Talent-Linked Firms *

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Abstract

Using a novel measure of overlap in inventor space, we identify a focal firm's talent-linked firms that demand and are supplied with an identical set of talents. We show that talent-linked firms dominate product market-related firms and technology-linked firms in explaining cross-sectional variations in focal firms' key fundamental and innovation characteristics: stock returns, valuation multiples, financial statement ratios, growth rates, and innovation values and activities. This outperformance of talent-linked firms is not easily attributable to other economic linkages among firms. It is more pronounced for the firms that are linked with inventors with a high network centrality and specific technology focus. Our findings highlight that talent-linked firms may complement prior industry classifications for benchmarking uses and help shed light on talent linkages among firms.

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"There's no better run company… They attract the most amazing talent. No one can compete."

(Baron Funds, 3Q21 Letter)

In today's talent-driven economy, talent possessed by a firm is a key dimension of the firm's value, innovation, and, ultimately, growth. Talented employees are, thus, arguably the most important assets for firms (Gambardella et al. 2011, Liu et al. 2017, Bhaskarabhatla 2021). Yet, talent is not easily observable and measurable, and the talent space of a firm is unstructured and high-dimensional. Researchers and practitioners in both economics and finance recognize how challenging it is to value talent-intensive firms and, thus, rely on industry classification schemes by which the firms are benchmarked.[1]

Industry classifications, however, may not be economically relevant benchmarks from a talent-driven economy point of view. Firms in the same industry classification are likely to have similar end-products, but economically related firms are not always operating in proximate product space. For instance, two economically related firms with the same technology may have minimal overlap in product space but can be related in terms of fundamentals and performance.

Prior studies show that economic linkages among firms include not only product-market linkages, but also others including technology (Lee et al. 2019), customer-supplier (Menzly and Ozbas 2010), and business-line (Cohen and Lou 2002) linkages. Nevertheless, these economic linkages do not fully appreciate talent linkages among firms. For example, Apple and Tesla provide different end-products, but they demand similar talents whilst being economically related.[2]

[1] With a proliferation of industry classification schemes, researchers and practitioners widely use the Standard Industrial Classification (SIC) scheme, the North American Industry Classification System (NAICS) scheme, the Global Industry Classification Scheme (GICS), and the Text-Based Network Classification (TNIC). These industry classification schemes heavily rely on overlap in product space among firms.
[2] See Balakrishnan (2015) for an interview with Elon Musk on Tesla's talent competitors.

In this study, we develop a talent proximity score that measures talent closeness between focal firms and peer firms and use it to identify each firm's talent-linked firms. We then address benchmarking problems in economics and finance. To create the talent proximity score, we use the patent distribution across inventors. The United States Patent and Trademark Office (USPTO) issues patents to inventors, and each patent includes inventors' names. We use this information to find overlapped inventors appearing in patents issued within the past five years and create an annual measure of talent closeness for all pairs of firms.

If an inventor contributes to two firms' patents, we assume that these firms not only demand but also are supplied with an identical set of talents. Simply, we interpret the inventor as a reduced form or a unique set of talents. Then, we identify these two firms that overlap in talent space, instrumented by overlap in inventor space, as talent-linked firms. As mentioned, talent has been recognized as a central driver of firms' values and innovation (Gambardella et al. 2011, Liu et al. 2017, Bhaskarabhatla 2021). We expect that talent-linked firms are economically related firms that outperform other economic benchmarks for explaining variations of focal firms' characteristics.

To measure talent closeness between firms, we first define $Talent\ proximity\ score_{ijt}$ as the following uncentered correlation of the patent distributions across inventors between focal firm *i* and peer firm j: $Talent\ proximity\ score_{ijt} = \frac{(I_{it}I'_{jt})}{(I_{it}I'_{it})^{1/2}(I_{jt}I'_{jt})^{1/2}}$, where $I_{it} = (I_{it1}, I_{it2}, \ldots, I_{itn})$ serves as a vector of firm *i*'s proportional share of patents across *n* inventors within the rolling-window of the past five years as of time *t*. In other words, we simply measure talent closeness between firms annually using the overlap in inventor names appearing in firms' previously issued patents. Appendix IA shows an example of how the measure is computed for each firm pair.

We then identify a focal firm's talent-linked firms by sorting firms using $Talent\ proximity\ score$. We interpret talent-linked firms as the focal firm's peers in the talent similarity sense. In this talent-driven economy, we expect that the focal firm's talent-linked firms are more likely to be economically related than firms operating in proximate product space because talent is the key determinant of firm value and innovation.

We provide evidence that talent closeness among firms reflects information about fundamental and innovation characteristics. We first show that talent-linked firms are not fully constrained by industry classifications. On average, 7% of the ten closest talent-linked firms for the focal firm are its ten closest product market-related firms (Hoberg and Phillips 2010, 2014), and 11% of them are the focal firm's ten closest technology-linked firms (Lee et al. 2019). We then show, for the group of focal firms, their talent-linked firms explain the cross-sectional variations in the following dimensions more than product market-related firms and technology-linked firms: stock returns, valuation multiples, financial ratios, and growth rates.

Firms' fundamental characteristics are closely related to their innovation characteristics. Talent linkages among firms are also likely to be closely related in terms of innovation characteristics. Indeed, we find that talent-linked firms explain the cross-sectional variations of focal firms' innovation characteristics more than product market-related firms and technology-linked firms.

We provide a battery of robustness tests for our baseline returns tests. We document our findings hold in sample sub-periods. We also show that our findings are robust to varying the number of peers for portfolio construction. Our results are consistent even with taking account of other economic linkages including similar customer-supplier, business-line, and executive linkages (Menzly and Ozbas 2010, Erkens 2011, Cohen and Lou 2012).

Last, we further examine whether the economic linkage we capture is a talent linkage. We show that talent-linked firms that are connected with an inventor, who has a high network centrality, explain focal firms' cross-sectional variations in stock returns more than other talent-linked firms. Our argument is that this central inventor is likely to increase knowledge spillover among firms. Likewise, we find that talent-linked firms that are linked with inventors who have specific technology focus outperform in explaining focal firms' cross-sectional variations in stock returns. The intuition is that this specialized inventor is more likely to connect firms than less specialized inventors. Taken together, our measure captures firms in similar talent spaces.

The outperformance of talent-linked firms in explaining the cross-sectional variations in the fundamental and innovation characteristics may come from several reasons. First, the talent proximity score is based on inventors. Their talents are likely to lead to firms' fundamental and innovation changes that are not captured in other economic benchmarks. Second, a set of talent-linked firms to the focal firm changes every year based on the annually updated talent proximity score. The score is symmetric between any two firms, but their relative importance may be different. This flexible set of talent-linked firms for each focal firm may contribute to the outperformance over other industry classifications as economic benchmarks.

We show that the talent proximity score follows a power-law distribution. Differently put, the closest talent-linked firm to the focal firm is much closer to the rest of the talent-linked firms to the focal firm. We can interpret this power-law distribution as follows: talent linkages to the focal firm decrease at an exponential rate, and only the small set of talent-linked firms are important to the focal firm in the talent closeness sense. This implies that a broad industry classification may not be informational.

In sum, we find economically related firms by identifying talent-linked firms. We show that talent linkages among firms capture the cross-sectional variations of firms' fundamental and innovation characteristics. Talent-linked firms are, thus, more informational to the focal firms in terms of fundamental and innovation characteristics than other economic benchmarks.

It is worth noting that our measure is based on the inventors contributing to firms' patents. Thus, our method may not apply to firms that have not issued a patent. However, a firm not issuing a patent is less likely to be a talent-intensive firm. In other words, these firms are easy-to-value firms that may not be in the need of economic benchmarks to value. Ultimately, our study identifies hard-to-value firms' economic benchmarks, so this limitation does not diminish the value of our study.

The remainder of the paper is structured as follows. Section I provides the background and literature of this study. Section II describes our data and variables. Section III presents our empirical strategies and results. Section IV provides robustness tests. Section V concludes our study.

I. Background

This study contributes to the literature on economic linkages among firms and firm value. First, prior studies document economic linkages among firms. These include product-market, technology, customer-supplier, business-line, and labor-market linkages (Hoberg and Phillips 2010, Lee et al. 2019, Li 2017, Gutierrez et al. 2019, Liu and Wu 2019). Our paper extends the relatively less studied literature on labor-market linkages specifically by providing evidence that there are talent linkages through overlapped inventor space among firms. We show that talent linkages capture strong economic affinities.

Second, there is a large body of literature on measures of innovation value. Prior studies focus on patents' scientific value, economic value, and technical novelty to measure firm innovation value. For example, the number of citations of a patent reflects its scientific value. Kogan et al. (2017) measure a patent's economic value in dollar terms using the patent's impact on stock returns, and Arts et al. (2021) develop text-based measures of patents to reflect technical novelty. Relatively recent studies provide evidence that inventors are a key determinant of these innovation values (Liu et al. 2017, Bhaskarabhatla 2021). We extend this literature by providing evidence that an inventor, who contributes to multiple firms' patents, links firms' innovation values and, ultimately, firm values.

II. Data description and defining talent-linked firms

A. Data and talent proximity score

We use the United States Patent and Trademark Office (USPTO) PatentsView database and the CRSP/Compustat Merged database for patent information and firms' financial information, respectively. We first collect all patents granted data, totaling 7,626,142 patent filings, during the period between 1976 and 2020 from the USPTO PatentsView database. Out of these patents, following prior work, we focus on 6,912,290 utility patents. The remaining patents are matched to PERMNOs, CRSP firm names, using the patent number and PERMNO linking table (Kogan et al., 2017). Patents with missing CRSP firm names are filtered out, and this leaves us with 2,425,923 patents. Table 1 shows details for our filters.

Our main sample focuses on listed firms with ordinary common shares on one of the following three exchanges: NYSE, NASDAQ, and AMEX. Following Bhojraj, Lee, and Oler (2003) and Lee et al. (2015), using Compustat quarterly data, we only focus on firm observations that do not miss total assets, total long-term debt, net income before extraordinary items, debt in current liabilities, and operating income after depreciation. We also drop firms that have no overlap in inventor space over the rolling-window of the past five years as of time t. These filters leave us with 3,402 unique firms between 1981 and 2020.

Inspired by Jaffe (1986) and Lee et al. (2015, 2019), we develop the talent proximity score,

$$Talent\ proximity\ score_{ijt} = \frac{(I_{it}I'_{jt})}{(I_{it}I'_{it})^{1/2}(I_{jt}I'_{jt})^{1/2}}, \qquad (1)$$

between two firms in calendar year t to measure the degree of talent closeness. In equation (1), $I_{it} = (I_{it1}, I_{it2}, \dots, I_{itn})$ serves as a vector of firm i's proportional share of patents across n inventors over the rolling-window of the past five years as of time t. This score is defined as the uncentered correlation of the patent distributions between two firms i and j. The talent proximity score has the following properties. First, it ranges from zero to one. If inventor names appearing in the formally issued patents within the previous five years between two firms perfectly overlap, the talent proximity is one. Second, the score is symmetric between any two firms. However, the relations between the two firms may be asymmetric. For example, firm i may be the closest peer of firm j in terms of talent but not vice versa. This characteristic allows identifying talent-linked firms' relative importance to the focal firm.

The talent proximity score reflects the degree of talent closeness between two firms. Our intuition follows the following simple logic: if an inventor contributes to firm i and firm j in issuing patents, these two firms are likely to demand the same talent. The inventor supplies the demanded talent if the inventor receives at least one patent grant in each firm i and j. Then, these two firms are classified as talent-linked firms.

We only use firms that have the product similarity score (or Text-Based Network Industry Classifications score) developed by Hoberg and Phillips (2010, 2014). This score is a measure of product-market closeness between two firms, and this score helps identify product market-related firms annually. We will compare the performance of talent-linked firms and product market-related firms as economic benchmarks to focal firms. The product similarity score is only available from 1988 to 2019. Each filtered firm pair is matched with the product similarity score using the lagged year to avoid look-ahead bias. After matching, our final sample consists of 2,989 unique focal firms between 1989 and 2020. We show more details of our filters in Table 1.

B. Descriptive statistics on talent-linked firms

We identify a focal firm's ten closest talent-linked firms using the talent proximity score. These top ten talent-linked firms for a given focal firm are considered peer firms in the talent similarity sense.

Figure 1 graphs four examples of the top ten talent-linked firms for each given focal firm. Panel A of Figure 1 shows the ten closest talent-linked firms of Tesla for 2015. The graph shows that Apple is captured as one of the closest talent-linked firms of Tesla in 2015. These two firms are known as talent competitors in the talent war while they do not overlap in product space. This example supports that talent-linked firms indeed transcend standard industry boundaries.

Panel B of Figure 1 illustrates the top talent-linked firms for Apple in 2015. This example first captures the aspects of customer-supplier linkages (Menzly and Ozbas 2010). Planar Systems is a leading display technology company. This company provides raw materials to Apple. Also, the example captures the aspect of a focal firm's business dimensions (Cohen and Lou 2012). Verifone is related to Apple's payment businesses while Microsoft represents Apple's main business competitor in computer businesses.

In Figure 1, Panel C shows the ten closest talent-linked firms for Apple in 2020. This example shows that our measure adapts to changing markets by dynamically updating talent closeness among firms. Square, a financial company, is the closest talent-linked firm of Apple in

2020 while Square was not one of the top peers of Apple in 2015. It reflects that our measure varies over time and provides a more dynamic and flexible structure of grouping schemes than standard industry groupings.

Panel D of Figure 1 shows the closest peer of Square in terms of talent is Twitter. This example illustrates the asymmetric characteristic of our measure in terms of the relationship between firms. In 2020, Square is the most important peer of Apple in the talent sense, but Apple is not the most important peer of Square.

The four examples in Figure 1 also suggest that the closest talent-linked firm's talent proximity score exhibits a disproportionately large share of talent closeness to a given focal firm. In other words, the closest talent-linked firm is far more similar to the focal firm in the talent sense. Panel A of Figure 2 graphs the talent proximity score as a function of the talent-linked firm ranking. The graph is more like a power-law trend than a linear trend. Panel B of Figure 2 shows that the log of peer rank and the log of average talent proximity score closely follow a linear trend. Using the 0.5 adjustment factor suggested by Gabaix and Ibargimov (2011), we find that the R^2 of the log-log linear fit is 99%. This confirms that the talent proximity score follows the power-law trend.

We interpret the power-law trend as follows. The overlap in talent space between firms decreases exponentially. Thus, only a small number of talent-linked firms is important to the focal firm. It implies that standard industry classifications may be too broad for identifying economic benchmarks for the focal firm.

Table 2 shows the proportion of correspondence in standard industry classifications of the focal firm and its ten closest talent-linked firms. Only 7% of the ten closest talent-linked firms are in the same product-market industry (Hoberg and Phillips 2010, 2014) as the focal firm while

11% of them are in the same technology-linked industry (Lee et al. 2019). Using relatively broad industry classifications, we also find that 30%, 32%, 47%, and 21% of the ten closest talent-linked firms are in the same SIC2, NAICS3, GICS2, and GICS6 as the focal firm. This low overlap implies that talent-linked firms are not constrained by industry classification schemes and suggests that any outperformance of our talent-linked firms as economic benchmarks over industry schemes will be due to new information captured in our talent proximity score.

III. Empirical analysis and results

We examine talent-linked firms' abilities to explain the cross-sectional variations in focal firms' monthly stock returns, fundamental characteristics, and innovation characteristics. Product market-related firms (Hoberg and Phillips 2010, 2014) and technology-linked firms (Lee et al., 2019) are used as alternative classification schemes because of their superior abilities to explain focal firms' characteristics when compared to other industry groupings.

A. Monthly returns

We first compare whether talent-linked firms explain the cross-sectional variation in focal firms' monthly stock returns relative to the two alternative industry schemes. We use the following cross-sectional regression for the period between January 1989 and December 2020:

$$RET_{it} = \alpha_t + \beta_t RET_{pt} + \epsilon_{it}, \qquad (2)$$

where RET_{it} represents the *CRSP* stock return of focal firm *i* at month *t*. To calculate the portfolio return of talent-linked firms for focal firm *i*, we use the talent proximity score serving as a weighting function:

$$RET_{pt} = \frac{\sum_{j \neq i} Talent\ proxmity\ score_{ijt} \times RET_{it}}{\sum_{j \neq i} Talent\ proxmity\ score_{ijt}} \qquad (3)$$

For example, the closest talent-linked firm's return has the highest weight in calculating the portfolio return, RET_{pt}. We then use the average R^2 from estimating cross-sectional regressions of equation (2) to compare the performance of explaining the cross-sectional variation in focal firms' monthly stock returns with the average R^2 from estimating equation (2) using other types of portfolio returns based on product market-related firms or technology-linked firms. The portfolio return of product market-related firms is weighted by *Product similarity score*, which is developed by Hoberg and Phillps (2010, 2014), and the portfolio return of technology-linked firms is weighted by Lee et al.'s (2019) *Technology similarity score.* Appendix A includes details of the two similarity measures.

As shown in Lee et al. (2015), we expect more economically related firms of the focal firm should contemporaneously correlate with the focal firm more in stock returns when compared to less economically related firms' stock returns. The intuition is as follows.

$$RET_{it} = \delta_t(\theta_i) + \epsilon_{it} \qquad (4)$$

$$RET_{P_{i(N)}} = \frac{1}{N}\sum_j RET_j = \frac{1}{N}\sum_j \delta_t(\theta_j) + \frac{1}{N}\sum_j \epsilon_{it} \qquad (5)$$

Equation (4) decomposes the return of focal firm *i* into the non-idiosyncratic component, $\delta_t(\theta_i)$, and the idiosyncratic component, ϵ_{it}. Fundamental characteristics of focal firm *i*, θ_i, affects how the focal firm responds to common economic shocks. Consider the market factor model of returns: $\theta_i = \beta_i$ and $\delta_i(\theta_i) = \beta_i(RET_m - RET_f)$. In equation (5), focal firm *i*'s benchmark portfolio including *N* peers is labeled as $P_{i(N)}$.

Higher R^2 from the tests of equation (2) reflects greater economic relatedness between focal firms and their peer firms. The intuition is presented in

$$\frac{\widehat{Cov}(RET_{it}, RET_{P_i})}{\widehat{Std}(RET_{P_i})} \approx \frac{\widehat{Cov}\left(\delta_t(\theta_i), \frac{1}{N}\sum_j \delta_t(\theta_j)\right)}{\widehat{Std}\left(\frac{1}{N}\sum_j(\delta_t(\theta_j) + \epsilon_{jt})\right)}. \qquad (6)$$

Benchmark portfolios lead to higher R^2 if peer firms' responses to economic shocks covary more strongly with focal firms' responses that are functions of their fundamental characteristics.

Equation (6) also shows that higher R^2 comes from minimizing the effects of idiosyncratic shocks. The effects are a function of the portfolio size, and the size effects may trade off with the numerator effect. Lewellen and Metrick (2010) discuss the optimal benchmark portfolio size, but the choice of optimal benchmark portfolio size is not the focus of this study. Thus, we include ten firms consistently in each focal firm's benchmark portfolio and take account of the portfolio size effects. In our robustness checks, we show that our findings are robust to changes in the number of peers in the portfolio.

In Table 3, Panel A shows our main results that talent-linked firms' portfolios outperform product market-related firms' portfolios and technology-linked firms' portfolios in explaining focal firms' cross-sectional variation in stock returns. On average, talent-linked firm portfolios explain 36.5% of the variation of focal firms' stock returns, which are significantly higher than the 23.9% and the 13.8% explained by focal firms' product market-related firms and technology-related firms, respectively. This outperformance of talent-linked firms' portfolios as economic benchmarks suggests that the talent proximity score contains economic linkages between firms that are not captured in prior industry classifications.

In Panel B, we further examine our measure is superior to measures based on other economic links. We exclude talent-linked firms that are also product-market peers, or tech-linked peers from the talent-linked firm portfolios. We also exclude talent-linked firms that are also executive-linked peers that overlap in executives and test whether our results hold in these filtered sampling criteria. As evident from Panel B, the average R^2 of talent-linked firm portfolios outperforms those of other types of portfolios. The differences in R^2 are both economically and statistically significant. Together, our results show that our measure captures something distinct from the other economic linkages.

B. Fundamental characteristics

In this section, we test how well talent-linked firms explain the cross-sectional variations in focal firms' key fundamental characteristics. As explained, more economically related firms should contemporaneously correlate with their focal firm more in fundamental characteristics. In this test, we focus on three groups of fundamental characteristics: valuation multiples, financial statement ratios, and growth rates.

We measure valuation multiples using three ways: price-to-book multiples, price-to-earnings multiples, and enterprise value-to-sales multiples. Our financial statement ratios focus on returns on equity, returns on net operating assets, asset turnover, profit margins, and leverage. Then, we measure firm growth using one-year-ahead realized sales growth. Appendix A shows the details of their constructions and definitions.

$$Fundamental_{it} = \alpha_t + \beta_t Fundamental_{pt} + \epsilon_{it} \tag{7}$$

We estimate regressions of equation (7) for these tests. $Fundamental_{it}$ is our variable of interest, and $Fundamental_{pt}$ represents the portfolio mean of economic benchmarks. Specifically, we use cross-sectional regressions of equation (7) for quarters from 1989 to 2020 except for one-year-ahead realized sales growth due to data availability. All the variables of interest are winsorized at 1% and 99% to take account of outliers.

Table 3 shows that talent-linked firm portfolios outperform both product-market peer portfolios and tech-linked peer portfolios for explaining cross-sectional variations of the focal firm's fundamental measures. The results are not only statistically significant at the 1% level for all key valuation multiples, financial statement ratios, and growth rates, but also economically significant.

C. Innovation characteristics

Why do talent-linked firms explain their focal firms' fundamental characteristics? Prior studies stress the importance of innovation on firm values, and talent is a key determinant of firm innovation (Gambardella et al. 2011, Liu et al. 2017, Bhaskarabhatla 2021). We, thus, expect talent-linked firms to explain not only their focal firms' fundamental characteristics, but also the focal firms' innovation characteristics.

In the following additional tests, we use three groups of innovation characteristics: innovation values, novelty, and activities. We measure innovation values using the following two ways: Kogan et al.'s (2017) patent value and the number of patent citations. We then measure innovation novelty using the following Arts et al.'s (2021) approach: the number of new keywords introduced by the patent (*New word*), the number of their reuses (*New word reuse)*, one minus the text-based cosine similarity between the patent and the patents in the previous five years of the focal patent (*1-Backward*), and the text-based cosine similarity between the patent and the patents in the five years after the focal patent over the text-based cosine similarity between the patent and the patents in the previous five years of the focal patent (*F/B*). We then measure innovation activities using the number of patents applied and the number of new patents issued formally.

We estimate the following regression for analysis:

$$Innovation_{it} = \alpha_t + \beta_t Innovation_{pt} + \epsilon_{it}, \quad (8)$$

where $Innovation_{it}$ is our variable of interest, and $Innovation_{pt}$ represents the portfolio mean for innovation characteristics using peer firms. We estimate cross-sectional regressions of equation (8) for every quarter from 1989 to 2018. We also winsorize innovation characteristic measures at 1% and 99%.

Table 4 reports that talent-linked firm portfolios also outperform product-market and tech-linked portfolios for explaining the cross-sectional variations in focal firms' innovation characteristics including innovation values, novelty, and activities well. The effects are both statistically significant and economically significant. These additional tests support our talent-linked firm portfolios are more economically related to their focal firms relative to other benchmark portfolios.

IV. Robustness

In this section, we examine whether our main results hold in sample sub-periods, alternative peer portfolio constructions, and taking account of other economic linkages.

A. Sample sub-periods

In Table 7, Panel A shows whether the average R^2 from monthly return regressions using talent-linked firms is higher than those of product-market related firms and technology-linked firms in sample sub-periods. We disaggregate our main sample period into the following three sample sub-periods: 1989-2000, 2001-2010, and 2011-2020. It turns out that our peer portfolios outperform the product-market firm portfolios and tech-linked firm portfolios in all the sample sub-periods. The results suggest that our main findings are not driven by certain sub-periods.

B. Alterations to the number of peers

We examine whether the number of talent-linked firms for the peer portfolio matters in our primary results. We increase the number of talent-linked firms used in the portfolios to 15, or 20. Panel B of Table 6 shows that the performance of these portfolios is still superior to the other two portfolios in explaining cross-sectional variations of focal firms' stock returns. The difference in R^2 persists even the group size increases, which indicates that our measure closely captures economic relatedness between firms regardless of the portfolio size.

C. Other economic links

We further examine whether our main results are driven by other economic links. Following prior studies, we create a portfolio of customer returns (Menzly and Ozbas, 2010), a portfolio of supplier returns (Menzly and Ozbas, 2010), and pseudo-conglomerate returns (Cohen and Lou 2012). Table 6 shows that the R^2 of talent-linked firms outperforms significantly the R^2s based on customer-supplier and business-line linkages. The difference is both economically and statistically significant. In sum, talent linkages among firms are not easily attributable to other economic links.

D. Intensity of talent linkages

Last, we investigate whether particular types of talent linkages give rise to stronger economic relatedness among firms. We first use the argument that more productive inventors have more talents, and they are likely to connect two firms stronger in terms of talents. We measure this talent productivity using the number of patents issued by inventors. If an inventor has issued patents above the sample median, we assign the inventor as a productive inventor. Table 8 shows that the R^2 of talent-linked firm portfolios that linked with productive inventors outperform the other two types of portfolios. The differences in R^2 are slightly greater than those of our baseline results.

We then conjecture that it could be possible that an inventor who co-works more than others gives rise to an increase in knowledge spillover. In other words, an inventor with a high network centrality would link two firms stronger in terms of talents. We run our baseline tests using the firms that are linked by the inventors who have coauthors more than the sample median. It turns out that the talent-linked firms that are linked to the focal firm with these central inventors exhibit higher R^2 than our baseline returns results.

We examine whether inventors with specific technology focus give rise to stronger connections between firms. A specialized inventor is likely to link two firms more in the talent similarity sense than other overlapped inventors. To identify an inventor with specific technology focus, we use the number of patent classes that the inventor has involved. If the number of classes is above the sample median, we assume that this inventor focuses on a specific technology. Table 8 shows that the inventor with specific technology focus leads to significantly higher R^2 than our baseline results. On top of that, firms that are connected with the inventor with both a high network centrality and specific technology focus give rise to the highest economic connections between firms. Taken together, these tests support that the economic linkages we capture are talent linkages.

V. Concluding thoughts

Most practitioners and researchers in economics and finance have used firms in the standard industry sector as economic benchmarks. However, standard industry groupings that are based on similar product spaces are rather broad (and rigid) and may not be economically relevant ones in this talent-driven economy. Talent is a key determinant of firm value, so we expect that firms that have similar talents are more likely to be economically related than firms operating in proximate product space.

In this study, we develop a novel measure that identifies economically related firms by using the overlap in talent space between two firms. We assume that an inventor contributes to multiple firms that demand the same talent. Another assumption is that firms are indeed supplied with the talent if the inventor contributes to their patents issued. Then, these firms are identified as talent-linked firms. Based on the assumptions, we measure talent closeness between firms annually using the overlap in inventor names appearing in patents issued within the previous five years. We then identify each firm's talent-linked firms.

The talent-linkage measure is better in explaining focal firms' characteristics than other measures. Talent-linked firms, that are identified by our measure, turn out to outperform product market-related firms and technology-linked firms in explaining variations in focal firms' stock returns, fundamental characteristics, and innovation characteristics. Our findings are robust and are not driven by certain sub-periods and other economic linkages.

We note that our approach may not be applied to firms that have not issued a patent in the previous five years as of a given year because our measure is built on the inventors contributing to firms' patents. However, a firm without patents is less likely to be a talent-intensive firm that is hard to value and needs economic benchmarks to value. This study, ultimately, is meant to identify hard-to-value firms' economic benchmarks, so the limitation does not detract the core value of our study.

Our results highlight the importance of talent linkages among firms. Firms are closely related to their talent-linked firms in terms of stock returns and firm characteristics. We believe that our finding creates opportunities for future research in both asset pricing and corporate finance using talent linkages among firms.

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Appendix A. Variable Definitions

Economic links

Talent proximity score is the talent closeness between two firms, defined as the following uncentered correlation of patent distributions between two firms *i* and *j*: $Talent_{ijt} = \frac{(I_{it}I'_{jt})}{(I_{it}I'_{it})^{1/2}(I_{jt}I'_{jt})^{1/2}}$, where $I_{it} = (I_{it1}, I_{it2}, \dots, I_{itn})$ serves as a vector of firm *i*'s proportional share of patents across *n* inventors within the rolling-window of the past five years as of time *t*. Following prior work, we limit our analysis to utility patents. We obtain patent information from the UPSTO PatentsView database.

Tech proximity score is the technology closeness between two firms, defined as the following uncentered correlation of patent distributions between two firms *i* and *j*: $Technology_{ijt} = \frac{(C_{it}C'_{jt})}{(C_{it}I'_{it})^{1/2}(C_{jt}I'_{jt})^{1/2}}$, where $C_{it} = (C_{it1}, C_{it2}, \dots, C_{itk})$ serves as a vector of firm *i*'s proportional share of patents across *k* technology classes within the rolling-window of the past five years as of time *t*. We obtain patent information from the UPSTO PatentsView database. See Lee et al. (2019) for further details.

Product similarity score is the text-based product similarity score between two firms. It's built based on the overlap of texts in product descriptions of 10-Ks of two firms *i* and *j*. We obtain the values of this measure from the Hoberg and Phillips data library. These data are available only for the period between 1988 and 2019.

Fundamental characteristics

Returns is the monthly stock return, defined as the raw return (CRSP variable *ret*) corrected with the approach suggested by Shumway (1997) for taking account of potential delisting bias.

P/B is the quarterly price-to-book ratio, defined as the market capitalization scaled by the total common equity (Compustat variable *ceqq*).

P/E is the quarterly price-to-earnings ratio, defined as the market capitalization, scaled by the net income before extraordinary items (Compustat variable *ibq*).

EV/S is the quarterly enterprise value-to-sales ratio defined as the enterprise value scaled by net sales (Compustat variable *saleq*). The enterprise value is defined as the sum of market capitalization and long-term debt (Compustat variable *dlttq*).

ROA is the quarterly return on net operating assets, defined as the net operating income after depreciation (Compustat variable *oiadp*), scaled by net operating assets. Net operating assets is the sum of property, plant, and equipment (Compustat variable *ppentq*) and current assets (Compustat variable *actq*) minus current liabilities ((Compustat variable *lctq*).

ROE is the quarterly return on equity, defined as the net income before extraordinary items (Compustat variable *ibq*) scaled by the total common equity (Compustat variable *ceqq*).

Asset turnover is defined as the quarterly total assets (Compustat variable *atq*), scaled by the quarterly net sales (Compustat variable *saleq*).

Profit margin is defined as the quarterly net operating income after depreciation (Compustat variable *oiadp*), scaled by the quarterly net sales (Compustat variable *saleq*).

Leverage is defined as the quarterly long-term debt (Compustat variable *dlttq*), scaled by the quarterly total stockholder's equity (Compustat variable *seqq*).

Sales growth is the one-year-ahead realized sales growth, defined as the future sales growth scaled by the current year net sales (Compustat variable *saleq*). The future sales growth is defined as the net quarterly sales one year ahead minus current year net sales.

<u>Innovation characteristics</u>

Patent value is the dollar value of a patent, measured as the product of the estimated stock return driven by the value of the patent and the market capitalization of the firm prior to the patent issuance date. See Kogan et al. (2017) for further details.

Forward citation is the number of a patent's forward citations received by the patents issued in the same year. We obtain the patent information from the USPTO PatentsView database.

New word is defined as the number of novel keywords of a patent that includes for the first time in the USPTO database. See Arts et al. (2021) for further details.

New word reuse is defined as the number of novel keywords of a patent introduced, weighted by the number of following patents which reuse the novel keywords. See Arts et al. (2021) for further details.

1-backward cosine is one minus the text-based cosine similarity between a base patent and all patents filed within the five years of the base patent. See Arts et al. (2021) for further details.

F/B is the forward cosine similarity over the backward cosine similarity, where the forward (backward) cosine similarity is defined as the text-based cosine similarity between a base patent and all patents filed after (within) the five years of the base patent.

 # patent is the number of patents issued in a given quarter. We obtain the patent information from the USPTO PatentsView database.

 # patent application is the number of quarterly patents applied (and ultimately granted). We obtain the patent information from the USPTO PatentsView database.

Figure 1. Examples of Talent-Linked Firms.

This figure shows four examples of the ten closest talent-linked firms for each focal firm. The *y*-axis is the talent proximity score, which measures talent closeness between a focal firm and its talent-linked firm for a given year. Panel A shows Tesla as the focal firm in 2015. Panels B and C show Apple as the focal firm in 2015 and 2020, respectively. Panel D shows Square as the focal firm in 2020.

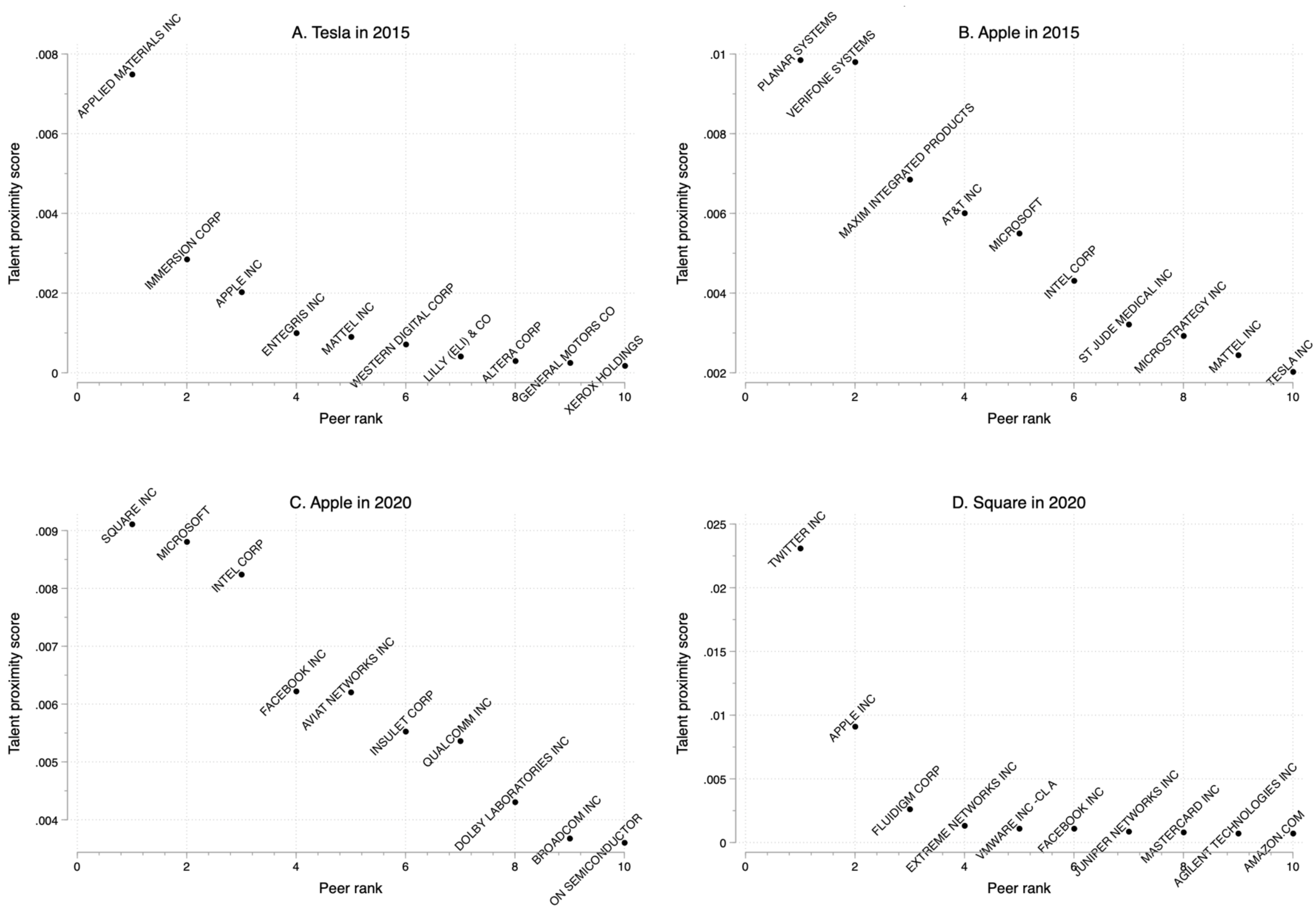

Figure 2. Distribution of the Average Talent Proximity Score.

This figure shows the distributions of the average talent proximity score. Panel A graphs the average talent proximity score for the firms that are identified as the closest 100 talent-linked firms to a focal firm. Panel B graphs the relationship between the log of the peer rank and the log average talent proximity score for the firms that are identified as the closest 100 talent-linked firms to a focal firm.

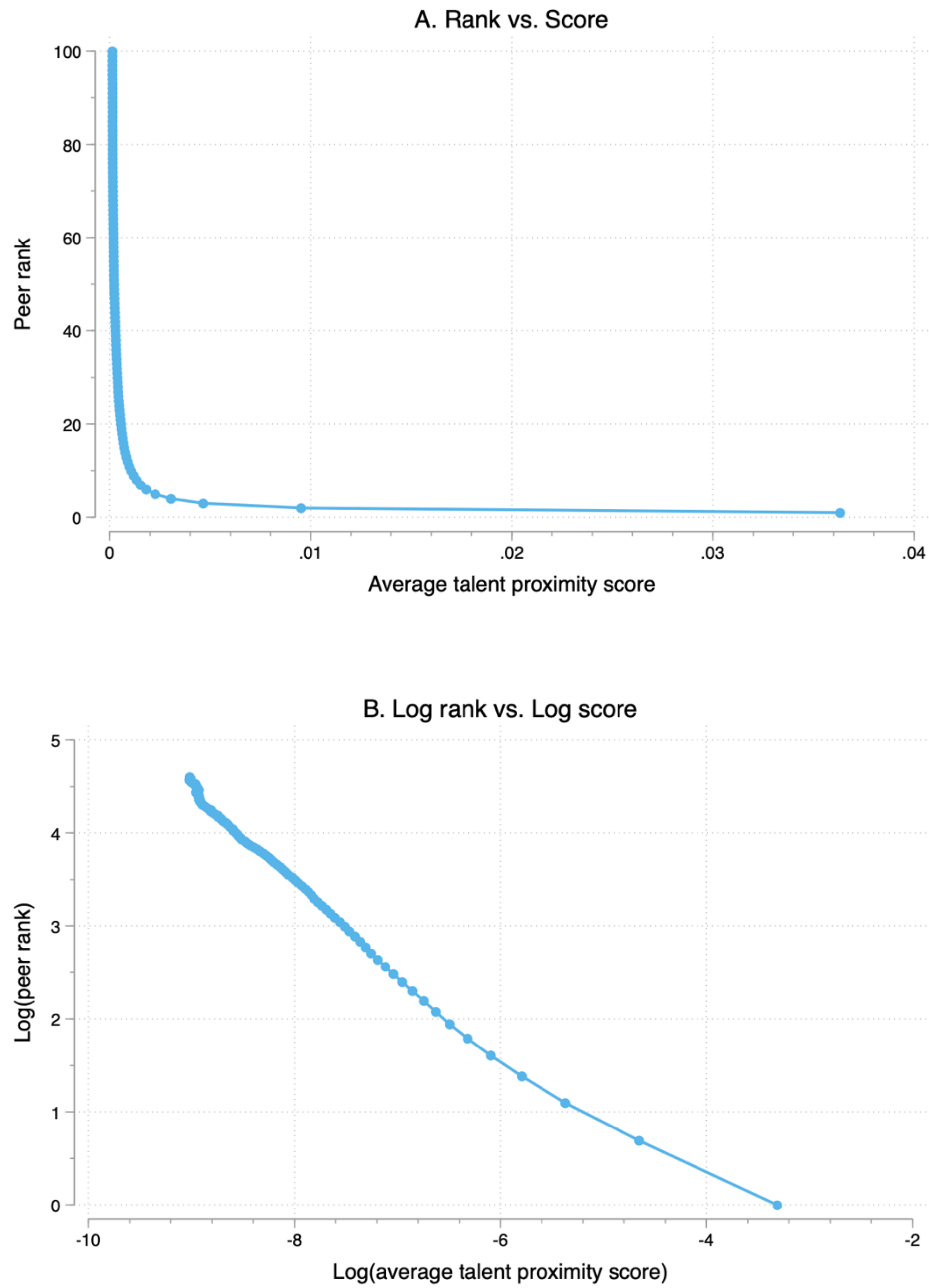

Table 1. Sample Construction.

This table illustrates the filtering process for constructing our main sample. We first download patent data between 1976 and 2020 from the USPTO PatentsView database. We exclude non-utility patents, reissued patents, and patents without matched CRSP firm names (Kogan et al. 2017). We focus on patents of listed firms with common stocks on the NYSE, AMEX, and NASDAQ. We create the talent proximity score as described in Appendix A and match it to the firm-quarter financial data between 1981 and 2020 from the Compustat database. We then match our focal firms with the Text-Based Network Industry Classification (TNIC) score, a pairwise product similarity score, provided by Hoberg and Phillips (2010, 2014). This filtering process leaves us with 2,989 unique focal firms for the period 1989-2020.

Filtering steps		No. of obs.
No. of patents in USPTO PatentsView, 1976-2020		7,626,142
less: non-utility patents	- 713,852	
less: reissued patents	- 29	
less: patents without matched CRSP firm names	- 4,486,338	
No. of filtered patents in the USPTO, 1976-2020		2,425,923
No. of firms with at least one filtered patent, 1976-2020		7,650
less: share code > 11, exchange code >3	- 1,286	
less: missing Compuastat quarterly data	- 338	
less: no overlap in inventors with other firms	- 2,624	
No. of focal firms, 1981-2020		3,402
No. of focal firms, 1981-2020		3,402
less: no match in the lagged TNIC score, 1989-2020	- 413	
No. of focal firms after matching, 1989-2020 (by Compustat gvkey)		2,989

Table 2. Correspondence with Industry Classifications.

This table provides the proportion of correspondence between talent-linked firms and other industry classifications. We first sort a focal firm's talent-linked firms by the talent proximity score and identify the focal firm's ten closest talent-linked firms. We report the average proportion that a talent-linked firm falls into the same industry classification as the focal firm. The first column shows the correspondence with the product-market industry classifications developed by Hoberg and Phillips (2010, 2014). The second column shows the correspondence with the technology-linked industry classifications developed by Lee et al. (2019). The rest of the columns reports the results using SIC2, NAICS3, GICS2, and GICS6.

Peer rank	Same Product	Same Tech	Same SIC2	Same NAICS3	Same GICS2	Same GICS6
1	0.096	0.150	0.331	0.338	0.501	0.242
2	0.082	0.122	0.326	0.334	0.486	0.227
3	0.074	0.116	0.325	0.334	0.491	0.224
4	0.075	0.112	0.319	0.329	0.481	0.222
5	0.075	0.105	0.307	0.324	0.479	0.217
6	0.067	0.101	0.285	0.305	0.460	0.199
7	0.068	0.100	0.279	0.308	0.458	0.196
8	0.072	0.102	0.294	0.320	0.465	0.204
9	0.064	0.099	0.272	0.305	0.459	0.195
10	0.064	0.098	0.272	0.306	0.448	0.192
Total	0.074	0.110	0.301	0.323	0.473	0.212

Table 3. Comparison of R^2 Values: Monthly Returns.

This table reports the average R^2 values from monthly cross-section regressions of the following model spanning from January 1989 to December 2020: $RET_{it} = \alpha_t + \beta_t RET_{pt} + \epsilon_{it}$, where RET_{pt} represents the returns of a portfolio of peers. Column 1 uses a portfolio consisting of the closest ten talent-linked firms. Column 2 uses a portfolio consisting of the closest ten product-market peers (Hoberg and Phillips 2010, 2014), and Column 3 uses a portfolio consisting of the closest ten technology-linked peers (Lee et al. 2019). Column 4 shows the differences in average R^2 between the talent-linked portfolio and the product-market portfolio, and Column 5 shows the differences in average R^2 between the talent-linked portfolio and the technology-linked portfolio. Panel B shows the results using a portfolio consisting of the closest ten talent-linked firms excluding product market peers or tech-linked peers. We also include the results using a portfolio consisting of the closest ten talent-linked firms excluding peers that overlap in executive space. Following Erkens (2011), we rely on the ExecuComp data to identify executives. Standard errors are shown in italics, and ***, **, and * denote significance levels at the 1%, 5%, and 10%, respectively.

Panel A: Baseline result

	Talent (1)	Product (2)	Tech (3)	(1) – (2) (4)	(1) – (3) (5)
RET_{pt}	0.365***	0.239***	0.138***	0.127***	0.228***
	0.005	*0.004*	*0.003*	*0.004*	*0.005*
Number of months	384	384	384	384	384

Panel B: R^2 after excluding other peers

	Talent (1)	Product (2)	Tech (3)	Talent-Product (4)	Talent-Tech (5)
RET_{pt} (excluding product-market peers)	0.370***	0.239***	0.138***	0.131***	0.232***
	0.005	*0.004*	*0.003*	*0.005*	*0.005*
RET_{pt} (excluding tech-linked peers)	0.373***	0.239***	0.138***	0.134***	0.235***
	0.005	*0.004*	*0.003*	*0.005*	*0.005*
RET_{pt} (excluding executive-linked peers)	0.324***	0.219***	0.139***	0.105***	0.185***
	0.005	*0.004*	*0.003*	*0.005*	*0.005*
Number of months	384	384	384	384	384

Table 4. Comparison of R^2 Values: Fundamental Characteristics.

This table reports the average R^2 values from monthly cross-section regressions of the following model spanning from the first quarter of 1989 to the fourth quarter of 2020: $Fundamental_{it} = \alpha_t + \beta_t Fundamental_{pt} + \epsilon_{it}$, where $Fundamental_{pt}$ represents the fundamental measure of a portfolio of peers. All variables are described in Appendix A. Column 1 uses a portfolio consisting of the closest ten talent-linked firms. Column 2 uses a portfolio consisting of the closest ten product-market peers, and Column 3 uses a portfolio consisting of the closest ten technology-linked peers. Column 4 shows the differences in average R^2 between the talent-linked portfolio and the product-market portfolio, and Column 5 shows the differences in average R^2 between the talent-linked portfolio and the technology-linked portfolio. All the variables that we examined are wisorized at 1% and 99%. Standard errors are shown in italics, and ***, **, and * denote significance levels at the 1%, 5%, and 10%, respectively.

	Talent (1)	Product (2)	Tech (3)	(1) – (2) (4)	(1) – (3) (5)
Valuation multiples					
P/B$_{pt}$	0.347***	0.197***	0.102***	0.150***	0.245***
	0.010	*0.005*	*0.005*	*0.011*	*0.011*
P/E$_{pt}$	0.313***	0.098***	0.058***	0.215***	0.255***
	0.012	*0.003*	*0.003*	*0.012*	*0.012*
EV/S$_{pt}$	0.274***	0.218***	0.122***	0.056***	0.152***
	0.012	*0.006*	*0.006*	*0.013*	*0.013*
Financial statement ratios					
ROE$_{pt}$	0.326***	0.169***	0.091***	0.157***	0.236***
	0.011	*0.005*	*0.005*	*0.012*	*0.013*
ROA$_{pt}$	0.350***	0.186***	0.088***	0.165***	0.262***
	0.009	*0.006*	*0.005*	*0.012*	*0.011*
Asset turnover$_{pt}$	0.265***	0.210***	0.118***	0.055***	0.148***
	0.012	*0.006*	*0.006*	*0.013*	*0.013*
Profit margin$_{pt}$	0.266***	0.217***	0.116***	0.049***	0.149***
	0.012	*0.005*	*0.006*	*0.013*	*0.014*
Leverage$_{pt}$	0.341***	0.187***	0.081***	0.154***	0.260***
	0.013	*0.005*	*0.004*	*0.012*	*0.012*
Sales growth$_{pt}$	0.316***	0.149***	0.078***	0.167	0.238***
	0.012	*0.006*	*0.005*	*0.013*	*0.012*
Number of quarters	128	128	128	128	128

Table 5. Comparison of R^2 Values: Innovation Characteristics.

This table reports the average R^2 values from monthly cross-section regressions of the following model: $Innovation_{it} = \alpha_t + \beta_t Innovation_{pt} + \epsilon_{it}$, where $Innovation_{pt}$ represents the innovation measure of a portfolio of peers. All variables are described in Appendix A. Column 1 uses a portfolio consisting of the closest ten talent-linked firms. Column 2 uses a portfolio consisting of the closest ten product-market peers, and Column 3 uses a portfolio consisting of the closest ten technology-linked peers. Column 4 shows the differences in average R^2 between the talent-linked portfolio and the product-market portfolio, and Column 5 shows the differences in average R^2 between the talent-linked portfolio and the technology-linked portfolio. We winsorize all the variables at 1% and 99%. Standard errors are shown in italics, and ***, **, and * denote significance levels at the 1%, 5%, and 10%, respectively.

	Talent (1)	Product (2)	Tech (3)	(1) – (2) (4)	(1) – (3) (5)
Innovation values					
Patent value$_{pt}$	0.447***	0.337***	0.208***	0.110***	0.239***
	0.009	*0.009*	*0.005*	*0.008*	*0.009*
Forward citation$_{pt}$	0.432***	0.335***	0.257***	0.099***	0.177***
	0.008	*0.005*	*0.004*	*0.006*	*0.009*
Innovation novelty					
New word$_{pt}$	0.447***	0.342***	0.287***	0.106***	0.160***
	0.007	*0.008*	*0.006*	*0.006*	*0.005*
New word reuse$_{pt}$	0.443***	0.327***	0.275***	0.116***	0.168***
	0.007	*0.007*	*0.005*	*0.006*	*0.006*
1-Backward$_{pt}$	0.494***	0.314***	0.203***	0.180***	0.291***
	0.009	*0.011*	*0.005*	*0.009*	*0.010*
F/B$_{pt}$	0.495***	0.311***	0.206***	0.184***	0.288***
	0.009	*0.010*	*0.005*	*0.009*	*0.011*
Innovation activities					
# patent application$_{pt}$	0.451***	0.383***	0.273***	0.068***	0.178***
	0.007	*0.008*	*0.005*	*0.008*	*0.009*
# patent issued$_{pt}$	0.441***	0.359***	0.275***	0.082***	0.166***
	0.007	*0.007*	*0.005*	*0.006*	*0.010*
Number of quarters	128	128	128	128	128

Table 6. R^2 Robustness Test: Sub-Periods and Alternative Portfolio Size.

This table reports the average R^2 values from monthly cross-section regressions of the following model: $RET_{it} = \alpha_t + \beta_t RET_{pt} + \epsilon_{it}$, where RET_{pt} represents the returns of a portfolio of peers. Panel A shows the results using three sub-periods. In Panel A, Column 1 uses a portfolio consisting of the closest ten talent-linked firms. Column 2 of Panel A uses a portfolio consisting of the closest ten product-market peers, and Column 3 uses a portfolio consisting of the closest ten technology-linked peers. In Panel A, Column 4 shows the differences in average R^2 between the talent-linked portfolio and the product-market portfolio, and Column 5 shows the differences in average R^2 between the talent-linked portfolio and the technology-linked portfolio. Panel B shows the sensitivity of the results to the number of peers used in the portfolio. Standard errors are shown in italics, and ***, **, and * denote significance levels at the 1%, 5%, and 10%, respectively.

Panel A: Sample sub-periods

	Talent (1)	Product (2)	Tech (3)	(1) – (2) (4)	(1) – (3) (5)
Jan. 1989 - Dec. 2000	0.459***	0.290***	0.145***	0.170***	0.315***
	0.005	*0.006*	*0.005*	*0.008*	*0.007*
Jan. 2001 - Dec. 2010	0.348***	0.209***	0.142***	0.139***	0.205***
	0.006	*0.006*	*0.004*	*0.006*	*0.005*
Jan. 2011 - Dec. 2020	0.270***	0.207***	0.124***	0.063***	0.145***
	0.005	*0.006*	*0.004*	*0.007*	*0.006*

Panel B: Alternative portfolio size

	Talent (1)	Product (2)	Tech (3)	Talent-Product (4)	Talent-Tech (5)
Top 10 peers	0.365***	0.239***	0.138***	0.127***	0.228***
	0.005	*0.004*	*0.003*	*0.004*	*0.005*
Top 15 peers	0.365***	0.214***	0.097***	0.151***	0.268***
	0.005	*0.004*	*0.002*	*0.005*	*0.005*
Top 20 peers	0.362***	0.201***	0.080***	0.160***	0.281***
	0.005	*0.004*	*0.002*	*0.005*	*0.005*
Number of months	384	384	384	384	384

Table 7. R^2 Robustness Test: Other Economic Linkages.

This table reports the average R^2 values from monthly cross-section regressions of the following model spanning from January 1989 to December 2020: $RET_{it} = \alpha_t + \beta_t RET_{pt} + \epsilon_{it}$, where RET_{pt} represents the returns of a portfolio of peers. Panel A uses a portfolio consisting of the closest ten talent-linked firms. Columns 2 and 3 use a portfolio consisting of the focal firms' customers and suppliers, respectively. These portfolios closely follow Menzly and Ozbas (2010) and rely on Bureau of Economic Analysis Input-Output data. Column 4 uses a portfolio of the same line of businesses by creating pseudo-conglomerate returns (Cohen and Lou, 2012). We use Compustat Segment data to identify each firm's business lines. In Panel A, Column 5 shows the differences in average R^2 between the talent-linked portfolio and the customer portfolio, and Column 7 shows the differences in average R^2 between the talent-linked portfolio and the business-line portfolio. Standard errors are shown in italics, and ***, **, and * denote significance levels at the 1%, 5%, and 10%, respectively.

	Talent (1)	Customer (2)	Supplier (3)	Business (4)	(1) – (2) (5)	(1) – (3) (6)	(1) – (4) (7)
RET_{pt}	0.365***	0.005***	0.005***	0.007***	0.364***	0.364***	0.364***
	0.005	*0.000*	*0.000*	*0.001*	*0.005*	*0.005*	*0.005*
# months	384	384	384	384	384	384	384

Table 8. Intensity of Talent Linkages.

This table reports the average R^2 values from monthly cross-section regressions of the following model spanning from January 1989 to December 2020: $RET_{it} = \alpha_t + \beta_t RET_{pt} + \epsilon_{it}$, where RET_{pt} represents the returns of a portfolio of peers. The first row is the baseline result from Table 3. The second row uses the returns of a portfolio of talent-linked firms that are overlapped with only inventors with the above median number of patents. The third row uses the returns of a portfolio of talent-linked firms that are overlapped with only inventors with the above median number of coauthors. The fourth row uses the returns of a portfolio of talent-linked firms that are overlapped with only inventors with the below median number of technology classes. The last row uses the returns of a portfolio of talent-linked firms that are overlapped with only inventors with the below median number of technology classes and the above median number of coauthor classes. Standard errors are shown in italics, and ***, **, and * denote significance levels at the 1%, 5%, and 10%, respectively.

	Talent (1)	Product (2)	Tech (3)	(1) – (2) (4)	(1) – (3) (5)
RET_{pt}	0.365***	0.239***	0.138***	0.127***	0.228***
	0.005	*0.004*	*0.003*	*0.004*	*0.005*
# Patens>median	0.367***	0.239***	0.138***	0.128***	0.229***
	0.005	*0.004*	*0.003*	*0.005*	*0.005*
# Coauthor>median	0.433***	0.239***	0.138***	0.195***	0.296***
	0.006	*0.004*	*0.003*	*0.006*	*0.006*
# Tech class<median	0.768***	0.239***	0.138***	0.530***	0.630***
	0.008	*0.004*	*0.003*	*0.008*	*0.008*
# Coauthor >median	0.845***	0.238***	0.138***	0.606***	0.707***
& # Tech class<median	*0.007*	*0.004*	*0.003*	*0.007*	*0.007*
Number of months	384	384	384	384	384

INTERNET APPENDIX

for

Talent-Linked Firms [*]

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(NOT INTENDED FOR PUBLICATION)

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Appendix IA. Talent Proximity Score Example.

Consider three firms 1, 2, and 3 in a talent-driven economy. Suppose each firm's patent history is as follows:

Firm 1: Patent 1, invented by Inventor A and Inventor B in 2014
Patent 2, invented by Inventor A and Inventor B in 2015
Firm 2: Patent 3, invented by Inventor A and Inventor C in 2017
Firm 3: Patent 4, invented by Inventor D in 2018

The corresponding inventor spaces (# patents of Inventor A, # patents of Inventor B, # patents of Inventor C, # patents of Inventor D) are as follows:

Firm 1: (2, 2, 0, 0)
Firm 2: (1, 0, 1, 0)
Firm 3: (0, 0, 0, 1)

We calculate a measure of talent closeness for each pair of firms in year *t* using:

$$Talent\ proximity\ score_{ijt} = \frac{(I_{it}I_{jt}')}{(I_{it}I_{it}')^{1/2}(I_{jt}I_{jt}')^{1/2}},$$

where $I_{it} = (I_{itA}, I_{itB}, I_{itC}, I_{itD})$ serves as a vector of firm *i*'s proportional share of patents across inventors. We obtain the following vectors:

$I_{1,2019} = (0.5, 0.5, 0, 0)$
$I_{2,2019} = (0.5, 0, 0.5, 0)$
$I_{3,2019} = (0, 0, 0, 1)$

Then, the talent proximity scores in 2019 are

$$\begin{aligned}
Talent\ proximity\ score_{1,2,2019} &= \frac{0.5*0.5+0.5*0+0*0.5}{(0.5*0.5+0.5*0.5)^{\frac{1}{2}}(0.5*0.5+0.5*0.5)^{\frac{1}{2}}} \\
&= 0.5 \\
&= Talent_{2,1,2019} \\
Talent\ proximity\ score_{2,3,2019} &= \frac{0.5*0+0.5*0+\ 0*1}{(0.5*0.5+0.5*0.5)^{\frac{1}{2}}(1*1)^{\frac{1}{2}}} \\
&= 0 \\
&= Talent_{3,2,2019} \\
Talent\ proximity\ score_{1,3,2019} &= \frac{0.5*0+0.5*0+0*1}{(0.5*0.5+0.5*0.5)^{\frac{1}{2}}(1*1)^{\frac{1}{2}}} \\
&= 0 \\
&= Talent_{3,1,2019}
\end{aligned}$$