Talent Retention Risk and Corporate Investment

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Abstract

This paper studies the effect of the risk of losing talent on corporate investment. We construct a firm-level measure of talent retention risk (TRR) based on other firms' job postings for skilled labor in the local labor market which captures the outside options of the firm's talent. We validate that TRR correlates with CFOs' talent retention concerns in the Duke CFO Survey and TRR predicts firms' talent outflows in the LinkedIn data. Using this measure we show that (i) TRR reduces firm investment after controlling for Q; (ii) Rising TRR explains 13%-27% of the widening investment-Q gap from 2010 to 2017; (iii) All investment effects are driven by retention risk for middle-managers but not other skilled labor suggesting that managers are the core talent.

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1 Introduction

Economists and policymakers have long been interested in understanding the determinants of corporate investment. Recent surveys of CFOs unveil that talent concerns outweigh financial concerns and dominate corporate investment in the 21st century (Jagannathan et al. (2016), 2011 Q3 Duke CFO Survey). Moreover, CFOs frequently cite attracting and retaining skilled labor as a top challenge for internal risk management.[1] Despite the first-order importance of talent retention concerns revealed by the surveys, little is known about how talent retention risk evolves over time, and how such evolution relates to recent patterns in corporate investment (Gutiérrez and Philippon (2017)), likely due to challenges in measurement.

In this paper, we construct the first measure of firms' talent retention risk (TRR) based on an on-the-job search framework. We define talent as occupations that require a college degree and 4-year working experience.[2] In each local labor market (MSA), we compute the ratio of job postings for talent by other firms (v) and the total employment of talent (e). This v-e ratio represents the abundance of an employed talent's outside options. Variations in this ratio thus capture changes in the likelihood for the firm to lose a talent. For instance, an influx of job postings for financial managers by IT companies can increase the risk for a bank in the MSA to lose its financial managers. We define a firm's TRR as the average v-e ratio across MSAs weighted by the firm's talent presence in each MSA. Numerous studies have shown that turnovers of skilled labor are highly costly (e.g., Belo et al. (2017a)). TRR thus intuitively captures the average likelihood for the firm to lose a talent and pay the turnover cost.

We next present evidence bolstering our interpretation that TRR indeed captures the risk for firms to lose talent. First, we access the microdata data of the Duke CFO Survey and show that a firm's TRR is positively related to its CFO electing "attracting and retaining qualified employees" as the top three firm-specific concerns. This relation holds even after we control for firm and time fixed effects. This finding suggests that CFOs indeed perceive a greater challenge in talent retention when their talent's outside options are more abundant, supporting our on-the-job search approach. Second, we access the LinkedIn microdata and show that a firm's TRR strongly relates to talent outflows from the firm in the current and next year. This finding confirms that firms cannot fully hedge against TRR, and that TRR can indeed cause materialized talent loss to firms.

[1] See Section 2 for a summary of several CFO surveys.

[2] Our definition suggests that about 5% of employees are talent in an average firm in our sample (see Table 1), consistent with prior findings (Baghai et al. (2021)).

Equipped with this measure, we study the impact of talent retention risk on corporate investment guided by a standard Q theory. In our framework, TRR can affect investment and Q through two channels. First, TRR reduces expected capital productivity which lowers both investment and marginal Q. Second, we hypothesize that TRR also increases adjustment costs for capital formation as suggested by prior literature and survey evidence.[3] For instance, the Duke CFO survey shows that the shortage of talent is the dominating reason for firms to bypass otherwise "positive net present value projects." Interpreting the NPV as the value for installed capital, just like in the definition of Q, then talent shortage naturally represents the adjustment costs not accounted for in the NPV that led to the bypassing. It is well-known that adjustment cost can create a wedge between investment and Q, as $I = \frac{1}{\gamma}(Q-1)$ in a standard Q theory where γ is the quadratic adjustment cost parameter. Hence, TRR can dampen investment even after controlling for Q.

We next present three empirical results supporting the predictions of our simple framework. First, we show that TRR significantly reduces next period investment in 2010-2018 even after controlling for Tobin's Q, total Q that includes intangibles (Peters and Taylor (2017)), other common predictors for investment, and fixed effects by firm and year. Firms in top quintile sorted by TRR have investment rate 1.3% lower than firms in the bottom quintile. We further conduct a battery of endogeneity assessments, and we show that this negative effect is not driven by firms' endogenous choice of local labor market (i.e., an omitted variable concern) and other firms' predatory job postings for talents (i.e., a reversal causality concern). These findings suggest that TRR can dampen investment beyond the influence of Q.

Second, we present evidence that directly supports our model's predicted relation for investment, Q and TRR. Our framework suggests that $I = \frac{1}{\gamma}(Q-1)$, which indicates that investment should be better characterized by an *interaction* between TRR and Q if TRR is indeed a source of capital adjustment cost. Consistent with this prediction, we show significant negative coefficient of interaction term no matter Q is measured as Tobin's Q or total Q. Intuitively, these findings suggest that talent retention risk particularly dampens firm investment when the firm needs to growth at a faster pace.

Third, we conduct a body of subsample analyses showing that the above effects of TRR are indeed stronger among firms that are likely to be constrained by talent during capital formation. Prior literature indicates that new investment projects rely

[3]Prior studies on the nature of capital adjustment cost (Cooper and Haltiwanger (2006) and Ito et al. (1999)) and and on firm organization (Prescott and Visscher (1980) and Garicano (2000)) suggest that talent is crucial for solving the tasks before projects are up-and-running such as team building and solving unusual tasks.

more heavily on talent if they embody challenges that are new to existing projects. Hence, talent can be a particularly important source of capital adjustment cost when new investment projects are different from firms' existing projects. Consistent with this view, we show that the above effects of TRR alone and also the interaction effects of TRR and Q are both driven by firms in the new product innovation stage of life-cycle (Hoberg and Maksimovic (2021)), firms in fast growing sectors (Crouzet and Eberly (2020)), and firms engaging more in R&D. In addition, consistent with the survey evidence highlighting the shortage of middle managers as the core source of adjustment cost, we decompose our TRR measure based on management occupations and non-management occupations within our talent occupations. We show that our TRR results are driven primarily by management occupations.

After establishing the role of TRR in affecting investment through capital adjustment cost, we study an important time-series implication of our findings. Seminal work by Gutiérrez and Philippon (2017) shows that capital investment by U.S. firms is lackluster despite high Tobin's Q in the 21st century, resulting in a widening gap between actual investment and investment predicted by Q (*investment-Q gap*). Several recent studies have proposed explanations for this time-series phenomena including declining competition (Gutiérrez and Philippon (2017)), rising intangibles (Gutiérrez and Philippon (2017) and Crouzet and Eberly (2020)), and measurement errors in discount rate for the Q calculation (Gormsen and Huber (2022)). We study the widening investment-Q gap through a standard Q theory, in which adjustment cost is the only source for the wedge between investment and Q. Hence, if TRR increases over time, the rising capital adjustment cost can dampen investment but not Q, resulting in a widening gap between them.

We first present three time-series plots reflecting that firms are facing increasing challenges to retain their talent. First, we plot the time-series of our TRR measure, which shows that TRR increased sixfold from 2010 to 2018. Second, we show a rising percentage of CFOs electing talent retention as their top firm-specific concerns in the Duke CFO Surveys. Third, we plot a rising outflow rate of talent from incumbent employers in the LinkedIn data, suggesting that job-to-job moves by talent indeed increase in our sample period. The three plots present a unified message that firms are facing increasing challenges in retaining their talent. Hence, they are indeed likely to face increasing adjust costs during the beginning period of capital formation.

We next analyse whether the rising TRR can contribute to the widening investment-Q gap. We first confirm a widening investment-Q gap in our sample period of 2010-2018 following the empirical test of Gutiérrez and Philippon (2017). In particular, we regress investment on Tobin's Q, firm controls, firm-fixed effects, and year dummies. We observe increasingly negative coefficients for the year dummies indicating that the investment-Q gap widened by about 3.6 percentage points over the past decade. Following the diagnose method by Gutiérrez and Philippon (2017), we include TRR and the interaction of TRR and Tobin's Q in the above regression, and we interpret the explanatory power by TRR through changes in the year dummy coefficients. We find that rising TRR explains 13 percent of the widening investment-Q gap in the overall sample. Yet, there are substantial heterogeneities across firms. TRR explains 27 percent of the widening investment-Q gap in fast-growing industries compared to zero percent in other industries; and the same pattern holds if we use Total Q instead of Tobin's Q. TRR explains 20 percent in early-life-cycle firms compared to -4 percent in other firms; and TRR explains 24 percent in high-R&D firms compared to -8 percent in other firms. The numbers are similar if we consider the investment-Total Q gap. In summary, these results suggest that rising challenges of retaining talent explains a sizable fraction of the lackluster investment as compared to Q mainly in fast growing innovative firms.

Our study relies on a central thesis of the organization capital literature that some intangible capital of a firm is embodied in the firm's key talent (Prescott and Visscher (1980) and Eisfeldt and Papanikolaou (2013)). A large body of literature explored the implication of organization capital on firm valuation (Peters and Taylor (2017), Eisfeldt et al. (2020), Eisfeldt and Papanikolaou (2013), among others). Eisfeldt and Papanikolaou (2013) show theoretically and empirically that organization capital is riskier than physical capital because key talent can leave the firm during economic states with high stochastic discount factor. Motivated by survey evidence, we apply this thesis to explaining corporate investment. In particular, our empirical findings suggest that the inability for firms to retain their talent plays an important role for understand the lackluster capital investment in the past decade.

Our work also contributes to explaining the widening investment-Q gap in the 21st century discovered by Gutiérrez and Philippon (2017). Gutiérrez and Philippon (2017) examine a large spectrum of potential explanations and show that accounting for intangible in the Q calculation only partially explains the puzzle. Crouzet and Eberly (2020) develop a structural model that shows the interaction between rent and intangible explains a large fraction of the gap. More recently, Gormsen and Huber (2022) show that the actual discount rate adopted by firms are greater than asset market suggested, resulting in an overestimation of Q in the prior literature. We approach the investment-Q gap puzzle through a standard Q theory with quadratic adjustment cost. We show a battery of evidence along with the CFO survey results supporting that talent retention risk is a source of capital adjustment cost, and rising TRR explains a sizable fraction of the widening investment-Q gap.

Finally, our measure of talent retention risk is related to the mobility of employees across firms. A large body of literature study the implications of labor mobility for firms (Donangelo (2014), Shen (2021), Jeffers (2019), among others). In particular, Jeffers (2019) shows that increases in state-level enforceability of non-compete agreements between firms boost up firm investment especially for firms with more skilled labor. Shen (2021) explores shocks to the mobility of skilled immigrant workers and shows that relaxing mobility constraints negatively influences firm value. While these studies based on policy shocks demonstrate the causation of labor mobility to firm investment and value, they cannot be used to understand time-series of changes in talent mobility nor the implications for the dynamics of corporate investment (Gutiérrez and Philippon (2017)). Our study fills this void by constructing a talent retention risk measure based on an on-the-job search framework. Our measure helps us connect talent mobility to the wedge between investment and Q and demonstrate the importance of talent retention to the widening investment-Q gap in the past decade.

This paper is organized as following: Section IA.1 presents a simple Q theory framework connecting talent retention risk to firm investment and Q. Section 3 presents the data and measure for our firm-level talent retention risk. Section 4 presents our main results of TRR on investment. Section 5 presents a battery of subsample analysis results that are consistent with our framework. Section 6 presents the implication of rising TRR for explaining the widening investment-Q gap, and Section 7 Concludes.

2 CFO Survey Evidence

In this section, we provide a brief summary of CFO surveys regarding "drivers for forgoing corporate investments" and regarding CFOs' view on the most pressing concerns of internal risk management.

2.1 Surveys on Forgoing Corporate Investments

2.1.1 Kellogg CFO Survey

An important study by Jagannathan et al. (2016) analyzes the 2003 Kellogg CFO survey about firms' investment and cost of capital. A focal question asks the CFOs to choose how much they agree with the following two statements which we label as talent concerns and financial concerns for forgoing investment:

- **[Talent concerns:]** *"There are some (otherwise) good projects we cannot take due to limited access to capital markets.*
- **[Financial concerns:]** *We cannot take all (otherwise) profitable projects due to limited resources in the form of limited qualified management and manpower.*

They show in their Figure 2 that 55% CFOs attribute forgoing otherwise profitable projects to talent concerns, while 39% CFOs attribute to financial concerns.[4]

2.1.2 Duke CFO Survey

Similarly, question 12 of the 2011 Q3 Duke CFO Survey 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 view the lack of "management time and expertise" as the reason for bypassing otherwise valuable investment projects, while 43% CFOs attribute it to the lack of funding.

2.2 Surveys on CFOs' Most Pressing Internal Risk Concerns

2.2.1 Duke CFO Survey

In the December 2019 Duke CFO Survey, for the question about "During the past quarter, which items have been the most pressing concerns for your company's top management team?", among the total of 434 CFOs being interviewed, 195 of them chose "difficulty attracting/retaining qualified employees." In fact, talent retention is the number one concern, followed by "economic uncertainty," which is chosen by 154 CFOs.

The same pattern appears in many other waves of surveys. For example, in the December 2018 Duke CFO Survey, talent retention is also the number one concern, chosen by 46.7% of CFOs, and is followed by "government policies", by 32.1%. Again, in

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

the December 2017 Duke CFO Survey, talent retention is still the number one concern, chosen by 42.9% of CFOs, and is followed by ”cost of benefits”, by 33.6%, and ”data security”, by 31.7%.

2.2.2 Deloitte CFO Signals™ Survey

The 2022 2Q Deloitte CFO Signals survey has a total of 97 CFOs participating, with 72% from public companies and 28% from privately held companies. The survey reports that ”CFO's top internal risk worries were again dominated by talent and concerns over retention” and ”talent and retention are CFOs' top internal risks in 2Q 2022. Among the 97 CFOs, 37 of them choose ”talent” as the keyword of internal risk worries. The CFOs express concerns over ”getting the right talent to move technology investments forward” and ”resource management as turnover increases and the rate for specialized roles increases.” Another 37 of CFOs choose ”retention” as the keyword of internal risk worries, indicating ”loss of talent due to attrition” and ”talent turnover.”

3 Data and Measure

3.1 Data

This section describes the data used in the study. We compile several large-scale labor market datasets for the purpose of estimating firms' exposures to talent retention risks.

Our job posting data is derived from Burning Glass Technologies (BGT), which describes itself as "the world's leading provider of real-time labor market data products and analysis" with data covering the near-universe of U.S. online posted job vacancies. BGT has one of the world's largest real-time, proprietary databases of jobs and talent, with openings data collected from more than 50,000 sources (e.g., job boards, company websites, newspapers, and public agencies) on a daily basis. To date, BGT has more than one billion deduplicated job postings and collects more than 3.4 million postings every day. Specifically, it uses a sophisticated deduplication system to collect and process job posts and parses the ads into a systematic and machine-readable form with detailed information covering title, occupation, employer firm name, industry, location, skills, qualifications, and other features. Our job posting data cover the electronic job postings in the U.S. from January 1, 2010 to December 31, 2018. The data has been used to examine the labor market in studies such as Hershbein and Kahn (2018), Deming and Kahn (2018), Blair and Deming (2020), Deming and Noray (2020), Bloom et al. (2021), and Acemoglu et al. (2022).

To acquire information about firm's granular local employment information, we follow Brau and Fawcett (2006), Tuzel and Zhang (2017), and Michaels et al. (2019) and rely on ReferenceUSA, a business directory dataset that spans both private and public business entities in the U.S. ReferenceUSA's business data covers tens of millions of businesses – from Fortune 500 companies to small mom-and-pop stores. Detailed business information can be obtained to examine latitude and longitude, number of employees, estimated sales, location, credit rating, public/private, year established, among others. Relevant to our study, it covers detail firm's establishment-level employment from 2007 to 2018.

Our workforce dynamics data (inflow, outflow, and turnover) are obtained from Revelio Labs, a leading provider of labor market analytics. The data provider continuously gathers unstructured data containing employees' online profiles and resumes from various websites and social media platforms (such as LinkedIn). They absorb and standardize hundreds of millions of public employment records to create one the world's first universal HR databases. To ensure reliable data are available for a large panel of firms, the data provider begins the dataset in 2008. The raw data contain more than 380 million online public profiles and resumes of employees from more than 5,000 public companies.

In addition to the employment data, we use Duke CFO survey data to understand how financial executives view the economy and prospects for their business, especially firm's top concerns and planned capital investments in our setting. The survey is designed to provide direct information on how U.S. companies are perceiving and reacting to the current economic environment. Graham and Harvey (2001) describe how the survey is conducted and provide an overview of the survey results.

We also combine several other standard firm-level data for our analysis. We use Standard and Poor's Compustat database to obtain firm accounting and financial information. We also obtain firm segment information from Compustat. Moreover, we acquire O*NET/OES data to identify occupational characteristics and employment classification, specifically, O*NET for occupational characteristics that helps categorize talent and OES for occupational employment by MSA/Industry.

3.2 TRR Construction

Conceptually, we use the labor market vacancy-to-employment (VE) ratio as a measure of firm level talent retention risk, which features the probability of a skilled employee being approached by other firms. VE ratio captures the labor market tightness for the job-to-job movements, as in Pissarides (1994) and Garibaldi and Moen (2010). For an employee searching for potential outside options, the chance of being successfully matched with a new job increases with the VE ratio. Meanwhile, from the firm's perspective, the probability of its employees being poached by other employers also rises when the labor market is tight.

We take a bottom-up approach to construct the firm-level VE ratio, i.e., talent retention risk (TRR). Within each firm, we first build a VE ratio for each occupation at each MSA and then calculate the average of the occupation-MSA level VE ratio into firm-level talent retention risk, weighted by the occupation employment shares within the firm. Figure IA.2 illustrates the detailed process using a hypothetical case of Tesla. In this hypothetical example, Tesla has two branches: one in San Francisco and another in Austin. For the financial manager occupation, ω share of financial managers is located in San Francisco, and $1 - \omega$ is located in Austin. In San Francisco, the talent retention risk of the financial manager is measured by its local VE ratio, where the denominator is the total number of financial managers in San Francisco from the OES MSA-Occupation Employment Panel, and the numerator is the total number of job post for financial managers in San Francisco. To instrument the exogenous local demand for financial managers, we exclude the job posts from Tesla's top 3 industries. The talent retention risk of financial managers for Tesla is the weighted average of the VE ratios for financial managers in San Francisco and Austin. The weights are ω and $1 - \omega$, respectively.

Given the lack of data regarding firm-MSA-level occupation employment shares, we combine the establishment data from ReferenceUSA with the industry-occupation matrix from the Bureau of Labor Statistics. For each firm, we observe the location, NAICS industry, and employment size for each of its establishments. Then, we estimate the number of employees by each SOC 5-digits occupation for each establishment by assuming the same employee occupation distribution within the same NAICS 4-digits industry. Next, we aggregate the establishment-occupation level employment size into a firm-MSA-occupation level employment size panel. We drop those firm-MSA-occupation pairs if the firm has not previously posted any job for the given occupation at the given MSA. The lack of previous job posts is an indicator of the potential measurement error introduced by the imputation process using the BLS industry-occupation matrix. We covert BGT job post flows into a monthly stock with a law of motion that assumes a fixed daily job filling rate of 1%.

To address the endogeneity concern that local competitors change job posting behaviors because of industry trends that also affect the firm of interest, we exclude all job posts from the firm's top 3 industries when calculating the local occupation VE ratio. The talent retention risk measure constructed in this way is labeled as TRR hereafter.

We also develop two additional versions of firm-level talent retention risks to further address other potential concerns. First, firms may strategically enter or exit MSAs with tight labor markets, and such entry and exit decisions can be correlated with other financial decisions. To fix the geographic employment distribution of a firm, we construct the Balanced TRR, which uses a restricted sample with MSA-firm pairs that presents through our sample period. Second, unobserved variations in local economic environments could drive VE ratios and firm decisions. To capture the exogenous variations in talent retention risk that is uncorrelated local shocks, we use a Bartik-style instrument to measure local occupation VE ratios. Similar in the spirits of Bartik and Bartik Timothy (1991) and Blanchard and Katz (1999), we construct a Bartik VE ratio of a given occupation at a given MSA by the national VE ratio of the occupation after excluding the MSA. And the Bartik VE ratios are then aggregated into the firm-level Bartik TRR.

3.3 Descriptives

Our analysis focus on the skilled occupations. We define an occupation as skilled if the occupations requiring a college degree & 4-year working experience in the O*NET database of occupational characteristics and worker requirements information across the U.S. economy. Figure IA.3 illustrates the occupation distribution of skilled labor used in our talent retention measure.

Our sample period ranges from 2010 to 2018. We begin with the sample of Compustat firms that appear both in Refernece USA and BGT. We then eliminate observations that lack the data required to calculate the control variables. Our final sample contains 11,822 firm–year observations. The literature has developed multiple measures of Tobin's q. In our setting, We compute Tobin's Q following Gutiérrez and Philippon (2017) as the market value of the firm divided by book assets. We also use total Q developed in Peters and Taylor (2017) in our analysis, which incorporates capital stocks of both tangible and intangible capital. We also winsorize relevant variables by year at 1% and 99%.

Table 1 shows the descriptive statistics. Notably, a talent in our sample has an average TRR of 4% (VE ratio). Following our definition, firms on average have about 5% skilled labor. Relative to average Compustat firms, our sample covers firms with similar investment and Q but with larger firm size.

3.4 Validation

We consider an array of validation tests that illustrate that our primary TRR measure captures the risk of firm's loss of talents. We show that our TRR can positively predict both the CFO perceived talent losing risk as well as the realized outflow of talent. In addition, we note that our TRR measure is derived using a combination of highly-granular labor market data, to ensure consistency with our theoretical foundation and ease of interpretation.

3.4.1 Duke CFO Survey of Managerial Perceptions

We validate TRR by first examining whether CFOs are more likely to view difficulty in attracting or retaining qualified employees as the most pressing concerns when our TRR measure is high.

$$\text{TRR}_{\text{CFO perceived},i,t} = \beta \cdot \text{TRR}_{i,t} + \text{Firm FE} + \text{Qurater FE} + \epsilon_{i,t}.$$

In Table 2, we regress CFOs' perceived talent retention risk on our TRR measure. The dependent variable $\text{TRR}_{CFOperceived}$ is an indicator variable equal one if the CFO includes "Difficulty attracting/retaining qualified employees" in the top 4 most pressing concerns. Our data structure allows us to include firm fixed effects, which absorb any firm-specific omitted variables, and quarter fixed effects. Standard errors are clustered at the firm level.

Columns (1) and (2) in Panel A show that CFO's perceived talent retention risk is positively correlated with our TRR measure. It provides evidence that our TRR measure captures the subjective risk of losing talent. Further, it suggests our TRR measure can have materialized effects on firm decisions, given the extensive evidence on the importance of executive's belief in firm investment decisions, as shown by Gennaioli et al. (2016).

3.4.2 Linkedin Workforce Dynamics

To further validate our TRR as a measure of difficulty in attracting or retaining talent, we examine whether TRR leads to talent outflow based on the Revelio data. In Panel B of Table 2, we regress

$$\text{Log Outflow of Talent}_{i,t+k} = \beta \cdot \text{TRR}_{i,t} + \gamma \cdot \text{Emp}_{i,t} + \text{Firm FE} + \text{Year FE}\epsilon_{i,t},$$

where $\text{TRR}_{i,t}$ is the measured talent retention risk of firm i in year t. Outflow of $\text{Talent}_{i,t+k}$ is the number of skilled employees who leave firm i in year $t+k$, $k \in \{-1, 0, 1, 2\}$. $\text{Emp}_{i,t}$ is the log of the number of employees. We include firm fixed effects, which absorb any firm-specific omitted variables, and year fixed effects. Standard errors are clustered at the firm level.

Columns (1)-(4) in Panel B of Table 2 show that firms experience more talent outflow when TRR is high. A one standard deviation increase in TRR is associated with about a one percent increase in talent outflow. The predictive power is strongest contemporaneously and for the next year and declines as extending the forecast horizon. Most importantly, our TRR is uncorrelated with last year's talent outflow, which suggests that our TRR measures the exogenous innovation of talent retention risk that is not reversely driven by the firm's previous labor market performance.

Moreover, Table IA.3 shows that our TRR can predict talent outflow even if controlling for firm characteristics, including cash flow, firm size, age, Tobin's Q, and employment. In addition, to address the potential concern that our TRR only captures the talent retention risk for the fasting growing industries, where online job posting is a more common practice, we regress talent outflow on the interaction term of TRR and fast-growing industry dummy, as defined by Crouzet and Eberly (2020). We find that our TRR measure predicts talent outflow in both fast-growing industries and other industries. Notably, the predictive power is equally strong as the interaction term of TRR and fast-growing industry dummy is not statistically significant.

Our validation provides useful insights that firms cannot stop talent exits when facing high TRR. In the following analysis, we will show that they actively hire to counteract talent loss due to the increasing TRR, which can be very costly, as shown by Blatter et al. (2012).

4 Talent Retention Risk and Corporate Investment

4.1 Main Findings

We first examine whether talent retention risk can affect corporate investment. The dependent variable in Table 3 is a measure of firm's capital investment scaled by property, plant and equipment (CAPX/PPEGT). All tests include firm and year fixed effects, and standard errors are clustered by firm. Following prior literature on investments, we include standard controls for all tests. Control variables $X_{i,t}$ are Tobin's Q, cash flow, firm size, and firm age. We control for firm size as smaller firms tend to be more volatile and to grow faster. The inclusion of firm size and age also proxy firm's financial constraints. For example, Hoberg and Maksimovic (2015) and Hadlock and Pierce (2010) document that younger and more innovative firms face more financial constraints. The regression specification we estimate is as follows:

$$CAPX_{i,t+1}/PPEGT_{i,t} = \beta TRR_{i,t} + X_{i,t} + FirmFE + YearFE + \epsilon_{i,t},$$

where $CAPX_{i,t+1}/PPEGT_{i,t}$ is the capital investment of firm i in year $t+1$, and $TRR_{i,t}$ measures the talent retention risk in year t.

Columns (1)-(4) of Table 3 show that firms invest less when TRR is high. Column (1) shows our baseline model that does not includes any controls, and we find that firms are less likely to incur capital investments when they face higher talent retention risks. Column (2) adds the controls, and the coefficient estimate of TRR is significant at the 1% level with signs that reinforce the importance of talent in investment decisions. Columns (3) includes Tobin's Q as an additional control and presents consistent result, indicating that Tobin's Q cannot explain the impact of TRR on capital investments.

In Column 4, the documented negative coefficient is robust in specification controlling for total Q, which incorporates firm's intangible capital following Peters and Taylor (2017). Overall, we provide evidence that capital investments are dampened by TRR in the past decade. Our findings provide support that the risk of limited management and manpower may potentially explain the the missing investment, beyond the influence of Q.

The above findings are not likely to be driven by endogeneity for the following reasons. First, we exclude all job posts from the firm's top 3 industries when calculating local occupation VE ratios. This way addresses the potential omitted variable concern that local competitors change job posting behaviors because of industry trends that also affect the firm of interest. In other words, our TRR measure captures the local labor market competition from employers who do not compete with the firm of interest in the product markets.

Furthermore, the decrease in capital investment can also be predicted by our Balanced TRR and Bartik TRR. The Balanced TRR addresses the concern that firms may strategically enter or exit MSAs with tight labor markets and invest accordingly. We construct the balanced TRR using a sample with only the MSA-firm pairs show up through our sample period to fix firms' geographic employment distributions.

Last, our Bartik TRR tries to exclude unobserved variations in local economic environments that could drive both VE ratios and firm decisions. We construct a Bartik VE ratio of a given occupation at a given MSA using the national VE ratio of the occupation after excluding the MSA. And the Bartik VE ratios are then aggregated into the firm-level Bartik TRR to capture the exogenous variations in talent retention risk unrelated to local economic conditions.

4.2 Robustness: TRR and Planned Investment

Based on what CFOs actually say about their investment obstacles, we want to understand why do CFOs forgo profitable projects in practice. Importantly, future realized investment is a combination of management investment plans and unexpected shocks, which indicates the importance of examining how TRR affects the planned investments at the firm level. Our conceptual framework in Section IA.1 also relates planned investment to TRR.

With our survey data, we are able to examine whether CFOs are concerned about TRR when doing capital budgeting. From Duke CFO Survey, we obtain planned investment. In Table 4, we use the following regression specification:

$$Planned\ CAPX_{i,t} = \beta TRR_{i,t} + X_{i,t} + FirmFE + YearFE + \epsilon_{i,t}$$

By including firm fixed effects, our specification absorb any firm-specific omitted variables. We also include year fixed effects. Moreover, we also control for Tobin's Q, cashflow, firm size, and age. Standard errors are clustered at firm level.

Table 4 shows that our TRR measure also negatively predicts the CFO's planned investment. The estimated coefficients are negative for all three versions of TRR and statistically significant for two of the three, noting that the sample size for the merged CFO survey data and TRR has only 353 observations. The result is also consistent with our finding that TRR is positively associated CFO's perceived difficulty attracting and retaining qualified employees.

4.3 Heterogeneous TRR Effects by Firms' Tobin Q

We examine the heterogeneous talent retention effects by firms' Tobin's Q. Our model in Section IA.1 predicts that high-Q firms are more sensitive towards the talent retention risk. Intuitively, high-Q firm's investment is more sensitive towards any changes in capital adjustment cost, which directly depends on firm's stock of talent and indirectly on the talent retention risk.

Consistent with the model, in Table 5, we find that capital investments by high-Q firms are disproportionately dampened by the rising talent retention concerns. And the negative interaction between TRR and firm's Q is statistically significant. Moving from a firm with Tobin's Q at the 10th percentile to a firm with Tobin's Q at the 90th percentile, one percentage increase in TRR leads to a lower capital investment ratio by 2.5 percentage.

Furthermore, the stronger effects of TRR on high-Q firms is robust to various measures of TRR and Q. Table 5 shows the estimated interaction effects between Tobin's Q and all our three measures of TRR are always statistically significant negative. Moreover, if we concern about whether Tobin's Q is an accurate proxy for one additional unit of capital, the same results also hold if we use Total Q defined by Peters and Taylor (2017).

5 Where TRR Matters and Whose TRR Matters?

5.1 TRR and New Capital Formation Industries

Previous literature show that new capital investment of innovative firms may differ from their old capital. Our theoretical framework on capital adjustment costs suggests that talent retention risk may affect investment of innovative firms more as the new capital formation process demands more talent inputs and managerial expertise. Thus, we hypothesize that TRR would increase adjustment costs for capital formation. To test this conjecture, we conduct a battery of subsample analysis on firms with differentiated exposure to new capital formation using three complementary approaches.

First, new capital formation is the main theme in fast growing sectors, which likely involves more adjustment costs. The economic value that is generated by new ideas are more likely to be constrained by talent during capital formation. We follow Crouzet and Eberly (2020) to group fast-growing industries defined by Fama-French 5-sectors. Second, previous literature indicates that new investment projects depend significantly on talents if they involve challenges that are unique from existing projects. Viewing firms as a portfolio of products, Hoberg and Maksimovic (2022) model a firm's product life cycle with four stages: (1) Life1 - product innovation, (2) Life2 - process innovation, (3) Life3 - stability and maturity, and (4) Life 4 - product discontinuation. Empirically, they estimate the stages of a firm's product portfolio as a four-element vector {Life1, Life2, Life3, Life4}. We use the Life1 stage to capture firm's exposure to the life cycle of new capital formation. As a stage with products that have not established their positions in the product market space, Life1 capacity is risky and acquired before the outcome of product development is known. This stage involves the highest level of product uncertainties and likely requires the most decision-making and expert information from talents. Lastly, we conjecture that the effects of talent retention risks are likely to be stronger when firms are engaging actively in the RD activities. The production process of new inventions and business ideas are argued to involve highly skilled personnel.

Panel A in Table 6 presents the results for fast-growing industries. In the left and right side panels, we demonstrate the analyses of the effects of TRR alone (the first two columns in the left side panel) and also the interaction effects (the other two columns in the right side panel). Consistent with our expectations, we find that the effects of TRR are indeed stronger among firms that are in those sectors with more new capital formation. Panel B in Table 6 is based on firm life cycles. We use high-Life1 estimation from Hoberg and Maksimovic (2022) as a measure of firms' exposure to early product life cycle stage. We find that our findings of TRR are more pronounced in Life1 firms with more intensity of product innovation. Lastly, Panel C in Table 6 shows our findings based on firm's RD activities. We continue to find that TRR dampens investments for innovative firms. Overall, our results provide support that talent can be a particularly significant source of capital adjustment cost when firms are involved in new capital formation.

5.2 Manager vs. Non-managers

It is important to examine which talent matters for corporate finance. We first focus on the talent retention risk for managers versus non-managers, as a large literature shows that managers are pivotal for firms, for example, Bloom et al. (2013) and Lazear et al. (2015). Then we do a more comprehensive search for each occupation in SOC-2 digits to identify the crucial talents that matter for investment decisions.

Using the same bottom-up approach, we estimate the management talent retention risk by first calculating the VE ratios for each management occupation for a given firm in a given MSA and then aggregating them into a firm level TRR(mgmt) weighted by the employment shares. Our TRR(mgmt) mostly captures the retention risk for middle managers, which take the lion's share of employment in the overall management occupation. TRR(mgmt) does not measure and does not attempt to measure the risk of losing executives. Similarly, we construct a talent retention risk measure for all other non-management occupations.

Conceptually, the manager retention risk can be particularly important for the following reasons. First, Lazear et al. (2015) document a large effect of middle managers on team productivity. Middle managers can boost team productivity in many ways. For example, Hoffman and Tadelis (2021) document that a manager's interpersonal skills can help to reduce employee turnover. Adhvaryu et al. (2022) show middle managers can reallocate tasks inside a team to match with subordinates' productivity. Halac and Prat (2016) analyze a theoretical framework where middle managers need to invest time and attention to better monitor their subordinates. However, both the reallocation and monitoring channels require information, skill, and practices that are firm-specific or even employee-specific, which can not be easily persevered within the firm upon the leaving of a manager (Bloom et al. (2020)). Moreover, the managerial loss can not be easily replaced by new hires, as many of the skills and traits are hard to observe (Adhvaryu et al. (2019)), and it takes time for the newly hired managers to learn and develop the firm or employee-specific knowledge. Last but not least, the leaving of a good manager can trigger turnovers of other employees and lead to bigger loss of firm's human capital (Lazear et al. (2015)).

To test the importance of manager retention risk on investment, we run the following regression:

$$CAPX_{i,t+1}/PPEGT_{i,t} = \beta \cdot TRR_{i,o,t} + X_{i,t} + FirmFE + YearFE + \epsilon_{i,t},$$

where $CAPX_{i,t+1}/PPEGT_{i,t}$ is the capital investment of firm i in year $t+1$, and $TRR_{i,t}$ measures the overall talent retention risk of firm i in year t, while $TRR(mgmt)_{i,t}$ captures the retention risk specifically for managers, and $TRR(nonmgmt)_{i,t}$ for all other skilled occupations. Control variables $X_{i,t}$ are tobin's q, cash flow, firm size, and firm age. We include firm fixed effects, which absorb any firm-specific omitted variables, and year fixed effects. Standard errors are clustered at firm level.

In Table 7, we find that the manager retention risk negatively predicts a firm's investment. However, the retention risk of non-management occupation appears not to affect firm's investment decisions. The results confirm the specialty of middle managers' roles.

To further identify the importance of middle managers and which other occupations matter in firm's investment decisions, we repeat our CAPX regression using alternative TRR based on each broad occupation:

$$CAPX_{i,t+1}/PPEGT_{i,t} = \beta \cdot TRR_{i,o,t} + X_{i,t} + FirmFE + YearFE + \epsilon_{i,t},$$

where $CAPX_{i,t+1}/PPEGT_{i,t}$ is the capital investment of firm i in year $t+1$, and $TRR_{i,o,t}$ measures the talent retention risk for occupation o of firm i in year t. Control variables $X_{i,t}$ are tobin's q, cash flow, firm size, and firm age. We include firm fixed effects, which absorb any firm-specific omitted variables, and year fixed effects. Standard errors are clustered at firm level.

When constructing the talent retention risk measures at SOC-2 digits level, we use the VE ratios of all corresponding SOC-5 digits occupations. We include both skilled and non-skilled labor to make sure the definition of skilled occupation does not drive our results.

Table IA.2 shows that the retention risk of the management occupation still stands out as the strongest predictor of future investment. Most notably, the manager retention risk measure after excluding executives is equally capable of predicting capital investment. This finding again demonstrates the importance of middle managers.

Among the non-management occupations, we find the retention risk of the computer and mathematical occupation also negatively predict future investment. The result is consistent with the literature that stresses the growing importance of information technology in business decisions and performance (Brynjolfsson and Hitt (2000)).

6 Implications for Rising Investment-Q Gap

In this section, we further investigate whether the rising challenge in retaining talent can be a reason for the widening investment-Q gap. Notably, our measure uses only the variation of job postings by other firms in the local labor market. Hence, it is less likely to be affected by the firm's endogenous actions. Equipped with this measure, we provide three new empirical facts.

We first follow Gutiérrez and Philippon (2017) to estimate the widening investment-Q gap. Using their empirical specification, we estimate the year fixed effects in a firm investment regression after controlling for Q and other firm characteristics, including cash flow, firm size, and age:

$$CAPX_{i,t+1}/PPEGT_{i,t} = \sum_t \beta_t YearDummy_t + \alpha Q_{i,t} + X_{i,t} + FirmFE + \epsilon_{i,t}$$

Consistent with their findings, we document an increasing divergence between investment and Q in the Panel A of Figure 5. In Panel B, we show that the investment-Q Gap widened more for high-Q firms.

Next, we attempt to explain the widening investment-Q gap. Specifically, we examine how much rising TRR contributes to the widening investment-Q gap in the 2010s, by extending the Gutiérrez and Philippon (2017)'s Model with TRR Control:

$$CAPX_{i,t+1}/PPEGT_{i,t} = \sum_t \gamma_t YearDummy_t + \psi TRR_{i,t} + \alpha Q_{i,t} + X_{i,t} + FirmFE + \epsilon_{i,t}$$

In Table 8, we show that our TRR measure can explain about 16% of the increase in the investment-Q gap between 2010 and 2017. As Tobin's Q may overestimate Q because it does not account for intangible capital, we provide robustness tests using Total Q as an alternative in the bottom panel of Table 8. Crouzet and Emberly (2022) argue that Total Q is not a sufficient statistic for CAPX. Nevertheless, we repeat our analyses using Total Q from Peters and Taylor (2017). Our results are generally consistent.

Lastly, we find that the explanatory power from rising TRR on investment-Q gap mainly comes from high Q firms. And it does not matter whether we define high Q firms based on Tobin's Q or Total Q or based on a dummy variable indicating fasting growing sectors. The stronger explanatory power for high-Q firms is not surprising, as we already show that our TRR cross-sectionally predicts firm investment much better for high-Q firms. However, the stronger explanatory power for high-Q firms is very important to explain the widening investment-Q gap, which we show is mostly driven by high-Q firms.

7 Conclusion

Recent surveys of CFOs unveil that constraints in skilled labor are the dominant obstacle for corporate investment in the 21st century, and companies frequently highlight attracting and retaining skilled labor as a top challenge for internal risk management. In this paper, we construct the first measure of firms' talent retention risk (TRR) based on an on-the-job search framework to capture changes in the likelihood for the firm to lose a talent. A battery of tests validate our TRR. First, we show that a firm's TRR is positively related to its CFO electing "attracting and retaining qualified employees" as the top three firm-specific concerns using Duke CFO survey. Second, we show that a firm's TRR strongly relates to talent outflows using LinkedIn microdata.

Equipped with this measure, we study the impact of talent retention risk on corporate investment. We hypothesize that TRR increases adjustment costs for capital formation as suggested by prior literature and survey evidence. We present empirical results supporting the predictions of our simple framework. First, we show that TRR significantly reduces next period investment in 2010-2018 even after controlling for Tobin's Q, total Q that includes intangibles (Peters and Taylor (2017)), other common predictors for investment, and fixed effects by firm and year. Second, we show significant negative coefficient of interaction term no matter Q is measured as Tobin's Q or total Q. Intuitively, these findings suggest that talent retention risk particularly dampens firm investment when the firm needs to accumulate capital at a faster pace. Third, we conduct a body of subsample analyses showing that the above effects of TRR are indeed stronger among firms that are likely to be constrained by talent during capital formation, for example firms in the new product innovation stage of life-cycle (Hoberg and Maksimovic (2021)), firms in fast growing sectors (Crouzet and Eberly (2020)), and firms engaging more in R&D. In addition, consistent with the survey evidence highlighting the shortage of middle managers as the core source of adjustment cost, we decompose our TRR measure based on management occupations and non-management occupations within our talent occupations. We show that our TRR results are driven primarily by management occupations. Last but not the least, we find that rising challenges of retaining talent explains a sizable fraction of the lackluster investment as compared to Q mainly in fast growing innovative firms. Our findings uncover new insights on how talent market dynamics affect firms' investment activities in the past decade and provide important implications on the role of adjustments costs in the capital formation process. We also believe our TRR measure can prove useful in other settings, which may have natural applications to other disciplines such as strategy and management.

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Figure 1: **Talent Retention Concerns from the Duke CFO Survey**

This figure plots the percentage of CFOs electing "attracting and retaining qualified employees" as the top firm-specific concerns using the microdata of the Duke CFO Survey. During 2008Q4-2014Q1, the survey asked CFOs to elect from about 10 options to answer "*What are the top three internal, company-specific concerns for your corporation?*" During 2015Q1-2019Q4, the survey asked CFOs to elect from about 18 options to answer "*During the past quarter, which items have been the most pressing concerns for your company's top management team? (Choose up to 4)*" Both waves of survey include the option "attracting and retaining qualified employees." The survey did not ask related questions during the interim quarters. Because the survey changed the question in 2014, we shift the percentage of CFOs electing "attracting and retaining qualified employees" in the first quarter of the later wave to align with the percentage in the last quarter of the earlier wave. The pattern is very similar if we control for firm heterogeneities across surveys (see the Internet Appendix Figure IA.4).

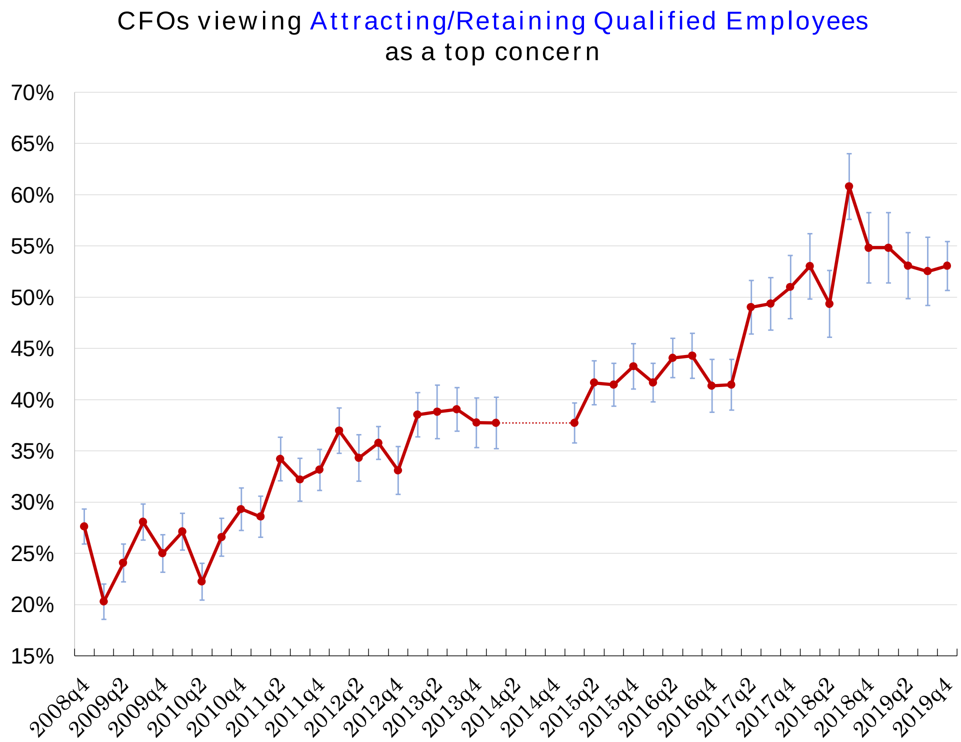


Figure 2: **Talent Outflows from the LinkedIn Microdata**

This figure plots average outflows of talent using the LinkedIn Workforce Dynamics microdata. Talent is defined as occupations that require a college degree and 4-year working experience (see Section 3). The figure plots the coefficients of the year dummies in the following regression specification:

$$\log(\text{Outflow of Talent}_{i,t} + 1) = \sum_t \beta_t \cdot \text{Year Dummy}_t + \text{Firm FE} + \epsilon_{i,t}$$

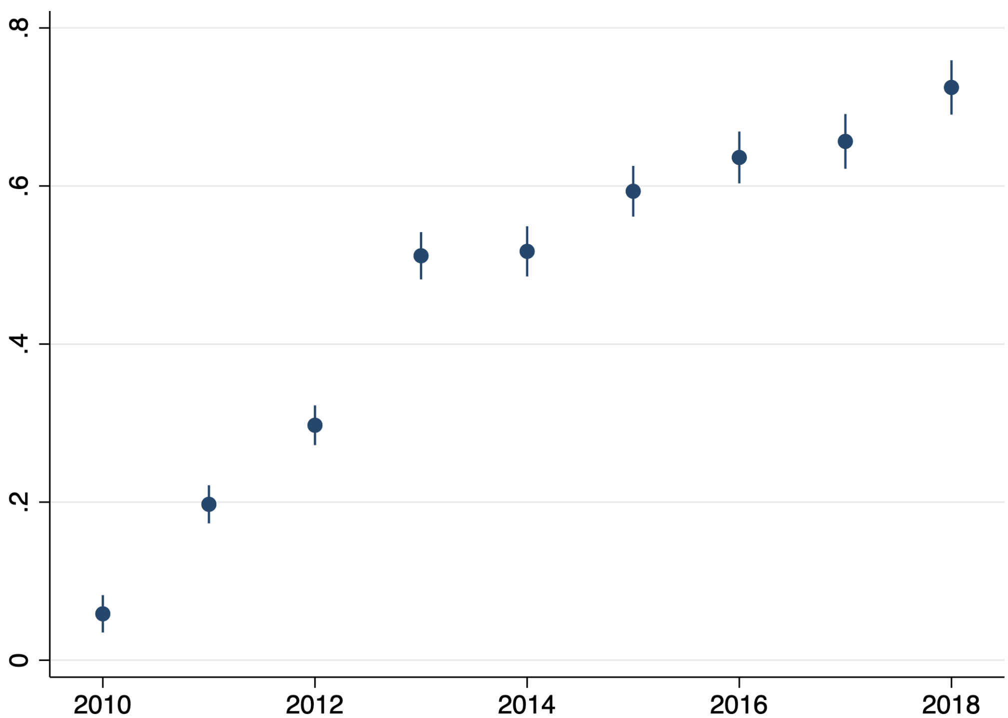


Figure 3: **Talent's Time Spent on Job Search**

This figure plots the percent of a skilled worker's time spent on job search in the American Time Use Survey database. See Section 3.3 for the definition of skilled occupations.

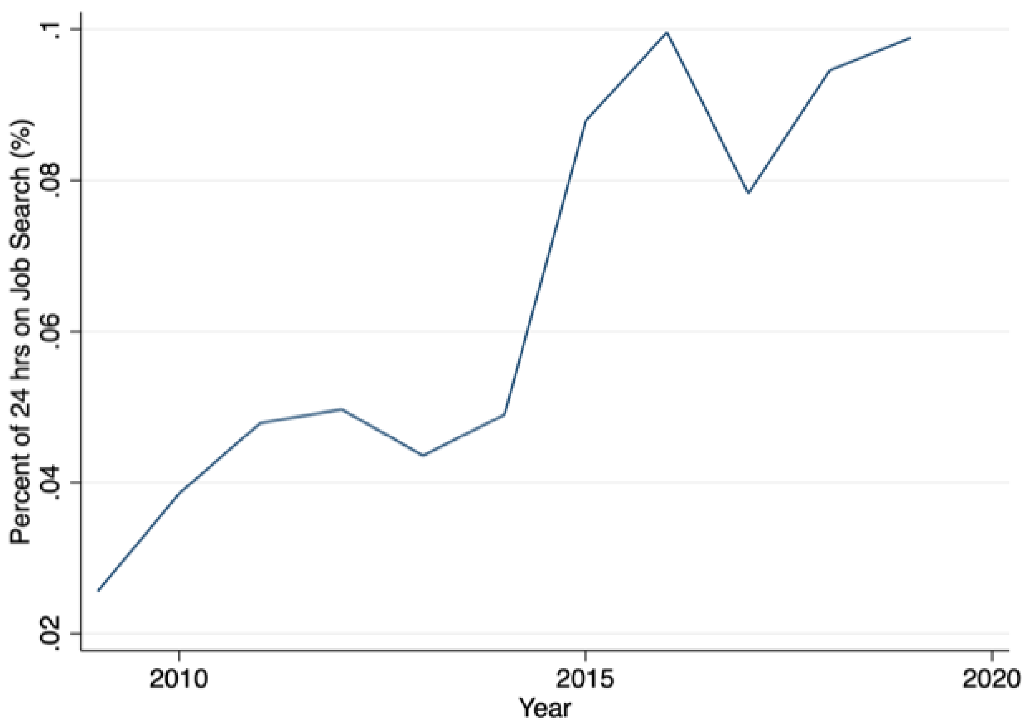


Figure 4: **Talent Retention Risk Measure**

This figure plots average talent retention risk (TRR) measure in each Fama-French 5-sectors for each year from 2010 to 2018. See Section 3 for the construction of firms' TRR.

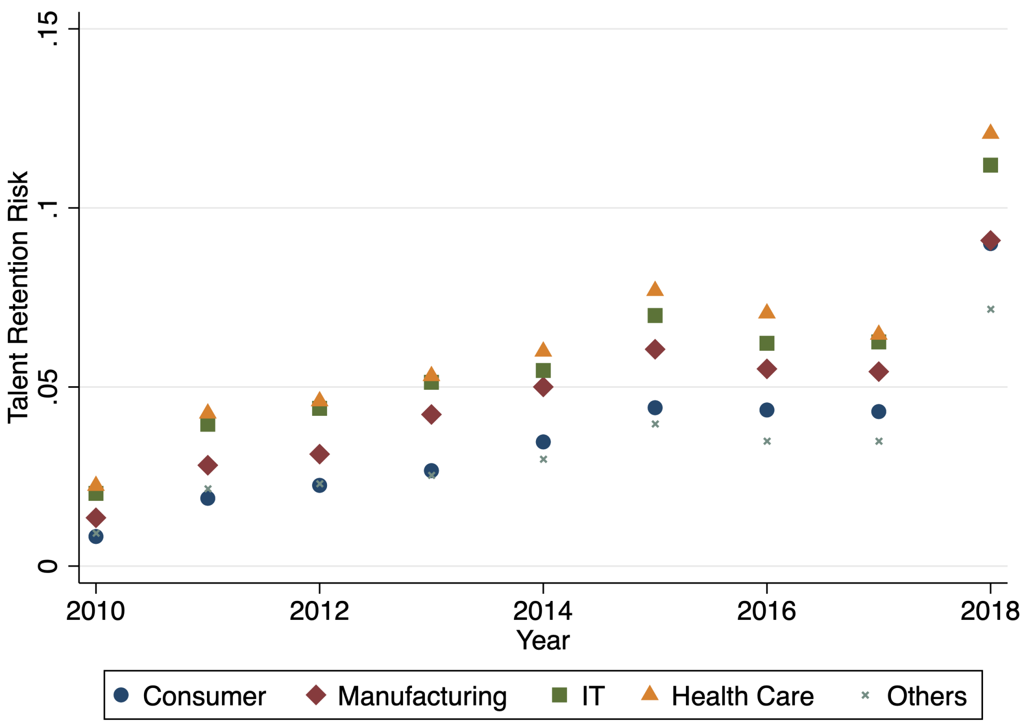


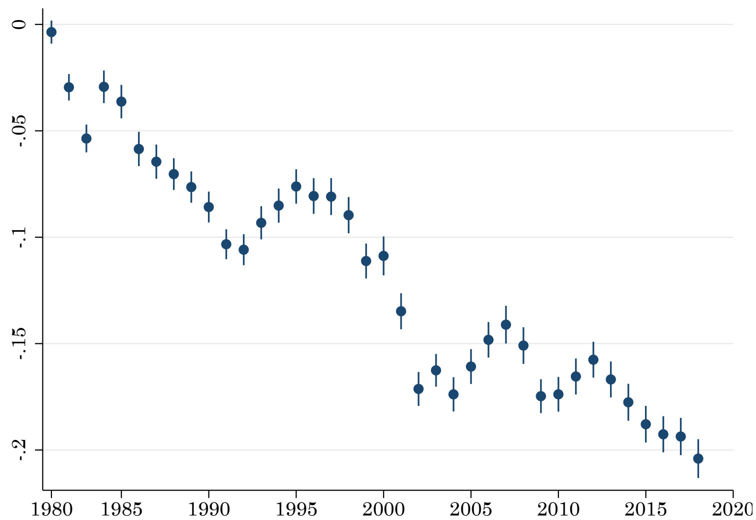
Figure 5: **Replicating Investment-Q Gap**

This figure illustrates the gap between realized investment and the predicted investment from Tobin's Q. Our estimation follows Gutiérrez and Philippon (2017) by running the following specification using non-financial U.S. firms,

$$\text{Investment}_{i,t+1} = \sum_t \beta_t \cdot \text{Year Dummy}_t + \alpha \cdot Q_{i,t} + X_{i,t} + \text{Firm FE} + \epsilon_{i,t}.$$

Investment is the ratio of capital expenditures (CAPX) and lagged tangible asset (PPEGT). β_t captures the change in Investment-Q Gap from starting year to year t. $Q_{i,t}$ is Tobin's Q in Panel A and total Q (Peters and Taylor (2017)) in Panel B. Control variables include cash flow, size, age. Standard errors are clustered at firm level.

Panel A: Tobin's Q



Panel B: Total Q

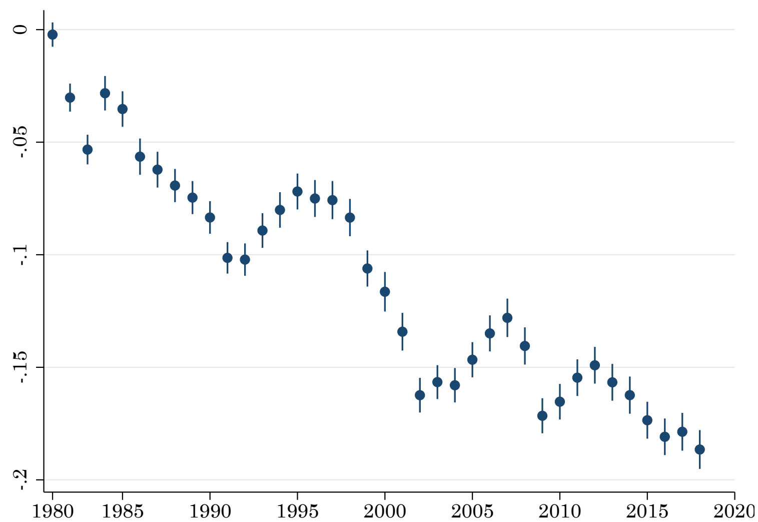


Table 1: **Summary Statistics**

This table presents the summary statistics of the variables in our sample. Our sample includes all Compustat firms with talent retention risk (TRR) measure from 2010 to 2018. Section 3 details the construction of the TRR measure. Share of Talent is the fraction of company employees in the talent occupations. Outflow is the natural logarithm of the number of talent leaving the firm in the year from the LinkedIn microdata. Turnover is the natural logarithm of the sum of number of talent leaving and joining the firm in the year. Planned Investment is the growth rate of the firm's CAPX reported in the Duke CFO Survey. Investment is next year's CAPX divided by this year's PPEGT. Q is Tobin's Q measured as the market value of the firm divided by book assets following Gutiérrez and Philippon (2017). Total Q includes intangible assets in the denominator and is obtained from Peters and Taylor (2017). Cashflow is the sum of income before extraordinary items (IB) and depreciation expense (DP) normalized by PPEGT. 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.

Variable	Mean	SD	Minimum	Median	$\text{Median}_{Universe}^{Compustat}$	Maximum	# obs.
TRR	0.040	0.045	0.000	0.025	-	0.225	11,822
Share of Talent	0.049	0.040	0.000	0.040	-	0.211	11,824
Outflow (log)	3.279	1.682	0.000	3.284	-	8.981	10,344
Turnover (log)	4.077	1.696	0.000	4.097	-	9.867	10,344
Planned Investment	0.060	0.209	-0.750	0.044	-	1.200	438
Investment	0.120	0.112	0.000	0.088	0.085	0.836	11,824
Q	1.755	1.427	0.150	1.305	1.412	12.791	11,636
Total Q	1.227	1.594	-6.700	0.798	0.820	18.764	11,497
Cash Flow	-0.028	2.430	-38.361	0.171	0.097	5.103	11,791
Size (log)	7.140	1.989	1.603	7.214	5.942	12.325	11,824
Age (log)	3.090	0.736	0.693	3.135	2.773	4.220	11,824

Table 2: **Validating the Talent Retention Risk Measure**

This table presents results of two separate validation tests for our talent retention risk (TRR) measure using Duke CFO Survey microdata (in Panel A) and the LinkedIn microdata (in Panel B). Section 3 details the construction of the TRR measure. Panel A reports the regression of CFO's perceived talent retention challenge on our TRR measure from 2015 to 2018 using the following specification:

$$\text{TRR}_{\text{CFO perceived},i,t} = \beta \cdot \text{TRR}_{i,t} + \text{Firm FE} + \text{Qurater FE} + \epsilon_{i,t},$$

where the dependent variable $\text{TRR}_{\text{CFO perceived},i,t}$ is a dummy variable equals 1 if the CFO includes "Difficulty attracting/retaining qualified employees" in the top 4 most pressing concerns in the Duke CFO Survey. Standard errors are clustered at firm level. Panel B reports the results of regressing talent outflow on our TRR measure from 2010 to 2018 using the following specification,

$$\text{Log Outflow of Talent}_{i,t+k} = \beta \cdot \text{TRR}_{i,t} + \gamma \cdot \text{Log Emp}_{i,t} + \text{Firm FE} + \text{Year FE} + \epsilon_{i,t},$$

where Log Outflow of $\text{Talent}_{i,t+k}$ is the natural logarithm of the number of talents who leave firm i in year $t+k$ plus 1, $k \in \{-1, 0, 1, 2\}$. Log $\text{Emp}_{i,t}$ is the natural logarithm of the number of employees. Standard errors are clustered at firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Does CFO Perceive Talent Retention Risk?		
	$\text{TRR}_{\text{CFO perceived}}$	
TRR	6.34**	7.86**
	(2.42)	(3.42)
Firm FE	Yes	Yes
Quarter FE	No	Yes
Observations	113	113
Adjusted R^2	0.32	0.25

Panel B: Does TRR Lead to Talent Outflows?				
	Log Outflow of Talent			
	t - 1	t	t + 1	t+2
TRR	0.40	0.48**	0.54**	0.39*
	(0.26)	(0.24)	(0.23)	(0.22)
Log Emp	0.34***	0.47***	0.55***	0.47***
	(0.05)	(0.05)	(0.05)	(0.05)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	9721	9726	9730	9730
Adjusted R^2	0.91	0.92	0.92	0.92

Table 3: **Talent Retention Risk and Investment Response**

This table reports the regression of firm future investment rate on the talent retention risk (TRR) measure in the following spefication:

$$\text{Investment}_{i,t+1} = \beta \cdot \text{TRR}_{i,t} + X_{i,t} + \text{Firm FE} + \text{Year FE} + \epsilon_{i,t},$$

where $\text{Investment}_{i,t+1}$ is next year's CAPX divided by current PPEGT. Section 3 details the construction of our TRR measure. Control variables $X_{i,t}$ include Tobin's Q, cash flow, firm size, and firm age. Standard errors are clustered at the firm level. Sample period is from 2010 to 2018. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
TRR	-0.128**	-0.143***	-0.135***
	(0.052)	(0.051)	(0.050)
Cashflow		0.004**	0.004**
		(0.002)	(0.002)
Size		0.007	0.015***
		(0.005)	(0.005)
Age		-0.139***	-0.114***
		(0.016)	(0.016)
Q			0.028***
			(0.002)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	11623	11589	11413
Adjusted R^2	0.533	0.545	0.566

Table 4: **Robustness of Investment Response to TRR**

This table reports the robustness check results for the investment response to talent retention risk (TRR) in Table 3 using an alternative measure of Q (in Column (2)), alternative measures of TRR (in Columns (3) and (4)) and an alternative investment measure (in Column (5)). See Table Table 3 for the regression specification. *Total Q* includes intangibles following Peters and Taylor (2017). *Balanced TRR* is an alternative TRR measure computed assuming that firms do reallocate talent across MSAs since their first year of appearance in our sample. *Bartik TRR* is an alternative TRR measure computed using a Bartik-instrumented job posting for talent in each MSA instead of the actual job posting for talent in the MSA. *Planned Investment* is CFO's planned growth rate in capital expenditure using the data from the Duke CFO Survey instead of the realized future investment. Standard errors are clustered at the firm level. Sample period is from 2010 to 2018. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Baseline (1)	Total Q (2)	Balanced TRR (3)	Bartik TRR (4)	Planned Investment (5)
TRR	-0.135***	-0.115**	-0.106**	-0.091**	-1.497**
	(0.050)	(0.053)	(0.052)	(0.038)	(0.690)
Q	0.028***		0.027***	0.028***	0.118
	(0.002)		(0.003)	(0.002)	(0.071)
Cashflow	0.004**	0.003*	0.007***	0.004**	-0.014
	(0.002)	(0.002)	(0.002)	(0.002)	(0.057)
Size	0.015***	0.002	0.017***	0.015***	0.010
	(0.005)	(0.005)	(0.005)	(0.005)	(0.110)
Age	-0.114***	-0.087***	-0.088***	-0.113***	-0.314
	(0.016)	(0.015)	(0.016)	(0.016)	(0.312)
Total Q		0.032***			
		(0.002)			
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	11413	11281	10080	11413	353
Adjusted R^2	0.566	0.587	0.530	0.565	0.192

Table 5: **Investment and Interaction of TRR and Q**

This table reports the results of regressing firm future investment on an interacting of talent retention risk (TRR) and Q using the following regression specification:

$$\text{Investment}_{i,t+1} = \gamma \cdot TRR_{i,t} \times Q_{i,t} + \beta \cdot \text{TRR}_{i,t} + \theta \cdot Q_{i,t} + X_{i,t} + \text{Firm FE} + \text{Year FE} + \epsilon_{i,t},$$

where $\text{Investment}_{i,t+1}$ is next year's CAPX divided by current PPEGT. Section 3 details the construction of our baseline TRR measure. See Table 4 for definitions of Balanced TRR and Bartik TRR. Panel A reports results using Tobin's Q while Panel B reports results using total Q from Peters and Taylor (2017). Control variables $X_{i,t}$ include cash flow, firm size, and firm age. Standard errors are clustered at the firm level. Sample period is from 2010 to 2018. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Baseline TRR (1)	Balanced TRR (2)	Bartik TRR (3)
	Panel A: Interacting with Tobin's Q		
TRR × Q	-0.091*** (0.029)	-0.095*** (0.032)	-0.054** (0.021)
TRR	0.051 (0.068)	0.076 (0.070)	0.016 (0.052)
Q	0.032*** (0.003)	0.032*** (0.004)	0.031*** (0.003)
Cash Flow	0.004** (0.002)	0.007*** (0.002)	0.004** (0.002)
Size	0.017*** (0.005)	0.019*** (0.005)	0.017*** (0.005)
Age	-0.110*** (0.015)	-0.084*** (0.016)	-0.110*** (0.016)
Observations	11,413	10,080	11,413
Adjusted R^2	0.567	0.532	0.567
	Panel B: Interacting with Total Q		
TRR × Total Q	-0.063*** (0.023)	-0.082*** (0.026)	-0.042*** (0.014)
TRR	-0.025 (0.061)	0.008 (0.064)	-0.034 (0.043)
Total Q	0.035*** (0.002)	0.036*** (0.003)	0.034*** (0.002)
Cash Flow	0.003* (0.002)	0.004** (0.002)	0.003* (0.002)
Size	0.004 (0.005)	0.007 (0.005)	0.004 (0.005)
Age	-0.083*** (0.015)	-0.072*** (0.016)	-0.083*** (0.015)
Observations	11,281	9,969	11,281
Adjusted R^2	0.588	0.548	0.588

Table 6: **Talent Retention Risk and Investment in Subsamples**

This table reports the regression of firm future investment rate on the talent retention risk (TRR) measure and the interaction between TRR and Tobin's Q in three subsample analyses. Panel A uses subsample divided by fast growing sectors (IT and Healthcare) and other sectors (Consumer, Manufacturing, and Others) following Crouzet and Eberly (2020). Panel B uses firm product life-cycle measure from Hoberg and Maksimovic (2021) and separates the sample into above average and below average product innovation life-cycle (life1) intensity. Panel C devide the sample into firms with and without positive R&D expense in Compustat. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. Sample period is from 2010 to 2018. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Panel A: Subsample by Industry Growth			
	Fast Growing		Others	
	(1)	(2)	(3)	(4)
TRR	-0.254***	-0.005	-0.016	0.046
	(0.089)	(0.111)	(0.047)	(0.081)
TRR × Q		-0.099***		-0.039
		(0.036)		(0.036)
Q	0.026***	0.032***	0.032***	0.034***
	(0.003)	(0.004)	(0.004)	(0.004)
Observations	3992	3992	7421	7421
Adjusted R^2	0.535	0.537	0.594	0.594
	Panel B: Subsample by Firm Product Life Cycle			
	High Product Innovation Stage		Low Product Innovation Stage	
	(1)	(2)	(3)	(4)
TRR	-0.203***	0.004	0.013	0.001
	(0.075)	(0.097)	(0.053)	(0.102)
TRR × Q		-0.084***		0.009
		(0.032)		(0.050)
Q	0.027***	0.031***	0.036***	0.035***
	(0.003)	(0.004)	(0.006)	(0.007)
Observations	5708	5708	5423	5423
Adjusted R^2	0.553	0.555	0.562	0.562
	Panel C: Subsample by Firm R&D Activity			
	Have R&D		Do not have R&D	
	(1)	(2)	(3)	(4)
TRR	-0.206***	0.042	0.038	0.070
	(0.069)	(0.090)	(0.060)	(0.102)
TRR × Q		-0.107***		-0.021
		(0.033)		(0.048)
Q	0.028***	0.034***	0.029***	0.030***
	(0.003)	(0.004)	(0.004)	(0.005)
Observations	5689	5689	5696	5696
Adjusted R^2	0.555	0.558	0.588	0.588

Table 7: **Decomposing TRR: Management vs. Non-Management**

This table reports our baseline investment regression in Table 3 by decomposing TRR into retention risk for talent from the management occupations (SOC 2-digit code = 11) and talent from non-management occupations. See Table 3 for regression specifications. Standard errors are clustered at the firm level. Sample period is from 2010 to 2018. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
TRR	-0.135***			
	(0.050)			
TRR(mgmt)		-0.145***		-0.159***
		(0.039)		(0.041)
TRR(nonmgmt)			-0.020	0.085
			(0.071)	(0.073)
Q	0.028***	0.028***	0.028***	0.028***
	(0.002)	(0.002)	(0.002)	(0.002)
Cashflow	0.004**	0.004**	0.004**	0.004**
	(0.002)	(0.002)	(0.002)	(0.002)
Size	0.015***	0.015***	0.015***	0.015***
	(0.005)	(0.005)	(0.005)	(0.005)
Age	-0.114***	-0.114***	-0.113***	-0.113***
	(0.016)	(0.016)	(0.016)	(0.015)
Observations	11,413	11,413	11,412	11,412
Adjusted R^2	0.566	0.566	0.565	0.566

Table 8: **TRR and the Widening Investment-Q Gap**

This table reports the contribution of TRR on the widening investment-Q gap. We follow Gutiérrez and Philippon (2017) and estimate the widening investment-Q gap by running the following baseline specification:

$$\text{Investment}_{i,t+1} = \sum_t \beta_t \cdot \text{Year Dummy}_t + \alpha \cdot Q_{i,t} + X_{i,t} + \text{Firm FE} + \epsilon_{i,t}.$$

We next follow Gutiérrez and Philippon (2017) and estimate the contribution of TRR on explaining the gap by including TRR into the baseline model,

$$\text{Investment}_{i,t+1} = \sum_t \gamma_t \cdot \text{Year Dummy}_t + \theta \cdot TRR_{i,t} \times Q_{i,t} + \psi \cdot TRR_{i,t} + \alpha \cdot Q_{i,t} + X_{i,t} + \text{Firm FE} + \epsilon_{i,t}.$$

Following Gutiérrez and Philippon (2017), the portion of investment-Q gap explain by the rising TRR is estimated by the difference between β_{2017} and γ_{2017}. Standard errors are clustered at the firm level. Sample period is from 2010 to 2018.

Table 8: **TRR and the Widening Investment-Q Gap**—*Continued*

Sample	ΔGap $_{2010-2017}$: Baseline Model β_{2017}	ΔGap $_{2010-2017}$: With TRR Control γ_{2017}	% TRR Explains $(\gamma-\beta)/\lvert\beta\rvert$
Panel A: Explaining Investment-Tobin's Q Gap			
All Firms	-0.0361	-0.0315	13%
	(0.0033)	(0.0039)	
Fast Growing Sectors	-0.0454	-0.0330	27%
	(0.0067)	(0.0082)	
Other Sectors	-0.0318	-0.0317	0%
	(0.0035)	(0.0040)	
High-Life1 Firms	-0.0494	-0.0395	20%
	(0.0056)	(0.0066)	
Low-Life1 Firms	-0.0283	-0.0295	-4%
	(0.0042)	(0.0049)	
R&D Firms	-0.0431	-0.0326	24%
	(0.0051)	(0.0062)	
Non-R&D Firms	-0.0306	-0.0329	-8%
	(0.0041)	(0.0047)	
Panel B: Explaining Investment-Total Q Gap			
Sample	ΔGap $_{2010-2017}$: Baseline Model	ΔGap $_{2010-2017}$: With TRR Control	% TRR Explains
All Firms	-0.0338	-0.0299	12%
	(0.0031)	(0.0037)	
Fast Growing Sectors	-0.0405	-0.0300	26%
	(0.0063)	(0.0075)	
Other Sectors	-0.0301	-0.0304	-1%
	(0.0034)	(0.0038)	
High-Life1 Firms	-0.0444	-0.0361	19%
	(0.0053)	(0.0061)	
Low-Life1 Firms	-0.0283	-0.0283	0%
	(0.0040)	(0.0046)	
R&D Firms	-0.0382	-0.0299	22%
	(0.0046)	(0.0057)	
Non-R&D Firms	-0.0302	-0.0319	-6%
	(0.0041)	(0.0046)	

Internet Appendix for "Talent Retention Risk and Corporate Investment"

AJ Chen Miao Ben Zhang Zhao Zhang

IA.1 Conceptual Framework

This section presents a simple framework based on the standard Q theory to guide our empirical tests of TRR on firm investment.

Consider a two-period investment model with convex adjustment costs. The firm is risk-neutral, maximizes shareholder value at $t = 0$, and uses a zero discount rate for simplicity.

At $t = 0$, the firm is endowed with k_0 physical capital. The firm decides investment I, and receives final payoff at $t = 1$. Importantly, the firm is also endowed with n_0 talent. Based on survey evidence, we assume that the firm cannot build up talent in short term. However, the firm may lose talent to other firms. At time $t = 0$, the firm observes job posting intensity in the local labor market which determines the probability p that each talent leaves the company after $t = 0$. Talent costs wage payment of w per unit.

The production function Cobb-Douglas with respect to physical capital and talent:

$$y_t = a_t k_t^{\alpha} n_t^{1-\alpha}$$

Capital accumulation follows:

$$k_1 = (1 - \delta)k_0 + I_0$$

Talent changes due to job posting intensity p as:

$$n_1 = (1 - p)n_0$$

Crucial, we assume assume that talent affects the firm's capital adjustment cost based on the CFO survey evidence and prior literature (Ito et al. (1999)):

$$C(I_0, k_0) = \frac{\phi(n_1)}{2}\left(\frac{I_0}{k_0}\right)^2 k_0$$

The firm maximizes value at $t = 0$ by choosing I_0, k_1.

$$\max_{k_1, I_0} \quad V_0 = y_0 - wn_0 - I_0 - C(I_0, k_0) + E_0[y_1 - wn_1]$$

s.t.

$$k_1 = (1-\delta)k_0 + I_0$$

The Lagrangian is:

$$L = a_0 k_0^{\alpha} n_0^{1-\alpha} - wn_0 - I_0 - C(I_0, k_0) + E_0[a_1 k_1^{\alpha} n_1^{1-\alpha} - wn_1] + q_0\left[I_0 + (1-\delta)k_0 - k_1\right]$$

$$\frac{\partial L}{\partial I_0} = 0 \Longleftrightarrow q_0 = 1 + \phi(n_1) I_0 \tag{1}$$
$$\frac{\partial L}{\partial k_1} = 0 \Longleftrightarrow q_0 = \alpha \bar{a}_1 n_1^{1-\alpha}\left(I_0 + (1-\delta)k_0\right)^{\alpha-1} \tag{2}$$

From (1) and (2), we have:

$$\left(1 + \phi(n_1) I_0\right)\left(I_0 + (1-\delta)k_0\right)^{1-\alpha} = \alpha \bar{a}_1 n_1^{1-\alpha}$$

Hence, I_0 is increasing in n_1.[5]

Theorem 1 *The firm invest less if the talent retention risk p is higher.*

[5]Take partial derivative of both sides with respect to n_1, we have:

$$(1-\alpha)\left(1+\phi(n_1)I_0\right)\left(I_0+(1-\delta)k_0\right)^{-\alpha}\frac{\partial I_0}{\partial n_1} + \left(I_0+(1-\delta)k_0\right)^{1-\alpha}\left(\phi(n_1)\frac{\partial I_0}{\partial n_1} + \phi'(n_1)I_0\right)$$
$$= \alpha(1-\alpha)\bar{a}_1 n_1^{-\alpha}$$

From equation (1), we see investment-q sensitivity is

$$\frac{\partial I_0}{\partial q_0} = \frac{1}{\phi(n_1)}$$

which increases with n_1 and decreases with p. Hence

$$\frac{\partial^2 I_0}{\partial q_0 \partial p} = \frac{\phi'(n_1)}{\phi(n_1)^2} \cdot n_0 < 0 \tag{3}$$

Theorem 2 *An increase in talent retention risk p reduces investment more for firms with a higher q.*

IA.2 Talent Turnover Cost

Since TRR is a labor market risk, we expect to see firms' direct reactions and responses in the labor market. More specifically, we examine whether firms actively hire to counteract talent loss due to the increasing TRR. Furthermore, we estimate the associated cost of talent turnover caused by TRR and compare the direct talent turnover cost with the decrease in capital investment. We argue that the direct talent turnover cost driven by the increase in TRR is sustantial part of the adjustment cost that firms have to pay.

Hence,

$$\frac{\partial I_0}{\partial n_1} = \frac{\alpha(1-\alpha)\bar{a}_1 n_1^{-\alpha} - \phi'(n_1) I_0 \left(I_0 + (1-\delta)k_0\right)^{1-\alpha}}{(1-\alpha)\left(1+\phi(n_1)I_0\right)\left(I_0+(1-\delta)k_0\right)^{-\alpha} + \left(I_0+(1-\delta)k_0\right)^{1-\alpha}\phi(n_1)} > 0$$

Because $\phi'(n_1) < 0$. Given that $n_1 = n_0(1-p)$,

$$\frac{\partial I_0}{\partial p} = -\frac{\partial I_0}{\partial n_1} < 0$$

We use the following specification:

$$\mathrm{Y}_{i,t+k} = \beta \cdot \mathrm{TRR}_{i,t} + X_{i,t} + \text{Firm FE} + \text{Year FE}\epsilon_{i,t},$$

where $\mathrm{TRR}_{i,t}$ is the measured talent retention risk of firm i in year t. $\mathrm{Y}_{i,t+k}$ measures the job posting, talent inflow, and talent turnover of skilled employees for firm i in year $t+k$, $k \in \{0,1\}$. $X_{i,t}$ is an array of firm characteristics including tobin's q, cash flow, firm size, firm age, and log of number of employees. We include firm and year fixed effects, which absorb any firm-specific omitted variables. Standard errors are clustered at firm level.

Table IA.4 summarizes the influence of our TRR measure on firm's job posting, talent inflow, and talent turnover in Columns (1)-(2), (3)-(4), and (5)-(6) respectively. First, we find the firms increase their job posting when TRR is high, which suggests that firm actively hire to counteract talent loss due to the increasing TRR. Second, we show that firms' active hiring is effective in the sense that the number of talent inflow rises following the increase in job posting. However, the percentage increase in talent inflow is only a third of the percentage increase in job posting. The difference demonstrate the frictions in the process of hiring new talent. Last, we find the overall talent turnover increases dramatically in high TRR period. A one standard deviation increase in talent retention risk leads to 3 percent increase in the talent turnover. The effect is strong both in the same year and one year after.

Many researchers have argued that losing and hiring new talents are very expensive, and the cost increases with the skill level, for example, Hamermesh and Pfann (1996), and Blatter et al. (2012). Our back-of-envelope calculation shows that the talent turnovers associated with TRR are costly for firms and can explain about 10% of the decrease in capital investment. Table IA.4 implies that one standard deviation higher TRR increases talent turnover count by two persons for a median firm in our sample, with the median number of total talent turnover being 64. Assume that the cost per turnover is the average annual salary, and given the median wage of skilled occupation is \$140K in the sample, a one standard deviation increase in TRR raises turnover cost by \$0.28M for a median firm. At the same time, the median of PPEGT is \$755M, and a one standard deviation increase in TRR reduces CPAX by \$2.9M.

Our assumption is that the talent turnover cost as one year of salary is likely to be a lower bound in the literature. Blatter et al. (2012) show the personnel cost for interviewing job candidates is about ten times for managers or skilled workers with a vocational degree than for low-skilled occupations, especially in large firms. Belo et al. (2017b) also assumes that skilled labor is ten times more expensive to adjust than unskilled labor. Given that the average recruiting cost for low-skill occupations is 10.5 weeks of salary in Blatter et al. (2012), our estimation of the recruiting cost for skilled workers could be more than 105 weeks of salary, which is twice as large as what we assumed.

Our back-of-envelope calculation aims to offer an approximation of direct adjustment cost associated with employee turnovers, which we find is about 10% of the decrease in capital investment. The overall adjustment cost driven by TRR will be much larger, as the literature shows an interaction effect between labor and adjustment frictions, where employee turnover indirectly makes capital adjustment costlier (Eslava et al. (2010)).

Table IA.1: **Managers in our TRR measure**

Manager Title	Emp. Share
Financial Managers	20%
Sales Managers	14%
Managers, All Other	14%
Computer and Information Systems Managers	13%
Construction Managers	9%
Architectural and Engineering Managers	8%
Marketing Managers	7%
Transportation, Storage, and Distribution Managers	4%
Human Resources Managers	4%
Purchasing Managers	3%
Natural Sciences Managers	2%
Training and Development Managers	1%
Compensation and Benefits Managers	1%
...	...

Figure IA.1: Top Chief Risk Concerns

This figure is generated by CFO Signals™: 2Q 2022. Talent and retention dominated CFOs' long list of internal worries this quarter.

Table IA.2: **A Comprehensive Search for "Which Talent Matters"**

We repeat our CAPX regression using alternative TRR based on each broad occupation. Sample period from 2010-2018.

$$CAPX_{i,t+1}/PPEGT_{i,t} = \beta \cdot TRR_{i,o,t} + X_{i,t} + FirmFE + YearFE + \epsilon_{i,t},$$

where $CAPX_{i,t+1}/PPEGT_{i,t}$ is the capital investment of firm i in year $t+1$, and $TRR_{i,o,t}$ measures the talent retention risk for occupation o of firm i in year t. Control variables $X_{i,t}$ are tobin's q, cash flow, firm size, and firm age. We include firm fixed effects, which absorb any firm-specific omitted variables, and year fixed effects. Standard errors are clustered at firm level.

SOC	Talent Definition	coef.	s.e.
11-0000	Management	-0.189***	(0.057)
11-0000	Management (ex. Executive)	-0.182***	(0.056)
13-0000	Business and Financial Operations	-0.112	(0.120)
15-0000	Computer and Mathematical	-0.098**	(0.044)
17-0000	Architecture and Engineering	0.019	(0.055)
19-0000	Life, Physical, and Social Science	0.044	(0.125)
21-0000	Community and Social Service	0.125	(0.376)
23-0000	Legal	0.067	(0.103)
25-0000	Educational Instruction and Library	-0.101	(0.376)
27-0000	Arts, Design, Entertainment, Sports, and Media	0.009	(0.038)
29-0000	Healthcare Practitioners and Technical	-0.088	(0.069)
31-0000	Healthcare Support	-0.330	(0.452)
33-0000	Protective Service	0.133	(0.169)
35-0000	Food Preparation and Serving Related	0.457	(0.460)
37-0000	Building and Grounds Cleaning and Maintenance	0.215	(0.550)
39-0000	Personal Care and Service	0.270	(0.454)
41-0000	Sales and Related	-0.066	(0.054)
43-0000	Office and Administrative Support	-0.009	(0.191)
45-0000	Farming, Fishing, and Forestry	0.508	(2.212)
47-0000	Construction and Extraction	0.836*	(0.450)
49-0000	Installation, Maintenance, and Repair	-0.162	(0.178)
51-0000	Production	0.068	(0.241)
53-0000	Transportation and Material Moving	-0.318	(0.225)

Table IA.3:
Does TRR Lead to Talent Outflows? Evidence Across Industries

	Log Outflow of Talent			
	t	t	t + 1	t+1
TRR	0.43*	0.59*	0.53**	0.61**
	(0.24)	(0.31)	(0.23)	(0.29)
TRR × Fast-growing		-0.32		-0.12
		(0.34)		(0.35)
Q	-0.03***	-0.03***	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Cashflow	0.01**	0.01**	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Size	0.29***	0.21***	0.38***	0.27***
	(0.03)	(0.04)	(0.03)	(0.04)
Age	0.28***	0.26***	0.12	0.09
	(0.08)	(0.08)	(0.08)	(0.08)
Emp		0.20***		0.25***
		(0.06)		(0.06)
Observations	9603	9562	9607	9566
Adjusted R^2	0.92	0.92	0.92	0.92

Table IA.4: **Talent Retention Risk and Employee Turnover**

Sample period from 2010-2018. Columns (1-2) Job Posting (t, t+1), Inflow (t, t+1), Total Turnover (t, t+1))

$$\mathrm{Y}_{i,t+k} = \beta \cdot \mathrm{TRR}_{i,t} + X_{i,t} + \text{Firm FE} + \text{Year FE}\epsilon_{i,t},$$

where $\mathrm{TRR}_{i,t}$ is the measured talent retention risk of firm i in year t. $\mathrm{Y}_{i,t+k}$ measures the job posting, talent inflow, and talent turnover of skilled employees for firm i in year $t+k$, $k \in \{0,1\}$. $X_{i,t}$ is an array of firm characteristics including tobin's q, cash flow, firm size, firm age, and log of number of employees. We include firm and year fixed effects, which absorb any firm-specific omitted variables. Standard errors are clustered at firm level.

	Log Job Post for Talent		Log Inflow of Talent		Log Turnover of Talent	
	t	t+1	t	t+1	t	t+1
TRR	2.06***	-0.21	0.61***	0.52**	0.69***	0.63***
	(0.38)	(0.36)	(0.21)	(0.22)	(0.20)	(0.20)
Q	0.01	0.08***	0.04***	0.08***	0.01	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Cashflow	-0.00	-0.01	0.00	-0.00	0.01	-0.00
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
Size	0.13**	0.29***	0.29***	0.27***	0.26***	0.28***
	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
Age	-0.02	0.18	-0.08	-0.06	0.06	0.01
	(0.13)	(0.13)	(0.08)	(0.08)	(0.07)	(0.08)
Emp	0.68***	0.52***	0.21***	0.08	0.20***	0.15***
	(0.09)	(0.09)	(0.06)	(0.05)	(0.06)	(0.06)
Observations	9293	9293	9562	9566	9562	9566
Adjusted R^2	0.87	0.88	0.93	0.93	0.95	0.95

Figure IA.2: **Measuring Talent Retention Risk: An Example**

This figure illustrates how we construction the measure of talent retention risk for a given firm. We first construct a talent retention risk measure for each occupation within a firm, and then aggregate the occupation talent retention risk into firm level risk using occupation employment share within the firm. In this hypothetical example, Tesla has two branches: one in San Francisco and another in Austin. For the financial manager occupation, ω share of financial managers locate in San Francisco, and $1-\omega$ share locate in Austin. In San Francisco, the talent retention risk of financial manager is measured by the vacancy to employment ratio. The denominator is the total number of financial managers in San Francisco from the OES MSA-Occupation Employment Panel. The numerator is the total number of job post for financial managers in San Francisco. To instrument the exogenous local demand for financial managers, we exclude the job posts from Tesla's top 3 industries. The talent retention risk of financial managers for Tesla is the weighted average of the vacancy to employment ratios for financial managers in San Francisco and Austin. The weights are ω and $1-\omega$ respectively.

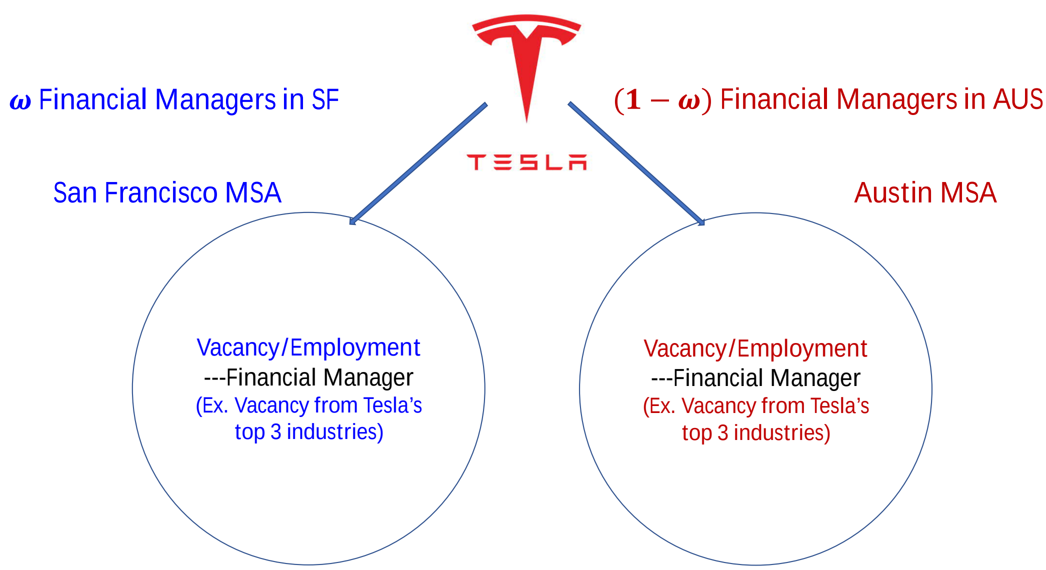


Figure IA.3: **Defining Skilled Labor**

This figure illustrates the occupation distribution of skilled labor used in our talent retention measure. We define an occupation as skilled if the occupations requiring a college degree & 4-year working experience in the O*NET database of occupational characteristics and worker requirements information across the U.S. economy. Occupation is defined at the 2010 SOC 2 digits level, and the occupation shares are from the OES National Employment Share database.

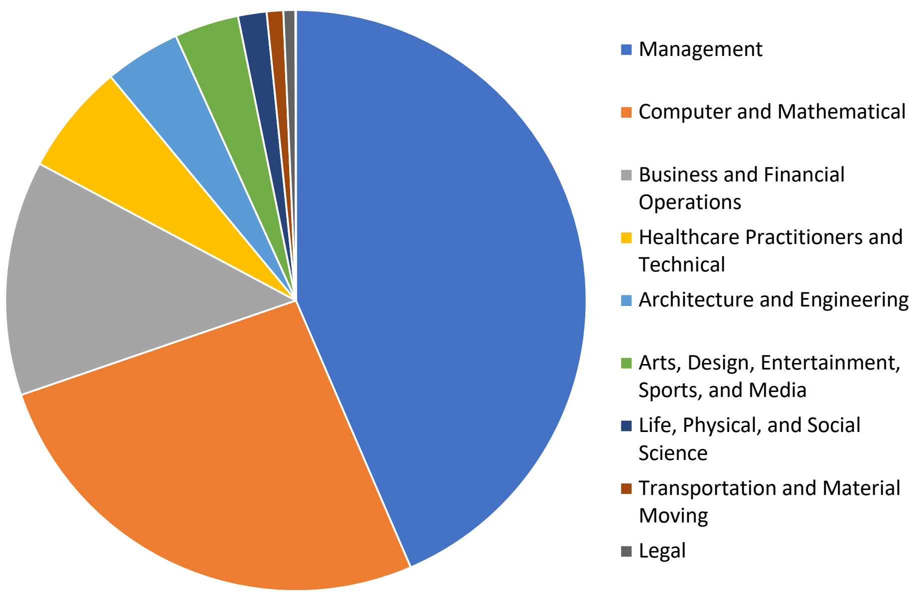


Figure IA.4: **Talent Retention Concerns in Duke CFO Survey (Controlling for Firm Heterogeneity)**

This figure plots the percentage of CFOs electing "attracting and retaining qualified employees" as the top firm-specific concerns using the microdata of the Duke CFO Survey. During 2008Q4-2014Q1, the survey asked CFOs to elect from about 10 options to answer "*What are the top three internal, company-specific concerns for your corporation?*" During 2015Q1-2019Q4, the survey asked CFOs to elect from about 18 options to answer "*During the past quarter, which items have been the most pressing concerns for your company's top management team? (Choose up to 4)*" Both waves of survey include the option "attracting and retaining qualified employees." The survey did not answer related questions during the transitional interim quarters. Because the survey changed the question in 2014, we shift the percentage of CFOs electing "attracting and retaining qualified employees" in the first quarter of the later wave to align with the percentage in the last quarter of the earlier wave. In each period, we run the following regression to extract the coefficients of the time dummies, β_t,

$$Dummy_{i,t} = \sum_t \beta_t YYYYQ_t + Revenue_{i,t} + Employment_{i,t} + FE_{Industry \times Ownership} + \epsilon_{i,t},$$

where $Dummy_{i,t}$ equals one if the CFO elect "attracting and retaining qualified employees" and standard errors are clustered by industry and quarter.