Technological Links and Predictable Returns

Charles M. C. Lee, Stephen Teng Sun, Rongfei Wang, and Ran Zhang[**]

First Draft: September 10, 2017
Current Draft: March 7, 2018

Journal of Financial Economics (Forthcoming)

Abstract

Employing a classic measure of technological closeness between firms, we show that the returns of technology-linked firms have strong predictive power for focal firm returns. A long-short strategy based on this effect yields monthly alpha of 117 basis points. This effect is distinct from industry momentum and is not easily attributable to risk-based explanations. It is more pronounced for focal firms that: (a) have a more intense and specific technology focus, (b) receive lower investor attention, and (c) are more difficult to arbitrage. Our results are broadly consistent with sluggish price adjustment to more nuanced technological news.

JEL classification: G10, G11, G14, O30

Keywords: Technology momentum, stock returns, return predictability, patents, technological closeness, limited attention, market efficiency

---

[**] Corresponding author: Charles M.C. Lee, Moghadam Family Professor of Management and Professor of Accounting, Graduate School of Business, Stanford University, 655 Knight Way, Stanford, CA 94305-7298; Tel: (650) 721-1295; Fax: (650) 725-9932; Email: CLEE8@stanford.edu. Stephen Teng Sun (st@gsm.pku.edu.cn) is Assistant Professor of Economics at the Guanghua School of Management, Peking University. Rongfei Wang (wangrongfei@pku.edu.cn) is a PhD Candidate in Accounting at the Guanghua School of Management, Peking University. Ran Zhang (RZHANG@gsm.pku.edu.cn) is Associate Professor of Accounting at the Guanghua School of Management, Peking University. We greatly appreciate the comments and suggestions from Nicholas Bloom, Jinhwan Kim, Kevin Li, Oliver Li, Dong Lou, Yan Luo, Eric So, Jennifer Tucker, Heng Yue, Tianyu Zhang, and workshop participants at Tsinghua University, Renmin University, 2017 International Symposium on Empirical Accounting Research in China, and 2018 Financial Accounting and Reporting Section (FARS) Midyear Meeting. We acknowledge constructive and careful comments from the anonymous referee.

Technological Links and Predictable Returns

First Draft: September 10, 2017
Current Draft: March 7, 2018

Abstract

Employing a classic measure of technological closeness between firms, we show that the returns of technology-linked firms have strong predictive power for focal firm returns. A long-short strategy based on this effect yields monthly alpha of 117 basis points. This effect is distinct from industry momentum and is not easily attributable to risk-based explanations. It is more pronounced for focal firms that: (a) have a more intense and specific technology focus, (b) receive lower investor attention, and (c) are more difficult to arbitrage. Our results are broadly consistent with sluggish price adjustment to more nuanced technological news.

JEL classification: G10, G11, G14, O30

Keywords: Technology momentum, stock returns, return predictability, patents, technological closeness, limited attention, market efficiency

1. Introduction

In today's knowledge-based economy, technological prowess is becoming an increasingly important determinant of firms' short-term profitability as well as long-term survival. Many of the largest firms in the world, such as Amazon, Google, Intel, and Samsung, may have minimal overlap in product space, yet are closely-aligned in terms of technological expertise. These technological affinities transcend traditional industry boundaries and are typically not readily discernible from firms' financial reports. Nevertheless, they can be key drivers of the economic fortune of today's businesses.

In this study, we examine the implications of technological affinity for market price discovery and firms' stock returns. Firms do not conduct their technological research in isolation; in contrast, they frequently interact with each other, leading to an innovation process characterized by common shocks and knowledge spillovers (Jaffe, Trajtenberg, and Henderson, 1993). These common shocks and spillover effects can in turn impact firms' stock returns. For example, firms working on areas of innovation that substantially overlap with each other are subject to similar supply-chain linkages, which serve as important transmission channels for common economic shocks (Acemoglu et al., 2012). Firms operate in proximate technology space may also use similar inputs of production, with inputs being broadly understood as anything required in the production process (e.g., human resources, key raw materials, production equipment, Information and Communication Technology (ICT), or intangible knowledge).[1] Technology spillovers

[1] For example, in response to a letter in *Nature Methods* pointing out that the CRISPR-Cas9 gene editing system can potentially go off target, stocks of firms using similar CRISPR technologies sank on May 30, 2017. As another example, consider the breakthrough in the production of silicon chips. The dramatic cost reductions associated with this innovation, in turn, had a significant impact on the vitality of the entire electronics industry.

could occur due to explicit inter-firm collaborations or, more frequently, the existence of overlapping expertise in the same technological domain (Bloom, Schankerman, and Van Reenen, 2013).

This paper finds evidence of return predictability across technology-linked firms. Specifically, we document a striking empirical relation wherein the stock returns of focal firms exhibit a predictable lag with respect to the recent returns of a portfolio of its technological peers ("tech-peers"). Focal firms whose tech-peers earn higher (lower) returns will themselves earn higher (lower) returns in subsequent months. A trading strategy using a proxy based on lagged tech-peers' returns yields monthly alpha of 117 basis points. These results are robust to an extensive set of control variables, hold in all four sample sub-periods, and do not seem easily reconciled with risk-based explanations. Rather, our evidence appears more consistent with sluggish price adjustment to nuanced news affecting closely-aligned tech-peers.

To test for return predictability among tech-linked firms, we implement the following portfolio strategy. For each focal firm *i* at month *t*, we calculate the weighted return of a portfolio of firms that share similar technology as the focal firm, $TECHRET_{it} = \sum_{j \neq i} TECH_{ijt} \cdot RET_{jt} / \sum_{j \neq i} TECH_{ijt}$, where RET_{jt} is the return of firm *j* at month *t* and $TECH_{ijt}$ measures the degree of technology closeness between firm *i* and *j* as of time *t*. Specifically, we follow Jaffe (1986) and Bloom, Schankerman, and Van Reenen (2013), and define $TECH_{ijt}$ as the uncentered correlation of the patent distributions between two firms *i* and *j*, $TECH_{ijt} = \frac{(T_{it}T_{jt}^{'})}{(T_{it}T_{it}^{'})^{1/2}(T_{jt}T_{jt}^{'})^{1/2}}$, where

$T_{it} = (T_{it1}, T_{it2}, \cdots, T_{it427})$ is a vector of firm *i*'s proportional share of patents across the 427 United States Patent and Trademark Office (USPTO) technology classes over the rolling past five years as of time *t* (footnote 17 provides a numerical example of how *TECH* is calculated). We then sort focal firms into deciles using returns earned by a portfolio of their tech-peers in the previous month. Our results show that the tech-peers' lagged returns have significant predictability for focal firm returns. Specifically, a portfolio that goes long in the focal firms whose tech-peers performed best in the prior month and goes short in the focal firms whose tech-peers performed worst in the prior month, yields an equal-weighted return of 117 basis points (t=5.47) per month. For the analogous value-weighted portfolio, the returns are 69 basis points per month (t=3.19). We refer to this return predictability as "technology momentum." We further confirm these return prediction results are robust to a variety of controls, including firm size, book-to-market, gross margin profitability, asset growth, R&D intensity, short-term reversal, and medium-term price momentum.

Two companies can be highly correlated in technology space, yet exhibit few other common traits. Consider the case of Illumina Inc. and Regeneron Pharmaceutical Inc. Illumina manufactures life science tools and provides genetic analysis services, and its patent technological fields range from optical (Class 359, 385), chemical apparatus (Class 442), to data processing (Class 702). Regeneron is a pharmaceutical firm that produces medicines for serious diseases, and its patents cover technological fields such as drugs (Class 424, 514), peptides (Class 530), and organic compounds (Class 536). Both firms are fueled by technological advancements in molecular and microbiology (Class 435). As shown in Figure 1, during 2002 to 2006, Regeneron (Illumina) had 48 (22) granted patents, with 25 (8) of these patents belonging to Class 435 (Chemistry: molecular biology and microbiology). The technology proximity score for these two firms is high: $TECH_{ijt} = \frac{(T_{it}T_{jt}^{'})}{(T_{it}T_{it}^{'})^{1/2}(T_{jt}T_{jt}^{'})^{1/2}}$ = 0.71. Yet these firms are not in the same industry (*SIC code: 3826 vs. 2834*) nor are they connected by supply-chain linkages. Furthermore, they are not product market competitors in the sense of Hoberg and Phillips (2016), as the text-based product similarity score for these firms is only 0.01 (see Hoberg and Phillips 2016, for how product similarity measures are computed).

This example illustrates the potential importance of technological affinity, as distinct from other economic linkages explored by prior studies. While it is natural for firms in the same industry to share similar technologies, close technological affinity can often cut across industrial boundaries. This is because firms that are closely aligned in technology space often come from many different industries. Bloom, Schankerman, and Van Reenen (2013) first highlighted the diversity of firms and industries represented in each patent category. We find the same pattern in our sample.[2] In fact, the non-overlapping nature of firms' product space and technology space is an important motivation for this study.

We conduct a number of tests to ensure the technology momentum effect is not a rediscovery of the well-known industry momentum effect (Moskowitz and Grinblatt, 1999; Hou, 2007). First, we show that the Pearson (Spearman) correlation between technology momentum (*TECHRET*) and industry momentum (*INDRET*) is only 0.203 (0.209) – see

[2] In our sample, an average (median) patent technology class contains firms from 10 (10) different 2-digit SIC industries and 31 (26) different 4-digit SIC industries. The average HHI concentration ratio in a patent technology class by different 2-digit (4-digit) industry is 0.37 (0.21), showing that various industries indeed secure patents in the same technology class. An HHI concentration ratio close to 1 in our case means the majority of patents in one technology class comes from one industry while a smaller ratio means patents are more evenly distributed among different industries in a given technology class.

Table 1 Panel B. Second, we show that the technology momentum results are robust to the presence of both current and lagged industry momentum. Finally, we re-run our tests with *TECHRET* measures computed using only tech-peers that are from a different industry (i.e., only instances where the focal firm and the linked firm are not from the same industry). This is clearly a draconian control procedure, as it excludes by design any technological linkage effects that may exist within a given industry group. Nevertheless, our results show that the technology momentum effect remains strong even after we exclude all tech-peers from the same Fama-French 48-industry classification, as well as all tech-peers with the same 3-digit SIC code as the focal firm.

To ensure that this lead-lag relation is not due to other known linkage channels, we also controlled for each focal firm's supplier and customer returns (Cohen and Frazzini, 2008). In addition, for focal firms that have more than one business line, we controlled for returns generated by a portfolio of its "pseudo-conglomerate" peer firms – i.e., a portfolio of single-line firms that collectively span the focal firms' lines of business (Cohen and Lou, 2012). Neither control had any significant effect on the technology momentum effect. Taken together, these tests show that the technology momentum we document is distinct from return momentum arising from industry links, customer-supplier links, and standalone-conglomerate firm links.

As a further robustness test, we employ the method in Burt and Hrdlicka (2016) to rule out any bias arising from correlated alphas between linked-firms due to common factor shocks.[3] Specifically, we sorted firms based on $TECHRET_{it}$ calculated using peer firms' idiosyncratic returns (obtained after adjusting each peer firm's return for common exposure

[3] We thank the reviewer for recommending this important test.

to Fama-French's four-factors) rather than their raw returns. Our results show that sorting on the idiosyncratic returns of technology-linked firms yields essentially the same return predictability patterns as sorting on their raw returns. These results indicate that the predictive information extracted from tech-peer returns is not due to common factor exposures.

To better understand the economic mechanism behind technology momentum, we also examine the sensitivity of the documented effect to firm characteristics associated with the nature of its technological expertise. First, we find that return predictability is stronger for focal firms that have higher *technology-intensity* (i.e., have higher R&D expenditures or have received more patent grants in the past five years). This result is intuitive, and suggests that technology momentum is stronger in firms that are more reliant on technological innovations for their success. Second, we document stronger technology momentum among focal firms with greater *technology-specificity* – i.e., firms whose patents belong to technology categories that have higher industry concentrations. This result is more difficult to interpret, but is broadly consistent with slower information diffusion when technological news occurs in patent categories with more specific industry applications.[4]

In addition, we find that return predictability is stronger for focal firms that are more likely to be overlooked by investors (i.e., firms that are smaller, have lower analyst following, lower institutional ownership, and thinner media coverage), and have higher

[4] One explanation for this result is that tech-peer returns simply contain more information about focal firm valuations when the focal firm technology has higher industry concentration. An alternative explanation is that investors are more likely to underestimate the full value implications of tech-peer returns when the focal firm technology has high industry concentration. Both scenarios would lead to a slower, or less complete, information diffusion process for firms with high *technology-specificity*. We discuss the details of how the technology-specificity measure is computed in Section 5.1.

arbitrage costs (i.e., higher idiosyncratic return volatility). Moreover, consistent with higher trading costs for the short-leg of the strategy, we also find a stronger (weaker) effect when the recent news is bad (good).[5] These results are broadly consistent with a sluggish price response process that is more pronounced when focal firms: (a) have a stronger and more specific technology focus, (b) receive lower investor attention, and (c) are more difficult to arbitrage.

We also examine the stock price reaction around subsequent earnings announcements for both the long- and the short-leg of the tech-momentum strategy. This test has been widely used in prior studies to separate mispricing from risk-based explanations (e.g., La Porta et al., 1997; Bernard and Thomas 1989; Gleason and Lee, 2003; Engelberg, McLean, and Pontiff, 2017). The idea is intuitive: earnings announcements help correct investor expectation errors about future cash flows; therefore, if an anomaly is associated with investor misperceptions about the firms' cash flows, then a disproportionate amount of its returns should be realized around subsequent earnings announcements. In contrast, if an anomaly is driven by changes in underlying risk, then strategy returns should accrue more evenly over subsequent periods. Our tests show that the tech-momentum anomaly spread is 417% higher on a day during an earnings announcement window than on a non-announcement day. This evidence is extremely difficult to square with standard risk models.[6]

[5] Prior studies suggest bad news tend to be incorporated into price more slowly (Hong, Lim, and Stein, 2000), either because investors are more reluctant to sell their losers, or because short-selling is more costly to implement (Beneish, Lee, and Nichols, 2015).

[6] Another concern is so-called "displacement risk", whereby a firm's value could be negatively impacted by competitors' (or new entrants) innovation. The idea is that a focal firms' return going forward may be higher because investors need to be compensated for this risk. However, we find no evidence technology momentum is more pronounced in more competitive industries, a central prediction of the displacement risk explanation.

To further distinguish between mispricing and risk explanations, we also examine the correlation between our tech-momentum signal and firms' future standardized unexpected earnings (*SUEs*). *SUEs* are not return-based, so this test is not confounded by imperfect controls for firm risk. At the same time, unexpected earnings are fundamental determinants of firm's future cash flows. If returns to the *TECHRET* hedge portfolio are driven by predictable changes in cash flows, rather than a compensation for risk, the *TECHRET* signal should also predict focal firms' future *SUEs*. Our results show that technology-peer returns do in fact strongly predict focal firm *SUEs*, with the predictability gradually decaying over the next three quarters. Consistent with a slow diffusion of cash flow relevant news, focal firms with high (low) tech-momentum report higher (lower) future *SUEs*, even after controlling for each firm's own lagged *SUEs*. These results again suggest that the return predictability associated with *TECHRET* reflects incomplete price reaction to cash flow news, rather than risk differences.

In addition to the tests reported in the main text of this study, our Internet Appendix provides a battery of other robustness tests. First, we document the robustness of the hedge portfolio returns to various perturbations in: the data requirements for *TECH*, the specific *TECH* threshold used, and alternative definitions for what qualifies as a micro-cap stock (Table IA1). Second, we report the robustness of return predictability by each of four sub-periods (Table IA2). In all four sub-periods, we find a technology momentum effect even after controlling for many other pricing anomalies. Third, we examine result sensitivity to the "age" of the *TECH* mapping (Table IA3). Our results show that the effect declines slightly with more "stale" *TECH* mappings, but is still significant even when we use three-year-old *TECH* data. Fourth, we report average monthly returns for various

(L, H) strategies where L is the number of lagged months used in portfolio formation and H is the number of months the portfolio is held (Table IA4). Our results show that in equal-weighted portfolios, the tech-momentum effect is statistically significant for combinations of L= 1 to 12 and H= 1 to 12; in value-weighted portfolios, the effect fades more quickly and is generally only significant for H =1 to 6. Finally, we report the lead-lag relation in patent flows and citation counts between tech-peers and focal firms (Table IA5). Specifically, we show that annual increases (decreases) in patent flows and citation counts among tech-peers reliably predict future increases (decreases) in these same variables for focal firms. This last test documents a lead-lag technology spillover effect, which sheds further light on the economic mechanism behind technology momentum.

In sum, we document robust return predictability across technology-linked firms. Specifically, the returns of technology-linked firms have strong predictive power for focal firm returns. This return predictability pattern is distinct from industry momentum, is incremental to a number of other anomaly variables, and is not easily attributable to risk-based explanations. The effect more pronounced for focal firms that: (a) have a more intense and more specific technology focus, (b) receive lower investor attention, and (c) are more difficult to arbitrage. Taken together, our results are broadly consistent with sluggish price adjustment to more nuanced technological news.

The remainder of the paper is organized as follows. Section 2 lays out the background for the setting we examine in the paper. Section 3 describes the data and variables. Section 4 presents our main results on technology momentum as well as robustness tests. Section 5 explores the underlying mechanism behind our results. Section 6 rules out risk-based explanations by conducting both return-based tests as well as examining the real-activity side of the technological link. Section 7 concludes.

2. Background

Our paper builds on and contributes to several strands of existing literature. First, our work relates to a large literature that examines investor belief revision in the context of new information. Tversky and Kahneman (1974) and Daniel, Hirshleifer, and Subrahmanyam (1998), among others, suggest that investors may overweigh their own prior beliefs and underweighting observable public signals. A large set of empirical works lends support to this view. For example, investors underreact to public announcements of corporate events (Kadiyala and Rau, 2004), stock splits (Ikenberry and Ramnath, 2002), goodwill write-offs (Hirschey and Richardson, 2003), and the real option value of business segments (Rao, Yue, and Zhou, 2017). Hou (2007) report a lead-lag pattern between weekly returns of large firms and small firms from the same industry. Jiang, Qian, and Yao (2016) find industry leaders' R&D growth predicts returns for other firms in the same industry. Our study is similar in spirit, but examines the pricing implications of firms' technological links, an increasingly important dimension of firm value that often transcends industry boundaries.

Our study is also related to a growing literature on investors' limited attention. Several theoretical works present a framework for understanding market pricing dynamics when a subset of investors have limited attention (e.g., Merton, 1987; Hong and Stein, 1999; Hirshleifer and Teoh, 2003; and Peng and Xiong, 2006). The central message from these models is that delayed information recognition due to investors' limited attention can give rise to return predictability patterns that are difficult to explain with traditional asset pricing models. These limited attention models have spawned a growing set of empirical work.[7] Particularly noteworthy are recent studies that document a lead-lag returns relation between firms that have close economic affinities, such as product market links, customer-supplier links, geographical links, labor market links, and business alliance links.[8] Our paper can be framed in terms of this literature, but we focus specifically on technology affinity. We show that technology-link is distinct from other well-documented economic links, such as industry or product market relations. This effect is also not due common exposure to certain risk factors (i.e., it survives the Burt and Hrdlicka (2016) tests).

Third, our work joins a burgeoning literature that studies the asset pricing implications of innovation-related activities. Existing works find various aspects of a firm's innovation activity, such as R&D intensity (Chan, Lakonishok, and Sougiannis, 2001), R&D growth (Penman and Zhang, 2002; Eberhart, Maxwell, and Siddique, 2004; Lev, Sarath, and Sougiannis, 2005), patent citations (Gu, 2005; Matolcsy and Wyatt, 2008), innovative efficiency (Hirshleifer, Hsu, and Li, 2013) and innovative originality (Hirshleifer, Hsu, and Li, 2017), all have predictive power for its future stock returns. Our work is distinct from this literature in that we focus on the predictive effect of innovations by tech-peer firms, rather than innovations at the focal firm itself.

Lastly, our work is related to a concurrent working paper by Bekkerman and Khimich (2017; hereafter BK) that also examines the pricing implications of firms' technological link. We became aware of BK's work as we were wrapping up our own. The motivating

[7] Exemplary studies include Huberman and Regev (2001), Barber and Odean (2007), DellaVigna and Pollet (2009), Hou (2007), Menzly and Ozbas (2010), and Hong, Torous and Valkanov (2007).
[8] See, for example, Hou (2007), Cohen and Frazzini (2008), Cohen and Lou (2012), Aobdia, Caskey, and Ozel (2014), Li, Richardson, and Tuna (2014), Huang (2015), Lee, Ma, and Wang (2015), Li (2015), Cao, Chordia, and Lin (2016).

research question and main results of the two studies are similar. However, our paper differs from BK in several important respects. First, BK apply textual analysis to patent documents to determine technological affinity, while our paper measures pairwise distance using patent technology class distribution (Jaffe, 1986).[9] One advantage of our measure is that it measures the degree of technology closeness between firms, providing an economically meaningful weighting scheme to construct weighted-average return of technology-linked firms. Second, due to more stringent data requirements, BK only examine stock returns from 1997 onward, while our approach enables us to study a much longer period (from 1963 onward). Overall, the two papers provide complementary evidence that firms' technological links contain valuable information that market prices only fully incorporate over time.

3. Data and variables

The main dataset used in this study pairs Google patent data with firm identifiers from the Center for Research in Security Prices (CRSP) database. This matched dataset is generously provided by Kogan et al. (2017).[10] Specifically, Kogan et al. (2017) use Optical Character Recognition (OCR) technology and several textual analysis algorithms to extract relevant information from patent documents, and then map the identified assignees to CRSP unique identifiers (PERMNO). This dataset covers 1.9 million CRSP-matched patents granted by the USPTO from 1926 to 2010.[11] We extract CRSP-matched

---

[9] The Jaffe (1986) approach is widely used in the economics and finance literature. A growing empirical literature has also utilized this approach to measure the distance between firms' in the technology space (such as Bena and Li, 2014; Qiu and Wan, 2015; Qiu, Wang and Wang, 2016; Li, Qiu, and Wang, 2016; Tan, Wang, and Yao, 2016). None of these studies focus on the issue of lead-lag patterns in returns.

[10] Google patent data with matching CRSP identifiers is available at https://iu.app.box.com/patents.

[11] The Google patent data has more extensive coverage than the NBER patent data developed by Hall, Jaffe, and Trajtenberg (2001). For example, during the same period covered by the NBER patent data (1976-

patent information from this database to construct our technology-linkage variables.

There are two important events in the life of each patent: the application date and the grant date. The application date is the date on which the inventor(s) filed for a new patent with the USPTO; the grant date is the date on which the patent is formally issued by the USPTO. The lag between these two dates is on average two to three years. Unless there is a federal holiday, the USPTO issues patents every Tuesday, and its publication, *Official Gazette*, lists detailed information on the patents granted on that day.[12] By the patent grant date, the fact that a particular firm owns a given patent should be public knowledge.[13] Therefore, by choosing the grant date as the effective date of each patent, we avoid look-ahead bias and ensure that the patent information is publicly available.

Our main sample consists of firms in the intersection of the Google patent data, CRSP and COMPUSTAT. We focus the analysis on common stocks (CRSP share codes 10 and 11) and exclude financial firms (those with one-digit SIC code = 6). To ensure that the relevant accounting and patent information are publicly known to investors in the market, we impose at least a six-month gap between fiscal-year end month and the portfolio formation date. Specifically, we first match the Google patent data for grant year *t* with COMPUSTAT accounting data for the most recent fiscal year (i.e. the fiscal year ended in calendar year *t*). We then match sample firms to CRSP stock returns from July year *t+1* to

---

2006), the Google patent data adds an average of 2,187 patents per year to the NBER patent data and corrects some errors.

[12] The USPTO patent information is available at https://www.uspto.gov/patent.

[13] After the American Inventors Protection Act (AIPA) came into effect on November 30, 2000, the USPTO began publishing patent applications 18 months after the application date. Therefore, for patents that were filed after November 30, 2000, knowledge of the filing will be public at the earlier of either: the publication date (exactly 18 months after the application date) or the grant date. However, even if patent details were released prior to grant date, some uncertainty remains as to whether it will ultimately be granted. To be conservative in constructing *TECH*, we use the patent grant date as the date on which investors have full public knowledge about a patent. This assumption is consistent with Kogan et al. (2017), who report elevated trading volume and return volatility around patent grant dates, suggesting investor awareness of these events.

June year *t+2*. We require firms to have non-missing market equity and SIC classification code from CRSP, and non-negative book equity data at the end of the previous fiscal year from COMPUSTAT. We further restrict our sample to firms that have at least one patent granted in a rolling-window of the past five years.[14] To reduce the impact of micro-cap stocks, we exclude stocks that are priced below one dollar a share at the beginning of the holding period.[15] We also employ the return correction approach suggested in Shumway (1997) to handle potential delisting bias.

Following Jaffe (1986) and Bloom, Schankerman, and Van Reenen (2013), we define our pairwise measure of technological closeness, $TECH_{ijt}$, as the uncentered correlation of the patent distributions between all pairs of firms *i* and *j*,

$$TECH_{ijt} = \frac{(T_{it}T_{jt}^{'})}{(T_{it}T_{it}^{'})^{1/2}(T_{jt}T_{jt}^{'})^{1/2}} \tag{1}$$

where $T_{it} = (T_{it1}, T_{it2}, \cdots, T_{it427})$ is a vector of firm *i*'s proportional share of patents across 427 USPTO technology classes over the rolling past five years as of time *t*.[16] Technology closeness ranges between zero and one, depending on the degree of overlap in technology

[14] In further robustness tests (Panel A, Internet Appendix Table IA1), we also imposed the requirement that sample firms have at least two, or at least three, years with granted patents in the rolling five-year window. Our results are robust to these perturbations.

[15] In further robustness tests (Panel B, Internet Appendix Table IA1), we also exclude any stock with price below five dollars a share, as well as any stock with a market capitalization below the 10th percentile of NYSE stocks. Neither variation had an appreciable impact on the results.

[16] The USPTO's U.S. Patent Classification System groups subject matters into technology classes (or major categories). Within each technology class, subclasses further delineate processes, structural features, and functional features of the subject matter. Currently there are 475 classes and over 165,000 subclasses. For example, the identifier "2/456" represents Class 2 (Apparel) and subclass 456 (Body cover). Over time, the USPTO has continued to fine tune its classification system, either by adding new classes or by adjusting the subclasses within a given class. These revisions do not significantly affect our methodology, as we only use the major classes available at a given point in time in constructing our mappings.

space, and is symmetric in firm ordering (i.e., $TECH_{ijt} = TECH_{jit}$).[17]

We then define technology-linked return (*TECHRET*) as the average monthly return of technology-linked firms in the technology space, weighted by pairwise technology closeness. Formally, technology-linked return for firm *i* and month *t* is defined as:

$$TECHRET_{it} = \frac{\sum_{j \neq i} TECH_{ijt} \cdot RET_{jt}}{\sum_{j \neq i} TECH_{ijt}} \qquad (2)$$

where RET_{jt} is the raw return of firm *j* at month *t*. Note that by construction, *TECH* serves as a weighting function in calculating the portfolio return of tech-peer firms, such that firms closer to the focal firm in technology space are given higher weight. *TECH* is calculated at the end of each calendar year *t* based on patent grant date that is publicly available, and then mapped to the return data from July year *t+1* to June year *t+2*.

The final sample consists of 561,989 firm-month observations spanning July 1963 to June 2012 (i.e., 588 months). Panel A of Table 1 presents descriptive statistics for our sample firms. The number of firms varies from a low of 189 firms in July 1963 to a high of 1,363 firms in June 2012. The sample firms cover almost 53% of the CRSP common

---

[17] As an illustration, consider three firms A, B, and C, with patent distribution across three technology classes, as follows: $T_A = (0,1,0),\ T_B = (0.5, 0.25, 0.25),\ T_C = (1,0,0)$. In this setting,

$$TECH_{AB} = \frac{0*0.5 + 1*0.25 + 0*0.25}{(0*0+1*1+0*0)^{1/2}(0.5*0.5+0.25*0.25+0.25*0.25)^{1/2}} = \frac{0.25}{0.61} = 0.41,$$

$$TECH_{AC} = \frac{0*1+1*0+0*0}{(0*0+1*1+0*0)^{1/2}(1*1+0*0+0*0)^{1/2}} = 0, \text{ and}$$

$$TECH_{BC} = \frac{0.5*1+0.25*0+0.25*0}{(0.5*0.5+0.25*0.25+0.25*0.25)^{1/2}(1*1+0*0+0*0)^{1/2}} = \frac{0.5}{0.61} = 0.82.$$

Intuitively, firms A and C have no patents in the same technology class and are thus assigned a technology affinity score of zero. These two firms would not be tech-peers for purposes of our analysis. Firm B has overlapping patents with both firm A and firm C. However, as shown above, Firm B is more closely aligned in technology space to firm C ($TECH_{BC}=0.82$), than it is to firm A ($TECH_{AB}=0.41$). This is because a higher proportion of B's patents are in the 1st technology class than in the 2nd technology class.

stock universe in terms of market capitalization. The lower coverage is not surprising as we only include firms that have received at least one patent grant over the past five years. We note that the average number of linked firms in any given technology category is 280. The pairwise technology closeness score (*TECH*) has an average of 0.11 with a standard deviation of 0.16, indicating that among our sample firm, some measure of technological linkage is quite common.[18]

In Panel B of Table 1, several correlation coefficients are noteworthy. The Pearson correlation between $TECHRET_{t-1}$ and RET_t is 0.028, providing raw evidence for the lead-lag effect along the technological link. Although $TECHRET_{t-1}$ exhibits trivial correlations with a number of traditional return predictors (i.e., size, book-to-market, gross profitability, asset growth, R&D intensity), it is considerably more correlated with industry return ($INDRET_{t-1}$), past one-month return (RET_{t-1}), and medium-term momentum (*MOM*) (Pearson correlations are 0.203 for $INDRET_{t-1}$, 0.123 for RET_{t-1}, and 0.031 for *MOM*). In subsequent analyses, we show the return predictability of $TECHRET_{t-1}$ holds after controlling for these, and other, variables.

4. Empirical results

4.1. Portfolio tests

Table 2 reports the main results of our paper. To construct this table, we sort all firms into deciles at the beginning of each month, based on the return earned by their technology-linked peers in the previous month ($TECHRET_{t-1}$). These decile portfolios are then

[18] Further robustness tests (see Internet Appendix Table IA1 Panel C) show these findings are insensitive to reasonable perturbations in the threshold for computing *TECHRET*. For example, our results are unchanged when we only include tech-peers that have a *TECH* score larger than 0.01 (Q1), 0.04 (Q2), or 0.12 (Q3). The results are also robust if we only include peer firms ranked in the top 50 in terms of their *TECH* score.

rebalanced at the beginning of each month to maintain either equal or value weights. Table values represent average monthly risk-adjusted returns (alphas) to the lowest decile (1) and highest decile (10) $TECHRET_{t-1}$ portfolio, as well as the average monthly return to a zero-cost portfolio that holds the top 10% of firms as ranked by $TECHRET_{t-1}$ and sells short the bottom 10% (L/S). We compute these returns by subtracting either the risk-free yield (Excess returns) or by using a variety of factor models (CAPM alpha, or 3- to 6-Factor alphas).

Table 2 Panel A provides strong evidence that technology-linked returns predict focal firm returns. Specifically, we find that the equal-weighted hedged *TECHRET* strategy (L/S), yields average monthly returns of 117 basis points (t=5.47), or roughly 14.0% per year. The corresponding value-weighted returns from the L/S portfolio are 69 basis points per month (t=3.19), or about 8.3% per year. In the next five columns, we control for other known return determinants. The same L/S strategy delivers CAPM abnormal returns of 1.22% (0.74%) per month in equal- (value-) weighted portfolios. This strategy delivers Fama and French (3-Factor; 1993) abnormal returns of 1.26% (0.80%) per month in equal- (value-) weighted portfolios. Augmenting this model by adding the stock's own price momentum (Carhart, 1997) only detracts slightly from the strategy, as the 4-Factor alpha remains 1.08% (0.65%) per months in equal- (value-) weighted portfolios. Finally, we adjust returns using the Fama and French (2015) five-factor model (5-Factor), and also conduct a test using the five-factor model plus the momentum factor (6-Factor). We find that the strategy's alpha actually increases after controlling for these factors, with the 5-Factor and 6-Factor strategies earning abnormal monthly returns of 1.37% (0.86%) and 1.21% (0.73%), respectively, in equal- (value-) weighted portfolios. These results show that high (low) tech-momentum stocks earn high (low) subsequent returns, after controlling for common risk factors.

In Panel B of Table 2, we report the portfolio alpha as well as the factor loadings on each of the Fama-French three factors and the Carhart momentum factor (*MOM*). The L/S hedge portfolio has a negative loading on the market return (*MKT*), and positive loadings on *SMB* and *MOM*. In other words, this strategy will do especially well in down markets, and when small firms and momentum firms do well. But even after controlling for these exposures, the strategy produces significant monthly alphas.

4.2. Regression results

In this section, we formally test our hypothesis in a regression framework while controlling for a number of other variables nominated by the anomalies literature. Specifically, in Table 3, we conduct Fama and MacBeth (1973) regressions where the dependent variable (in columns 1-3) is the focal firm raw return in month t (RET_t). The independent variable of interest is the return of the focal firm's technology-linked firms in month $t-1$ ($TECHRET_{t-1}$). To control for industry momentum also include the value-weighted industry return of the focal firm in month t-1 ($INDRET_{t-1}$) as an independent variable (see Cohen and Lou, 2012; Moskowitz and Grinblatt, 1999). Other control variables include lagged size, book-to-market, gross profitability, asset growth, R&D intensity. Lastly, we also include RET_{t-1}, a short-term return reversal variable, defined as the focal firm's stock return in month $t-1$, to control for the short-term reversal effect (Jegadeesh and Titman, 1993), and *MOM*, a medium-term price momentum variable, defined as the focal firm's stock return for the last 12 months except for the past one month, to control for the firm's own momentum effect (Chan, Jegadeesh, and Lakonishok, 1996).

All explanatory variables are based on last non-missing available observation for each month t and are assigned to deciles ranging from 0 to 1. Industry fixed effects are measured at two-digit SIC code industry level. Cross-sectional regressions are run each calendar month and the time-series standard errors are Newey-West adjusted (up to 12 lags) for heteroskedasticity and autocorrelation.

Table 3 columns 1-3 report the basic results. Consistent with the time-series factor-based tests, $TECHRET_{t-1}$ remains a strong predictor of next month's focal firm return in all three specifications. With industry fixed effects but before controlling for any other variables, the coefficient on $TECHRET_{t-1}$ is 0.629 with a t-statistic of 4.10, indicating that the average monthly return spread of the focal firms in the top and bottom deciles is 62.9 basis points. In column 2, we include size, book-to-market, gross profitability, asset growth, R&D intensity, reversal, and momentum as control variables. The coefficients on these control variables are also consistent with prior literature: size, asset growth, and reversal variable are significantly negatively correlated with future returns, while book-to-market, gross profitability, R&D intensity, and momentum are positively correlated with future returns.

Compared to Column 1, the coefficient on $TECHRET_{t-1}$ decreases only slightly and the corresponding t-statistic actually increases. In column 3, we further include lagged industry return as a control variable. Both the magnitude and the significance of the coefficient on $TECHRET_{t-1}$ actually increase after adding industry momentum as a control variable, indicating that the technology momentum effect is unlikely to be explained by the industry momentum effect documented by Hou (2007).

To further distinguish our technology-momentum effect from the industry momentum effect, we also report the results when each firm's industry-adjusted return (calculated as the difference between a focal firm's return and its contemporaneous industry return) is the dependent variable. Moskowitz and Grinblatt (1999) show that industry momentum is a short-lived effect that is strongest in the month immediately after portfolio formation. By subtracting industry return from the focal firm return, we purge out any predictability arising from monthly industry-wide auto-correlation in returns. Column 4 of Table 3 shows that the magnitude and significance of the coefficient for $TECHRET_{t-1}$ remains virtually the same when we use industry-adjusted returns. Note also that the coefficient on lagged industry returns, $INDRET_{t-1}$, becomes insignificant in column 4. This further suggests that the predictive power of $TECHRET_{t-1}$ comes from the delayed processing of firm-level news, rather than industry-wide return continuation (see Cohen and Lou (2012) for an expanded discussion of this argument).

In Table 4 Panel A, we further control for supplier and customer returns (Menzly and Ozbas, 2010), pseudo-conglomerate returns (Cohen and Lou, 2012), and stock turnover (Lee and Swaminathan, 2000). The coefficient on $TECHRET_{t-1}$ remains significant after controlling for return predictability along the supply-chain, for pseudo-conglomerate firms, as well as for differences in stock turnover. We note that the magnitude and significance of the coefficient for $TECHRET_{t-1}$ are qualitatively the same as our main results, indicating that the information diffused along the technological link cannot be explained by the information shocks from supply-chain, business segment, or differences in trading volume and stock liquidity.

Finally, to be absolutely certain we have not rediscovered the industry momentum effect, we also re-compute our *TECHRET* measure using only tech-peers from a different industry (i.e., where the focal firm and the linked firm are not in the same industry). This is clearly a draconian control measure, as it excludes by design any technological linkage effects that may exist within a given industry group. Because firms in the same industry are, on average, more closely related in technology space, we will almost certainly lose some important technology-related information. Nevertheless, as results in Panel B of Table 4 show, our main results are robust even when we compute *TECHRET* by excluding tech-peers that are from the same Fama-French (1997) 48 industry grouping as the focal firm. Similarly, we continue to find 6-Factor alphas that are both economically and statistically significant even when we exclude all tech-peers that belong to the same 3-digit SIC industry as the focal firm.

4.3. Predictability for time-period beyond one month

In Internet Appendix Table IA4, we consider the profitability of (L, H) strategies following Moskowitz and Grinblatt (1999) to show the speed of information diffusion. In the (L, H) strategy, the technology momentum portfolios are formed based on L-month lagged returns, held for H months, and rebalanced monthly. Both equal-weighted and value-weighted results are reported for the (L, H) strategy of the hedge portfolio that, each month, buys (shorts) stocks with tech-peer returns in the highest (lowest) decile. For brevity, we only report results for L = 1-, 3-, 6-, 12, and H = 1-, 6-, 12-, 24-, 36-months.

Among the strategies that we consider, the short-term (1,1) strategy (i.e., L=1, H=1) is the most profitable. This result is robust to Daniel et al. (1997) (DGTW) characteristic-adjusted returns and industry-adjusted returns. The profitability of the short-term 1-month strategy is not very sensitive to the length of the ranking period L. For example, the equal-weighted raw monthly return for the (1,1) strategy and the (12,1) strategy are

1.17% and 1.11%, respectively. Note that the value-weighted returns are smaller than the equal-weighted returns in all the strategies, indicating that the speed of information diffusion is quicker for larger firms. While the return predictability strongest in the short-term, we still find significant profits for strategies with holding periods as long as one year. For example, the equal-weighted raw monthly return for the (1, 12) strategy is 0.32% with a *t*-statistics of 3.90. However, return predictability generally diminished with longer holding periods. This pattern of fading predictability conforms to the information diffusion explanation, but is much more difficult to reconcile with a risk-based explanation.

We also examine the long-run return pattern of our technology momentum effect. If investors, on average, overreact to the news contained in lagged tech-peer returns, we should observe some return reversal over longer holding periods. On the other hand, if the effect we document is primarily an underreaction to the news that affects focal firms' fundamental value, we should see no return reversal in the future. In Figure 2, we evaluate these two alternative hypotheses by plotting the cumulative return to the *TECHRET* hedge portfolio in the six months after portfolio formation. Consistent with the results in Internet Appendix Table IA4, we continue to observe a modest upward drift through month six. In fact, we find no sign of a return reversal over the next 12 to 24 months. These findings are similar to the results from other inter-firm studies (Moskowitz and Grinblatt, 1999; Cohen and Frazzini, 2008; Cohen and Lou, 2012). Overall, the evidence points to a mechanism of delayed updating of focal firm prices to fundamental information, and not an overreaction phenomenon.

4.4. Correction for bias of correlated alphas between linked-firms

Burt and Hrdlicka (2016) find that correlated alphas between linked firms could bias network-based measures of information diffusion. The source of the bias they identify in measures of slow information diffusion is the misspecification (alpha) inherent in the underlying asset pricing model. This misspecification induces bias, because economically linked firms are more likely to have correlated alphas. This correlation makes sorting on the economically linked firms' (for example, customers') returns, which include alphas, an implicit sort on the alphas of the firms being predicted (for example, suppliers). To address this problem, the authors derive a correction method robust to delayed information flow along the economic link by subtracting the asset pricing model's predicted return from the sorting return.

Our portfolio construction procedure may also suffer from this correlated alpha bias. To deal with this potential problem, we follow Burt and Hrdlicka (2016) and use the tech-peers' idiosyncratic return, rather than their raw return, when constructing $TECHRET_{t-1}$. More specifically, we use the daily returns of each tech-peer firm over the previous 12 months to estimate its alpha and factor loadings to the 4-factor model (Fama and French, 1993, plus Carhart, 1997). We then use these parameter estimates, together with the realized factor returns, to obtain each tech-peer's idiosyncratic return for month *t-1*. These idiosyncratic returns then replace each firm's raw return in computing $TECHRET_{t-1}$. Table 5 reports the results when repeat our main tests using the Burt and Hrdlicka (2016) method. After removing correlated alphas, we still find that returns of tech-peers predict focal firm returns. These results indicate that the information being extracted from the returns of the tech-peer portfolio is largely orthogonal to the peer firms' common exposure to factor returns.

4.5. Other robustness tests

4.5.1. Technology-linked return predictability across time

In Internet Appendix Table IA2, we examine whether the return predictability power of technology-linked firms varies across time. We divide our full sample periods into 1963-1979, 1980-1989, 1990-1999, and 2000-2012. We then exactly repeat our baseline analysis from Table 3 for each sub-period. Our results hold up well to this time disaggregation. The coefficients of $TECHRET_{t-1}$ are all positive and statistically significant after controlling for various return determinants. In fact, the only surprise in Table IA2 is that there appears to be little industry momentum in the last sub-period, which runs from 2000-2012. It is difficult to tell whether this result reflects noise in a short sample or a structural decline in the industry momentum effect. What is more noteworthy from our perspective is that the technology momentum effect is robust in all four sub-periods.

4.5.2. Persistence of Technology Closeness

We also examine the sensitivity of our main result to the age of the technology closeness measure. Panel A of Internet Appendix Table IA3 shows the correlation between $TECHRET_{t-1}$ and its corresponding one-, two-, three-year lagged measures are strongly positive and significant. Panel B of the same table shows lagged versions of $TECHRET_{t-1}$ also predict focal firm returns. While predictability decreases with the number of lagged years, even three-years-old technology closeness measures work quite well. This suggests that the relative position of firms in technology space is quite sticky, or persistent, over time. One implication is that investors do not need extremely timely information on patents to implement this strategy. Even relatively “stale” technology mappings have some predictive power for focal firm returns.

5. Underlying mechanisms

Results from the analyses thus far suggest that the technology momentum we document maybe driven by slow dissemination of technology-related fundamental news. In this section, we further explore the cross-sectional sensitivity of our main results to various firm characteristics associated with: (a) the nature of its technological innovations, (b) the extent to which investors might be attentive to such innovations, and (c) the costs that investors face if they attempt to arbitrage the mispricing.

5.1. Technology-related channels

What specific characteristics of a tech-dependent firm would give rise to stronger technology momentum? In other words, what dimensions of a focal firm's technology are associated with greater return predictability? Given the increasing importance of technological capabilities to many firms, it seems important to provide some evidence along these lines. In this subsection, we evaluate the sensitivity of tech momentum to two important dimensions of a focal firm's technological capabilities: *technology intensity* and *technology specificity*.

We measure *technology intensity* by the size of its R&D spending or the number of patents, both scaled by sales.[19] We posit that technology momentum will be stronger for firms with higher technology intensity for two reasons: first, firms that are more technology-intensive should be more sensitive to (i.e., impacted more directly by) economic shocks to its tech-peers; second, more technology-intensive firms are also likely

[19] Our main results are unaffected when we use book equity as the denominator.

to be harder to value, leading to a slower and potentially stronger information diffusion effect (Hirshleifer, Hsu, and Li, 2013).

Columns 1-2 of Table 6 report the results. The coefficient estimate on the interaction term between the *R&D above median* dummy and $TECHRET_{t-1}$ is positive and statistically significant, 0.448 (t=3.10), indicating that the documented return effect is larger for firms with more R&D spending. In the same vein, column 2 shows that the coefficient on the interaction term between the *Patent above median* dummy and $TECHRET_{t-1}$ is also positive and significant, 0.470 (t=3.35). The difference seems economically large, as the technology-momentum effect is more than twice as large for the technology-intensive firms. These findings confirm our prediction that firms with higher technology intensity exhibit a stronger technology momentum effect.

Second, we examine how *technology specificity* affects technology momentum. While it is difficult to gauge precisely the specificity of a single patent, we can estimate the specificity of a technology class by calculating its applicability across different industries. For this purpose, a more (less) specific technology is defined as one that can be applied to a narrower (wider) number of distinct industries. More specifically, we compute an "industry concentration ratio" for each patent technology class in each year of our sample period.[20] We then construct a firm-level technology specificity measure by taking the weighted-average of the industry concentration ratios across all the technology classes to which a firm's patents belong. The weights for this purpose are that firm's proportional

[20] The industry concentration ratio of a technology class is defined as the sum of the squares of the patent share for each industry in the class (computed using data from the past rolling five years). For this purpose, each industry's patent share within a patent class is computed by summing all the patents belonging to the firms from that industry, divided by the total number of patents within that technology class. This industry concentration ratio is a type of Herfindahl measure, with higher (lower) values indicating the patents in that technology class are concentrated in a few (diffused across many) industries.

share of patents in a given class. In short, a higher (lower) *technology specificity* score means the firm's technology has, on average, more (less) specific usage across multiple industries.

The results in columns 3 and 4 of Table 6 show that technology momentum is stronger for focal firms with higher *technology specificity*. For these tests, we compare each firm's technology specificity to other firms from its own industry. Firms whose specificity score is *above* its industry median is assigned a value=1 for its specificity indicator variable. We use two different industry classifications: either Fama-French 48 (column 3) or 3-digit SIC industry codes (column 4). In both tests, firms with more specific technologies exhibit stronger tech-momentum, with the estimated coefficients indicating a 38% to 53% stronger effect for high-specificity firms.

This result is broadly consistent with slower information diffusion when technological news occurs in patent categories with more specific industry applications. One explanation is that tech-peer returns simply contain more information about focal firm valuations when the focal firm technology has higher industry concentration. An alternative explanation is that investors are more likely to underestimate the full value implications of tech-peer returns when the focal firm technology has high industry concentration. Both scenarios would lead to a slower, or less complete, information diffusion process for firms with high *technology-specificity.*

5.2. Investors' limited attention

If technology momentum is related to limited attention, we should observe a stronger effect for firms that receive less investor attention. Prior literature nominates four measures of investor attention: firm size, analyst coverage, institutional ownership, and media coverage.[21] We posit that smaller firms, and firms that have lower analyst coverage, lower institutional ownership and lower media coverage, receive less attention from investors and, therefore, will exhibit a more sluggish stock price reaction to the information contained in *TECHRET*.

To test this prediction, we define a size-based dummy variable that equals one if a focal firm is above the sample median in a given month in terms of the log value of market capitalization, and zero otherwise. Similarly, we capture the analyst coverage effect using a dummy variable that equals one if the number of analysts following a focal firm at the end of the previous month is above the sample median, and zero otherwise; and we define a dummy variable to capture the institutional ownership effect that equals one if the institutional holding at the end of the previous fiscal-year end is above the sample median. Finally, we construct a *News* variable, defined as the number of news coverage in the previous year, using news from RavenPack News Analytics database (Dow Jones Edition) with relevance score above sample median, to proxy for the media coverage of the focal firm. The results of the tests are reported in column 1 to 4 of Table 7. Consistent with our prediction, the coefficient estimates on the four interaction terms between the investor inattention dummies and $TECHRET_{t-1}$ are all negative and statistically significant. This result lends support to our hypothesis that the return effect is driven by investors' inattention to the technological linkage information.

---

[21] Hirshleifer, Hsu, and Li (2013) report that a strategy based on slow price adjustment to innovative efficiency is more pronounced for small firms. Analyst stock coverage and institutional ownership are commonly used in the literature as proxies for investor attention (e.g., Hou, 2007; Cohen and Frazzini, 2008; Menzly and Ozbas, 2010; Hirshleifer, Hsu, and Li, 2013; Jiang, Qian, and Yao, 2015). More recently, media coverage has also become popular as a proxy for investor attention (Drake, Guest, and Twedt, 2014; Twedt, 2016).

5.3. Cost of arbitrage

We also expect to see a stronger return effect for stocks with more binding arbitrage costs, as investors are less able (or willing) to fully update these firms' prices (Hirshleifer, Teoh, and Yu, 2011; Beneish, Lee, and Nichols, 2015). To test this conjecture, we use two measures to proxy for the cost of arbitrage: idiosyncratic volatility (*IdioVol*) and *Bad News*. Wurgler and Zhuravskaya (2002) argue that arbitrageurs' demand for a stock is inversely related to its arbitrage risk, which is reflected in its idiosyncratic volatility. Firms' cross-sectional sensitivity to market-wide sentiment is also a function of their idiosyncratic volatility (Baker and Wurgler, 2006 and 2007). In addition, prior research suggests that information diffusion into price is slower for bad news (Hong, Lim, and Stein, 2000), either because investors are more reluctant to sell their losers (Odean, 1998), or because short-selling is more costly to implement (Beneish, Lee, and Nichols, 2015). Therefore, we expect the technology momentum will be more pronounced for bad news.

To test this prediction, we define *IdioVol* as the standard deviation of the residuals from a regression of daily stock returns in the previous month on the Fama and French (1993) factors (at least ten daily returns required). Also, following Hong, Lim, and Stein (2000), we denote *Bad News* with an indicator variable that equals to one if $TECHRET_{t-1}$ falls in the worst-performing 30%, and zero otherwise.[22] Column 5 of Table 7 shows that the coefficient estimate on the interaction term between the idiosyncratic volatility dummy and $TECHRET_{t-1}$ is positive and statistically significant. Column 6 of Table 7 shows that the interaction term between an indicator of bad news and past technology-linked return ($TECHRET_{t-1}$) is also positive and statistically significant, 0.933 (t=2.15). For

[22] The min, mean, and max $TECHRET_{t-1}$ for *Bad News*=1 is -0.05, 0.01, and 0.00, respectively.

comparison, the unconditional coefficient on $TECHRET_{t-1}$ from Table 3 is 0.629. Both of these findings lend support to our prediction that the technology momentum effect is stronger for difficult-to-arbitrage stocks.

6. Risk explanations

In Section 4 we found that technology momentum cannot be explained by well-known risk factors, such as the Fama-French five-factors and the momentum factor. Nevertheless, it is still possible that other unobserved risks could drive our results. This would be the case, for example, if tech-peer returns can somehow proxy for changes in the focal firms' discount rates, which would then lead to changes in these firms' expected returns. We conduct several tests in this section examine this possibility.

6.1. Returns around earnings announcements

First, we examine stock price reactions around subsequent earnings announcements. This approach is widely used in the literature (see, for example, Bernard and Thomas, 1989; Chopra, Lakonishok, and Ritter, 1992; La Porta et al., 1997; Gleason and Lee, 2003; Engelberg, Mclean, and Pontiff, 2017). The idea is intuitive: if an anomaly is associated with mispricing, then it will be stronger in the earnings announcement window, as the release of these earnings helps to correct prior misconceptions about firms' expected cash flows. In contrast, if an anomaly is driven by changes in underlying risks, then the subsequent returns should accrue more evenly over subsequent periods. To conduct this test, we perform a simple regression analysis (the model specification we use is similar to Engelberg, Mclean, and Pontiff, 2017). Our unit of observation is firm-day rather than firm-month. Specifically, we regress the daily return of a stock (*DLYRET*) on the last month tech-peers' return (*TECHRET*), an earnings announcement window dummy (*EDAY*), and the interaction term made up of the two variables. We also include a set of control variables, consisting of the lagged values for each of the past ten days for stock returns, stock returns squared, and trading volume.

We present our results in Table 8. The earnings announcement window is defined as either the 1-day window (Panel A; columns 1 to 2) or a 3-day window (Panel B; columns 3 to 4), centered on the news release date. In both panels, the coefficient of the interaction term is positive and significant. Consistent with the mispricing explanation, returns to the *TECHRET* strategy are *much larger* during future earnings news releases. In column 2, the *TECHRET* coefficient is 0.398, while the *TECHRET* × *EDAY* interaction coefficient is 1.660. The coefficients show that for a *TECHRET* value of 0.07 (one standard deviation change) expected returns are higher by 2.79 basis points on non-earnings announcement days, and by an additional 11.62 basis points on earnings announcement days. Put differently, the return spread in a hedged *TECHRET* strategy is 4.17 times larger during an earnings announcement than on non-announcement days.[23] The above results are extremely difficult to square with any standard risk model.

6.2. Displacement risk

One alternative explanation for our documented tech-peer return predictability is that firms become riskier when other firms have good news on innovation, such as patent grants, in the same technology category as they are. It could be a displacement risk, meaning that firm's value could be dropping due to competitors' (or new entrants) innovation and the return going forward are higher because investors need to be compensated for this risk.

[23] For the analogous three-day earnings announcement test, according to column 4, the anomaly spread is 300% higher on a day during an earnings announcement window than on a non-announcement day.

To test this possibility, we examine whether return predictability differs as a function of the level of product market competition for the focal firm. The intuition is that if the focal firm is in a more competitive product market, it will face higher displacement risk. Our results show that a focal firm's level of product market competition has no effect on return predictability.[24] This evidence is not consistent with the displacement risk story.

Table 4 Panel B provides further evidence on displacement risk. To construct this panel, we compute the *TECH* variable using only tech-peers that are not from the same industry as the focal firms. These tech-peers are not product market competitors to the focal firms, so their price shocks (i.e. price momentum based from their returns) should not embody any displacement risk. The fact that technology momentum remains robust in this test again suggests displacement risk is unlikely to explain this phenomenon.

6.3. Investment-specific technological change

We also address the possibility that our technology momentum captures investment-specific technological change risk. We do so by directly controlling for the investment minus consumption (IMC) factor in computing risk-adjusted returns, and examining the loading of our hedge portfolio returns on this factor.[25] In the untabulated results, we find the loading of the hedged *TECHRET* portfolio on the IMC factor is essentially zero. The risk-adjusted return, or alpha, remains almost identical after controlling for this factor, indicating our results are not driven by investment-specific technological change risk.

---

[24] We find the same result using either the Fama-French 48-industry groupings or the 3-digit SIC groupings. These results are untabulated but are available upon request.

[25] Greenwood, Hercowitz, and Krusell (1997) suggest that investment-specific technological change explain aggregate economic growth; later works such as Kogan and Papanikolaou (2014), and Papanikolaou (2011) propose investment-specific technological change as a systematic risk priced in stock markets. IMC is the most well-known potential risk-factor regarding innovation or technological change. Hirshleifer, Hsu, and Li (2017) also test for this risk factor in their hedge portfolios based on innovation originality. We thank Dimitris Papanikolaou for providing the IMC factor returns.

6.4. Evidence from non-return-based metrics

Disagreements about whether return predictability reflects risk versus mispricing are often difficult to resolve using only realized returns and risk proxies. This is because return predictability can be attributed to risk, even if the source of risk is not directly identifiable or measurable (Lee and So, 2015). As an alternative approach, we also examine whether *TECHRET* has predictive power for focal firms' standardized unexpected earnings (*SUE*). *SUEs* capture unanticipated changes in firm's earnings and are not return-based, so this test would not be confounded by imperfect risk controls. At the same time, unexpected earnings are fundamental determinants of firm's future cash flows, so these results could further confirm that the return predictability is due to changes in unexpected cash flows, rather than a compensation for bearing more risk.

We first examine firms' future earnings predictability in multivariate regressions. Specifically, we test whether the stock return of the technology-linked firms predicts future unexpected earnings of the focal firm. The dependent variable is standardized unexpected earnings (*SUE*), defined as the unexpected earnings (year-over-year change in quarterly earnings before extraordinary items) scaled by the standard deviation of unexpected earnings over eight preceding quarters. The main explanatory variable of interest is one-quarter lagged *TECHRET*, computed using tech-peer returns from the past 3 months. Control variables include the focal firm's own lagged *SUEs*, up to 4 quarters. The dependent variable is winsorized at 1% and 99% in the cross-section, and all the explanatory variables are assigned to deciles ranging from 0 to 1. For consistency, sample is further restricted to firms having fiscal quarters ending in March, June, September, and December.

Panel A of Table 9 contains regression results under various model specifications. Column 1 presents a simple regression of *SUE* on one-quarter lagged *TECHRET*, with firm and quarter fixed effects. The estimated coefficient on one-quarter lagged *TECHRET* is 0.203 (t=8.65). In columns 2-4, we add the focal firms' own lagged *SUEs* as control variables, while also varying firm-industry-quarter fixed effects. Specifically, column 2 includes firm and quarter fixed effects; column 3 includes industry and quarter fixed effects, while column 4 reports the results for a cross-sectional Fama-Macbeth regression with industry fixed effects. Consistent with Bernard and Thomas (1989), the first three lags of *SUE* are positively associated with future *SUE*, and the coefficient of the fourth lag *SUE* is negative and significant. More importantly, under all these model specifications, *TECHRET* continues to positively predict future *SUEs*. These results further confirm that the short-window announcement returns we documented in Section 6.1 are driven by *TECHRET's* ability to anticipate the directional changes in focal firm fundamentals.

In Panel B of Table 9, we repeat the Fama-MacBeth model specification (same one used in column 4 of Panel A), but examine future *SUEs* over longer time periods. In each of these regressions, the dependent variable is a *SUE* from one of the next four quarters (t to $t+3$). The independent variables include lagged *SUEs* from the past four quarters, as well as an industry fixed effect. Our results show that the coefficient on *TECHRET* is always positive, but decreases monotonically from column 1 (SUE_t) to column 4 (SUE_{t+3}). Evidently the ability of *TECHRET* to forecast future unanticipated earnings decays over time, and becomes insignificant after 3 quarters. This pattern is once again consistent with a graduate diffusion of cash flow relevant news, rather than a change in discount rate or underlying risk.

7. Conclusion

Our paper establishes that technology-linked firms' returns predict focal firm returns. This technology momentum effect is robust after controlling for a variety of predictive variables, including: firm size, book-to-market, gross profitability, asset growth, R&D intensity, and short-term reversal and medium-term price momentum. It is distinct from, and cannot be explained by, previously documented lead-lag effects such as industry momentum, customer-supplier momentum, or standalone-conglomerate momentum. Applying the Burt and Hrdlicka (2016) methodology for removal of potential biases due to correlated alphas had minimal effect on the results.

We use three methods to distinguish between the mispricing explanation and risk explanation. First, we focus on returns around subsequent earnings announcements. Our results show that anomaly spreads are about 417% higher on a day of the earnings announcement window than on a regular day, a fact that is difficult to square with any standard risk model. Second, we rule out displacement risk, whereby a firm's value could be dropping due to competitors' (or new entrants) innovation, leading to higher future returns as investors demand compensation for this risk., We also rule out investment specific technology risk, finding almost identical return predictability after directly controlling for the IMC (investment minus consumption) factor. Finally, we show that technology-linked firms' past stock returns also have strong predictability for focal firm's future unexpected earnings (*SUEs*). These *SUEs* are not return-based, so this test is clearly not confounded by imperfect risk controls. At the same time, unexpected earnings are fundamental determinants of firm's future cash flows. The fact that high (low) *TECHRET* portends higher (lower) future *SUEs* is further evidence that the return predictability is driven by slow adjustment to fundamental news, rather than a compensation for bearing more risk.

Our tests document several factors that affect the magnitude of the technology momentum effect in the cross-section. First, we find that the return predictability is much stronger for focal firms with high *technology-intensity*. Specifically, we find the technology momentum effect is more than twice as strong for firms that invest more in R&D or possess more patents. Second, we find technology momentum is approximately 40% stronger for firms whose technology is applicable to a more specific set of industries. These findings suggest information dissemination is slower and less complete for firms whose technology is more intense and more industry specific. Further analysis shows that the technology momentum effect is also more pronounced for firms that are more susceptible to investor inattention, as well as firms associated with higher arbitrage costs. These findings are broadly consistent with the view that psychological biases, or information processing constraints, are contributing to the return predictability effect that we documented.

Evidence that stock prices are slow to reflect value-relevant technology-linked information suggests the potential for misallocation of resources, especially among technology-intensive firms. The effect we document is not isolated to a few firms; it is rather a pervasive pattern of return predictability affecting a large sample of companies. This finding seems especially troubling given the current trend of firms in the economy becoming increasingly more technology dependent.

Our results using limited attention proxies suggest that the problem may be mitigated, in part, by elevating the visibility of the technological mappings cross firms. The technology affinity mapping we used to construct the strategy is publicly available. And given our results, it is difficult to argue that this mapping should not be taken into account when forming expectations about technology-intensive firms' future cash flows. Certainly, from an investor's perspective, greater attention to technology-linkages could lead to better investment decisions. From a firm's perspective, educating investors on its technological capabilities, perhaps through greater media coverage, may likewise yield improvements in pricing efficiency.

More generally, our results point to the need to better understand the relation between equity valuation and firms' technological capabilities. For example, it appears that various aspects of a firm's technology, such as its intensity or specificity, may be quite valuation-relevant. In today's technology-driven world, it seems especially important for researchers to better understand the mechanism through which such technological attributes impact information processing costs, and thus market prices.

References

Aobdia, D., Caskey, J., Ozel, N. B., 2014. Inter-industry network structure and the cross-predictability of earnings and stock returns. Review of Accounting Studies, 19(3), 1191-1224.

Acemoglu, D., Carvalho, V. M., Ozdaglar, A., Tahbaz-Salehi, A., 2012. The network origins of aggregate fluctuations. Econometrica, 80(5), 1977-2016.

Barber, B. M., Odean, T., 2007. All that glitters: the effect of attention and news on the buying behavior of individual and institutional investors. Review of Financial Studies, 21(2), 785-818.

Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. The Journal of Finance, 61(4), 1645-1680.

Baker, M., Wurgler, J., 2007. Investor sentiment in the stock market. Journal of Economic Perspectives, 21(2), 129-152.

Bekkerman, R., Khimich, N., 2017. Technological similarity and stock return cross-predictability: evidence from patent big data. Unpublished working paper, University of Haifa and Drexel University.

Bena, J., Kai, L., 2014. Corporate innovations and mergers and acquisitions. The Journal of Finance, 69(5), 1923–1960.

Beneish, M., Lee, C. M., Nichols, D., 2015. In short supply: short-sellers and stock returns. Journal of Accounting and Economics, 60(2), 33-57.

Bernard, V. L., Thomas, J. K., 1989. Post-earnings-announcement drift: delayed price response or risk premium?. Journal of Accounting Research, 27(27), 1-36.

Bloom, N., Schankerman, M., Van Reenen, J., 2013. Identifying technology spillovers and product market rivalry. Econometrica, 81(4), 1347-1393.

Burt, A., Hrdlicka, C. M., 2016. Understanding network-based measures of information diffusion. Unpublished working paper, University of Washington.

Cao, J., Chordia, T., Lin, C., 2016. Alliances and return predictability. Journal of Financial and Quantitative Analysis, 51(5), 1689-1717.

Carhart, M. M., 1997. On persistence in mutual fund performance. The Journal of Finance, 52(1), 57-82.

Chan, L. K., Jegadeesh, N., Lakonishok, J., 1996. Momentum strategies. The Journal of Finance, 51(5), 1681-1713.

Chan, L. K., Lakonishok, J., Sougiannis, T., 2001. The stock market valuation of research and development expenditures. The Journal of Finance, 56(6), 2431-2456.

Chopra, N., Lakonishok, J., Ritter, J. R., 1992. Measuring abnormal performance: do stocks overreact?. Journal of Financial Economics, 31(2), 235-268.

Cohen, L., Frazzini, A., 2008. Economic links and predictable returns. The Journal of Finance, 63(4), 1977-2011.

Cohen, L., Lou, D., 2012. Complicated firms. Journal of Financial Economics, 104(2), 383-400.

Daniel, K., Grinblatt, M., Titman, S., Wermers, R., 1997. Measuring mutual fund performance with characteristic-based benchmarks. The Journal of Finance, 52(3), 1035-1058.

Daniel, K., Hirshleifer, D. A., Subrahmanyam, A., 1998. Investor psychology and security under-and overreactions. The Journal of Finance, 53(6), 1839-1885.

DellaVigna, S., Pollet, J. M., 2009. Investor inattention and Friday earnings announcements. The Journal of Finance, 64(2), 709-749.

Drake, M. S., Guest, N. M., Twedt, B. J., 2014. The media and mispricing: the role of the business press in the pricing of accounting information. The Accounting Review, 89(5), 1673-1701.

Eberhart, A. C., Maxwell, W. F., Siddique, A. R., 2004. An examination of long-term abnormal stock returns and operating performance following R&D increases. The Journal of Finance, 59(2), 623-650.

Engelberg, J., McLean, R. D., Pontiff, J., 2017. Anomalies and news. The Journal of Finance, Forthcoming.

Fama, E. F., MacBeth, J. D., 1973. Risk, return, and equilibrium: empirical tests. Journal of Political Economy, 81(3), 607-636.

Fama, E. F., French, K. R., 1992. The cross-section of expected stock returns. The Journal of Finance, 47(2), 427-465.

Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics, 33(1), 3-56.

Fama, E. F., French, K. R., 1997. Industry costs of equity. Journal of Financial Economics, 43(2), 153-193.

Fama, E. F., French, K. R., 2015. A five-factor asset pricing model. Journal of Financial Economics, 116(1), 1-22.

Gleason, C. A., Lee, C. M., 2003. Analyst forecast revisions and market price discovery. The Accounting Review, 78(1), 193-225.

Greenwood, J., Hercowitz, Z., Krusell, P., 1997. Long-run implications of investment-specific technological change. American Economic Review, 87(3), 342-362.

Gu, F., 2005. Innovation, future earnings, and market efficiency. Journal of Accounting, Auditing & Finance, 20(4), 385-418.

Hall, B. H., Jaffe, A. B., Trajtenberg, M., 2001. The NBER patent citation data file: lessons, insights and methodological tools. Unpublished working paper, NBER Working Paper No. 8498.

Hirschey, M., Richardson, V. J., 2003. Investor underreaction to goodwill write-offs. Financial Analysts Journal, 59(6), 75-84.

Hirshleifer, D., Teoh, S. H., Yu, J., 2011. Short arbitrage, return asymmetry, and the accrual anomaly. Review of Financial Studies, 24(7), 2429-2461.

Hirshleifer, D., Hsu, P. H., Li, D., 2013. Innovative efficiency and stock returns. Journal of Financial Economics, 107(3), 632-654.

Hirshleifer, D., Hsu, P. H., & Li, D. 2017. Innovative originality, profitability, and stock returns. Review of Financial Studies, forthcoming.

Hirshleifer, D., Teoh, S. H., 2003. Limited attention, information disclosure, and financial reporting. Journal of Accounting and Economics, 36(1), 337-386.

Hoberg, G., Phillips, G., 2016. Text-based network industries and endogenous product differentiation. Journal of Political Economy, 124, 1423-1465.

Hong, H., Lim, T., Stein, J. C., 2000. Bad news travels slowly: size, analyst coverage, and the profitability of momentum strategies. The Journal of Finance, 55(1), 265-295.

Hong, H., Torous, W., Valkanov, R., 2007. Do industries lead stock markets? Journal of Financial Economics, 83(2), 367-396.

Hong, H., Stein, J. C., 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. The Journal of Finance, 54(6), 2143-2184.

Hou, K., 2007. Industry information diffusion and the lead-lag effect in stock returns. Review of Financial Studies, 20(4), 1113-1138.

Huang, X., 2015. Thinking outside the borders: investors' underreaction to foreign operations information. Review of Financial Studies, 28(11), 3109-3152.

Huberman, G., Regev, T., 2001. Contagious speculation and a cure for cancer: a nonevent that made stock prices soar. The Journal of Finance, 56(1), 387-396.

Ikenberry, D. L., Ramnath, S., 2002. Underreaction to self-selected news events: the case of stock splits. Review of Financial Studies, 15(2), 489-526.

Jaffe, A. B., 1986. Technological opportunity and spillovers of R&D: evidence from firms' patents, profits, and market value. American Economic Review, 76(5), 984-1001.

Jaffe, A. B., Trajtenberg, M., Henderson, R., 1993. Geographic localization of knowledge spillovers as evidenced by patent citations. Quarterly Journal of Economics, 108(3), 577-598.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: implications for stock market efficiency. The Journal of Finance, 48(1), 65-91.

Jiang, Y., Qian, Y., Yao, T., 2015. R&D spillover and predictable returns. Review of Finance, 20(5), 769-1797.

Kadiyala, P., Rau, P. R., 2004. Investor reaction to corporate event announcements: underreaction or overreaction? The Journal of Business, 77(2), 357-386.

Kogan, L., Papanikolaou, D., 2014. Growth opportunities, technology shocks, and asset prices. The Journal of Finance, 69(2), 675-718.

Kogan, L., Papanikolaou, D., Seru, A., Stoffman, N., 2017. Technological innovation, resource allocation, and growth. Quarterly Journal of Economics, 132(2), 665-712.

Lee, C. M., Ma, P., Wang, C., 2015. Search-based peer firms: aggregating investor perceptions through internet co-searches. Journal of Financial Economics, 116(2), 410-431.

Lee, C. M., So, E. C., 2015. Alphanomics: the informational underpinnings of market efficiency. Foundations and Trends in Accounting, 9(2–3), 59-258.

Lee, C. M., Swaminathan, B., 2000. Price momentum and trading volume. The Journal of Finance, 55, 2017-2070.

Lev, B., Sarath, B., Sougiannis, T., 2005. R&D reporting biases and their consequences. Contemporary Accounting Research, 22(4), 977-1026.

Li, K., Qiu, J., Wang, J., 2017. Technological competition and strategic alliances. Unpublished working paper, University of British Columbia, McMaster University, and Wilfrid Laurier University.

Li, N., Richardson, S., Tuna, İ., 2014. Macro to micro: Country exposures, firm fundamentals and stock returns. Journal of Accounting and Economics, 58(1), 1-20.

Li, N., 2015. Labor market peer firms. Unpublished working paper, Rotman School of Management Working Paper No. 2558271.

Matolcsy, Z. P., Wyatt, A., 2008. The association between technological conditions and the market value of equity. The Accounting Review, 83(2), 479-518.

Menzly, L., Ozbas, O., 2010. Market segmentation and cross-predictability of returns. The Journal of Finance, 65(4), 1555-1580.

Merton, R. C., 1987. A simple model of capital market equilibrium with incomplete information. The Journal of Finance, 42(3), 483-510.

Moskowitz, T. J., Grinblatt, M., 1999. Do industries explain momentum? The Journal of Finance, 54(4), 1249-1290.

Newey, W. K., West, K. D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica, 55(3), 703-708.

Odean, T., 1998. Are investors reluctant to realize their losses? Journal of Finance, 53(5), 1775-1798.

Papanikolaou, D., 2011. Investment shocks and asset prices. Journal of Political Economy, 119(4), 639-685.

Peng, L., Xiong, W., 2006. Investor attention, overconfidence and category learning. Journal of Financial Economics, 80(3), 563-602.

Penman, S. H., Zhang, X. J., 2002. Accounting conservatism, the quality of earnings, and stock returns. The Accounting Review, 77(2), 237-264.

Porta, R. L., Lakonishok, J., Shleifer, A., Vishny, R., 1997. Good news for value stocks: further evidence on market efficiency. The Journal of Finance, 52(2), 859-874.

Qiu, J., Wan, C., 2015. Technology spillovers and corporate cash holdings. Journal of Financial Economics, 115(3), 558-573.

Qiu, J., Wang, J., Wang, W., 2016. Bankruptcy and the technology channel. Unpublished working paper, McMaster University, Wilfrid Laurier University, and University of Pennsylvania.

Rao, P., Yue, H., Zhou, X., 2017. Return predictability and the real options value of segments. Review of Accounting Studies, forthcoming.

Shumway, T., 1997. The delisting bias in CRSP data. The Journal of Finance, 52(1), 327-340.

Tan, H., Wang, J., Yao, L., 2016. Tracking analysts along the technological links. Unpublished working paper, York University, Wilfrid Laurier University, and Concordia University.

Tversky, A., Kahneman, D., 1974. Judgment under uncertainty: heuristics and biases. Science, 185(4157), 1124-1131.

Twedt, B., 2016. Spreading the word: price discovery and newswire dissemination of management earnings guidance. The Accounting Review, 91(1), 317-346.

Wurgler, J., Zhuravskaya, E., 2002. Does arbitrage flatten demand curves for stocks? Journal of Business, 75(4), 583-608.

Figure 1. Patent portfolio distribution of Illumina Inc. and Regeneron Pharmaceutical Inc.

This figure depicts the number of patents for Illumina Inc. and Regeneron Pharmaceutical Inc. across all the patent technology classes relevant to the two firms. During 2002 to 2006, Regeneron (Illumina) had a total of 48 (22) patents, with 25 (8) of these patents belonging to Class 435 (Chemistry: molecular biology and microbiology). The figure below provides an indication of each firm's patent distribution and, in particular, the degree to which these patent distributions overlap. In this example, the two firms have substantial technological overlap in Class 435. Because of this overlap, the two companies are deemed to be close tech-peers (*TECH* = 0.71). Our results show that this close technological affinity is an important economic linkage for the firms, even though they operate in different industries and are not a supplier or a customer to each other.

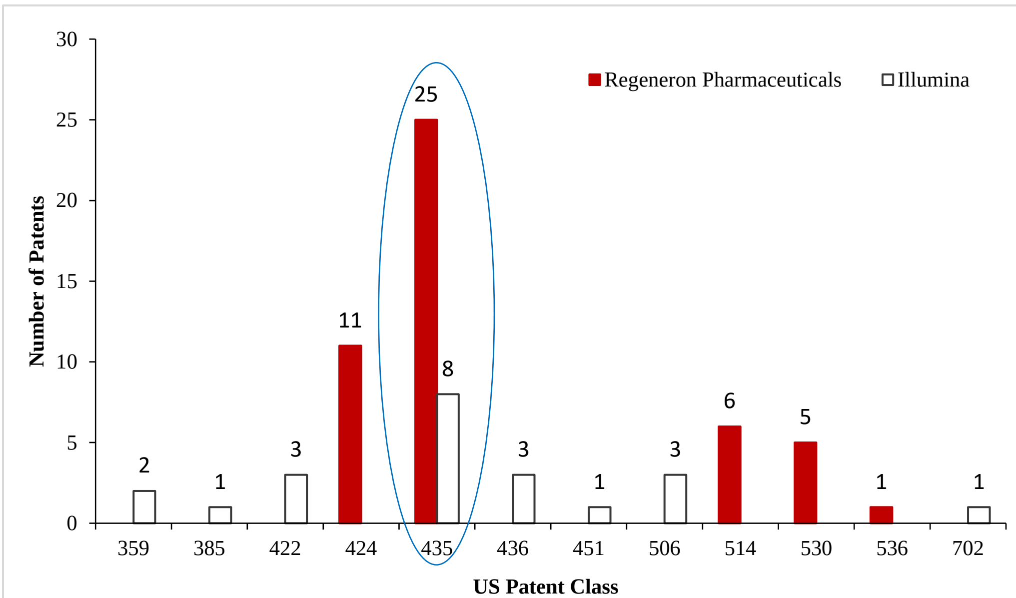

Figure 2. Hedge portfolio performance persistence.

This figure shows the cumulative returns of the hedge portfolio in the six months after portfolio formation. At the beginning of every calendar month, all firms are ranked in ascending order on the basis of the return of a portfolio of its tech-peers at the end of the previous month. The ranked stocks are assigned to one of ten decile portfolios. All stocks are value- (equal-) weighted within each portfolio, and the portfolios are rebalanced every calendar month to maintain value (equal) weights. The hedge portfolio is a zero-cost portfolio that buys the top decile and sells short the bottom decile. The graph depicts the cumulative returns to both an equal-weighted (dashed line) and a value-weighted (dotted line) portfolio. The sample excludes financial firms (any firm with a one-digit SIC code = 6) and stocks with a price of less than $1 at portfolio formation. Our total sample consists of 561,989 firm-month observations spanning July 1963 to June 2012.

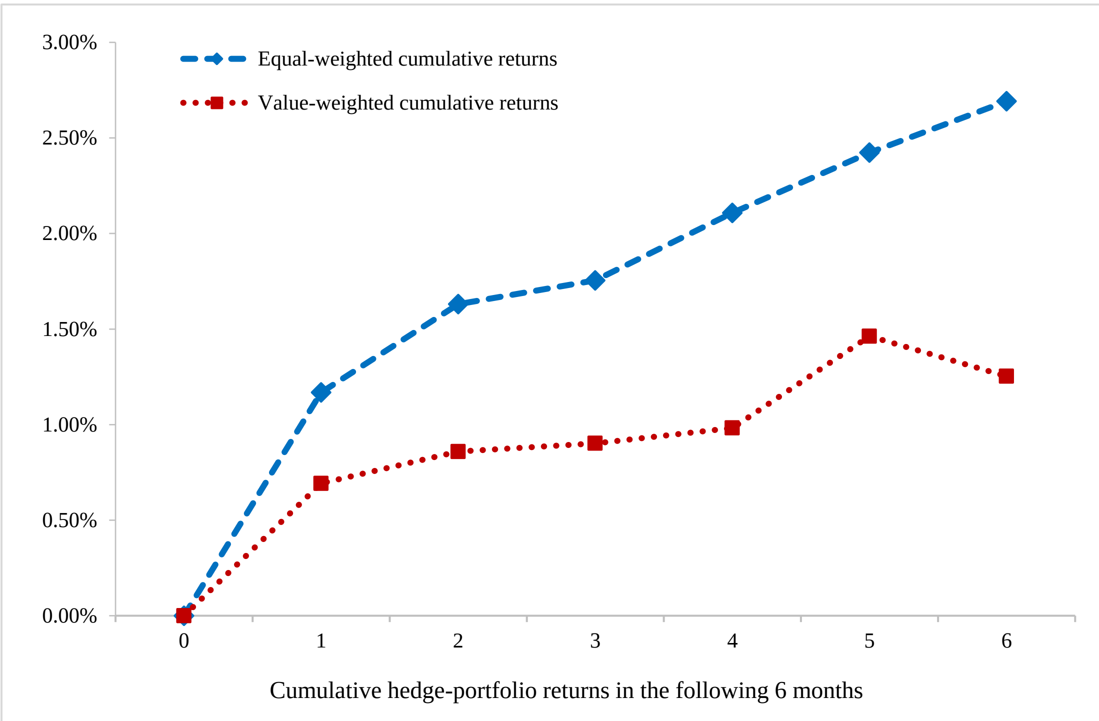

Table 1. Summary statistics.

This table presents summary statistics for the key variables used in the cross-sectional regressions. The sample includes all NYSE/AMEX/NASDAQ-listed securities with share codes 10 or 11 that are contained in the CRSP/COMPUSTAT merged data file. Financial firms (with one-digit SIC code = 6) and stocks with price less than $1 at portfolio formation are excluded. All variables except for future stock returns are winsorized within each cross-section at 1% and 99% level. % value of CRSP is the total market capitalization of our sample firms as a percentage of the total market capitalization of the CRSP universe, computed each month and averaged across all months. Panel A reports the sample coverage statistics, as well as simple descriptive statistics for the key variables. Panel B reports pairwise correlations, with 5% statistical significance indicated in bold. All variable definitions are in Appendix Table A1.

Panel A: Descriptive statistics

	Mean	Sd	Min	Q1	Med	Q3	Max
Sample description (cross-section)							
# of firms	956	293	189	908	961	1187	1363
% value of CRSP	52.56	5.94	37.72	48.50	50.72	58.03	65.93
Average # of tech-peers per focal firm	280	214	1	117	227	394	1251
Key variables							
TECH	0.11	0.16	0.00	0.01	0.04	0.12	1.00
RET	0.01	0.14	-1.00	-0.06	0.01	0.07	4.23
TECHRET	0.01	0.07	-0.34	-0.03	0.01	0.05	0.84
INDRET	0.01	0.06	-0.33	-0.02	0.01	0.04	0.30
SIZE	5.70	2.10	0.32	4.14	5.60	7.11	12.10
BM	0.71	0.58	0.02	0.33	0.56	0.92	6.16
GP	0.39	0.24	-0.84	0.25	0.37	0.52	1.29
AG	0.14	0.36	-0.60	0.00	0.08	0.18	8.83
RD	0.23	1.56	0.00	0.00	0.02	0.07	49.39
RET_{t-1}	0.01	0.13	-0.61	-0.06	0.01	0.08	2.20
MOM	0.17	0.58	-0.93	-0.15	0.08	0.35	17.67

Panel B: Pearson (Spearman) correlations above (below) the diagonal

		1	2	3	4	5	6	7	8	9	10
$TECHRET_{t-1}$	1		**0.203**	**0.123**	**0.031**	**0.010**	0.009	0.005	**-0.009**	-0.001	**0.028**
$INDRET_{t-1}$	2	**0.209**		**0.143**	**0.014**	0.011	0.003	0.010	0.001	-0.005	**0.028**
RET_{t-1}	3	**0.127**	**0.144**		0.007	**0.028**	**0.024**	**0.012**	**-0.021**	-0.002	**-0.046**
MOM	4	**0.035**	**0.013**	0.011		**0.089**	**0.049**	**0.048**	**-0.048**	-0.008	**0.027**
SIZE	5	**0.017**	0.008	**0.060**	**0.144**		**-0.349**	-0.002	**0.069**	**-0.019**	**-0.025**
BM	6	**0.012**	0.003	**0.016**	**0.044**	**-0.337**		**-0.259**	**-0.268**	**-0.187**	**0.025**
GP	7	0.003	0.011	**0.018**	**0.052**	**-0.041**	**-0.304**		**0.030**	**-0.108**	**0.012**
AG	8	**-0.009**	0.004	**-0.013**	**-0.049**	**0.146**	**-0.350**	**0.121**		**0.081**	**-0.020**
RD	9	0.000	-0.009	-0.009	**-0.031**	**-0.034**	**-0.231**	**0.114**	**0.058**		-0.003
RET_t	10	**0.029**	**0.028**	**-0.050**	**0.037**	**0.016**	**0.016**	**0.019**	**-0.011**	**-0.010**	

Table 2. Technology momentum strategy, abnormal returns 1963-2012.

This table reports abnormal returns and factor loadings for a technology momentum strategy. Panel A reports calendar-time portfolio abnormal returns. To construct this table, firms are ranked and assigned into decile portfolios at the beginning of every calendar month, based on the prior-month return to a portfolio of their tech-peers (*TECHRET*). All stocks are equally (value) weighted within a given portfolio, and the portfolios are rebalanced every calendar month to maintain equal (value) weights. All non-financial stocks with stock price greater than $1 at portfolio formation are included. Excess return is the raw return of the portfolio over the risk-free rate. Alpha is the intercept from a regression of monthly excess return on factor returns. Factor returns are from the Kenneth French Data Library, and factor models include: CAPM model; the Fama-French (1993) three-factor model; a four-factor model (Fama-French three-factor + Carhart (1997)'s momentum factor), Fama-French (2015) five-factor model, and six-factor model (Fama-French five-factor + momentum factor). L/S is the alpha of a zero-cost portfolio that holds the top 10% stocks ranked by *TECHRET* and sells short the bottom 10%. Panel B reports the alpha and the risk factor loadings, where the benchmark is a four-factor model (Fama-French three-factor + momentum factor). Returns and alphas are in monthly percent, *t*-statistics are shown below the coefficient estimates, with 5% statistical significance indicated in bold.

Panel A: Portfolio returns

Decile	Excess returns (%)	CAPM alpha (%)	3-Factor alpha (%)	4-Factor alpha (%)	5-Factor alpha (%)	6-Factor alpha (%)
1	0.42	-0.16	-0.33	-0.13	-0.27	-0.12
(Low)	(1.46)	(-1.04)	(-2.66)	(-1.09)	(-2.17)	(-0.99)
10	1.59	1.05	0.93	0.95	1.10	1.09
(High)	(5.38)	(5.37)	(6.41)	(6.36)	(8.11)	(7.97)
L/S	**1.17**	**1.22**	**1.26**	**1.08**	**1.37**	**1.21**
(Equal weights)	(5.47)	(5.70)	(5.88)	(4.98)	(6.49)	(5.76)
L/S	**0.69**	**0.74**	**0.80**	**0.65**	**0.86**	**0.73**
(Value-weights)	(3.19)	(3.40)	(3.62)	(2.91)	(3.81)	(3.24)

Panel B: Risk factor loadings

	Alpha	MKT	SMB	HML	MOM
1	-0.13	1.11	0.83	-0.08	-0.21
(Low)	(-1.09)	(40.08)	(21.52)	(-1.80)	(-7.84)
10	0.95	0.95	1.07	-0.21	-0.02
(High)	(6.36)	(27.59)	(22.34)	(-3.91)	(-0.45)
L/S	**1.08**	**-0.16**	**0.24**	-0.13	**0.20**
(Equal weights)	(4.98)	(-3.14)	(3.51)	(-1.70)	(4.03)
L/S	**0.65**	**-0.10**	0.01	-0.08	**0.16**
(Value-weights)	(2.91)	(-2.00)	(0.16)	(-1.05)	(3.17)

Table 3. Cross-sectional regressions, 1963-2012.

This table reports the result for four Fama-MacBeth return forecasting regressions. The dependent variable is either the focal firm's monthly return *RET* (the first three columns), or the firm's excess return over its value-weighted industry return *RET-INDRET* (column 4). The explanatory variables include tech-peer return (*TECHRET*), focal firm's value-weighted industry return (*INDRET*), firm size (*SIZE*), book-to-market ratio (*BM*), gross profitability (*GP*), asset growth (*AG*), R&D intensity (*RD*), the firm's own lagged monthly return (RET_{t-1}), and medium-term price momentum (*MOM*). All variables are defined in Appendix Table A1. All explanatory variables are based on last non-missing available observation for each month *t* and are assigned to deciles ranging from 0 to 1. The sample excludes financial firms (one-digit SIC code = 6) and stocks with a price less than $1 at portfolio formation. Cross-sectional regressions are run every calendar month, and the time-series standard errors are Newey-West adjusted (up to 12 lags) for heteroskedasticity and autocorrelation. Fama-MacBeth *t*-statistics are reported below the coefficient estimates. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

Dep. variable	(1)	(2)	(3)	(4)
×100	RET_t	RET_t	RET_t	RET_t - $INDRET_t$
$TECHRET_{t-1}$	0.629***	0.583***	0.735***	0.654***
	(4.10)	(5.92)	(6.54)	(6.06)
$INDRET_{t-1}$			0.552***	0.046
			(5.20)	(0.39)
SIZE		-0.834***	-0.793***	-0.805***
		(-3.38)	(-3.19)	(-3.41)
BM		0.619***	0.584***	0.525***
		(3.95)	(3.53)	(3.32)
GP		0.557***	0.442***	0.410***
		(4.26)	(3.46)	(3.19)
AG		-0.453***	-0.430***	-0.466***
		(-5.38)	(-4.84)	(-5.53)
RD		0.443*	0.374	0.401*
		(1.67)	(1.50)	(1.91)
RET_{t-1}		-2.291***	-2.164***	-2.181***
		(-12.79)	(-12.51)	(-12.49)
MOM		0.376*	0.428**	0.408**
		(1.83)	(1.99)	(2.10)
INTERCEPT	0.984**	1.571**	1.556***	1.012***
	(1.98)	(2.45)	(3.81)	(3.48)
Industry Fixed Effect	Yes	Yes	No	No
N	540,895	540,895	540,895	540,895
Average R^2	0.091	0.142	0.076	0.065

Table 4. Controlling for other economic links, 1963-2012.

This table examines the robustness of the main results to controls for a variety of other economic links discussed in prior studies. Panel A presents the results for a number of Fama-MacBeth return forecasting regressions that incorporate different controls. In column (2), we add lagged industry returns (*INDRET*) as well as the lagged returns from a portfolio of the focal firm's suppliers (*SUPPRET*) and customers (*CUSTRET*). These portfolios are constructed using BEA Input-Output data (at the summary industry level) following Menzly and Ozbas (2010). In column (3), a portfolio of pseudo-conglomerate returns (*PCRET*) is added based on Compustat Segment data following Cohen and Lou (2012). Due to data availability, the sample period for this analysis spans July 1977 to June 2012. In column (4), we also add each focal firm's annual turnover (trading volume divided by shares outstanding) as a control variable. Panel B reports equal- and value-weighted hedge portfolio returns that holds the top 10% high tech-peer return stocks and sells the bottom 10% low tech-peer return stocks. For this analysis, we exclude all tech-peers that are in the same industry as the focal firm. We report the results for two different industry classification schemes (Fama-French 48 industries or 3-digit SIC). All variables are defined in Appendix Table A1. All explanatory variables are based on last non-missing available observation for each month *t* and are assigned to deciles ranging from 0 to 1. Cross-sectional regressions are run every calendar month, and the standard errors are Newey-West adjusted (up to 12 lags) for heteroskedasticity and autocorrelation. Fama-MacBeth *t*-statistics are reported below the coefficient estimates. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

Panel A: Fama-MacBeth regression

	(1)	(2)	(3)	(4)
Dep. variable	RET_t	RET_t	RET_t	RET_t
×100	*Full sample*	*Add supply-chain*	*Add conglomerate*	*Add turnover*
$TECHRET_{t-1}$	0.583***	0.550***	0.439***	0.551***
	(5.92)	(5.70)	(3.42)	(5.77)
$INDRET_{t-1}$		0.576***	0.195	
		(6.26)	(1.63)	
$CUSTRET_{t-1}$		0.255***		
		(2.69)		
$SUPPRET_{t-1}$		0.073		
		(0.79)		
$PCRET_{t-1}$			0.351***	
			(2.88)	
TURNOVER				-0.194
				(-1.12)
SIZE	-0.834***	-0.683***	-0.651**	-0.897***
	(-3.38)	(-2.94)	(-2.25)	(-3.59)
BM	0.619***	0.588***	0.607***	0.565***
	(3.95)	(3.95)	(3.47)	(3.57)
GP	0.557***	0.433***	0.402***	0.516***
	(4.26)	(3.54)	(2.72)	(4.05)
AG	-0.453***	-0.383***	-0.278**	-0.438***

	(-5.38)	(-4.18)	(-2.01)	(-5.14)
RD	0.443*	0.177	0.285	0.501**
	(1.67)	(0.99)	(1.04)	(2.09)
RET_{t-1}	-2.291***	-2.080***	-2.181***	-2.296***
	(-12.79)	(-12.07)	(-11.75)	(-12.70)
MOM	0.376*	0.386*	0.249	0.412**
	(1.83)	(1.77)	(0.78)	(2.07)
INTERCEPT	1.633***	1.293***	1.617***	1.421***
	(3.14)	(3.32)	(3.22)	(2.62)
Industry Fixed Effect	Yes	No	No	Yes
N	540,895	369,554	163,062	525,394
Average R^2	0.142	0.086	0.087	0.154

Panel B: Abnormal returns after excluding all tech-peers from the same industry as the focal firm

	Equal-Weighted		Value-Weighted	
	Excess returns (%)	6-Factor alpha (%)	Excess returns (%)	6-Factor alpha (%)
Exclude peers from same Fama-French 48 industry grouping	**0.78**	**0.84**	**0.40**	**0.43**
	(4.69)	(4.96)	(1.99)	(2.05)
Exclude peers from same 3-digit SIC industry grouping	**0.88**	**0.96**	**0.52**	**0.63**
	(5.30)	(5.66)	(2.68)	(3.06)

Table 5. Burt and Hrdlicka (2016) adjustments, 1963-2012.

This table reports calendar-time portfolio returns using Burt and Hrdlicka (2016) adjustments. To construct this table, we use portfolio returns computed using tech-peers' idiosyncratic returns instead of their raw returns to sort focal firms into decile portfolios at time *t*. For each tech-peer firm, we first estimate its alpha and its factor loadings using the 4-factor model (Fama and French, 1993; Carhart, 1997) and the previous 12 months of daily data (*t-12* to *t-1*). We then use these parameter estimates, together with the realized factor returns, to obtain each tech-peer's idiosyncratic return at time *t*. Technology-linked idiosyncratic return (*TECHRET_IDIO*) of a focal firm is the average monthly idiosyncratic return of tech-peers, weighted by pairwise technology closeness. In the table below, we report results for each of ten portfolios sorted on *TECHRET_IDIO*, as well as for the zero-cost hedged portfolio, L/S, which holds the top 10% high *TECHRET_IDIO* stocks and shorts the bottom 10%. Alpha is the intercept on a times-series regression of the monthly returns for each portfolio using various asset pricing models. Returns and alphas are in monthly percent, *t*-statistics are shown below the coefficient estimates, and 5% statistical significance is indicated in bold.

Decile	Excess returns (%)	CAPM alpha (%)	3-Factor alpha (%)	4-Factor alpha (%)	5-Factor alpha (%)	6-Factor alpha (%)
1	0.56	-0.01	-0.22	0.02	-0.18	0.01
(Low)	(2.00)	(-0.03)	(-1.94)	(0.19)	(-1.51)	(0.13)
2	0.72	0.17	-0.01	0.19	-0.01	0.15
	(2.74)	(1.30)	(-0.13)	(2.13)	(-0.11)	(1.70)
3	0.73	0.18	0.00	0.13	-0.03	0.08
	(2.87)	(1.58)	(0.03)	(1.65)	(-0.36)	(0.98)
4	0.84	0.32	0.13	0.27	0.10	0.22
	(3.45)	(2.84)	(1.69)	(3.70)	(1.31)	(3.01)
5	0.89	0.36	0.17	0.30	0.14	0.25
	(3.64)	(3.24)	(2.24)	(4.12)	(1.83)	(3.44)
6	1.01	0.48	0.30	0.42	0.31	0.40
	(4.12)	(4.44)	(4.05)	(5.68)	(4.04)	(5.43)
7	1.09	0.56	0.40	0.48	0.46	0.52
	(4.44)	(5.09)	(5.75)	(6.88)	(6.59)	(7.50)
8	1.14	0.60	0.47	0.53	0.56	0.61
	(4.48)	(4.86)	(5.76)	(6.49)	(7.11)	(7.62)
9	1.47	0.92	0.82	0.91	0.97	1.03
	(5.40)	(6.26)	(8.18)	(9.00)	(10.35)	(10.95)
10	1.54	0.98	0.87	0.88	1.07	1.06
(High)	(5.09)	(5.01)	(6.32)	(6.22)	(8.68)	(8.45)
L/S	**0.98**	**0.99**	**1.09**	**0.86**	**1.25**	**1.05**
(Equal weights)	(5.16)	(5.19)	(5.84)	(4.62)	(6.94)	(5.97)
L/S	**0.67**	**0.68**	**0.80**	**0.59**	**0.93**	**0.74**
(Value weights)	(3.26)	(3.32)	(3.88)	(2.84)	(4.46)	(3.60)

Table 6. Technological characteristics of focal firms, 1963-2012.

This table reports the results of a series of cross-sectional analyses designed to evaluate the sensitivity of technology momentum to various characteristics of the focal firm's technology. The tests are Fama-MacBeth return forecasting regressions where the dependent variable is the monthly focal firm stock return (*RET*). The explanatory variables are the lagged tech-peer return (*TECHRET*), assigned to deciles ranging from 0 to 1, plus a number of interaction terms. *R&D* is research and development expenditures scaled by sales of the previous fiscal year. *Patent* is the log of number of patent grant in the last five years scaled by sales of the previous fiscal year. *Specificity_FF48* (*Specificity _SIC3*) measures the technology specificity of the focal firm. It is calculated as the average industry concentration ratio of each technology class, weighted by the technology class share of the firm's patents, where the industry is defined either by the Fama-French 48 or the 3-digit SIC industry grouping. For this purpose, the industry concentration ratio of a given technology class is the sum of the squares of the patent share for each industry (i.e., the patent number from firms in that industry out of total patent number in that technology class) in the past rolling five years. All the interaction terms are based on indicator variables that take the value of one if the underlying variable is above the median in the cross-section, and zero otherwise. All regressions also include the dummy itself, *SIZE*, *BM*, *GP*, *AG*, *RD*, RET_{t-1}, *MOM*, and industry dummy as controls. These variables are described in Appendix Table A1. Cross-sectional regressions are run every calendar month and the time-series standard errors are Newey-West adjusted (up to 12 lags) for heteroskedasticity and autocorrelation. Fama-MacBeth *t*-statistics are reported below the coefficient estimates. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

Dep. variable *×100*	(1) RET_t	(2) RET_t	(3) RET_t	(4) RET_t
$TECHRET_{t-1}$	0.355***	0.348***	0.496***	0.445***
	(3.80)	(3.72)	(4.98)	(4.97)
$TECHRET_{t-1}$ ×	0.448***			
R&D>median	(3.10)			
$TECHRET_{t-1}$ ×		0.470***		
Patent>median		(3.35)		
$TECHRET_{t-1}$ ×			0.187*	
Specificity _FF48>median			(1.76)	
$TECHRET_{t-1}$ ×				0.236**
Specificity _SIC3 >median				(2.36)
Controls (SIZE, BM, GP, AG, RD, RET_{t-1}*, MOM, and interaction dummies)*	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes
N	540,895	540,895	540,895	540,895
Average R^2	0.145	0.146	0.145	0.146

Table 7. Limited attention and cost of arbitrage, 1963-2012.

This table reports the results of a series of cross-sectional analyses designed to evaluate the sensitivity of technology momentum to proxies for limited attention and arbitrage costs. The tests are Fama-MacBeth return forecasting regressions where the dependent variable is the monthly focal firm stock return (*RET*). The explanatory variables are the lagged tech-peer return (*TECHRET*), assigned to deciles ranging from 0 to 1, plus a number of interaction terms. All variables are described in Appendix Table A1. *Size* is the log value of market capitalization at the end of the previous month. *Analyst* is the number of analysts covering the firm at the end of the previous month. *InstitOwn* is the percentage of institutional ownership at the end of the previous fiscal-year end. *News* is the number of news items with a relevance score of 90 or more in the previous year, using data from RavenPack News Analytics (Dow Jones Edition). *IdioVol* is the standard deviation of the residuals from a regression of daily stock returns in the previous month on the Fama and French (1993) factors (at least ten daily returns required). *Bad News* is an indicator variable that equals to one if *TECHRET* falls in the bottom 30% in the cross-section. All the interaction terms are based on indicator variables that take the value of one if the underlying variable is above the cross-sectional median, and zero otherwise. Each regression also includes "Other Controls": *SIZE*, *BM*, *GP*, *AG*, *RD*, RET_{t-1}, *MOM*, as well as interaction and industry dummies. The sample excludes financial firms (with one-digit SIC code=6) and stocks with price less than $1 at portfolio formation. Cross-sectional regressions are run every month and the time-series standard errors are Newey-West adjusted (up to 12 lags). Fama-MacBeth *t*-statistics are reported below the coefficient estimates. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

Dep. variable ×*100*	(1) RET_t	(2) RET_t	(3) RET_t	(4) RET_t	(5) RET_t	(6) RET_t
$TECHRET_{t-1}$	0.839***	0.829***	0.897***	0.838***	0.293***	0.544***
	(5.58)	(5.07)	(4.75)	(4.41)	(3.33)	(3.41)
$TECHRET_{t-1}$ ×	-0.592***					
Size>median	(-3.05)					
$TECHRET_{t-1}$ ×		-0.434**				
Analyst>median		(-2.50)				
$TECHRET_{t-1}$ ×			-0.519***			
InstitOwn>median			(-2.72)			
$TECHRET_{t-1}$ ×				-0.804***		
News>median				(-3.00)		
$TECHRET_{t-1}$ ×					0.509***	
IdioVol>median					(3.35)	
$TECHRET_{t-1}$ ×						0.933**
Bad News						(2.15)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	540,895	462,323	412,786	165,300	540,895	540,895
Average R^2	0.146	0.119	0.119	0.108	0.147	0.145

Table 8. Anomaly returns on earnings announcement days, 1972-2012.

This table reports regressions of announcement window daily returns (*DLYRET*) on day-fixed effects, the *TECHRET* variable, earnings day dummy variables, and other lagged control variables (coefficients unreported). Tech-peer return (*TECHRET*) of a focal firm is the average monthly return of tech-peers weighted by pairwise technology closeness in the previous month. An earnings announcement is defined as the 1-day or 3-day window centered on an earnings release, i.e., days *t-1*, *t*, and *t+1*. *EDAY* is a dummy variable and equals to 1 if the daily observation is during an announcement window, and zero otherwise. Following Engelberg, Mclean, and Pontiff (2017), we obtain earnings announcement dates from the Compustat quarterly database, examine the firm's trading volume scaled by market trading volume for the day before, the day of, and the day after the reported earnings announcement date, and define the day with the highest volume as the earnings announcement day. Control variables include lagged values for each of the past 10 days for stock returns, stock returns squared, and trading volume. Standard errors are clustered on time. *T-statistics* are in parentheses, coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively. The sample period is from January 1972 to June 2012.

	Panel A: 1-day window		***Panel B: 3-day window***	
Dep. variable	(1)	(2)	(3)	(4)
×100	*DLYRET*	*DLYRET*	*DLYRET*	*DLYRET*
TECHRET	0.291*	0.398**	0.296*	0.401**
	(1.69)	(2.25)	(1.72)	(2.26)
TECHRET × EDAY	1.610***	1.660***	0.121***	0.120***
	(4.85)	(4.97)	(14.32)	(13.94)
EDAY	0.264***	0.272***	0.432***	0.504***
	(14.02)	(14.41)	(2.85)	(3.29)
Lagged Controls	No	Yes	No	Yes
Day Fixed Effects	Yes	Yes	Yes	Yes
N	10,522,482	10,522,112	10,522,482	10,522,112
Average R^2	0.105	0.112	0.105	0.112

Table 9. Future unexpected earnings, 1966-2010.

This table reports forecasting regressions of future standardized unexpected earnings (*SUEs*), defined as unexpected earnings (year-over-year change in quarterly earnings before extraordinary items) scaled by the standard deviation of unexpected earnings over the eight preceding quarters. *TECHRET* is calculated based on past 3-month returns of technology-linked firms. The dependent variable is winsorized at 1% and 99% in the cross-section, and all the explanatory variables are assigned to deciles and scaled to range from 0 to 1. For consistency, the sample is restricted to firms with fiscal quarters ending in March, June, September, and December. Panel A reports regressions of next quarter's *SUE*. In columns 2-4, we add 1-quarter to 4-quarter lags of the firm's own *SUEs* as control variables. Column 2 includes firm and quarter fixed effects, column 3 includes industry and quarter fixed effects, while column 4 uses Fama-MacBeth regression with industry fixed effects. Panel B reports regressions of future *SUE* from the next 4 fiscal quarters on *TECHRET* and control variables. In parentheses below the coefficient estimates, *t*-statistics are reported using standard errors adjusted for within-firm and year clustering (OLS) or up to 4 lags serial correlation (Fama-MacBeth). Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

Panel A: Earnings predictability for next quarter

	(1)	*(2)*	*(3)*	*(4)*
	SUE_t	SUE_t	SUE_t	SUE_t
$TECHRET_{t-1}$	0.203***	0.128***	0.127***	0.079***
	(8.65)	(7.36)	(6.51)	(4.29)
SUE_{t-1}		1.674***	1.847***	1.905***
		(37.54)	(37.59)	(26.78)
SUE_{t-2}		0.655***	0.751***	0.736***
		(28.90)	(29.32)	(23.63)
SUE_{t-3}		0.427***	0.521***	0.494***
		(21.77)	(23.29)	(19.09)
SUE_{t-4}		-0.683***	-0.518***	-0.489***
		(-23.32)	(-15.85)	(-13.54)
Firm Fixed Effect	Yes	Yes	No	No
Industry Fixed Effect	No	No	Yes	Yes
Quarter Fixed Effect	Yes	Yes	Yes	No
N	101,922	101,922	101,922	101,922
Adj/Avg. R^2	0.213	0.408	0.362	0.412

Panel B: Earnings predictability over longer periods

	(1)	*(2)*	*(3)*	*(4)*
	SUE_t	SUE_{t+1}	SUE_{t+2}	SUE_{t+3}
	Quarter 1	*Quarter 2*	*Quarter 3*	*Quarter 4*
$TECHRET_{t-1}$	0.079***	0.064***	0.032*	0.008
	(4.29)	(3.01)	(1.76)	(0.37)
Controls	Yes	Yes	Yes	Yes
N	101,922	99,179	96,448	93,835
Average R^2	0.412	0.413	0.413	0.412

Appendix

Table A1. Variable definitions.

Variable	Definition
TECH	$TECH_{ijt}$ is the technology closeness defined as the uncentered correlation between firm *i* and *j*: $TECH_{ijt} = \frac{(T_{it}T_{jt}^{'})}{(T_{it}T_{it}^{'})^{1/2}(T_{jt}T_{jt}^{'})^{1/2}}$, where $T_{it} = (T_{it1}, T_{it2}, \cdots, T_{it427})$ is a vector of firm *i*'s proportional share of patents across 427 USPTO technology classes over the past rolling five years as of time *t*. Technology closeness is calculated at the end of each year *t* based on patent issue dates that were publicly available at that time, and then mapped to the return data from July year *t+1* to June year *t+2*. The Google patent data is generously provided by Kogan et al. (2017), who matched patents granted between 1926 to 2010 to firm identifications in the CRSP database.
TECHRET	Technology-linked return, defined as the weighted average return of a focal firm's technology-linked firms. Formally, $TECHRET_{it}$, the technology-linked return for firm *i* and month *t*, is defined as: $TECHRET_{it} = \sum_{j\neq i} TECH_{ijt} \cdot RET_{jt} / \sum_{j\neq i} TECH_{ijt}$.
RET	Stock monthly raw return, adjusted for delisting bias based on Shumway (1997).
INDRET	Industry return, defined as value-weighted average industry return following Moskowitz and Grinblatt (1999). Specifically, for each month, we construct 20 industry portfolios using CRSP two-digit SIC codes and calculate value-weighted average returns within each industry as industry returns.
SIZE	Firm size, defined as log value of market equity.
BM	Book-to-market ratio, defined as book equity divided by market value at the end of fiscal year.
GP	Gross profitability, defined as revenue minus cost of goods sold scaled by assets.
AG	Asset growth, defined as year-over-year growth rate of total asset.
RD	R&D intensity, defined as research and development expenditures scaled by sales.
RET_{t-1}	Lagged monthly raw return, or short-term return reversal variable, defined as focal firm's stock return in month *t-1*.
MOM	Medium-term price momentum variable, defined as focal firm's stock return for the last 12 months except for the past one month.
SUE	Standardized unexpected earnings, defined as the unexpected earnings (year-over-year change in quarterly earnings before extraordinary items) scaled by the standard deviation of unexpected earnings over eight preceding quarters.

Internet Appendix for

Technological Links and Predictable Returns

March 7, 2018

In this Internet Appendix, we present the results of a battery of other robustness tests. First, we document the robustness of the hedge portfolio returns to various perturbations in: the data requirements for *TECH*, the specific *TECH* threshold used, and alternative definitions for what qualifies as a micro-cap stock (Table IA1).

Second, we report the robustness of return predictability by each of four sub-periods (Table IA2). In all four sub-periods, we find a technology momentum effect even after controlling for many other pricing anomalies.

Third, we examine result sensitivity to the "age" of the *TECH* mapping (Table IA3). Our results show that the effect declines slightly with "stale" *TECH* mappings, but is still significant even when we use three-year-old *TECH* data.

Fourth, we report average monthly returns for various (L, H) strategies where L is the number of lagged months used in portfolio formation and H is the number of months the portfolio is held (Table IA4). Our results show that in equal-weighted portfolios, the tech-momentum effect is statistically significant for combinations of L= 1 to 12 and H= 1 to 12; in value-weighted portfolios, the effect fades more quickly and is generally only significant for H =1 to 6.

Finally, we report the lead-lag relation in patent flows and citation counts between tech-peers and focal firms (Table IA5). Specifically, we show that annual increases (decreases) in patent flows and citation counts among tech-peers reliably predict future increases (decreases) in these same variables for focal firms.

1. Robustness to Test Parameters

In Table IA1 and IA2, we repeat our main analysis while varying a number of different test parameters. In the first test, we require stocks to have at least two or three years (in past five years) with positive number of patents to calculate technology closeness. In the second test, we drop micro-cap stocks from our sample. In the third test, we only keep technology peers with technology closeness above certain thresholds. In the fourth test, we evaluate the predictive power of *TECHRET* across four sub-periods.

1.1. Restrict data requirement to calculate technology closeness

In Table IA1 Panel A, we report returns to the hedge portfolio to various perturbations in the data requirements when computing technology closeness. Specifically, we require focal firms to have granted patents in at least two or three years (out of the past five years). These hedge portfolios are constructed in the same manner as those reported in Table 2 of our main paper. As can be seen in Table IA1 Panel A, our *TECHRET* measure has significant forecasting power for returns when we implement those two restrictions.

1.2. Excluding micro-cap stocks

To alleviate the concern that our results are driven by micro-cap stocks, we exclude stocks with price less than $5 or market capitalization below the 10th NYSE percentile. Both equal- and value-weighted schemes still generate significant hedge returns in this setting, as shown in the Panel B of Table IA1.

1.3. Using alternative technology closeness cut-off values

In our main tests, a tech-peer is defined as a firm with any technological overlap with the focal firm (i.e. any firm whose *TECH* value is greater than 0.00). To evaluate the sensitivity of our results to this cut-off value, we re-ran our tests using alternative peer firm samples in which *TECH* is required to be greater than: 0.01 (Q1), 0.04 (Q2), or 0.12 (Q3). We also conducted a test where the peer sample is limited to just the top 50 tech-peers.

Our results show that the predictive power of *TECHRET* is robust in all those settings. The results are in Table A1 Panel C.

1.4. Technology-linked return predictability across time

In Table IA2, we examine how the return predictability power of technology-linked firms varies across time. We divide our full sample periods into 1963-1979, 1980-1989, 1990-1999, and 2000-2012. We then exactly repeat our baseline analysis from Table 3 for each sub-period. The findings in Table IA2 show that our results hold up well to this time disaggregation. The coefficients on $TECHRET_{t-1}$ are positive and statistically significant for all four sub-periods after controlling for various return determinants.

In fact, the only surprise in Table IA2 is that there appears to be little industry momentum in the last sub-period, which runs from 2000-2012. The coefficient on $INDRET_{t-1}$ is not significant for 2000-2012, while it is significant for the first three sub-periods. It is difficult to tell whether this result reflects noise in a short sample period or a structural decline in the industry momentum effect, perhaps due to increased arbitrage activities. What is more noteworthy from our perspective is that although industry momentum may be declining over time, the technology momentum that we document remains robust in all four sub-periods.

2. Persistence of the Technology Closeness Measure

In this section, we examine the persistence, or stickiness, of technology closeness. More specifically, we examine the return predictability power of our technology momentum strategy when the tech-affinity mapping measure, *TECH*, is lagged by one-, two-, or three-years. To do this, we compute four versions of the *TECHRET* variable ($TECHRET_{t-1}$, $TECHRET\_L1_{t-1}$, $TECHRET\_L2_{t-1}$, $TECHRET\_L3_{t-1}$), each representing the tech-peer computed returns using a different lag in *TECH* mappings. Panel A of Table IA3 reports the correlations for these four variables. The results show that the correlation between $TECHRET_{t-1}$ and each of its corresponding one-, two-, three-year lagged measures is strongly positive and significant. For instance, the Pearson correlation between $TECHRET_{t-1}$ and $TECHRET\_L1_{t-1}$ is 0.843. As the number of the lags increases, the correlation coefficient decreases, but the Pearson correlation between $TECHRET_{t-1}$ and $TECHRET\_L3_{t-1}$ is still positive and significant, at 0.610.

In Panel B of Table IA3, we show that the lagged versions of $TECHRET_{t-1}$ all have power to predict focal firm returns. For example, the version using one-year lagged mappings ($TECHRET\_L1_{t-1}$) generates equal-weighted returns of 88 basis points per month (t=4.22), or roughly 10.6% per year. Controlling for other known return determinants generates equally good or even better results. Results for $TECHRET\_L2_{t-1}$ and $TECHRET\_L3_{t-1}$ further confirm the return predictability of this strategy when we use older *TECH* mappings. While predictability power decreases as the number of lags increases, a strategy based on three-year-old technology closeness measures still has some predictive power for focal firm returns. Evidently investors do not need extremely timely information on patents to implement this strategy, as even relatively "stale" technology mappings have some predictive power for focal firm returns.

3. Predictability for Time-Period beyond One Month

In Table IA4, we consider the profitability of (L, H) strategies following Moskowitz and Greenblatt (1999) to show the speed of information diffusion. In the (L, H) strategy, the technology momentum portfolios are formed based on L-month lagged returns, held for H months, and rebalanced monthly. Both equal-weighted and value-weighted results are reported for the (L, H) strategy of the hedge portfolio that, each month, buys (shorts) stocks with technology-linked returns in the highest (lowest) decile. For brevity, we only report the L = 1-, 3-, 6-, 12-month lagged and H = 1-, 6-, 12-, 24-, 36-month holding period strategies.

Among the strategies that we consider, the short-term (1,1) strategy (i.e., L=1, H=1) is the most profitable. This result is robust when we use Daniel et al. (1997) (DGTW) characteristic-adjusted returns and industry-adjusted returns. We find the profitability of a short-term ($H=1$) strategy is not particularly sensitive to the length of ranking period L. For example, the equal-weighted raw monthly return for a (1,1) strategy is 1.17%, and the corresponding return for a (12,1) strategy is 1.11%. The value-weighted returns are generally smaller than the equal-weighted returns, which is consistent with faster information diffusion among larger firms. While the return predictability is strongest for the first month, we still find significant profits for strategies with longer holding periods. For example, the equal-weighted raw monthly return for 12-month holding period, specifically the (1, 12) strategy, is 0.32% with t-statistics of 3.90. However, the return predictability diminished to insignificant in the longer holding period, and the decay is much quicker for value-weighted portfolios, supporting the view that the information diffusion along the technological link is a gradual process.

In Figure 1, we show the cumulative returns to the hedge portfolio in the six months after portfolio formation. Consistent with the results in Table IA5, we also observe modest additional upward drift through month six. Extending the holding period to 12 or 24 months produces similar patterns. Similar to the return lag reported in other inter-firm studies (Moskowitz and Grinblatt, 1999; Cohen and Frazzini, 2008; Cohen and Lou, 2012), we see no reversal over the long-run, suggesting that we are capturing a mechanism of delayed updating of focal firm prices to fundamental information.

4. Lead-Lag Effect of Innovation-Related Activities

We also examine the predictability of future innovation-related activities along technological links to provide further evidence that the lead-lag pattern we documented in stock returns has its root in real activities. For this analysis, we consider two important innovation-related activities: patent flows and citation counts. First we define patent flow (*PNUM*) as the number of new patents applied for in a given year, and citation count (*CNUM*) as the number of adjusted forward lifetime citations received by new patents applied for in a given year. We then calculate technology-linked patent flow (*TECHPNUM*) and technology-linked citation count (*TECHCNUM*) in the same manner as *TECHRET*. Finally, we take the log value of innovation-related variables in the multivariate regressions.[1] Specifically, technology-linked patent count (*TECHPNUM*) of each focal firm is defined as the average number of patents applied by its technology-linked peers in a given year, weighted by pairwise technology closeness. Technology-linked citation count (*TECHCNUM*) of each focal firm is defined as the total number of adjusted forward life-time citations received by the patents applied by its technology-linked peers in a given year, weighted by pairwise technology closeness. Control variables include lagged log value of *PNUM* and *CNUM*, log value of market capitalization, book-to-market ratio, leverage, log value of firm age, and log value of R&D capital. For consistency, the

[1] There are two types of truncation problems in patents data: one is the application-grant lags that affect patent counts; the other is citation truncation lags that affect citation counts (Hall, Jaffe, and Trajtenberg, 2001, 2005). To adjust for application-grant lags, we follow Hall, Jaffe, and Trajtenberg (2001) in using a 3-year lag and ending our sample period in 2007. To adjust for citation truncation lags, we follow Kogan et al. (2017) to scale the raw number of forward citations by the average number of forward citations received by the patents applied in the same year (i.e., adjusted forward citations).

sample is further restricted to firms having fiscal years ending in December.

We report the regression results of future innovation-related activities in Table IA5. Panel A presents the results for future patent flows. The coefficient of *LNTECHPNUM* is significantly positive, indicating that when more patents are applied by the technology-linked firms in year *t-1*, the focal firms will have more patent applications (that are ultimately granted) in year *t*. For illustration, in column 4, the coefficient of 0.048 (*t*=3.37) on *LNTECHPNUM* implies that 1% increase in *TECHPNUM* in year *t-1* will predict a 0.048% increase in *PNUM* for the focal firm in year *t*.

Panel B reports the analogous results for future citation counts. The significantly positive coefficient on *LNTECHCNUM* indicates that the adjusted forward citation counts of technology-linked peers in year *t-1* is a significant leading indicator of adjusted forward citation counts for the focal firm in year *t*. These results demonstrate that technology-linked firms' innovation-related activities are positively associated with similar activities of the focal firm in the future.

These results are robust to various model perturbations (i.e., year, industry, or firm fixed effects), and they highlight the technology spillover effect along the technological links first documented by Bloom, Schankerman, and Van Reenen (2013). In the context of our analysis, these pieces of evidences are consistent with slow price adjustment and mispricing to real activities associated with technological spillover effects. Unless these real activities are somehow directional indicators of changes in risk (i.e., increased patent flows and citation counts among tech-peers portend greater risk for focal firms), these findings are difficult to square with the risk explanation.

References

Bloom, N., Schankerman, M., Van Reenen, J., 2013. Identifying technology spillovers and product market rivalry. Econometrica, 81(4), 1347-1393.

Cohen, L., Frazzini, A., 2008. Economic links and predictable returns. The Journal of Finance, 63(4), 1977-2011.

Cohen, L., Lou, D., 2012. Complicated firms. Journal of Financial Economics, 104(2), 383-400.

Daniel, K., Grinblatt, M., Titman, S., Wermers, R., 1997. Measuring mutual fund performance with characteristic-based benchmarks. The Journal of Finance, 52(3), 1035-1058.

Hall, B. H., Jaffe, A. B., Trajtenberg, M., 2001. The NBER patent citation data file: lessons, insights and methodological tools. Unpublished working paper, NBER Working Paper No. 8498.

Hall, B. H., Jaffe, A., Trajtenberg, M., 2005. Market value and patent citations. RAND Journal of Economics, 36(1), 16-38.

Kogan, L., Papanikolaou, D., Seru, A., Stoffman, N., 2017. Technological innovation, resource allocation, and growth. Quarterly Journal of Economics, 132(2), 665-712.

Moskowitz, T. J., Grinblatt, M., 1999. Do industries explain momentum? The Journal of Finance, 54(4), 1249-1290.

Table IA1. Robustness of hedge portfolio results.

This table presents the results of three sets of robustness checks for hedge portfolio results. The right column reports the equal-weighted (EW) and value-weighted (VW) returns of the hedge portfolio that, each month, buys (shorts) stocks with technology-linked returns in the highest (lowest) decile. *N* is the average number of stocks for each month in the decile portfolio. In Panel A, we impose the requirement that focal firms must have been granted patents in at least two (or three years) out of the past five years. In Panel B, we exclude stocks with price less than \$5 or market capitalization below the 10th NYSE percentile. In Panel C, we compute *TECHRET* using a sample with *TECH* greater than 0.01 (i.e., first quartile), 0.04 (i.e., median), 0.12 (i.e., third quartile), or the top 50 technological closed stocks.

		EW		VW	
	N	Excess returns (%)	6-Factor alpha (%)	Excess returns (%)	6-Factor alpha (%)
Panel A: Data requirement for TECH					
Focal firms must have granted patents in two of the past five years	76	**1.18**	**1.31**	**0.84**	**0.83**
		(5.16)	(5.83)	(3.81)	(3.55)
Focal firms must have granted patents in three of the past five years	63	**1.29**	**1.41**	**0.77**	**0.74**
		(5.27)	(5.87)	(3.32)	(3.07)
Panel B: Exclude micro stocks					
Stock price greater than 5 dollars	83	**1.05**	**1.08**	**0.66**	**0.69**
		(5.00)	(5.22)	(3.12)	(3.14)
Market value above 10th NYSE percentile	94	**1.14**	**1.17**	**0.69**	**0.72**
		(5.32)	(5.57)	(3.18)	(3.17)
Panel C: Use only tech-peers with TECH values above a certain threshold					
TECH greater than 0.01 (first quartile)	95	**1.14**	**1.19**	**0.70**	**0.74**
		(5.35)	(5.65)	(3.22)	(3.26)
TECH greater than 0.04 (median)	95	**1.11**	**1.18**	**0.55**	**0.58**
		(5.28)	(5.65)	(2.48)	(2.51)
TECH greater than 0.12 (third quartile)	95	**1.07**	**1.12**	**0.64**	**0.65**
		(5.13)	(5.43)	(2.89)	(2.81)
Top 50 technological peer firms	95	**1.06**	**1.11**	**0.56**	**0.53**
		(5.12)	(5.34)	(2.57)	(2.33)

Table IA2. Return predictability in sub-periods.

This table reports Fama-MacBeth forecasting regressions of stock returns in four sub-periods. The dependent variable is focal firm return in month *t*. The explanatory variables include technology-linked return (*TECHRET*), industry return (*INDRET*), firm size (*SIZE*), book-to-market ratio (*BM*), gross profitability (*GP*), asset growth (*AG*), R&D intensity (*RD*), lagged monthly return (RET_{t-1}), and medium-term price momentum (*MOM*). All explanatory variables are based on last non-missing available observation for each month *t* and are assigned to deciles ranging from 0 to 1. Industry fixed effects are added at the two-digit SIC industry code level. The sample excludes financial firms (firms with one-digit SIC code = 6) and stocks with price less than $1 at portfolio formation. Cross-sectional regressions are run every calendar month, and the time-series standard errors are Newey-West adjusted (up to 12 lags) for heteroskedasticity and autocorrelation. Fama-MacBeth *t*-statistics are reported below the coefficient estimates. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

Dep. variable	(1)	(2)	(3)	(4)
×100	RET_t	RET_t	RET_t	RET_t
Time Period	196307-197912	198001-198912	199001-199912	200001-201206
$TECHRET_{t-1}$	0.792***	0.496***	1.051***	0.583***
	(5.34)	(3.45)	(3.44)	(2.92)
$INDRET_{t-1}$	0.756***	0.810***	0.493***	0.072
	(4.97)	(3.43)	(2.71)	(0.33)
SIZE	-0.850*	-0.249	-0.714	-1.265**
	(-1.89)	(-0.55)	(-1.56)	(-2.40)
BM	0.660**	0.880***	0.201	0.581**
	(2.11)	(2.75)	(0.50)	(2.34)
GP	0.161	0.912***	0.314	0.591**
	(0.79)	(5.32)	(1.21)	(2.46)
AG	-0.489***	-0.288**	-0.436***	-0.442*
	(-3.15)	(-2.25)	(-2.77)	(-1.93)
RD	0.198	-0.249	1.524**	0.126
	(1.23)	(-0.86)	(2.37)	(0.23)
RET_{t-1}	-2.590***	-2.356***	-1.895***	-1.715***
	(-7.95)	(-10.33)	(-6.16)	(-4.43)
MOM	0.799***	0.765***	0.730**	-0.572
	(3.05)	(2.62)	(2.38)	(-1.04)
INTERCEPT	1.496*	1.207*	1.117*	2.314**
	(1.93)	(1.83)	(1.82)	(2.33)
Industry Fixed Effect	No	No	No	No
N	121,576	109,260	129,340	179,732
Average R^2	0.099	0.062	0.060	0.069

Table IA3. Persistence of technology closeness measure.

In this table, we examine the return predictability power of the strategy when the tech-affinity mapping measure, *TECH*, is lagged by one-, two-, or three-years. Technology-linked return (*TECHRET*) of a focal firm is the average monthly return of other firms in the technology space weighted by pairwise technology closeness. We compute four versions of *TECHRET* ($TECHRET_{t-1}$, $TECHRET\_L1_{t-1}$, $TECHRET\_L2_{t-1}$, $TECHRET\_L3_{t-1}$), each representing tech-peer returns computed returns using a different lag in *TECH* mappings. At the beginning of every calendar month, stocks are ranked in ascending order on the basis of one of these four technology-linked returns at the end of the previous month. The ranked stocks are then assigned to one of ten decile portfolios. Returns and alphas are expressed in monthly percent, *t*-statistics are shown below the coefficient estimates. Panel A reports pairwise correlations between current and lagged *TECHRETs* at 1 to 3 years (i.e., *TECHRET_L1*, *TECHRET_L2*, *TECHRET_L3*), with 5% statistical significance indicated in bold. Panel B reports hedge portfolio returns when using current year *TECHRET* and lagged *TECHRETs* at 1 to 3 years (i.e., *TECHRET_L1*, *TECHRET_L2*, *TECHRET_L3*).

Panel A: Pearson (Spearman) correlations above (below) the diagonal

	$TECHRET_{t-1}$	$TECHRET\_L1_{t-1}$	$TECHRET\_L2_{t-1}$	$TECHRET\_L3_{t-1}$
$TECHRET_{t-1}$		**0.843**	**0.715**	**0.610**
$TECHRET\_L1_{t-1}$	**0.844**		**0.839**	**0.712**
$TECHRET\_L2_{t-1}$	**0.725**	**0.843**		**0.840**
$TECHRET\_L3_{t-1}$	**0.627**	**0.721**	**0.842**	

Panel B: Hedge portfolio returns

Hedge portfolio	Excess returns (%)	CAPM alpha (%)	3-Factor alpha (%)	4-Factor alpha (%)	5-Factor alpha (%)	6-Factor alpha (%)
Equal weights						
TECHRET	1.17	1.22	1.26	1.08	1.37	1.21
	(5.47)	(5.70)	(5.88)	(4.98)	(6.49)	(5.76)
TECHRET_L1	0.88	0.94	1.00	0.86	1.14	1.02
	(4.22)	(4.55)	(4.82)	(4.10)	(5.61)	(4.98)
TECHRET_L2	0.93	0.98	1.03	0.87	1.09	0.96
	(4.78)	(5.08)	(5.31)	(4.45)	(5.65)	(4.97)
TECHRET_L3	0.93	0.98	1.05	0.91	1.11	0.99
	(5.05)	(5.28)	(5.64)	(4.82)	(5.94)	(5.30)
Value weights						
TECHRET	0.69	0.74	0.80	0.65	0.86	0.73
	(3.19)	(3.40)	(3.62)	(2.91)	(3.81)	(3.24)
TECHRET_L1	0.58	0.64	0.70	0.53	0.74	0.60
	(2.66)	(2.93)	(3.13)	(2.36)	(3.25)	(2.64)
TECHRET_L2	0.66	0.70	0.78	0.63	0.79	0.67
	(3.00)	(3.21)	(3.52)	(2.79)	(3.47)	(2.91)
TECHRET_L3	0.41	0.47	0.49	0.34	0.51	0.39
	(1.89)	(2.16)	(2.20)	(1.51)	(2.23)	(1.68)

Table IA4. Average monthly returns for (*L*, *H*) strategy.

This table shows average monthly profits for technology momentum strategies over the July 1963 through June 2012 time period. The technology momentum portfolios are formed based on *L*-month lagged returns and held for *H* months. Both equal-weighted (EW) and value-weighted (VW) results are reported for the (*L*, *H*) strategy of the hedge portfolio that, each month, buys (shorts) stocks with technology-linked returns in the highest (lowest) decile. For brevity, we only report the *L* = 1-, 3-, 6-, 12-month lagged and *H* = 1-, 6-, 12-, 24-, 36-month holding period strategies. Panel A reports the raw returns. Panel B reports DGTW-adjusted return following Daniel et al. (1997). Specifically, firms in our sample are first sorted each month into size quintiles, and then within each size quintile, we further sort firms into book-to-market quintiles. Within each of these 25 portfolios, firms are again sorted into quintiles based on the firm's past 12-month return, skipping the most recent month. Stocks are value-weighted within each of these 125 portfolios to form a benchmark that is subtracted from each individual stock's raw return. Panel C reports industry-adjusted returns, where the value-weighted average industry returns is calculated following Moskowitz and Grinblatt (1999).

		Panel A: Raw returns					*Panel B: DGTW-adjusted returns*					*Panel C: Industry-adjusted returns*				
L	*H* =	1	6	12	24	36	1	6	12	24	36	1	6	12	24	36
1	EW	1.17	0.44	0.32	0.07	0.01	0.79	0.30	0.22	0.06	0.01	0.99	0.36	0.25	0.06	0.00
		(5.47)	(3.68)	(3.90)	(1.27)	(0.16)	(5.72)	(3.65)	(3.64)	(1.42)	(0.47)	(5.21)	(3.68)	(3.90)	(1.33)	(0.14)
	VW	0.69	0.21	0.20	0.05	0.01	0.45	0.11	0.11	0.04	0.01	0.31	0.09	0.07	0.02	0.00
		(3.19)	(1.91)	(2.31)	(0.76)	(0.12)	(3.30)	(1.56)	(1.96)	(1.10)	(0.44)	(2.28)	(1.34)	(1.47)	(0.52)	(0.09)
3	EW	0.91	0.47	0.38	0.05	-0.02	0.68	0.31	0.27	0.07	0.03	0.74	0.38	0.29	0.05	-0.02
		(4.06)	(2.92)	(3.43)	(0.69)	(-0.32)	(5.02)	(2.99)	(3.76)	(1.43)	(0.69)	(3.77)	(3.01)	(3.49)	(0.84)	(-0.36)
	VW	0.45	0.19	0.21	0.03	-0.02	0.35	0.09	0.12	0.06	0.03	0.23	0.06	0.05	-0.01	-0.03
		(1.95)	(1.18)	(1.66)	(0.32)	(-0.29)	(2.52)	(0.95)	(1.65)	(0.98)	(0.71)	(1.62)	(0.65)	(0.68)	(-0.11)	(-0.68)
6	EW	1.03	0.61	0.44	0.02	-0.04	0.65	0.41	0.32	0.06	0.02	0.84	0.47	0.34	0.02	-0.04
		(4.55)	(3.34)	(3.04)	(0.19)	(-0.59)	(4.75)	(3.59)	(3.57)	(0.98)	(0.48)	(4.54)	(3.32)	(3.05)	(0.30)	(-0.74)
	VW	0.41	0.35	0.26	-0.02	-0.04	0.19	0.15	0.14	0.03	0.04	0.16	0.09	0.06	-0.03	-0.03
		(1.80)	(1.88)	(1.67)	(-0.15)	(-0.39)	(1.39)	(1.38)	(1.60)	(0.46)	(0.75)	(1.17)	(0.83)	(0.70)	(-0.41)	(-0.59)
12	EW	1.11	0.68	0.31	-0.11	-0.11	0.71	0.46	0.26	0.02	0.00	0.86	0.50	0.24	-0.08	-0.09
		(5.21)	(3.61)	(1.80)	(-0.80)	(-1.19)	(5.73)	(4.17)	(2.54)	(0.21)	(0.05)	(5.32)	(3.48)	(1.82)	(-0.79)	(-1.32)
	VW	0.61	0.43	0.12	-0.13	-0.08	0.36	0.22	0.09	-0.02	0.00	0.20	0.12	-0.01	-0.09	-0.05
		(2.69)	(2.16)	(0.65)	(-0.82)	(-0.67)	(2.68)	(1.90)	(0.81)	(-0.27)	(0.00)	(1.56)	(1.01)	(-0.07)	(-0.96)	(-0.66)

Table IA5. Future innovation-related activities.

This table reports forecasting regressions of future patent flows and citation counts. Technology-linked patent flow (*TECHPNUM*) of each focal firm is defined as the average number of patents applied by its technology-linked peers in a given year, weighted by pairwise technology closeness. Technology-linked citation count (*TECHCNUM*) of each focal firm is defined as log of the total number of adjusted forward life-time citations received by the patents applied by its technology-linked peers in a given year, weighted by pairwise technology closeness. Each focal firm's patent flow (*PNUM*) is the number of new patents applied for (and ultimately granted) in a given year. Citation count (*CNUM*) is the number of adjusted forward life-time citations received by new patents applied for (and ultimately granted) in a given year. We take the log value of innovation-related variables in the regressions. To adjust for citation truncation lags, we follow Kogan et al. (2017) and use adjusted forward citations, defined as the raw number of forward citations scaled by the average number of forward citations received by the patents applied for in the same year. *SIZE* is the log of market capitalization. *BM* is the book-to-market ratio. *LEV* is book equity divided by total assets. *AGE* is the number of years listed on COMPUSTAT as of the end of the previous fiscal year. *RDC* is R&D capital calculated assuming 20% capitalization rate. All variables are winsorized at 1% and 99% in the cross-section. The sample excludes financial firms (one-digit SIC code = 6) and covers 1963 to 2007. For consistency, the sample is further restricted to firms with fiscal years ending in December. All *t*-statistics are reported in parentheses and are computed using standard errors adjusted for within-firm and year clustering (in the OLS specifications), or for up to 4 lags serial correlation (in the Fama-MacBeth specification). According to the specifications, firm/industry/year fixed effects are added. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

Panel A: Future patent flows

	(1)	(2)	(3)	(4)
	$LNPNUM_t$	$LNPNUM_t$	$LNPNUM_t$	$LNPNUM_t$
$LNTECHPNUM_{t-1}$	0.128***	0.065***	0.061***	0.048***
	(3.46)	(3.16)	(5.18)	(3.37)
$LNPNUM_{t-1}$		0.519***	0.826***	0.823***
		(29.92)	(113.88)	(116.34)
$SIZE_{t-1}$		0.124***	0.070***	0.072***
		(10.38)	(14.90)	(12.82)
BM_{t-1}		0.047	0.056	0.003
		(0.99)	(1.65)	(0.08)
LEV_{t-1}		0.033	-0.035	-0.002
		(0.66)	(-1.02)	(-0.05)
$LNAGE_{t-1}$		0.027	-0.015	-0.029
		(0.60)	(-1.52)	(-1.57)
$LNRDC_{t-1}$		0.040***	0.049***	0.055***
		(4.60)	(10.01)	(7.74)
Firm Fixed Effect	Yes	Yes	No	No
Industry Fixed Effect	No	No	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	No
N	23,749	23,749	23,749	23,749
Adj/Avg. R^2	0.861	0.906	0.883	0.896
Regression Method	OLS	OLS	OLS	Fama-MacBeth

Panel B: Future citation counts

	(1)	(2)	(3)	(4)
	$LNCNUM_t$	$LNCNUM_t$	$LNCNUM_t$	$LNCNUM_t$
$LNTECHCNUM_{t-1}$	0.201***	0.122***	0.095***	0.074***
	(5.10)	(4.76)	(6.98)	(4.04)
$LNCNUM_{t-1}$		0.425***	0.776***	0.773***
		(22.89)	(78.18)	(80.84)
$SIZE_{t-1}$		0.135***	0.088***	0.092***
		(9.45)	(15.01)	(11.31)
BM_{t-1}		0.047	0.048	-0.027
		(0.95)	(1.45)	(-0.63)
LEV_{t-1}		0.045	-0.021	0.042
		(0.85)	(-0.63)	(1.14)
$LNAGE_{t-1}$		0.044	-0.027**	-0.020
		(0.76)	(-2.09)	(-0.91)
$LNRDC_{t-1}$		0.029***	0.057***	0.067***
		(2.85)	(9.63)	(7.10)
Firm Fixed Effect	Yes	Yes	No	No
Industry Fixed Effect	No	No	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	No
N	23,749	23,749	23,749	23,749
Adj/Avg. R^2	0.838	0.872	0.837	0.855
Regression Method	OLS	OLS	OLS	Fama-MacBeth