748	0.807	0.81

Table V
Shift-Share 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 and the national growth rates of the vacancy-to-employment ratio of each talent occupation as the shift (see equation (6)). *NonPeer IV* refers to a refined instrument that uses only job postings outside the firm's top three segment industries when constructing the instrument. 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$_{t+1}$		Total Investment$_{t+1}$	
IV Type:	IV	NonPeer IV	IV	NonPeer IV
	(1)	(2)	(3)	(4)
2SLS(TRP)	-5.352**	-5.501***	-11.277***	-10.881***
	(2.091)	(2.129)	(3.567)	(3.587)
Q	0.654***	0.654***		
	(0.063)	(0.063)		
Total Q			2.159***	2.159***
			(0.144)	(0.144)
Cash Flow	2.002***	1.999***	2.976***	2.987***
	(0.442)	(0.442)	(0.973)	(0.974)
Size	-0.878***	-0.877***	-2.044***	-2.046***
	(0.193)	(0.193)	(0.458)	(0.457)
Age	-2.656**	-2.650**	-18.106***	-18.132***
	(1.253)	(1.253)	(2.508)	(2.507)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	11,110	11,110	9,863	9,863
F-stat.	131.414	140.012	126.929	133.616

Table VI
Talent Retention Pressure and Firm Labor Effects

This table reports the results of regressing firms' labor variables in the current or next year on their talent retention pressure (TRP). *Talent Wage Rate* is the natural logarithm of the average hourly wage rate of the firm's talent. *Talent Promotion Rate* is the percentage of talent employees in the firm experiencing an increase in seniority (promotion) in the year using the Revelio Labs microdata. *Job Posting for Talent* is the natural logarithm of one plus the firm's number of job postings for talent in the year using the Lightcast data. *Talent Growth Rate* is the net changes in the number of talent divided by the firm's total number of talent at the beginning of the year and multiplied by 100 using the Revelio Labs microdata. *TRP* is the firm's average employment exposure to local talent market competition defined in equation (1). Firm controls include firms' Tobin's Q, cash flow, size, and age in the current year. Industry is classified at the NAICS 4-digit level. 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: Talent Wage Rate				*Panel B: Talent Promotion Rate*			
	t		$t+1$		t		$t+1$	
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
TRP	0.088**	0.119***	0.052	0.050	0.814**	1.075***	0.285	0.186
	(0.036)	(0.039)	(0.036)	(0.038)	(0.369)	(0.413)	(0.415)	(0.474)
Firm Control	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	N	Y	N	Y	N	Y	N
Year-Industry FE	N	Y	N	Y	N	Y	N	Y
Observations	12,354	11,877	9,544	9,104	7,860	7,397	6,172	5,755
Adjusted R^2	0.796	0.793	0.812	0.809	0.526	0.493	0.532	0.497
	Panel C: Job Posting for Talent				*Panel D: Talent Growth Rate*			
	t		$t+1$		t		$t+1$	
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
TRP	0.446***	0.206*	0.230	-0.063	-1.038	-1.436	-1.865*	-1.727*
	(0.121)	(0.116)	(0.155)	(0.136)	(1.829)	(2.128)	(1.024)	(0.953)
Firm Control	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	N	Y	N	Y	N	Y	N
Year-Industry FE	N	Y	N	Y	N	Y	N	Y
Observations	12,799	12,215	9,846	9,311	8,884	8,422	8,885	8,423
Adjusted R^2	0.857	0.874	0.859	0.879	0.267	0.232	0.259	0.221

Table VII
Talent Retention Pressure and Firms' Talent Productivity

This table reports the results of regressing firms' average talent productivity on their talent retention pressure (TRP). The dependent variable 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 (1). Firm controls include firms' Tobin's Q, cash flow, size, and age in the current year. Industry is classified at the NAICS 4-digit level. 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.

	Firms' Average Talent Productivity			
	t		$t+1$	
	(1)	(2)	(3)	(4)
TRP	-0.800	-1.084	-3.192**	-2.610*
	(1.919)	(1.968)	(1.386)	(1.372)
Firm Control	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	N	Y	N
Year-Industry FE	N	Y	N	Y
Observations	12,643	12,046	9,751	9,216
Adjusted R^2	0.674	0.660	0.678	0.663

Table VIII
Heterogeneous Effects: Superstar vs. Laggard Firms

This table reports the results of regressing firms' capital investment and talent outflow rate 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 NAICS 4-digit industry category in the year (Gutierrez and Philippon (2020)). *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). *Talent Outflow Rate* is the number of talent leaving the firm to join another firm next year divided by the total number of talent this year and multiplied by 100 using the Revelio Labs microdata. *TRP* is the firm's average employment exposure to local talent market competition defined in equation (1). Firm controls include firms' Tobin's Q, cash flow, size, and age in the current year. Industry is classified at the NAICS 4-digit level. 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$_{t+1}$		Total Investment$_{t+1}$		Talent Outflow Rate$_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
TRP× Superstar	3.319***	3.176***	5.614***	4.215**	-2.622*	-5.871***
	(0.818)	(0.908)	(1.542)	(1.753)	(1.476)	(1.928)
TRP	-1.821***	-1.820***	-2.684***	-2.163**	2.831***	3.021***
	(0.518)	(0.448)	(0.893)	(0.997)	(0.989)	(1.145)
Superstar	-0.811*	-0.994**	-0.714	-0.477	0.774	1.686**
	(0.426)	(0.391)	(0.610)	(0.652)	(0.531)	(0.674)
Firm Control	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	N	Y	N	Y	N
Year-Industry FE	N	Y	N	Y	N	Y
Observations	11,985	11,396	10581	10,009	8,885	8,423
Adjusted R^2	0.720	0.758	0.807	0.810	0.445	0.404

Table IX
Labor Policies: Superstar vs. Laggard Firms

This table reports the results of regressing firms' labor policies 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 NAICS 4-digit industry category in the year (Gutierrez and Philippon (2020)). *Talent Wage Rate* is the natural logarithm of the average hourly wage rate of the firm's talent. *Talent Promotion Rate* is the percentage of talent employees in the firm experiencing an increase in seniority (promotion) in the year using the Revelio Labs microdata. *Job Posting for Talent* is the natural logarithm of one plus the firm's number of job postings for talent in the year using the Lightcast data. *Talent Growth Rate* is the net changes in the number of talent in next year divided by the firm's total number of talent at the beginning of next year and multiplied by 100 using the Revelio Labs microdata. *TRP* is the firm's current average employment exposure to local talent market competition defined in equation (1). Firm controls include firms' Tobin's Q, cash flow, size, and age in the current year. Industry is classified at the NAICS 4-digit level. 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.

	Talent Wage Rate$_t$		Talent Promotion Rate$_t$		Job Posting for Talent$_t$		Talent Growth Rate$_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TRP×Superstar	0.161**	0.149**	-0.189	0.105	0.665**	0.163	2.653*	3.820*
	(0.064)	(0.066)	(0.719)	(0.816)	(0.316)	(0.353)	(1.500)	(2.003)
TRP	0.072*	0.110***	0.829*	0.968**	0.377***	0.194	-2.073*	-2.016*
	(0.037)	(0.040)	(0.454)	(0.477)	(0.122)	(0.118)	(1.080)	(1.199)
Superstar	-0.040**	-0.031	0.036	0.010	-0.194	-0.101	-1.104**	-1.599**
	(0.020)	(0.019)	(0.233)	(0.260)	(0.136)	(0.160)	(0.542)	(0.748)
Firm Control	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	N	Y	N	Y	N	Y	N
Year-Industry FE	N	Y	N	Y	N	Y	N	Y
Observations	12,257	11,782	7,860	7,757	12,799	12,215	8,885	8,423
Adjusted R^2	0.795	0.791	0.526	0.511	0.857	0.874	0.259	0.221

Internet Appendix for

“Talent Market Competition and Firm Growth”

AJ Chen Miao Ben Zhang Zhao Zhang

IA.1: Robustness to Alternative Talent Definitions

In this section, we summarize the robustness of our key findings under various alternative definitions of talent. Our baseline definition of a firm's talent ranks occupations by their cognitive skills (Autor and Acemoglu (2011)) within the firm's industry and classifies the occupations in the top decile as talent. To check the robustness of our main investment results in Tables IV and VIII, we permute our baseline TRP measure by varying the definition of a firm's talent in three different dimensions.

Robustness 1: Alternative talent definition based on other occupation characteristics. Our baseline definition of talent is based on occupations' required cognitive skills following Autor and Acemoglu (2011) because cognitive skills tend to complement capital, making the baseline definition of talent closely aligned with our conceptual framework, as discussed in Section II.A. In this permutation, we use occupations' average wage rate and requirements on work experience as alternative characteristics for ranking occupations. We measure an occupation's wage rate in each year by averaging the hourly wage rate of occupations in the OEWS establishment-occupation level microdata. We measure an occupation's work experience requirement based on the propensity of the occupation requiring 4 years or more work experience in the O*Net V22.3 (2018) dataset.[65] The alternative firm-level TRP measures defined based on wage rates and work experience requirements are 74% and 80% correlated with our baseline TRP measure, respectively. Internet Appendix Table IA.9 shows that the alternative TRPs indeed also capture firms' concerns about talent competition in their 10-Ks. Internet Appendix Tables IA.17 and IA.18 show that our main investment results are mostly robust to using wage rates and work experience requirements to define talent.

One skill metric that fails to generate similar results is the occupations' college degree

[65] The results are qualitatively similar if we use other criteria, such as 2 years or more.

requirement. O*Net database provides a metric regarding the likelihood for an occupation to require a college degree. We observe that ranking SOC 6-digit occupations by the intensity of college degree requirements results in only a modest correlation with rankings by other measures—0.50 with work experience requirements and 0.48 with cognitive skill requirements—while the correlation between work experience and cognitive skill requirements is much higher at 0.73. Second, unlike the TRPs defined based on other skill requirements that pass the 10-K-based validation test in the Internet Appendix Table IA.9, TRP defined on college degree requirements does not. Regressions of firms' "Share of Talent-Concern Sentences in 10-K Report" on firms' college-degree-based TRP, following the specifications of Columns (1)-(3) in Internet Appendix Table IA.9, yield very weak estimates of 0.026 (s.e.=0.017), 0.029 (s.e.=0.017), and 0.023 (s.e.=0.015), respectively. While a deeper exploration of the underlying distinction between education and other skill metrics is beyond the scope of our paper, we observe that the ranking based on college degree requirements fails to classify some key occupations as firms' talent. A salient example is Chief Executives (SOC=11-1011), which is ranked 168 out of about 800 occupations by college degree requirements in the O*NET database, but ranked 13 and 9 by cognitive skill and work experience requirements, respectively.

Robustness 2: Alternative talent definition based on uniform classification. Our baseline definition of talent ranks occupations within each NAICS 4-digit industry. Section II.A and Internet Appendix IA.4 provide evidence that the within-industry approach captures firms' talent relatively better than the uniform approach for firms in traditionally considered low-skilled industries (see examples in the Internet Appendix Table IA.3). In this permutation, we examine the robustness of our main results to ranking occupations nationally based on their cognitive skills and select occupations in the top deciles as talent uniformly across industries. This alternative definition of talent classifies more employees as talent in traditionally viewed high-skill industries such as education, healthcare, and law services than the within-industry definition of talent, but fewer employees as talent in restaurants and retail.

The corresponding alternative firm-level TRP measure defined based on the uniform classification is 70% correlated with our baseline TRP measure. Internet Appendix Table IA.4 shows that our main investment results are robust to using the uniform classification definition of talent. In addition, we show in the Internet Appendix Table IA.9 that the alternative TRP also capture firms' concerns about talent competition in their 10-Ks.

Robustness 3: Alternative talent definition based on various cutoffs in the ranking. Our baseline definition of talent classifies occupations in the top decile of the ranking as talent. We choose the top decile to balance two concerns of measuring talent: If we set the cutoff to be too loose, we will likely include too many low-cognitive skill occupations as talent. This will weaken our investment predictions, as low-skill workers may transition in and out of unemployment, making the V/E ratio a noisy measure of their labor market tightness and hence our firm-level TRP measure to be noisy. In addition, low-skilled occupations may be less complementary to capital, making the measure unsuitable for testing our hypothesis, which relies on talent-capital complementarity. On the other hand, if we go the other extreme and set the cutoff to be too tight, we are likely to be left with only a couple of or no talent occupations for certain firms. This will also reduce our testing power by introducing measurement errors in firms' TRP. In this perturbation, we vary the cutoff to be looser or tighter than our baseline 10% cutoff, i.e., from 5% to 25%. The Internet Appendix Figure IA.3 plots the coefficients of the alternative TRP in our baseline investment regressions where each alternative TRP corresponds to an alternative cutoff labeled in the x-axis. We observe that our results are generally robust when we vary the cutoffs from 5% to 20%.

IA.2: Construction of Main Sample

Our final sample includes Compustat firms with calculated TRP measures, covering the period from 2010 to 2018, where 2010 is the first year when Lightcast job posting data became widely available. We further require that Compustat firms are U.S.-based, have total assets exceeding \$1 million, employ more than 50 workers, and have at least 10% of their total employment represented in the OEWS data. Our final sample includes 13,502 firm-year observations and 11,985 observations after requiring the firm to have non-missing firm controls and more than one observation in the sample for firm fixed effects. The step-by-step match statistics are as follows:

- We begin with 52,722 firm-year observations of U.S.-incorporated firms from the Compustat database with non-missing total assets, representing 8,994 unique firms between 2010 and 2018.
- Merging with the BLS OEWS data and applying a minimum 10% employment coverage requirement, we are left with 17,992 firm-year observations for 3,565 unique firms.[66]
- We further require the firms to have total assets exceeding \$1 million and more than 50 employees, leaving a sample of 14,357 firm-year observations for 2,883 unique firms.
- For the regression sample, we further require non-missing values for Tobin's Q, age, cash flow, and investment, and each firm needs to have more than one observation in the sample for estimating firm fixed effects, resulting in a final sample of 11,985 firm-year observations for 2,095 unique firms.

IA.3: Data Work with Revelio Labs Microdata

We use Revelio Labs' individual job position data to study how a talent worker's job-to-job transition is related to the local talent market competition measure, defined by the MSA-occupation-level vacancy-to-employment ratio (V/E).

The Revelio Labs' individual-position data extracts workers' LinkedIn profiles and provides each worker's start and end year-month in each job position, as well as several charac-

[66]The employment coverage ratio is the firm's total employment from the OEWS database divided by the total employment reported in the Compustat database in the year.

teristics of the job position, including the 8-digit O*Net occupation code, the location with the metropolitan area name, and the employer name and Compustat firm identifier, gvkey, if the employer is a publicly-traded company in the Compustat database.

We start by converting the individual-position level data into individual-year panel data by filling all the months within the start and end year-month and keeping only the December snapshot of each worker's occupation, metropolitan area, and firm information.

Next, following Revelio Labs' methodology of measuring firm-level outflow counts, we identify a worker experiencing a *job-to-job transition* in year $t+1$ if the worker is employed in a different firm at $t+1$ from her current firm at time t.

Finally, we require the observations in the individual-year level panel data to include only workers working in metropolitan areas in the United States, with non-missing O*Net occupation codes and non-missing gvkey of employers. The resulting panel data includes 96.55 million individual-year observations from 2010 to 2018. We merge MSA-occupation-year-level vacancy-to-employment ratios to the Revelio Labs individual-year panel for regression analyses in Section III.A.

To merge with our talent definition at the SOC 5-digit level, we convert the original SOC 8-digit codes to the SOC 5-digit level. Following our methodology in Section II.A, we identify a worker as talent for the Compustat firm if the worker's occupation ranks within the top 10% of the cognitive skill distribution within the firm's NAICS 4-digit industry. Our final sample focusing on talent workers includes 26.39 million individual-year observations.

Data limitation A major limitation of the Revelio Labs microdata is that it mapped all job titles into only a subset of (rather than the universe) the SOC 8-digit occupation codes. In particular, Revelio Labs microdata only covers 382 (out of the over 900) SOC 8-digit occupation categories. This issue arises because Revelio Labs first mapped the raw job title texts to their own occupation classification, called "Role_k1500," via a major undertaking of textual analysis, and then they built a crosswalk from Role_k1500 to a subset of 382

SOC 8-digit codes. Hence, while no individual is dropped from the data, the individual's occupation codes are likely to be mis-assigned if her true occupation codes fall outside the 382 categories. This two-step procedure can introduce non-trivial measurement errors and affect our worker-level and firm-level analyses using the data.

For the worker-level analyses in Section III.A, as the two-step procedure mapped *all* workers' job titles exclusively to a *subset* (instead of the universe) of SOC occupation codes, workers who should be mapped to SOC codes outside the subset were falsely included in the subset, inflating the number of employees in the 382 occupations. The measurement error can introduce attenuation bias to our worker-level regression analyses as our MSA-occupation-level V/E ratios are likely to be incorrectly assigned to some workers in the sample, making it difficult for us to observe significant effects.

For the firm-level analyses, the data issue from the Revelio Labs primarily brings noise for measuring a firm's talent. On the one hand, it leads to missing talent occupations for various industries, such as Social and Community Service Managers, Environmental Engineers, and Medical Scientists. Hence, when aggregating talent employees to the firm-level, we are likely to systematically miss talent in certain industries. On the other hand, the over-inclusion issue can add non-talent to firms' talent outflow rate measure. Overall, the data issue likely introduces significant mismatches between talent from Revelio Labs (which produces the firm-level talent outflow rate) and the BLS OEWS microdata (which produces the firm-level TRP), reducing the power for TRP to predict firm outflows in Panel B of Table II.

Given the data limitation, we caveat our empirical results that use the Revelio Labs data in Section III. This limitation also makes the Revelio Labs data not ideal for constructing our main talent retention pressure measure.

IA.4: Extracting Talent Concerns from 10-K Reports

Our sample consists of 10-K filings for publicly-traded firms from 2010 to 2018, extracted from the SEC Electronic Data Gathering, Analysis and Retrieval (EDGAR) database. The dataset provides the texts of 10-K documents in each year and header information from each document, including fiscal year, filing date, reporting period, and the central index key (CIK), which enables us to link each 10-K document to the Compustat database.

Measuring firms' talent concerns in 10-Ks To quantify firms' discussions on talent concerns, we develop wordlists on talent-related terms and on retention-related terms. To create these lists, we reviewed randomly selected samples of the filings and explored a word2vec word-embedding model trained on n-grams from all 10-Ks spanning 1997 to 2021 to identify words potentially associated with the theme "talent" (Mikolov (2013) and Mikolov et al. (2013)). We apply the two-list structure from Qiu and Wang (2021) and assign word2vec-generated keywords and some keywords from Qiu and Wang (2021) to List 1 and List 2 in Section III.C.

A sentence (or paragraph) in the 10-K document is labeled to mention talent if it directly mentions keywords "talent" or "talents" or it mentions a *combination* of List 1 and List 2 in Section III.C. We define a combination as either a keyword from List 1 immediately followed by a keyword in List 2, e.g., "key employee," or a keyword from List 1 followed by another single word and then a keyword in List 2, e.g., "key technical employee." For completeness, we allow for both singular and plural forms of the keywords.

Given our objective to capture firms' concerns about talent market competition, we also construct a competition-related wordlist, i.e., List 3 in Section III.C. This wordlist includes all variants of attraction, retention, and competition. A sentence (or paragraph) is labeled to mention competition if it includes one of the keywords in List 3.

Finally, a sentence is labeled as mentioning "talent concerns" if the sentence mentions both talent and competition discussed above. Aggregating a firm's total number and share of sentences mentioning talent concerns in its 10-K in a year gives us the final measures in Section III.C.

Robustness checks We perform extensive robustness checks by permuting the methods above. Internet Appendix Table IA.8 shows that our TRP measure robustly captures firms' talent concerns when using the alternative textual measures.

- Robustness 1: Using conservative "talent" keywords. In this permutation, we construct our measures using only conservative keywords for talent in List 1: "talent", "essential", "key", "core", "skill", "important", "best", "top", and "exceptional". This permutation excludes keywords such as "qualified", "experienced", "professional", "competent", and "capable."

- Robustness 2: Using conservative "retention" keywords. In this permutation, we construct our measures using only retention-related or competition-related keywords in List 3 but not recruiting or attraction-related keywords.

- Robustness 3: Alternative types of measure. In this permutation, we measure firms' talent concerns using total word counts of talent-concern sentences (instead of the number of share of the sentences) and separately use the share/number/word count of talent-concern paragraphs (instead of sentences).

Extracting examples of firms' talent occupations in 10-Ks Firms sometimes highlight the specific occupations they view as crucial for their success. We extract these talent occupations based on a combination of GPT prompting and manual checking. We start collecting sentences and paragraphs mentioning talent keywords in the above procedure. Then, we run the following prompt using the gpt-4o-mini-2024-07-18 model for each text:

```
{
"model": "gpt-4o-mini-2024-07-18",
```

"messages": [
{ "role": "user", "content":
"You are provided with a list of occupation titles and SOC codes from the following link: https://www.bls.gov/oes/current/oes_stru.htm. Please answer the following question based on the given sentence with sentence IDs: \n\n
a) Identify all occupations with their SOC codes that are directly referred to in the following sentences: \n\n
b) <INSERT_SENTENCES_STRING_HERE>" }
]
}

The above procedure identifies potential SOC 6-digit occupations that GPT detects as mentioned in the firm's 10-K sentences. We then manually review the sentences and remove false positives.

Firms' self-disclosed talent occupations include not only top executives but also many industry-specific roles that cannot be easily identified if we rank occupations solely by skills without considering industry specificity. Internet Appendix Table IA.3 provides examples of these industry-specific talent occupations, such as head chefs for restaurants, store managers for clothing firms, and first-line supervisors for construction firms. These examples suggest that even industries traditionally considered low-skilled have their own distinct talent. However, these talent occupations are often overshadowed by those from high-skilled industries when using a uniform classification of talent—i.e., ranking all occupations across industries in each year by cognitive skills (or wages or work experience requirements) and selecting the top decile—leading to false negatives. This observation guides our design of the baseline definition of firms' talent to be based on a within-industry ranking of occupations by cognitive skills, as described in Section II.A.

IA.5: Instrumenting TRP Using Government Military Procurement Spending

As mentioned in Section IV.C, we further reinforce the identification of the causal effects of TRP on firm investment by exploiting quasi-exogenous variations in local V/E ratios driven by federal military procurement spending (Barro and Redlick (2011) and Nakamura and Steinsson (2014)). Compared to the shift-share instruments, our examination of military procurement spending focuses on a specific but clearly identified quasi-exogenous driver for firms' TRP. Leveraging this design, we find results consistent with our baseline results and shift-share IV results, reinforcing the causal inference of TRP's negative effects on firm investment.

Empirical design From 2010 to 2018, the U.S. Department of Defense spent \$248-\$359 billion on procurement spending for products and services, accounting for 1.4%-2.1% of GDP.[67] Importantly, businesses winning the government military contracts are concentrated in a small number of industries, such as aerospace product manufacturing, ship building, and scientific research and development services (Cox et al. (2024) and Barattieri et al. (2023)). The winning of the government military procurement contracts by the **military-related industries** in an MSA quasi-exogenously increases the local demand for relevant talent occupations ($V/E_{m,o,t}$). The heightened demand can thus increase the talent retention pressure for **non-military-related firms** in the same area and dampen their investment. Therefore, our identifying assumption is that changes in $V/E_{m,o,t}$ due to local military-related industries winning government military contracts are unlikely to negatively affect the investment of non-military-related firms in the area through mechanisms other than local talent market competition channel.

[67] See data from the FY 2018 Defense Spending by State from U.S. Department of Defense.

Data Our data source for federal military procurement contracts is www.USAspending.gov, which covers all federal procurement contracts exceeding $25,000. Each entry traces a contract from its issuing agency to the recipient firm and the firm's NAICS industry, as well as the county where the award is executed. We focus specifically on military procurement contracts, as they are less likely to be influenced by national and local macroeconomic conditions than other government expenditures. Between 2010 and 2018, there are 1.979 million unique military procurement contracts per year, with an average spending of $153,435 per contract. The contracts in our database account for about 90% of total U.S. military procurement purchases (Nakamura and Steinsson (2014)).

Based on the data, we categorize *military-related industries* are the top three industries receiving the most military contracts in our sample, including NAICS 3364 (Aerospace Product and Parts Manufacturing), NAICS 3366 (Ship and Boat Building), and NAICS 5417 (Scientific Research and Development Services).[68] Importantly, these industries also employ occupations that are talent in many other industries, such as Industrial Engineers, Computer and Information Analysts, and General and Operations Managers.

Next, we categorize *non-military-related industries* as other NAICS 4-digit industries without any input-output connection to the three military-related industries, i.e., industries outside the top three customer and supplier industries of each of the three military-related industries. Finally, we classify the rest industries as irrelevant and exclude them from our analyses. We next construct a military-spending-based instrument for the TRP of non-military-related firms in our Compustat firm sample of 9,444 firm-year observations.

Instrumenting TRP of non-military-related firms We construct the instrument for non-military-related firms' TRP in three steps. First, we measure local military procurement spending, $S_{m,t}$, as total military procurement contracts in dollars received by military-related

[68]These three industries account for more than 40% of total military contracts in dollar amount. Results are qualitatively similar if we expand this classification to the top five or ten industries as shown in Panels B and C in Table IA.16, which collectively account for more than 50% and 70% of total military contracts in dollar amount, respectively.

industries in the MSA m in year t normalized by the industries' total employment in the MSA-year.

Second, following the literature, we compute the fitted value of MSA-occupation-level V/E ratio by regressing $\frac{V_{m,o,t}}{E_{m,o,t}}$ on the local military spending $S_{m,t}$, while allowing for different sensitivities of occupations' V/E ratios to local military spending (Nakamura and Steinsson (2014)) and different average level of talent markets' tightness (Nekarda and Ramey (2011) and Belenzon and Cioaca (2021)). Specifically, our specification is as follows:

$$\frac{V_{m,o,t}}{E_{m,o,t}} = \sum_{o} \beta_o \cdot \mathbb{1}_o \times \ln\left(S_{m,t} + 1\right) + \psi_{m,o} + \epsilon_{m,o,t}.^{69} \tag{IA.0.1}$$

Third, combining the fitted value $\widehat{\frac{V_{m,o,t}}{E_{m,o,t}}}$ estimated from equation (IA.0.1) with firm talent shares across MSA-occupation, $s_{f,m,o,t}$, we obtain a military-spending instrument for TRP for non-military-related firms as:

$$\mathrm{IV}^{\mathrm{Mil}}_{f,t} = \sum_{m,o} s_{f,m,o,t} \times \widehat{\frac{V_{m,o,t}}{E_{m,o,t}}}. \tag{IA.0.2}$$

2SLS results We examine non-military-related firms' investment response to TRP instrumented by $\mathrm{IV}^{\mathrm{Mil}}_{f,t}$, using 2SLS regressions based on the specification of equation (5). To control for industry heterogeneity associated with national military procurement spending, we include industry-year fixed effects. The findings align with our panel regression results. In Table IA.16, we observe that TRP induced by military spending in the top three military-related industries dampens physical investment in firms without any input-output connection to the military-related industries. A one-standard-deviation increase in TRP reduces firm physical investment by around 8% of the average investment rate (Panel A Column 2). This economic

[69] Occupations with higher β_o are those with job postings more sensitive to military-related industries winning government contracts. In the data, we observe some of these occupations are employed and considered talent in a wide range of industries, such as Computer and Information Research Scientists, Actuaries, Aerospace Engineers, Biomedical Engineers, Marine Engineers and Naval Architects, and Survey Researchers, suggesting that military procurement spending shocks can potentially impose talent retention pressure on firms from other industries.

magnitude aligns with the range observed in our baseline results and shift-share instrument findings. Finally, Column 3 of Panel A shows that the instrumented TRP also dampens firm total investment, although the statistical significance is weaker. In summary, the consistent findings under the shift-share instrument, which leverages occupations' national V/E ratio, and also the military-spending-based instrument, which leverages quasi-exogenous shocks to local military-related industries, strongly support the causal effect of TRP on firm investment.

IA.6: Examining Occupational Mobility

In this section, we explore how our results are affected by occupational mobility, i.e., the probability of a talent employee switching out of her current occupation (Schubert et al. (2025)). To empirically examine the relevance of talent mobility, we begin by measuring each talent occupation's job switching probability ($SwitchProb_o$) using Revelio Labs individual panel data from 2010 to 2018. Combining the occupational $SwitchProb_o$ with firms' occupation distribution in the BLS data, we measure firms' talent cross-occupation mobility ($TCOM$) as the average of $SwitchProb_o$ for their talent:

$$TalentCrossOccMobility(TCOM)_{f,t} = \frac{\sum_o Emp_{f,o,t} \times SwitchProb_o}{\sum_o Emp_{f,o,t}}.$$

In Internet Appendix Table IA.19, we find some evidence that TRP's effects on firm investments are strong and significant among firms with low-$TCOM$, consistent with the view that our measurement captures labor market tightness for low-mobility occupations; on the other hand, the coefficient of TRP for firms with high-$TCOM$ is also negative and large, although statistically insignificant. A T-test of the coefficients between low-$TCOM$ and high-$TCOM$ suggests they are not statistically different.

One caveat is that our results can be affected by measurement noise due to data limitations. Specifically, Revelio Labs microdata covers only 382 out of over 800 occupations. We discuss in the Internet Appendix IA.3 that this data limitation is non-trivial as it systematically misses certain talent occupations in certain industries. Hence, we need to impute the switching probability for occupations not covered in the Revelio Labs data. The procedure makes our split of high- and low-$TCOM$ less precise, which could affect the findings between the two subsamples.

IA.7: Comparing Economic Magnitudes

In this section, we detail the calculation of the economic magnitudes of TRP's effects on firm investment, and the comparison with the magnitudes from seven existing studies on the investment effects of labor variables, including Shen (2021), Bai et al. (2020), Sanati (2025), Tong (2024), Fallick and Hassett (1999), Silva (2021), and Jeffers (2023).

Magnitudes of TRP's Investment Effects: Table I shows that the sample standard deviation of firms' TRP is 0.144, the sample mean of firms' physical investment rate is 5.002 percentage points (pp.). Using these two statistics and regression coefficients, we estimate that a one-standard-deviation increase in firm TRP reduces firm physical investment rate by **0.21pp.** in the baseline case, and by 0.37pp.∼0.77pp. when estimated using instruments. This range of magnitudes corresponds to **4.24%∼15.41% of the sample mean of physical investment rate**. Detailed calculations are provided below, and all estimates are summarized in Panel A of Table IA.20:

- **Baseline TRP**: From Table IV, we observe that a 1-SD increase in TRP leads to a $0.21pp. = 1.472 \times 0.144$ decline in physical investment rate. This effect corresponds to a **4.24%** $= 0.21pp./5.002pp.$ decline relative to the sample mean investment rate of $5.002pp.$
- **TRP (Shift-share IV)**: From Table V, we observe that a 1-SD increase in TRP, esti-

mated from the 2SLS using the shift-share IV, leads to a $0.77\% = 5.352 \times 0.144$ decline in physical investment rate. This effect corresponds to a **15.41%** $= 0.77pp./5.002pp.$ decline relative to the sample mean investment rate of 5.002%.

- **TRP (Military IV)**: From Panel B of Table IA.16, we observe that a 1-SD increase in TRP, estimated from the 2SLS using the IV based on local government military procurement spending shocks, leads to a $0.37pp. = 2.595 \times 0.144$ decline in physical investment rate, depending specifications of the shocks. This effect corresponds to a **7.47%** $= 0.37pp./5.002pp.$ decline relative to sample mean investment rate of 5.002pp.

Using a similar procedure, we estimate that a one-standard-deviation increase in firm TRP reduces firm total investment rate by **0.29pp.** in the baseline case and 0.65pp.∼1.62pp. when estimated based on instruments. This range corresponds to **1.64%∼9.08% of the sample mean of total investment rate**. More details of the estimates are summarized in Panel B of Table IA.20.

Magnitudes in the Literature Several recent studies examine the effect of labor variables and firm investment using specific policy shocks. These estimates ofthen reflect the local average treatment effects (LATE) based on the responses of "compiler firms" that are specific to the shocks rather than the average treatment effects (ATE) across all firms. Nevertheless, we show that the magnitudes of our TRP's investment effects lie within the range of magnitudes reported in these studies. Panel C of Table IA.20 reports each study's economic magnitudes. Below, we detail our calculation of the magnitudes:

1. **Skilled Labor Mobility (Shen, 2021)**: Shen (2021) estimates shocks to mobility of firms' skilled foreign-born labor using Green Card allocation imperfections and examines the effects on firm investment rate defined as $(\text{CAPX+R\&D})/\text{AT}_{t-1}$, which has a sample mean of 10.3pp. reported in Table 2. Table 9 of Shen (2021) reports that a 1-SD decrease in the standardized mobility leads to a 0.1pp.∼0.2pp. increase in raw investment rate. This effect corresponds to a **1%∼2%** increase relative to the sample

mean investment rate of 10.3pp., which is reported as the headline magnitudes on page 4693.

2. **Labor Protection (Bai et al., 2020)**: Bai et al. (2020) estimate shocks to labor protection based on states' adoption of Wrongful Discharge Laws and examine the effects on firm investment rate defined as CAPX/AT$_{t-1}$, which has a sample mean of 8.33pp. (as reported in their Table 2). The standard deviation of their main explanatory variable, *Good faith*, is 0.41 (also reported in Table 2). From Table 3 of Bai et al. (2020), we can calculate that a 1-SD increase in labor protection leads to a $0.22pp. = 0.54 \times 0.41$ decrease in raw investment rate, or **2.66%**$=$ $(0.22pp./8.33pp.)$ relative to the sample mean investment rate. Bai et al. (2020) report economic magnitudes in terms of the state law change dummy instead of a 1-SD change, resulting in a higher headline number of 6.5% on page 662.

3. **Unionization (Fallick and Hassett, 1999)**: Fallick and Hassett (1999) estimate the effects of union certification elections on firm investment, where firm investment rate is defined as I/K in Cummins et al. (1994). The mean of investment rate in the preferred sample can be calculated from statistics in Tabe 1 as $17.91pp. = 0.18 \times (2102/(2102 + 38)) + 0.13 \times (38/(2102 + 38))$. The sample standard deviation of the key independent variable YESWIN can be computed from Table 1 as well, 0.132. Table 3 (row 3) reports the regression estimates which indicate that a 1-SD increase in unionization leads to a $0.61pp. = 0.046 \times 0.132$ decrease in raw investment rate. This effect corresponds to a **3.39%**$=$ $0.61pp./17.91pp.$ decrease relative to the mean investment rate.

4. **Wage Convergence Pressure (Silva, 2021)**: Silva (2021) estimates the effects of wage convergence pressure on firm investment, where wage convergence pressure is computed as the average wage rate of the firm's other divisions using the Census microdata. Firm investment rate is defined as CAPX/SALES in the Census microdata, which has a sample mean of $3.423pp.$ as reported in Table 1. The sample standard deviation of wage convergence pressure (log(FIRM_WAGE)) is 1.619, also reported in

Table 1. Table 8 (Column 3) reports the regression estimates which indicates that a 1-SD increase in wage convergence pressure leads to a $0.5pp. = 0.309 \times 1.619$ increase in raw investment rate to substitute labor with capital. This effect corresponds to a **14.60%**$= 0.50pp./3.423pp.$ increase relative to the mean investment rate.

5. **Labor Mobility (Sanati, 2025)**: Sanati (2025) estimates the effects of labor mobility on firm investment, where mobility is instrumented by state courts' changes in stand on the inevitable disclosure doctrine and firm investment rate is defined as (CAPX + AQC -SPPE)/AT. The sample standard deviation of firms' labor mobility is 0.327. Table 7 (Column 4) of Sanati (2025) uses the full sample and indicates that a 1-SD increase in mobility leads to a $1.99pp. = (0.065 - 0.004) \times 0.327$ decrease in raw investment rate for high skill firms. Given that the sample mean investment rate for high skill firms is 11.0 percentage points (pp.) as reported in Table 4, this effect corresponds to a **18.13%**$= 1.99pp./11.0pp.$ decrease relative to the mean investment rate.

6. **Worker Health Care Costs (Tong, 2024)**: Tong (2024) examines the investment effects of increases in health insurance market concentration which increases firms' health care costs paid to workers. Firm investment is defined as the sum of CAPX and R&D divided by lagged total assets, which has a sample mean of 11.4pp. as reported in Panel B of Table 1. Based on estimates in Table 7, the paper states that a 1-SD increase in the concentration measure *leads to 6.5% increase in average health costs* (page 1103), and *a 1% increase in average health care costs is associated with a 0.8% decrease in the total investment level* (page 1104). We can thus compute that a 1-SD increase in the health care insurance market concentration leads to **5.2%**$= 6.5 \times 0.8\%$ decrease in firm investment rate relative to the sample mean. Using the coefficient in Table 7 (Column 4), we can infer that the 1-SD effect on the investment rate translates to $0.59\text{pp.} = 6.5\% \times 0.09$. Note that this magnitude is based on 1-SD of the changes in health insurance market concentration instead of changes in firms' log(average insurance expense), as the paper does not provide the standard deviation of the key independent

variable.

7. **State Adoption of NonCompete Clause (Jeffers, 2023)**: Jeffers (2023) estimates the effects of state adoption of noncompete clause on firm investment rate defined as (CAPX-SPPE)/AT_{t-1}, which has a sample mean of 3%. Jeffers (2023) does not report magnitudes in terms of 1-SD changes but in terms of state adoption of noncompete. Based on results in Table 4, Jeffers (2023) estimates that state adoption of noncompete increases knowledge firms' physical investment by **34% to 39%** of the sample mean investment rate, which are reported as the headline numbers on page 28.

In summary, these studies suggest that a one-standard deviation change in labor-related variables may affect firm investment by 1% to 18% of the sample mean. The baseline estimates of our TRP's effect is 1.6% for total investment and 4.2% for physical investment. These estimates appear to be in the similar order of magnitude with those found in the literature. Our estimates based on instruments, which ranges from 3.66% to 15.41% of the sample mean (depending on the instruments and investment variables), appear to join the higher IV estimates from the literature.

Why the Magnitudes from IV Estimates Are Larger than OLS's? TRP's effect on firms' physical investment estimated from our shift-share IV is 3.6 times that estimated from the OLS, and 1.8–2.1 times larger using the military-procurement IV. 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}. Hence, relative to the literature, the "amplification effect" of IV in our case lies at the lower end of the range from prior studies. In what follows, we shed light on the discrepancy between our shift-share IV estimates and the OLS estimates.

Fully diagnosing why IV estimates generate greater magnitudes than OLS is challenging and case-specific. Jiang (2017) offers two diagnostic tests to enhance the transparency of the instrument estimates. First, instruments can be weakly correlated with TRP, which could inflate the IV magnitudes in a finite sample.[70] This "weak instrument" argument is unlikely the reason for our case though, as Table V shows that the first-stage F-statistic is much greater than the rule of thumb threshold of 10. In addition, we examine our instrument's potency by reporting the partial R^2 of the instrument on TRP. Internet Appendix Table IA.10 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.[71]

Second, Jiang (2017) emphasizes the importance of investigating the economic reasons for why β_{IV} exceeds β_{OLS}. Two explanations are relevant in our setting. First, if TRP's effects are heterogeneous across firms, and firms with investments most responsive to TRP are more likely to be picked up by the IV, then the IV estimates naturally yield a greater magnitude than the OLS estimates which captures the average responses across all firms. This is the amplification of IV estimates due to the "complier effects". If the "complier effect" explanation drives the magnitude difference, then, we should view the OLS magnitude to be closer to the true magnitude, as our focus is on estimating the average effect across all firms rather than just the compliers. A second possibility is that the IV addresses endogeneity or measurement error in TRP. If local economic shocks simultaneously drive job postings and firms' investment decisions in offsetting ways, OLS estimates may be attenuated, and IV magnitudes may more closely reflect the true effect.

Methodologies for separating heterogeneous treatment effects from the endogeneity effects in explaining the gap between IV estimates and OLS estimates are still inconclusive to the best of our knowledge. A recent study by Ishimaru (2024) develops an econometric framework to empirically decompose the IV-OLS coefficient gap in linear regressions when the true causal effects of the treatment are nonlinear in treatment intensity and heterogeneous across observations (e.g. Card (1999, 2001a); Angrist and Krueger (1991)). The difference between IV and OLS estimates can be attributed to three sources. First, when the impact of TRP

[70] The intuition is that $\beta_{IV} = \frac{\widehat{Cov(z,y)}}{\widehat{Cov(z,x)}}$, so a low dominator can inflate β_{IV}.

[71] 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).

on investment is heterogeneous across firms, years, and other observables, both IV and OLS estimates can be interpreted as weighted averages of heterogeneous treatment effects. OLS assigns greater weight to observations with larger variation in the baseline TRP (Angrist and Krueger, 1999), while IV places greater weight on observations where the instrument is more strongly correlated with baseline TRP or exhibits greater variation. Consequently, IV and OLS estimates may diverge because they apply different weighting schemes, with variation in the baseline TRP and in the shift-share IV potentially arising from different sets of observations (i.e. complier effect). Second, if TRP has a nonlinear effect on investment, the estimates may diverge when baseline TRP and the shift-share IV vary at different treatment levels. Finally, any residual gap between IV and OLS may reflect endogeneity bias in OLS or measurement error in either variable.[72]

We implement the decomposition of Ishimaru (2024) and find that for the effects on physical investment, the IV-OLS gap of $\beta_{IV} - \beta_{OLS} = -3.983$ can be decomposed into

$$\begin{aligned}\beta_{IV} - \beta_{OLS} &= 45.37\% \text{ (difference in weights due to heterogeneous responses)}\\ &+ 0.03\% \text{ (difference in weights due to nonlinear responses)}\\ &+ 54.59\% \text{ (residual)},\end{aligned}$$

and for total investment, the gap of $\beta_{IV} - \beta_{OLS} = -9.259$ can be decomposed into

$$\begin{aligned}\beta_{IV} - \beta_{OLS} &= 52.17\% \text{ (difference in weights due to heterogeneous responses)}\\ &+ 0.05\% \text{ (difference in weights due to nonlinear responses)}\\ &+ 47.78\% \text{ (residual)}.\end{aligned}$$

For both investment effects, we observe that heterogeneous responses explain about half of differential magnitudes between IV and OLS and the rest half is due to the residual, while the nonlinear effects has near to zero contribution to the gap.

[72] Based on this intuition, Ishimaru (2024) develops a Stata package "ivolsdec" to decompose the IV-OLS gap available at https://sites.google.com/view/ishimaru/home/ivolsdec.

Online Appendix Table IA.23 reports the decomposition results. Following equation 5, both specifications include the full set of controls, firm fixed effects, and year fixed effects, allowing for heterogeneous treatment effects across firms and over time, as well as by firm size, Tobin's q, cash flow, and age. The decomposition further includes a quadratic term in TRP to capture nonlinearities in treatment effects and results are robust to adding a cubic term. Column 1 reports the IV–OLS coefficient gap with respect to investment, comparing estimates based on the shift-share IV (Table V) and the baseline TRP (Table IV).[73] Columns 2–4 decompose the IV–OLS difference into three components: (i) complier effects due to differences in weights with heterogeneous treatment effects, (ii) differences in weights across treatment levels under non-linear effects, and (iii) a residual component potentially reflecting endogeneity biases in OLS estimations or measurement errors in either variables. The results suggest that 45 to 52 percent of IV-OLS coefficient gap is explained by heterogeneous treatment effects, with IV estimates placing greater weight on observations where investments are more sensitive to TRP shocks.

Headline Number of Economic Magnitude of TRP: In summary, these analyses suggest that endogeneity bias and measurement errors in the TRP is unlikely to fully explain the larger magnitudes of IV relative to the OLS. Instead, the different weightings between IV and OLS estimates likely play a sizable role as well. This suggests that the magnitudes from the shift-share IV approach may be too large for our goal of estimating the average effects across all firms. Another side evidence supports the shift-share IV magnitudes to be too large is that our magnitudes estimated from an alternative IV based on government military procurement spending yields an IV-OLS gap less than half of the size of that for the shift-share IV (see Internet Appendix Table IA.16). Given these results, we view that the range between OLS and IV estimated magnitudes appears to be a proper way to present the economic magnitude of TRP on firm investment—a one-standard-deviation increase in TRP

[73]Note that $\beta_{IV} - \beta_{OLS}$ is slightly different from directly subtracting the coefficient of 2SLS(TRP) in Column (1) of Table V with the coefficient of TRP in Column (2) of Table IV, as the framework of Ishimaru (2024) re-estimates $\beta_{IV} - \beta_{OLS}$ using the sample of firms with non-missing TRP and shift-share IV measures.

reduces firm physical investment by 4.2% $\sim$ 15.4% relative to the sample mean and reduces firm total investment by 1.6% $\sim$ 9.1% relative to sample mean.

IA.8: Implications for Industry Concentration

Our findings in Section VI.A suggest that the rising talent retention pressure significantly dampens the investment 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 NAICS 4-digit industry's top 4 concentration ratio (CR4) as the sales share of the top 4 firms in the industry based on the Compustat universe.[74] We next compute the median value of firms' TRP and other firm control variables within each NAICS 4-digit industry in the year (Gutiérrez and Philippon (2018)).[75] A large body of literature suggests that firm investment takes some time to become productive, reflecting the time-to-build feature of investment (Kydland and Prescott (1982)). Therefore, we hypothesize that heterogeneous investment responses between laggard and superstar firms at $t+1$ are more likely to manifest in industries' sales concentration ratios at $t+2$. We test this hypothesis by estimating the following regression at the industry-year level:

$$\mathrm{CR4}_{i,t+2} = \beta \cdot \mathrm{TRP}_{i,t} + X_{i,t} + \mathrm{IndFE} + \mathrm{YearFE} + \epsilon_{f,t}. \tag{IA.0.3}$$

Supporting our hypothesis, we observe in Table IA.24 a positive relationship between industry concentration in the later year and their median TRP in the current year. This

[74] Concentration ratio is commonly used to measure industry concentration (see Opler and Titman (1994), Hou and Robinson (2006), Bustamante and Donangelo (2017), Gutiérrez and Philippon (2018) and many others). We follow Gutiérrez and Philippon (2018) and construct industries' CR4 by requiring the industry to have more than 5 firms in the Compustat database. Results are similar if we do not include this filter.

[75] 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. To balance this, we use firms' total assets to weight the median calculation. Results are similar if we use firm employment as the weight.

suggestive evidence offers a cautionary note that talent market competition could potentially contribute to rising industry concentration by dampening the growth of laggard firms but not superstar firms. However, 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.

IA.9: Implications for Lackluster U.S. 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.[76] In this section, we explore the contribution of rising TRP to the widening investment-Q gap.

1. A Model of TRP and Lackluster Investment

We start by providing a simple model to convey the intuition that the rising talent market competition can dampen the average firm's capital investment and widen the average firm's investment-Q gap a la Gutiérrez and Philippon (2017).[77]

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

[76] 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 (2025) 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.

[77] In this model, we do not consider the heterogeneity between superstar and laggard firms, which we leave for future theoretical studies.

adjustment costs $C(I_0, k_0) = \frac{\beta}{2}\left(\frac{I_0}{k_0}\right)^2 k_0$. Capital accumulates as follows:

$$k_1 = (1-\delta)k_0 + I_0, \tag{IA.0.4}$$

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.[78] 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.[79] Motivated by numerous prior micro-level findings on voluntary employee turnover, we assume that the firm cannot change employee satisfaction in the short run for simplicity.[80] Without loss of generality, we assume talent satisfaction is uniformly

[78]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.

[79]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.

[80]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

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.[81] 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:

$$\underbrace{\left(\frac{V_0}{sN_0}\right)^{\gamma}\left(\frac{1}{2} - s\right)}_{\text{marginal benefit of OJS}} = \underbrace{c}_{\text{marginal cost of OJS}}. \tag{IA.0.5}$$

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

when their talent's outside job options expand.

[81] 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.

We next define a firm's *talent retention pressure*, ψ, as the average probability for each of its talents 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.[82] The firm's number of talent thus evolves as follows:

$$n_1 = (1 - \psi) n_0 + \frac{\psi N_0}{V_0} v_0^{'}. \tag{IA.0.6}$$

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.[83] We assume that a new hire's productivity is $\rho < 1$ times the productivity of an existing employee (Silva and Toledo (2009)).[84] As a result,

$$y_1 = k_1^{\alpha} \left[a_1 (1 - \psi) n_0 + \rho a_1 \frac{\psi N_0}{V_0} v_0^{'} \right]^{1-\alpha} \tag{IA.0.7}$$

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

$$\max_{v_0^{'}, I_0} \; \mathcal{V}_0 = y_0 - w_0 n_0 - I_0 - \frac{\beta}{2} \left(\frac{I_0}{k_0} \right)^2 k_0 - \kappa v_0^{'} + r E_0 [y_1 - w_1 n_1], \tag{IA.0.8}$$

subject to equations (IA.0.4), (IA.0.6), and (IA.0.7).

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

[83] 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 the annual pay while the indirect costs are also high.

[84] Internet Appendix Table VII provides further evidence that firms' average talent productivity is lower following higher talent retention pressure.

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*). Therefore, 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: The first order condition of equation (IA.0.8) 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

$$\left[1 + \beta \frac{I_0}{k_0} \right] [(1-\delta)k_0 + I_0]^{1-\alpha} = r\alpha E_0[a_1^{1-\alpha}][1 - (1-\rho)\psi]^{1-\alpha} n_0^{1-\alpha}. \qquad \text{(IA.0.9)}$$

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

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

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,[85] 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 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 (IA.0.4)) and talent (equation (IA.0.6)) into a Lagrangian function of firms' optimization problem.

$$L = \left[rE_0[a_1^{1-\alpha}]k_1^{\alpha}\left[(1-\psi)n_0 + \rho(n_1 - (1-\psi)n_0)\right]^{1-\alpha} - w_1 n_1\right] - I_0 - \frac{\beta}{2}\left(\frac{I_0}{k_0}\right)^2 k_0 - \kappa v_0^{'}$$
$$- q_k\left[k_1 - k_0(1-\delta) - I_0)\right] - q_n\left[n_1 - n_0(1-\psi) - \frac{\psi N_0}{V_0}v_0^{'}\right].$$

[85] 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 first order conditions with respect to k_1 and n_1 results in:

$$\left[\frac{q_n + w_1}{(1-\alpha)\rho}\right]^{\frac{1}{\alpha}} = \left(\frac{q_k}{\alpha}\right)^{\frac{1}{\alpha-1}}.$$

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.

2. *Implications for Firm and Aggregate Investment-Q Gap*

Dynamics of firms' TRP and impulse responses Consistent with the public notion that firms are increasingly concerned about talent retention, we observe in Panel A of Figure 3 that the cross-sectional median TRP for firms doubled from 2010 to 2018.[86] Reinforcing this finding, we observe similar trends in other data. In Panel B, firms increasingly highlight talent retention and attraction in their SEC 10-K annual reports. Similarly, in Panel C, a growing number of firms identify these issues as their top internal concerns in the Duke CFO Survey.

The extent to which rising TRP can contribute to the dynamics of firm investment also depends on the persistence of TRP and its effects. In particular, if TRP has a short half-life, one may expect firms to delay investment, resulting in longer-term reversals in investment. We have shown earlier that TRP is positively autocorrelated within a firm, with a within-firm autocorrelation of 0.42 corresponding to 0.8 years of half-life.[87] In Figure IA.4, we estimate

[86]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.

[87]To be most consistent with our empirical impulse response analysis later that includes firm fixed effects, we

reduced-form impulse responses of TRP on firms' talent outflows and investment based on local projections. Consistent with the persistence of TRP, we observe that TRP persistently predicts a high yearly outflow rate and low yearly investment for firms over the next 2 years, and the effects diminish at $t+3$. Importantly, we do not observe immediate reversals of the effects, suggesting that the rising TRP tends to persistently dampen investment at the firm level.[88]

Rising TRP and widening investment-Q gap After examining the features of firms' TRP, we now explore the implications for aggregate investment. Whether TRP has contributed to the lackluster *aggregate* investment in the past decade is ultimately a quantitative question. On the one hand, the significantly increased firm-level TRP can lead to a widening investment-Q gap for an *average* firm, as we demonstrate in an extended theoretical framework above. On the other hand, our findings in Section VI.A show that large superstar firms' investment is inelastic to TRP. Since superstar firms dominate aggregate investment, the rising TRP may not contribute to the *aggregate* investment trends.

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.,

$$\mathrm{Inv}_{f,t+1} = \sum_{s} \beta_s \cdot \mathrm{YearDummy}_s + \alpha \mathrm{Q}_{f,t} + \mathrm{FirmFE} + \epsilon_{f,t}. \tag{IA.0.10}$$

The coefficients for the year dummies, β_s, represent the trend of the investment-Q gap without considering the impact of TRP. We call this estimation the baseline Q model. We next run

report the within-firm autocorrelation by first demeaning TRP within the firm and then compute the standard autocorrelation using the demeaned TRP. The full sample autocorrelation of TRP without demeaning within the firm is 0.76.

[88] In addition, we also observe from Figure IA.4 that TRP is not significantly associated with firms' investment or talent outflow rate at $t-1$, mitigating the concerns about reverse causation.

the same regression but control for TRP, i.e.,

$$\text{Inv}_{f,t+1} = \sum_{s} \zeta_s \cdot \text{YearDummy}_s + \alpha \text{Q}_{f,t} + \gamma \text{TRP}_{f,t} + \text{FirmFE} + \epsilon_{f,t}. \tag{IA.0.11}$$

The coefficients for the year dummies in this model, ζ_s, represent the trend of the investment-Q gap accounting for 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 IA.5 shows the results. Panel A plots the estimates of β_s and ζ_s and the standard error bars for the average firm, and Panels B and C display 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;[89] 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 IA.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 on firms, it is essential to examine granular firm-level data.

[89] 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.

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

This table reports two labor market characteristics of talent (see Section II.C for the definition of industry-specific 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 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 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 they are not employed by the same employer and the same job they reported working as his/her main job in the previous month's survey, 2) those who were in unemployment or not in the labor force in month $t-1$ but was employed in month $t-2$, and 3) those who were in unemployment or not in labor force both in month $t-1$ and $t-2$ but were employed in month $t-3$. Conditional on having a job, employees are considered as movers from non-employment in month t if they were in unemployment or not in the 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
Comparison: TRP based on Within-Industry vs. Uniform Classifications

This table reports the results of regressing firms' concerns about talent competition mentioned in their 10-K annual reports on their contemporaneous talent retention pressure (TRP) measure in the full sample and two subsamples. We separate firms into two subsamples based on their NAICS 4-digit industries with average talent share above or below the median (i.e., *High-Skilled Industries* or *Low-Skilled Industries*), where talent is defined under the uniform classification. *TRP (baseline)* is based on talent defined using the within-industry rankings of occupations' cognitive skills. *TRP (uniform)* is based on talent defined using the nationwide uniform rankings of occupations' cognitive skills. *Share of Talent-Concern Sentences in 10-K Report* is the percentage of sentences in the firm's 10-K report that mention both talent keywords and competition/retention/attraction keywords (see Section III.C). *Number of Talent-Concern Sentences in 10-K Report* is the number of such sentences in the firm's 10-K report in the year. Industry is classified at the NAICS 4-digit level. See Table I for definitions of all 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. For ease of comparison, variables in each sample are standardized to have a mean of zero and a standard deviation of one.

	All	Low-Skilled Industries	High-Skilled Industries	All	Low-Skilled Industries	High-Skilled Industries
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Share of Talent-Concern Sentences			
TRP (baseline)	0.050***	0.051*	0.048**			
	(0.017)	(0.027)	(0.022)			
TRP (uniform)				0.034**	0.016	0.046**
				(0.016)	(0.029)	(0.020)
			Panel B: Number of Talent-Concern Sentences			
TRP (baseline)	0.106***	0.109***	0.094***			
	(0.022)	(0.036)	(0.024)			
TRP (uniform)				0.059***	0.043	0.070***
				(0.019)	(0.035)	(0.021)
Year-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.3
Examples of Industry Talent Not Captured by Uniform Classification

This table presents examples of occupations that are key employees in firms' 10-K annual reports but not captured by the uniform classification of talent discussed in Section II.A. These examples are obtained by extracting 10-K paragraphs containing talent keywords (see Section III.C), followed by analysis using GPT 4o-mini to identify corresponding SOC 6-digit occupations and manual verification checks. See more details in the Internet Appendix IA.4.

Limited Service Restaurants (NAICS 7221)	
Chefs and Head Cooks (SOC 35-1011)	"Our ability to expand our business successfully will depend upon numerous factors, including: hiring, training and retaining skilled management, **chefs** and other qualified personnel to open, manage and operate new restaurants..." — Mccormick & Schmick's Seafood Restaurants, Inc. (2009 Annual Report)
Metal Ore Mining (NAICS 2122)	
Geoscientists, Except Hydrologists and Geographers (SOC 19-2042)	"...we compete for resources such as professional **geologists**, camp staff, helicopters and mineral exploration supplies. [...] It is our intention to also retain a North American educated **geoscientist** to evaluate and conform to American standards." — Oro East Mining, Inc. (2011 Annual Report)
Cut and Sew Apparel Manufacturing (NAICS 3152)	
First-Line Supervisors of Retail Sales Workers (SOC 41-1011)	"Successful implementation of this portion of our growth strategy depends on a number of factors including, [...] our ability to hire, train and retain qualified **store managers**..." — American Apparel, Inc. (2012 Annual Report)
Navigational, Measuring, Electromedical, and Control Instruments Manufacturing (NAICS 3345)	
Electronics Engineers, Except Computer (SOC 17-2072)	"The success of the Company's business therefore depends on its ability to attract and retain engineers and other technical personnel. There are a limited number of **microwave engineers**. [...] Competition for such personnel is intense." — ORBIT/FR, Inc. (2010 Annual Report)
Utility System Construction (NAICS 2371)	
First-Line Supervisors of Construction Trades and Extraction Workers (SOC 47-1011)	"...To preserve our project management and technological expertise as core competencies, we continuously recruit and develop qualified personnel, and maintain ongoing training programs for engineers and **field supervision** and craft personnel.." — Chicago Bridge & Iron Company (2011 Annual Report)
Health and Personal Care Stores (NAICS 4461)	
Pharmacists (SOC 29-1051)	"...our continued success depends on our ability to attract and retain **pharmacists** and other pharmacy professionals. Competition for qualified **pharmacists** and other pharmacy professionals is strong." — Omnicare, Inc. (2009 Annual Report)
Specialized Freight Trucking (NAICS 4842)	
Heavy and Tractor-Trailer Truck Drivers (SOC 53-3032)	"Difficulty in attracting and retaining drivers could negatively affect our operations and limit our growth. There is substantial competition for qualified personnel, particularly **drivers, in the trucking industry.**" — Patriot Transportation Holding, Inc. (2016 Annual Report)

Table IA.4
Robustness: Main Results Using Alternative Talent Definition Based on Uniform Classifications of Occupations by Cognitive Skills

This table reports our baseline investment results using an alternative definition of talent, which is based on ranking occupations uniformly across industries rather than within the industry as in the main analysis. To construct this alternative talent measure, we first compute each SOC 5-digit occupation's cognitive skills following our baseline approach in Section II.A. Then, we rank occupations by their cognitive skills in the U.S. economy (instead of within-industry in our baseline measure) each year, and we classify an occupation as talent if it ranks in the top 10% of the ranking. We then construct a firm-level talent retention pressure (*TRP_Alt*) based on this new talent definition. Panel A shows the results of our main investment test in Table IV. Panel B shows the results of the heterogeneous investment effects between superstar and laggard firms in Table VIII. 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. See the Internet Appendix IA.1 for more discussions.

	Panel A: Baseline Investment Results				*Panel B: Superstar vs. Laggard*	
	Physical Investment		Total Investment		Physical	Total
	(1)	(2)	(3)	(4)	(5)	(6)
TRP_Alt	-1.070***	-1.177***	-1.422**	-1.607**	-1.346***	-1.853**
	(0.405)	(0.363)	(0.702)	(0.784)	(0.380)	(0.826)
TRP_Alt × Superstar					2.190***	3.052**
					(0.767)	(1.492)
Superstar					-1.096**	-0.669
					(0.445)	(0.750)
Firm Control	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	N	Y	N	N	N
Year-Industry FE	N	Y	N	Y	Y	Y
Observations	11,661	11,070	10,281	9,705	11,070	9,705
Adjusted R^2	0.721	0.761	0.809	0.814	0.761	0.814

Table IA.5
Correlation Matrix of Firm-Level Variables

This table presents the correlation matrix of the variables in our Compustat firm sample from 2010 to 2018. Section II details our sample selection. *TRP* is the firm's talent retention pressure constructed as the average vacancy-to-employment ratio for MSA-occupations (excluding the firm's own vacancy) weighted by the firm's talent distribution across MSA-occupations in the year (see equation (1)). *Talent Outflow Rate* is the number of talent leaving the firm next year divided by the total number of talent this year and multiplied by 100 using the Revelio Labs microdata. *Talent Growth Rate* is the net changes in the number of talent from this year to next year divided by the firm's total number of talent this year and multiplied by 100 using the Revelio Labs microdata. *Talent Wage Rate* is the natural logarithm of the average hourly wage rate of the firm's talent from the BLS OEWS microdata. *Talent Promotion Rate* is the percentage of talent employees in the firm experiencing an increase in seniority (promotion) in the Revelio Labs microdata. *Talent Job Posting* is the natural logarithm of one plus the firm's number of job postings for talent in the year from the Lightcast data. *Physical Investment* is next year's capital expenditure (#CAPX) divided by this year's total assets (#AT) and multiplied by 100. *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) and multiplied by 100. 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). *Cash Flow* 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(11)	(12)	(13)
(1) TRP												
(2) Talent Outflow Rate	0.156											
(3) Talent Growth Rate	-0.032	-0.412										
(4) Talent Job Posting	0.039	0.033	-0.026									
(5) Talent Wage Rate	0.334	0.024	0.004	-0.186								
(6) Talent Promotion Rate	0.165	0.196	0.045	0.114	0.107							
(7) Physical Investment	-0.093	0.080	0.212	0.009	-0.101	0.028						
(8) Total Investment	0.108	0.422	0.349	-0.074	0.136	0.236	0.285					
(9) Q	0.080	0.254	0.284	0.014	0.060	0.223	0.515	0.099				
(10) Total Q	0.091	0.264	0.308	0.063	0.055	0.222	0.579	0.062	0.821			
(11) Cash Flow	-0.085	-0.156	0.027	0.205	-0.155	-0.099	-0.135	0.150	0.086	0.005		
(12) Size	0.056	-0.192	-0.028	0.624	0.044	0.085	-0.235	0.053	0.011	-0.129	0.267	
(13) Age	0.222	-0.169	-0.113	0.123	0.070	0.024	-0.274	-0.082	-0.084	-0.027	0.078	0.157

Table IA.6
Robustness: Talent Market Competition and Job-to-Job Transition

This table shows that known predictors of worker turnovers do not subsume the predictive power of local talent market competition. Columns (1) and (2) report the baseline results of regressing a talent employee's job-to-job (J2J) transition indicator at year $t+1$ on local talent market competition ($V/E_{m,o,t}$) for all Compustat sample (firms in Panel A of Table II) and the sample of firms with talent retention pressure (TRP) measure constructed from the BLS OEWS microdata (firms in Panel B of Table II), respectively. Columns (3)-(6) include proxies for two known predictors of employee voluntary turnover: talent wage premium and talent job satisfaction at t. *Wage Premium* is the ratio of firm f's talent employees' average hourly wage rate in the MSA-occupation and the local average hourly wage rate for the MSA-occupation in the year. The sample standard deviation of talent hourly wage premium proxy is 13.906. $Satisfaction_{f,o,t}$ is the job satisfaction rating provided by firm f's talent employees in occupation o based on the Glassdoor individual review data ranging from 1 to 5. The sample standard deviation of talent satisfaction rate is 0.941. The individual-year-level J2J transition indicator is constructed from the individual's LinkedIn resume data provided by the Revelio Labs. The sample includes a partial list of talent employees of Compustat firms from 2010 to 2018. See more details in Section III.A. Standard errors are clustered at the MSA-occupation level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Individual Talent Job-to-Job Transition$_{t+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$V/E_{m,o,t}$	0.547***	0.700***		0.808***		1.162***
	(0.154)	(0.211)		(0.232)		(0.340)
Wage Premium$_{f,m,o,t}$			-0.015***	-0.015***		
			(0.003)	(0.003)		
Satisfaction$_{f,o,t}$					-0.100***	-0.090***
					(0.030)	(0.030)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,390,758	7,774,598	4,515,301	4,515,301	3,348,662	3,348,662
Adjusted R^2	0.022	0.022	0.023	0.023	0.016	0.016

Table IA.7
Talent Market Competition and Talent Job-to-Job Transition (Weighted)

This table reports the results of regressing talent employees' job-to-job (J2J) transition indicator at year $t+1$ multiplied by 100 on the local talent market competition measure at t, i.e., vacancy-to-employment ratio ($V/E_{m,o,t}$), where a local talent market is defined at the MSA-occupation level. Column (1) reproduces the results in Panel A of Table II, where the regression is equal-weighted across individuals, while Columns (2)-(4) are weighted by the inverse of firms' number of talent to match the firm-level regressions in Panel B of Table II. $V/E_{-m,o,t}$ is the vacancy-to-employment ratio of the individual's occupation from all MSAs except for the individual's MSA, representing talent market competition outside the local area. $V/E_{m,-o,t}$ is the vacancy-to-employment ratio of the individual's occupation from all occupations except for the individual's occupation within the MSA, representing local talent market competition outside the individual's occupation. The sample includes a partial list of talent employees from Compustat firms with LinkedIn profiles from 2010 to 2018 in the Revelio Labs microdata. Standard errors, reported in parentheses, are clustered at the MSA-occupation level in Panel A and the firm level in Panel B. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Individual Talent Job-to-Job Transition$_{t+1}$			
	(1)	(2)	(3)	(4)
V/E$_{m,o,t}$	0.547***	1.312***	1.321***	1.539***
	(0.154)	(0.323)	(0.323)	(0.396)
V/E$_{-m,o,t}$			-0.443	
			(1.347)	
V/E$_{m,-o,t}$				-0.330
				(0.490)
Weighted	N	Y	Y	Y
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Observations	26,390,758	26,390,758	26,390,758	26,390,758
Adjusted R^2	0.022	0.065	0.065	0.065

Table IA.8
Robustness: Talent Retention Pressure and Firm Concerns in 10-Ks

This table shows the results of regressing various alternative measures of firms' talent concerns in their 10-K annual reports on their talent retention pressure (TRP). *Alternative Type of Measure* represents the cluster of alternative measures based on the total word count of talent-concern sentences and the share/number/word count of talent-concern paragraphs in a firm's 10-K annual report. *Using Conservative "Talent" Keywords* represents the alternatives of baseline measures using only conservative keywords for talent in List 1: "talent", "essential", "key", "core", "skill", "important", "best", "top", and "exceptional". These alternative measures exclude keywords such as "qualified", "experienced", "professional", "competent", and "capable" when identifying firms' talent-concern sentences in 10-K annual reports. *Using Conservative "Retention" Keywords* represents the alternatives of baseline measures using only "retention"-related or "competition"-related keywords in List 3 but not "recruiting" or "attraction"-related keywords. 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 Variables from 10-Ks	(1)	(2)	(3)
Share of Talent-Concern Sentences (Baseline)	0.135***	0.129***	0.061***
	(0.021)	(0.021)	(0.021)
Number of Talent-Concern Sentences (Baseline)	3.590***	3.089***	1.673***
	(0.393)	(0.383)	(0.401)
Total Words of Talent-Concern Sentences (Alternative Type of Measure)	101.849***	90.076***	43.099***
	(14.255)	(14.427)	(15.779)
Share of Talent-Concern Paragraphs (Alternative Type of Measure)	0.268***	0.263***	0.125**
	(0.052)	(0.051)	(0.054)
Number of Talent-Concern Paragraphs (Alternative Type of Measure)	2.479***	2.128***	1.039***
	(0.304)	(0.298)	(0.319)
Total Words of Talent-Concern Paragraphs (Alternative Type of Measure)	258.507***	223.236***	100.093***
	(36.405)	(36.104)	(38.217)
Share of Talent-Concern Sentences (Using Conservative "Talent" Keywords)	0.089***	0.088***	0.031*
	(0.016)	(0.017)	(0.017)
Number of Talent-Concern Sentences (Using Conservative "Talent" Keywords)	2.410***	2.134***	0.988***
	(0.299)	(0.298)	(0.302)
Share of Talent-Concern Sentences (Using Conservative "Retention" Keywords)	0.119***	0.114***	0.051***
	(0.019)	(0.019)	(0.019)
Number of Talent-Concern Sentences (Using Conservative "Retention" Keywords)	3.198***	2.763***	1.459***
	(0.349)	(0.341)	(0.361)
Firm Control	N	Y	Y
Year FE	Y	Y	N
Year-Industry FE	N	N	Y

Table IA.9
Robustness: 10-K Validation Test Using Alternative Talent Definitions

This table reports the robustness check results of Table III which regresses firms' concerns about talent competition mentioned in their 10-K annual reports on their contemporaneous talent retention pressure (TRP) measure. Panel A shows results where talent is classified based on within-industry rankings of occupations' average hourly wage rate in the OEWS microdata. Panel B shows results where talent is classified based on within-industry rankings of occupations' work experience requirements in the O*Net database. Panel C shows results where talent is classified based on national rankings of occupations' cognitive skill requirements. See the Internet Appendix IA.1 for more details. *TRP_Alt* is the firm's talent retention pressure defined in equation (1) based on the corresponding alternative talent definition in each Panel. *Share of Talent-Concern Sentences in 10-K Report* is the percentage of sentences in the firm's 10-K report that mentions both talent keywords and competition/retention/attraction keywords (see Section III.C). *Number of Talent-Concern Sentences in 10-K Report* is the number of such sentences in the firm's 10-K report in the year. Firm controls include firms' Tobin's Q, cash flow, size, and age in the current year. Industry is classified at the NAICS 4-digit level. See Table I for definitions of all 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.

	Share of Talent-Concern Sentences in 10-K Report			Number of Talent-Concern Sentences in 10-K Report		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Talent Defined Based on Occupation Wage Rate					
TRP_Alt	0.084***	0.075***	0.065***	2.711***	2.156***	1.659***
	(0.017)	(0.017)	(0.017)	(0.315)	(0.315)	(0.326)
Firm Control	N	Y	Y	N	Y	Y
Year FE	Y	Y	N	Y	Y	N
Year-Industry FE	N	N	Y	N	N	Y
Observations	12,284	11,921	11,346	12,284	11,921	11,346
Adjusted R^2	0.011	0.067	0.221	0.035	0.092	0.240
	Panel B: Talent Defined Based on Occupation Work Experience Requirement					
TRP_Alt	0.125***	0.126***	0.072***	3.483***	3.124***	1.979***
	(0.018)	(0.018)	(0.018)	(0.333)	(0.325)	(0.340)
Firm Control	N	Y	Y	N	Y	Y
Year FE	Y	Y	N	Y	Y	N
Year-Industry FE	N	N	Y	N	N	Y
Observations	12,226	11,864	11,286	12,226	11,864	11,286
Adjusted R^2	0.019	0.077	0.222	0.050	0.107	0.242
	Panel C: Talent Defined Based on Uniform Classification of Occupations					
TRP_Alt	0.133***	0.141***	0.046*	3.647***	3.321***	1.446***
	(0.027)	(0.026)	(0.026)	(0.482)	(0.464)	(0.467)
Firm Control	N	Y	Y	N	Y	Y
Year FE	Y	Y	N	Y	Y	N
Year-Industry FE	N	N	Y	N	N	Y
Observations	12,343	11,979	11,407	12,343	11,979	11,407
Adjusted R^2	0.011	0.070	0.219	0.031	0.093	0.235

Table IA.10
First-Stage Results of the Shift-Share IV

This table presents first-stage results for the relationship between actual talent retention pressure (TRP) and the main shift-share instrument (IV) in Column (1) of Table V, 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. 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
	(1)	(2)
IV		0.426***
		(0.037)
Q	0.001	0.001
	(0.002)	(0.002)
Cashflow	-0.021*	-0.018
	(0.011)	(0.012)
Size	0.007*	0.008*
	(0.004)	(0.004)
Age	0.041	0.028
	(0.034)	(0.033)
Firm FE	Y	Y
Year FE	Y	Y
Observations	11,110	11,110
Adjusted R^2	0.619	0.640

Table IA.11
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.12
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). *2SLS(TRP)* is the shift-share instrumented talent retention pressure, where the instrument is 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

Table IA.13
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 (6). 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.14
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). *2SLS(TRP)* is the shift-share instrumented talent retention pressure, where the instrument is 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.13: 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)	-5.352***	-9.063***	-6.477**	-7.581**	-6.194*	-4.653
	(2.091)	(2.649)	(2.558)	(3.143)	(3.255)	(3.131)
Q	0.654***	0.658***	0.655***	0.656***	0.655***	0.653***
	(0.063)	(0.064)	(0.063)	(0.064)	(0.063)	(0.063)
Cashflow	2.002***	1.924***	1.978***	1.955***	1.984***	2.017***
	(0.442)	(0.444)	(0.444)	(0.446)	(0.447)	(0.445)
Size	-0.878***	-0.850***	-0.869***	-0.861***	-0.872***	-0.883***
	(0.193)	(0.196)	(0.194)	(0.193)	(0.191)	(0.191)
Age	-2.656**	-2.504**	-2.610**	-2.565**	-2.622**	-2.685**
	(1.253)	(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

Table IA.15
Robustness: Shift-Share IV for TRP Addressing Input-Output Channel

This table reports the robustness check results of our 2SLS regression results in Table V. Column (1) reports the first stage result, and Columns (2) and (3) report the second stage results of the 2SLS regressions of firms' capital investment on their talent retention pressure (TRP) instrumented by an alternative shift-share instrumental variable (see Section IV.B). *IV(NonPeer & Non-I/O)* refines the main shift-share instrument (defined in equation (6)) by using job postings outside the focal firm's peer industries and the focal firm's input-out-connected industries. We define a focal firm's peer industries as the top three NAICS 4-digit industries of the focal firm in the Compustat Segment data. We define a focal firm's input-output-connected industries as the top three supplier industries or the top three customer industries of the focal firm's peer industries. The NAICS 4-digit input-output connections are computed from the BEA industry-by-industry total requirements table. *2SLS(TRP)* is the firm's talent retention pressure instrumented by *IV(NonPeer & Non-I/O)*. *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. See Section IV.B for the discussions.

	TRP	Physical Investment	Total Investment
	(1)	(2)	(3)
IV(NonPeer&Non-I/O)	0.366***		
	(0.037)		
2SLS(TRP)		-8.059***	-13.556***
		(2.748)	(4.494)
Firm Control	Y	Y	Y
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	11,110	11,110	9,863
F stat.	-	90.542	82.433

Table IA.16
Instrumenting TRP Using Government Military Procurement Spending

This table reports the first stage result (in Column (1)) and the second stage results (in Columns (2) and (3)) of the 2SLS regression of non-military-related firms' investment next year on their talent retention pressure (TRP) instrumented by $\text{IV}^{\text{Mil}}_{f,t}$, which is driven by local military-related industries winning government military procurement contracts (see equation (IA.0.1)). Panel A shows results using our baseline instrument where we define military-related industries as the top 3 industries receiving the most government military procurement spending, and we restrict the test sample to include only non-military-related firms from industries without input-output connections to the top 3 military-related industries. In Panels B and C, we show results using alternative instruments where we expand the definition of military-related industries as the top 5 and top 10, respectively, and we restrict the test sample to include only non-military-related firms from industries without input-output connections to the respective military-related industries. Internet Appendix IA.5 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). See Table I for the definitions of other variables. Industry is classified at the NAICS 4-digit level. 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.

	TRP	Physical Investment	Total Investment
	(1)	(2)	(3)
	Panel A: Shocks from Top 3 Military-Related Industries		
IV^{Mil}	0.628***		
	(0.021)		
2SLS(TRP)		-3.054***	-3.989*
		(0.881)	(2.106)
Firm Control	Y	Y	Y
Firm FE	Y	Y	Y
Year-Industry FE	Y	Y	Y
Observations	9,444	9,444	8,314
	Panel B: Shocks from Top 5 Military-Related Industries		
IV^{Mil}	0.624***		
	(0.022)		
2SLS(TRP)		-2.595***	-4.542**
		(0.916)	(2.308)
Firm Control	Y	Y	Y
Firm FE	Y	Y	Y
Year-Industry FE	Y	Y	Y
Observations	8,517	8,517	7,437
	Panel C: Shocks from Top 10 Military-Related Industries		
IV^{Mil}	0.616***		
	0.024		
2SLS(TRP)		-2.645***	-3.909
		(0.939)	(2.502)
Firm Control	Y	Y	Y
Firm FE	Y	Y	Y
Year-Industry FE	Y	Y	Y
Observations	7,138	7,138	6,216

Table IA.17
Robustness: Main Results Using Alternative Talent Definition Based on Occupation Wage Rate

This table reports our baseline investment results using an alternative definition of talent, which is based on occupations' average wage rates rather than the cognitive skill requirements used in the main analysis. To construct this alternative talent measure, we first compute each SOC 5-digit occupation's average hourly wage rates yearly from the BLS OEWS microdata. Then, we rank occupations by their wage rates (instead of cognitive skills in our baseline measure) within each NAICS 4-digit industry each year, and we classify an occupation as talent if it ranks in the top 10% of the ranking. We then construct a firm-level talent retention pressure (*TRP_Alt*) based on this new talent definition. Panel A shows the results of our main investment test in Table IV. Panel B shows the results of the heterogeneous investment effects between superstar and laggard firms in Table VIII. 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. See the Internet Appendix IA.1 for more discussions.

	Panel A: Baseline Investment Results				*Panel B: Superstar vs. Laggard*	
	Physical Investment		Total Investment		Physical	Total
	(1)	(2)	(3)	(4)	(5)	(6)
TRP_Alt	-0.956**	-0.904**	-1.922**	-1.865**	-1.071***	-2.078**
	(0.452)	(0.387)	(0.763)	(0.783)	(0.404)	(0.826)
TRP_Alt × Superstar					2.661***	2.948*
					(0.882)	(1.692)
Superstar					-0.935**	-0.274
					(0.428)	(0.685)
Firm Control	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	N	Y	N	N	N
Year-Industry FE	N	Y	N	Y	Y	Y
Observations	11,926	11,335	10,529	9,953	11,335	9,953
Adjusted R^2	0.717	0.754	0.808	0.811	0.755	0.811

Table IA.18
Robustness: Main Results Using Alternative Talent Definition Based on Occupation Work Experience Requirement

This table reports our baseline investment results using an alternative definition of talent, which is based on occupations' work experience requirements rather than the cognitive skill requirements used in the main analysis. To construct this alternative talent measure, we first compute each SOC 5-digit occupation's propensity of requiring 4 years of working experience based on the O*Net database. Then, we rank occupations by their work experience requirement (instead of cognitive skills in our baseline measure) within each NAICS 4-digit industry each year, and we classify an occupation as talent if it ranks in the top 10% of the ranking. We then construct a firm-level talent retention pressure (*TRP_Alt*) based on this new talent definition. Panel A shows the results of our main investment test in Table IV. Panel B shows the results of the heterogeneous investment effects between superstar and laggard firms in Table VIII. 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. See the Internet Appendix IA.1 for more discussions.

	Panel A: Baseline Investment Results				*Panel B: Superstar vs. Laggard*	
	Physical Investment		Total Investment		Physical	Total
	(1)	(2)	(3)	(4)	(5)	(6)
TRP_Alt	-1.347***	-1.245***	-1.513*	-1.290	-1.396***	-1.512
	(0.483)	(0.437)	(0.869)	(0.900)	(0.458)	(0.949)
TRP_Alt × Superstar					2.218**	2.956*
					(0.876)	(1.657)
Superstar					-0.854**	-0.269
					(0.390)	(0.620)
Firm Control	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	N	Y	N	N	N
Year-Industry FE	N	Y	N	Y	Y	Y
Observations	11,862	11,263	10,487	9,900	11,263	9,900
Adjusted R^2	0.718	0.755	0.808	0.811	0.755	0.811

Table IA.19
Main Effects in Subsamples of Firms by Talent Mobility

This table reports the baseline effect of TRP on firms' physical investment (Table IV) in two subsamples of firms with high and low average talent cross-occupation mobility ($TCOM$). $TCOM$ is defined in Internet Appendix IA.6. Column (3) shows the t-statistics of the test on the coefficients of TRP between the two subsamples. 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.

	Firms with Low-$TCOM$ (1)	Firms with High-$TCOM$ (2)	Difference (3)
TRP	-1.439***	-0.822	$t = 0.994$
	(0.444)	(0.956)	
Firm Control	Y	Y	
Firm FE	Y	Y	
Year FE	Y	Y	
Observations	5,693	5,564	
Adj. R^2	0.705	0.738	

Table IA.20
Economic Magnitudes of Investment Effects

This table reports the economic magnitudes regarding the effects of firms' talent retention pressure (TRP) on their physical investment in Panel A, the effects of firms' TRP on their total investment in Panel B, and the magnitudes of other measures of firms' labor-related variables on firm investment in prior studies in the literature for references in Panel C. The statistic noted with * refers the magnitudes estimated using a dummy variable of state adoption events instead of a 1-standard-deviation change in the independent variable. Internet Appendix Section IA.7 details the step-by-step calculation of the statistics as well as the definitions of investment rates in the prior studies.

	Sample mean of investment rate	1-SD effect on investment rate	1-SD effect as a % of mean investment rate
Panel A: Effects of TRP on Firm Physical Investment			
TRP (baseline)	5.00pp.	0.21pp.	4.24%
2SLS(TRP) (Military Procurement IV)	5.00pp.	0.37pp.	7.47%
2SLS(TRP) (Shift-Share IV)	5.00pp.	0.77pp.	15.41%
Panel B: Effects TRP on Firm Total Investment			
TRP (baseline)	17.89pp.	0.29pp.	1.64%
2SLS(TRP) (Military Procurement IV)	17.89pp.	0.65pp.	3.66%
2SLS(TRP) (Shift-Share IV)	17.89pp.	1.62pp.	9.08%
Panel C: Effects of Labor Variables on Firm Investment in Literature			
Skilled Labor Mobility (estimated from GreenCard Shock, *Shen (2021)*)	10.30pp.	0.2pp.	2%
Labor Protection (estimated from State Law Change, *Bai et al. (2020)*)	8.33pp.	0.22pp.	2.66%
Unionization (estimated from Union Certification Election, *Fallick and Hassett (1999)*)	17.91pp.	0.61pp.	3.39%
Worker Health Care Costs (estimated from Health Insurer Concentration, *Tong (2024)*)	11.4pp.	0.59pp.	5.20%
Wage Convergence Pressure (estimated from other divisions, *Silva (2021)*)	3.42pp.	0.50pp.	14.6%
Labor Mobility (estimated from Court Decisions, *Sanati (2025)*)	11.00pp.	1.99pp.	18.13%
Labor Mobility (estimated from State NonCompete Adoption, *Jeffers (2023)*)	3pp.	-	34%~39%*

Table IA.21
Main Findings Using Shift-Share Instruments of Firm TRP

This table reports the second stage results of our main findings estimated using the 2SLS regressions, where firms' talent retention pressure (TRP) is instrumented by a shift-share instrumental variable constructed following equation (6)). *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). *Talent Outflow* is the number of talent leaving the firm to join another firm next year divided by the total number of talent this year and multiplied by 100 using the Revelio Labs microdata. *Talent Wage* is the natural logarithm of the average hourly wage rate of the firm's talent. *Talent Promotion* is the percentage of talent employees in the firm experiencing an increase in seniority (promotion) in the year using the Revelio Labs microdata. *Job Posting for Talent* is the natural logarithm of one plus the firm's number of job postings for talent in the year using the Lightcast data. *Talent Growth Rate* is the net changes in the number of talent divided by the firm's total number of talent at the beginning of the year and multiplied by 100 using the Revelio Labs microdata. *2SLS(TRP)* is the shift-share instrumented talent retention pressure, where the instrument is defined in equation (6). Firm controls include firms' Tobin's Q, cash flow, size, and age in the current year. Industry is classified at the NAICS 4-digit level. 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.

	Investment		Talent Outflow	Talent Retention		Talent Replacement	
	Physical Inv$_{t+1}$	Total Inv$_{t+1}$	Outflow Rate$_{t+1}$	Wage$_t$	Promotion$_t$	Job Posting$_t$	Talent Growth$_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2SLS(TRP)	-5.352**	-11.277***	7.595**	0.280**	2.930*	1.915***	-4.217
	(2.091)	(3.567)	(3.685)	(0.130)	(1.645)	(0.733)	(6.310)
Firm Control	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	11,110	9,863	8,300	10,748	7,128	11,853	7,906
	Comparison of 2SLS and OLS estimates						
Same Sign as OLS?	Y	Y	Y	Y	Y	Y	Y
β_{IV}/β_{OLS}	3.6	5.5	3.1	3.2	3.6	4.3	2.3

Table IA.22
Heterogeneous Effects: Superstar vs. Laggard Firms (2SLS)

This table reports the second stage results of the 2SLS regressions of firms' capital investment next year on the interaction between their current talent retention pressure (TRP) instrumented by a shift-share instrumental variable and their superstar status. *2SLS(TRP)* is the shift-share instrumented talent retention pressure, where the instrument is defined in equation (6). *Superstar* is a dummy variable equal to one if the firm's sales rank in the top 4 of the NAICS 4-digit industry category in the year (Gutierrez and Philippon (2020)). *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). Firm controls include firms' Tobin's Q, cash flow, size, and age in the current year. Industry is classified at the NAICS 4-digit level. 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$_{t+1}$		Total Investment$_{t+1}$	
	(1)	(2)	(3)	(4)
2SLS(TRP)× Superstar	4.270***	3.465**	8.024***	4.877
	(0.468)	(1.740)	(2.317)	(3.191)
2SLS(TRP)	-6.037***	-5.471*	-12.038***	-11.106*
	(2.152)	(2.963)	(3.653)	(6.033)
Superstar	-1.710***	-1.401***	-2.324***	-1.341
	(0.471)	(0.533)	(0.752)	(0.951)
Firm Control	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	N	Y	N
Year-Industry FE	N	Y	N	Y
Observations	11,110	10,517	9,863	9,285

Table IA.23
IV-OLS Gap Decomposition

This table reports the decomposition of the gap between the coefficients of the OLS (Table IV) and the shift-share IV (Table V) estimates for TRP's effects on firm investment following the econometric framework of Ishimaru (2024). Column (1) reports the IV–OLS coefficient gap estimated from the framework of Ishimaru (2024) controlling for firm characteristics, firm fixed effects, and year fixed effects. Columns (2)–(4) decompose the IV–OLS gap and report the contribution from three components: (i) differences in weights of observations given by 2SLS and the OLS estimates under heterogeneous treatment effects ("Complier Effect"), (ii) differences in weights across treatment levels under non-linear effects, and (iii) a residual component potentially reflecting endogeneity biases in the OLS estimator or measurement errors in either variables. See more details of the decomposition in Internet Appendix IA.7.

	IV–OLS (1)	Complier Effect (2)	Non-linear Effect (3)	Residual (4)
Physical Investment	-3.983	45.37%	0.03%	54.59%
Total Investment	-9.259	52.17%	0.05%	47.78%

Table IA.24
Talent Retention Pressure and Industry Concentration

This table reports the results of regressing NAICS 4-digit 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 at $t+2$ based on the Compustat database. The independent variables are a series of within-industry median values of firms' TRP and other characteristics, weighted by firm total assets. See Section IA.8 for more details and Table I for the definitions of other variables. 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.

	Industry-level CR4	
	(1)	(2)
TRP	0.058**	0.062***
	(0.023)	(0.022)
Q		0.005
		(0.005)
Cashflow		0.031
		(0.043)
Size		0.018
		(0.015)
Age		0.016***
		(0.006)
Industry FE	Y	Y
Year FE	Y	Y
Observations	1,167	1,167
Adjusted R^2	0.969	0.970

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.

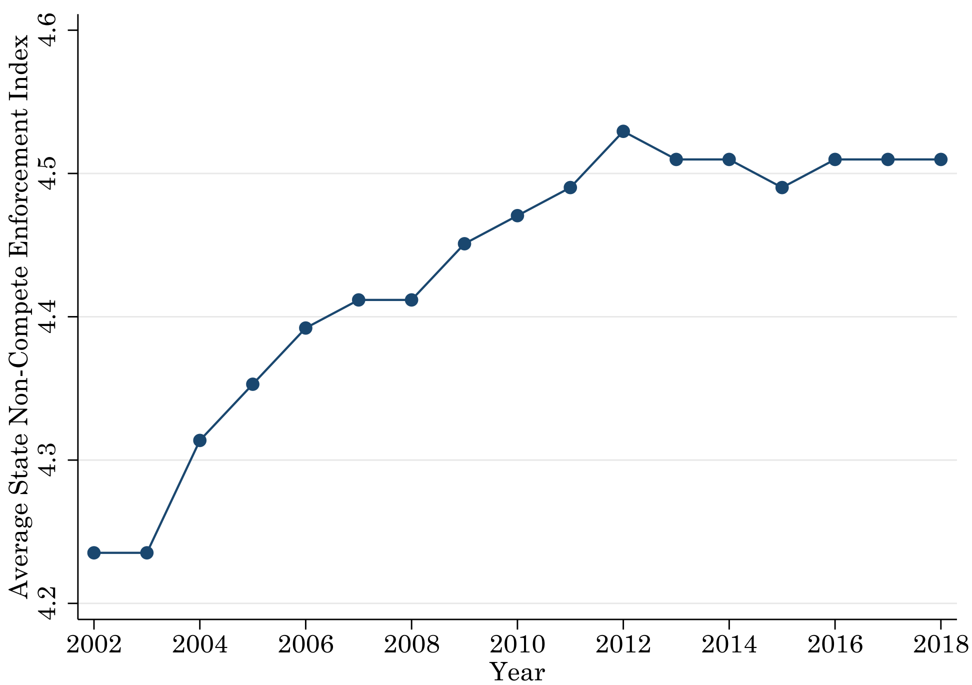


Figure IA.2: Percentage of Hires That Are Job-to-Job by Occupation

This figure plots the means and 95% confidence intervals for the percentage of hires that are job-to-job (relative to hiring from nonemployment) for occupations categorized as talent under the baseline within-industry ranking (see more details in the Internet Appendix IA.1). For each industry in each year from 2010 to 2018, we group occupations into those categorized as talent under both the baseline within-industry ranking and the uniform ranking (*Talent (Within-Industry) & Talent (Uniform)*) and those categorized as talent under the within-industry ranking but not under the uniform ranking (*Talent (Within-Industry) & NonTalent (Uniform)*). For each occupation in each year, we merge the percentage of hires that are job-to-job (*J2J Percentage*) based on the CPS data (see details in Table IA.1). The dot represents the mean of the J2J Percentage for occupations in the two groups, while the vertical bars represent the 95% confidence intervals based on standard errors triple clustered by occupation, industry, and year.

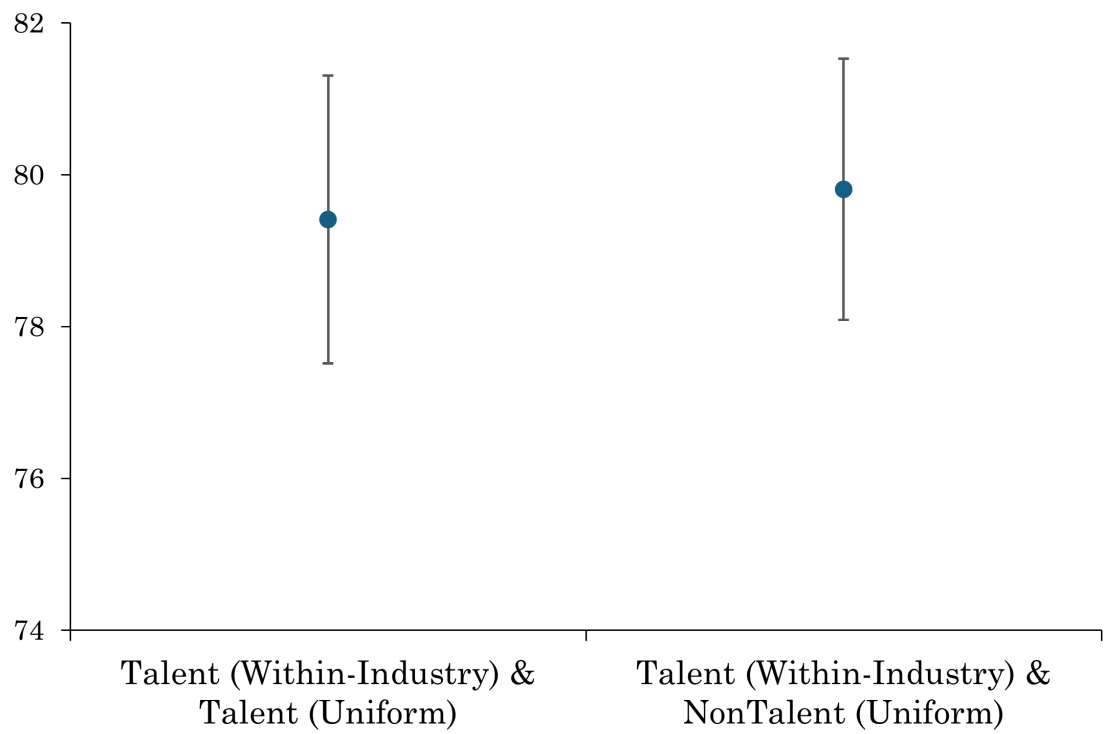
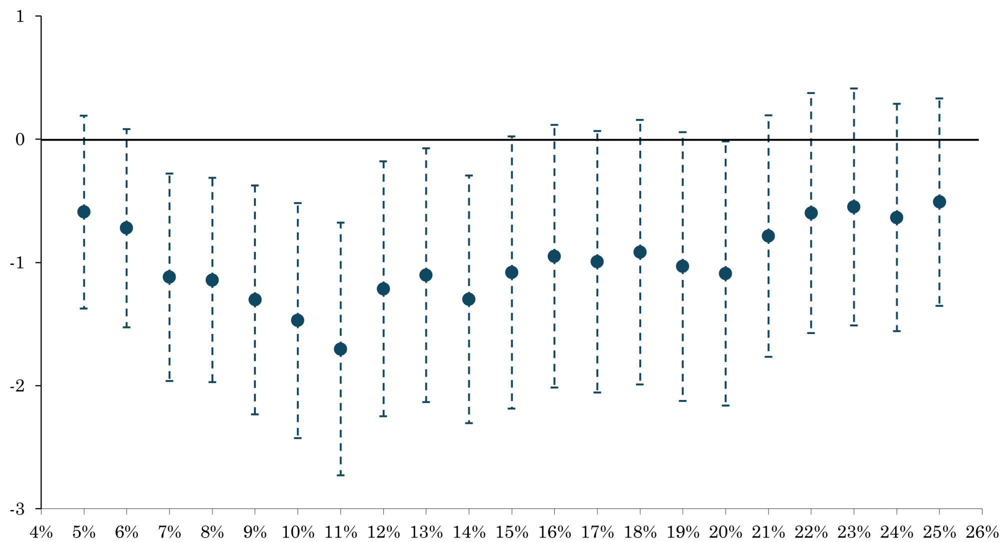


Figure IA.3: Robustness of Investment Results to Various Talent Cutoffs

This figure plots the coefficients and 95% confidence intervals for regressing firm investment on talent retention pressure when talent is defined based on various cutoffs of cognitive skill ranking within the industry. The cutoff in our baseline definition in the main text is 10%. Panel A plots the coefficients using physical investment (CAPX/AT), and Panel B plots the coefficients using total investment as in Peters and Taylor (2017). Each dot represents an estimated coefficient of the alternative TRP in equation (5). See the Internet Appendix IA.1 for more discussions.

Panel A: Physical Investment and TRP



Panel B: Total Investment and TRP

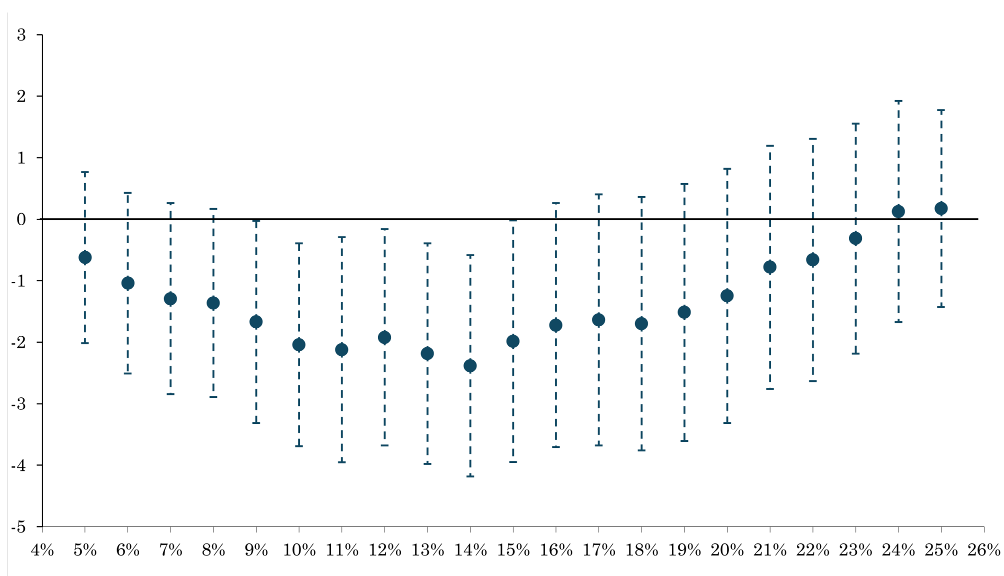
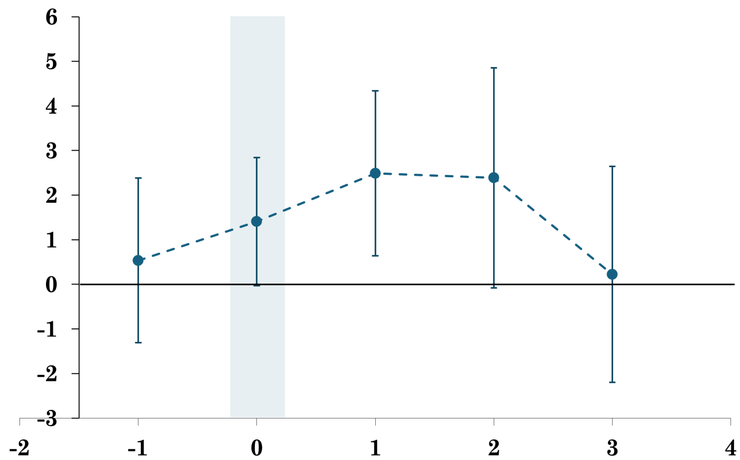


Figure IA.4: Firms' Impulse Responses to Talent Retention Pressure

This figure plots the impulse responses of firms' talent outflow rate (Panel A) and physical investment (Panel B) to their talent retention pressure (TRP). The reduced-form impulse responses are estimated using local projections. In Panel A, we regress firms' talent outflow rate from $t-1$ to $t+3$, one at a time, on their TRP at t using equation (3). In Panel B, we regress firms' physical investment from $t-1$ to $t+3$, one at a time, on their TRP at t using equation (5). All regressions control for firm characteristics, firm fixed effects, and year fixed effects. All standard errors are clustered at the firm level. The vertical bars represent the 95% confidence intervals of the point estimates.

Panel A: Impulse Response of Firm Talent Outflow



Panel B: Impulse Response of Firm Investment

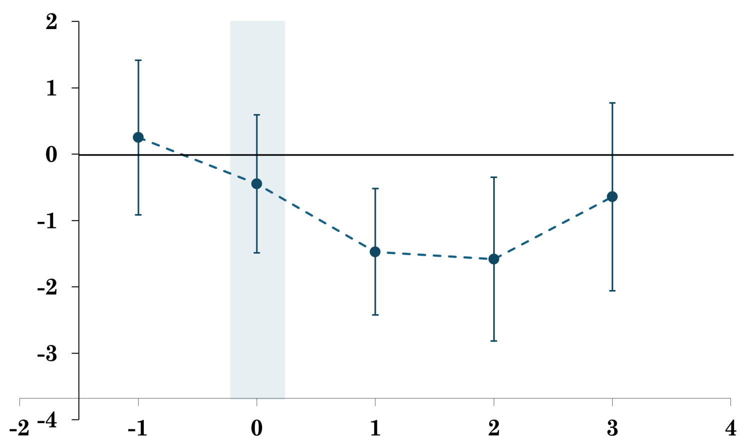
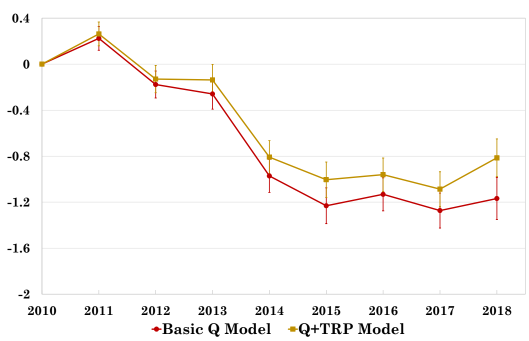


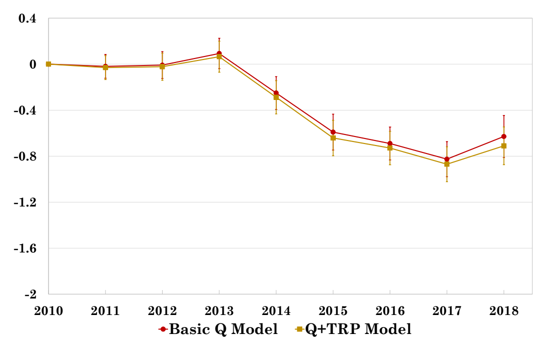
Figure IA.5: Talent Retention Pressure and Investment-Q Gap

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 (IA.0.10) and (IA.0.11). 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 (IA.0.10)) and the yellow line is based on a regression controlling for talent retention pressure (i.e., Q+TRP Model in equation (IA.0.11)). 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 NAICS 4-digit industry category in the year, and laggard firms are the rest.

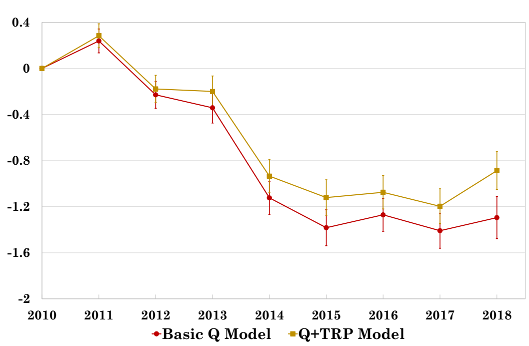
Panel A: Average Firms' Investment-Q Gap



Panel B: Superstar Firms' Investment-Q Gap



Panel C: Laggard Firms' Investment-Q Gap



Panel D: Aggregate Investment-Q Gap