Internet Appendix for

Technological Links and Predictable Returns

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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.

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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 10^{th} 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.

	N	EW		VW	
		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 10^{th} 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