Patent Intensity, Firm Life Cycle, and the Long-Run Return and Risk Dynamics of Technological Innovators

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December 13, 2024

ABSTRACT

We introduce patent intensity (PI), patents granted divided by market capitalization, to classify technological-innovator types starting from 1926. PI-portfolios earn large return spreads for a decade post-formation, and standard factors fail to capture these differences. We further show that traditional value, investment, and profitability premiums are much weaker or reversed among patenters versus non-patenters, explaining their general difficulty pricing innovation. Incorporating firm dynamics through expected growth or intangibles reconciles observed returns, with high-PI loadings revealing a life-cycle of persistent expected growth, increasing investment, and improving profitability. Life-cycle dynamics in risk are essential to accurately capturing technological innovators' long-run returns.

Keywords: technological innovation, patent intensity, long-run stock returns, firm life-cycle, fundamentals-based factor models, risk dynamics.

JEL Classification: G12, E20.

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Abstract

We introduce patent intensity (PI), patents granted divided by market capitalization, to classify technological-innovator types starting from 1926. PI-portfolios earn large return spreads for a decade post-formation, and standard factors fail to capture these differences. We further show that traditional value, investment, and profitability premiums are much weaker or reversed among patenters versus non-patenters, explaining their general difficulty pricing innovation. Incorporating firm dynamics through expected growth or intangibles reconciles observed returns, with high-PI loadings revealing a life-cycle of persistent expected growth, increasing investment, and improving profitability. Life-cycle dynamics in risk are essential to accurately capturing technological innovators' long-run returns.

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1. Introduction

Arrow (1962) conjectured high required returns to innovation because of imperfections in the market for knowledge: indivisibility, inappropriability, and uncertainty of outcomes (p. 609).[1] Further characterizing uncertainty, the benefits of technological innovation to firms can take years or decades to emerge (Scherer, 1965, 1998, Hall and Lerner, 2010). A long-run view is therefore necessary to understand the dynamics of how financial markets price innovative firms, which are key drivers of economic growth.[2]

In the broader empirical asset pricing literature, well-deserved skepticism has arisen related to the overabundance of return anomalies and factors (Cochrane, 2011). One essential finding from this literature is that many anomalies are short-lived, leading to the view that "long-term discount rates do not vary across firms."[3] Long-term discount rates are important because firm costs of capital provide a central link between asset pricing and corporate finance, and long-term effects on required returns are necessary to impact key real investment decisions.[4]

In this paper, we leverage nearly one hundred years of patent data to investigate technological innovators and non-innovators from a long-run point of view. We follow portfolio dynamics for a decade following formation, and document the evolution of returns, characteristics, alphas, and risk from the perspective of fundamentals-based factor models. The results provide new evidence of substantial variations in long-run returns across different portfolios of innovators and non-innovators. Further, fundamentals-based factor models differ significantly and persistently in their ability to accurately capture these returns. As emphasized by Cochrane (2011), a long-horizon perspective brings discipline and renewed purpose to empirical asset pricing by prioritizing persistent firm variations that are deeply connected to real variables and decisions.

[1]Related or specific drivers of high costs of capital for innovators include embedded real options that leverage risk (Berk, Green, and Naik, 2004), and financing frictions such as information asymmetry (Hall, 2002).

[2]See Schumpeter (1911), Solow (1957), Romer (1986, 1990), Hall (1987), Grossman and Helpman (1991), Aghion and Howitt (1992), and Kogan, Papanikolaou, Seru, and Stoffman (2017).

[3]See Keloharju, Linnainmaa, and Nyberg (2021).

[4]See, e.g., Cochrane (2011), p. 1064, and Binsbergen and Opp (2019).

Our study pursues this objective by focusing on technological innovation, a primitive, long-lasting shock, which following Arrow's economic reasoning provides a natural candidate to drive strong variation in long-run returns, as well as risk dynamics driven by changing fundamentals.

Our analysis builds on a simple new measure of technological innovation, patent intensity (PI), the ratio of patents granted to a firm in the past twelve months divided by current market capitalization. The measure is easy to calculate and transparent, requires no accounting data, and extends back to 1926. From an investor's point of view, PI ranks firms according to their patents produced per dollar invested. High-PI portfolios give the cheapest way to purchase equity interest in the recently produced public-market patent stock and its stream of future rents.

The PI variable is motivated by theories of innovation heterogeneity and firm life cycle.[5] Klepper (1996) and Akcigit and Kerr (2018) propose that firms with valuable existing assets innovate differently from other firms, focusing on enhancements of their incumbencies through less risky "process" or "inside" innovations.[6] In contrast, firms without valuable existing assets must pursue more lottery-like innovations in unpredictable directions, such as new product markets (Cohen and Klepper, 1996), or "outside" innovations that can result in major break-throughs (Akcigit and Kerr, 2018). Consistent with this literature, low-PI firms are older, larger, with valuable and profitable assets in place, and less risky. High-PI firms are younger, smaller, with less valuable and profitable assets in place, and riskier.[7]

Patent intensity is also a natural candidate to capture the crucial distinction between *growth* and *expected growth.* Cochrane (1991) makes the key point that invest-

[5]The concept of firm life cycle is widespread in economics, from early writings (Schumpeter, 1934) to modern general equilibrium formulations (Klette and Kortum, 2004).

[6]Early work includes Utterback and Abernathy (1975) and Abernathy, Utterback, et al. (1978). Bena, Garlappi, and Grüning (2016) examine incremental and radical innovations in a dynamic "horse race". Bustamante and Zucchi (2022) study explorative versus exploitative innovation in a model of industry equilibrium.

[7]Further, the presence of valuable and profitable assets in place for low-PI firms enables internal cash-flow funding, while high-PI firms lack such funding, which is an important friction for innovative firms (Hall, 2002).

ment returns, and therefore under appropriate conditions stock returns, decrease in the investment rate today but increase with the investment rate in the future.[8] Hou, Mo, Xue, and Zhang (2021, HMXZ) apply this logic to the cross-section of stock returns, providing a simple setting where returns can be approximated by:[9]

$$R_{i,t+1} \approx \frac{X_{i,t+1}}{1 + aIA_{it}} + (1-\delta)\frac{1 + aIA_{i,t+1}}{1 + aIA_{it}}, \tag{1}$$

where R_{it}, X_{it}, and IA_{it} respectively denote a stock return, the corresponding return on assets, and the investment-to-assets ratio, and δ and a are parameters for depreciation and adjustment costs. The key point is that in a "static" one-period model, $IA_{i,t+1} = 0$, implying that investment and profitability are sufficient to characterize returns (Hou, Xue, and Zhang, 2015). In a dynamic model, the growth in investment-to-assets in the second term should play an important role. It is therefore essential to distinguish between firms that are growing now (high IA currently) and firms whose growth is expected to improve (growth in IA, following Cochrane (1991)). Innovation is a natural candidate to accelerate growth, and we show that patent intensity concentrates heavily on this channel.

Early evidence on innovation and stock returns from Chan, Lakonishok, and Sougiannis (2001) shows little average return difference in a twenty-one year sample between firms with and without reported R&D. Within the subset of firms that report R&D, however, innovation intensity (R&D scaled by market capitalization) produces a positive return spread that is not explained by factor models, which they interpret as mispricing. HMXZ interpret the same anomaly differently, building an "expected growth" factor that captures the initial return spreads of R&D-intensity portfolios. HMXZ consider only the year following portfolio formation and only portfolios of innovators, and by the nature of their study, which addresses one hundred and fifty different anomalies, their discussion of innovation is limited.[10] Our analysis builds in multiple directions:

[8]See Cochrane (1991), p. 210 and p. 217, equation 15.

[9]See HMXZ, p. 5, equation 1. See also Li, Wang, and Yu (2021).

[10]Their discussion of R&D portfolios is contained in their paper's penultimate paragraph (p. 37).

We extend to patent data allowing nearly one-hundred years of returns and provide the new measure of patent intensity, consider both innovators and non-innovators, analyze long-run dynamics in returns, risk, and characteristics over a decade, and explain the reasons for differences in pricing across different fundamentals-based factor models.

Empirically, over our nearly one-hundred year sample PI-sorted portfolios produce a significant return spread of approximately 7% in the first year following portfolio formation, remaining positive and statistically significant for an entire decade. The point estimate stays at 7% in the second year, declines to 5% in year three, and varies between 3-5% annually over the remaining years. These large, persistent return spreads provide new evidence that long-run discount rates do vary across firms.

We also show differences in the ability of fundamentals-based factor models to capture these long-run returns. Fama and French (1993, 2015, FF) and Hou, Xue, and Zhang (2015, HXZ) invoke static or steady-state valuation models to motivate fundamental pricing factors based on market/book ratios (Tobin's q), capital investment, and profitability.[11] These models' foundations in steady-state valuation do not address theories of growth that highlight the changing nature of innovative firms, which we show to be empirically important. Consistent with this mismatch, the FF and HXZ models fail to accurately reflect technological innovator returns. In fact, the five-factor Fama and French model (FF5) and the $q4$ model of HXZ produce larger spreads in alphas than returns. Long-short alpha point estimates are 6-8% annually for the first three years following portfolio formation and 4-5% for the remainder of the decade, all highly statistically significant. These results imply very large differences between long-run realized returns and model-implied discount rates.

We explain these differences between model-implied and realized returns. Most broadly, we show that the traditional value, investment, and profitability anomalies are reversed or substantially weakened within the set of technological innovators, which impacts estimated factor-model alphas. For example, high PI firms on average have

[11] See Fama and French (1995) equation 2, Fama and French (2015) equation 3, and Hou, Xue, and Zhang (2015) equation 1.

negative profitability loadings, but since their realized returns are not punished for this covariance, their alphas persistently increase with this benchmarking. Such basic differences between innovators and non-innovators have long-run importance beyond patent intensity: The simple categorization of being a non-innovator produces statistically significant negative FF3 and FF5 alphas of 1.5-2% annually for ten years following portfolio formation, with virtually no decay. Basic innovator minus non-innovator alpha differences are also highly significant for ten years, amounting to 2-3% annually, again with virtually no decay. Thus, even for the simplest sort into innovative versus non-innovative firms, standard fundamentals-based factor models produce strong and persistent mismatches between model-implied and actual long-run returns.

The HMXZ $q5$ model addresses dynamic influences on expected returns through expected growth, and accurately captures the returns of patent-intensity portfolios not only immediately after formation, but at horizons up to ten years. Our results show that the $q5$ and FF5 models, while often viewed as close competitors based on short-horizon returns, dramatically differ in their ability to capture long-run returns related to technological innovation. Beyond reducing alphas, an asset pricing model should quantify economic risks and thereby connect firms' attributes and risk exposures to their cost of capital and pricing. Since PI-sorted return differences are persistent, their risk dynamics must also be persistent, but predictably changing as firms evolve in order to explain realized returns at all horizons, a challenging task (Baba-Yara, Boons, and Tamoni, 2024). Our analysis uncovers risk dynamics that match the technological-innovator life cycle and their long-run returns: loadings on expected growth are initially large and decline over time, investment and profitability increase, and all combine to produce model-implied expected returns that accurately reflect realized returns at all horizons.

We further use patent intensity portfolios to demonstrate the relation of expected growth to two related pricing approaches, cash-based profitability (e.g., Ball, Gerakos, Linnainmaa, and Nikolaev, 2016) and intangibles (e.g., Eisfeldt, Kim, and Papanikolaou, 2022). We show the key ingredients of these approaches that are required to accurately capture the long-run returns of patent-intensity portfolios, the risk dynamics they imply, and their relationships with expected growth. Regardless of pricing model, the facts regarding life-cycle risk dynamics of technological innovators, and reconciliation with long-run returns, are new to the literature.

Our work is most broadly relevant to the large literature that uses production-based asset pricing models to explain aspects of the cross-section of returns including size, value, investment, and profitability.[12] Innovation is a natural source of investment opportunities and growth options, which are central to this class of models.[13] General equilibrium models of innovation and returns include Papanikolaou (2011), Gârleanu, Kogan, and Panageas (2012), Gârleanu, Panageas, and Yu (2012), Kung and Schmid (2015), Garlappi and Song (2017), and Kogan, Papanikolaou, and Stoffman (2020). Models of intangible capital (e.g., Eisfeldt and Papanikolaou, 2013, Peters and Taylor, 2017) provide further foundations for understanding innovative capacity. Despite the central importance of firm dynamics throughout this literature, few studies have explicitly documented time-varying risk loadings driven by real firm assets or decisions.[14] We show ten years of factor-beta dynamics originating from firms' patenting. To our knowledge, our findings are the first to demonstrate innovation as a source of risk dynamics, and the decade-long impacts on factor betas that we find are both novel and economically important. This new evidence of persistent risk dynamics originating from innovation can be used to guide and calibrate future theories.

Our study also adds to a small but growing literature that emphasizes long-run variations in the cross-section of returns and firm discount rates. Cochrane (2011) highlights the discipline a long-run perspective can add to the factor zoo, while also ob-

[12] Production based models that motivate returns related to size, book/market, investment, and profitability include Berk, Green, and Naik (1999), Gomes, Kogan, and Zhang (2003), Carlson, Fisher, and Giammarino (2004), Zhang (2005), Cooper (2006), Hackbarth and Johnson (2015), Kogan, Li, and Qiao (2020), and Kogan, Li, and Zhang (2023).

[13] See, for example, Li (2011) and Lin (2012). Theoretical and empirical foundations of the connection between technological growth and asset prices include Greenwood and Jovanovic (1999), Hobijn and Jovanovic (2001), Pástor and Veronesi (2009), and Kogan and Papanikolaou (2010, 2013, 2014).

[14] For example, Hackbarth and Morellec (2008) document beta dynamics around mergers, and Carlson, Fisher, and Giammarino (2010) show risk dynamics around seasoned equity offerings.

serving the formal equivalence of analyzing prices versus returns.[15] Studies that develop new insights from a long-run perspective by emphasizing prices include Cohen, Polk, and Vuolteenahu (2009), Binsbergen, Boons, Opp, and Tamoni (2023) and Cho and Polk (2024), while studies that use long-run returns include Keloharju, Linnainmaa, and Nyberg (2021), Chernov, Lochstoer, and Lundeby (2022), and Baba-Yara, Boons, and Tamoni (2024). This literature adds discipline to the factor zoo by advancing the higher hurdle of persistent return effects, while also improving the connection of asset pricing to real investment and corporate finance by prioritizing the long-run discount factors that should drive real investment decisions. Our empirical methodology is based on long-run returns, and accommodates risk dynamics in multiple factors.[16] Regarding drivers of expected returns, Cochrane discusses characteristic persistence as a key economic prerequisite for long-lasting discount rate effects,[17] and we correspondingly focus on innovation, a highly persistent and impactful firm fundamental.

Finally, our research connects to many additional studies that relate innovation to the stock market (e.g., Hsu, 2009, Cohen, Diether, and Malloy, 2013, Hirshleifer, Hsu, and Li, 2013).[18] Empirical studies of R&D typically begin their samples in 1976 due to data limitations, and commonly use the data as reported, with pervasive missing values often dropped from analysis or set to zero. More recent literature emphasizes the importance of missing R&D data, including efforts to impute missing observations.[19] An attractive feature of patent-intensity is the wide availability of patent data from 1926 with no missing data, which is essential to our long-run analysis, enabling the

[15]See p. 1064.

[16]Current empirical implementation of abnormal price frameworks focuses on single-factor specifications, due to substantial expansion of analysis required for multifactor environments. See Cho and Polk (2024), page 3, as well as page 38, footnote 37.

[17]For example, he writes, "Since momentum amounts to a very small time-series correlation and lasts less than a year, I suspect it has little effect on long-run expected returns and hence the level of stock prices. Long-lasting characteristics are likely to be more important." (p. 1064)

[18]See also Lev and Sougiannis (1996), Eberhart, Maxwell, and Siddique (2004), Gu (2005), Hirshleifer, Hsu, and Li (2018), Bena and Garlappi (2020), Kelly, Papanikolaou, Seru, and Taddy (2021), Eisfeldt, Kim, and Papanikolaou (2022), and Stoffman, Woeppel, and Yavuz (2022).

[19]See for example Koh and Reeb (2015) and Koh, Reeb, Sojli, Tham, and Wang (2022). Studies of real earnings management also emphasize the incentives to overstate or understate R&D in different circumstances (e.g., Baber, Fairfield, and Haggard, 1991, McVay, 2006, Sun, 2021).

simple, transparent calculation of a reliable PI measure for every sample firm.

2. Patent Intensity

The patent data we use in our study, and procedures for merging with CRSP and Compustat data, are standard. The United States Patent & Trademark Office (USPTO) provides complete patent data, with downloadable text starting in 1976.[20] For patents filed between 1926-1975, Kelly, Papanikolaou, Seru, and Taddy (2021) provide cleaned and tabulated data from USPTO image files.[21] Combining these two sources covers all United States patents issued from 1926-2022. We link patents to public companies using CRSP permno-patent links from Kogan, Papanikolaou, Seru, and Stoffman (2017).[22]

Figure 1, Panel A, shows annual patent counts beginning in 1926 for i) the entire patent sample, ii) the subsample in which at the time of granting the assignee trades on the NYSE, AMEX, or Nasdaq exchanges and is in the CRSP database, and iii) a smaller subsample restricted to US-based CRSP assignees (shrcd is 10 or 11). Panel B shows for the two subsamples their annual shares of all patents awarded. For most of the past century, US-based CRSP assignees comprise from twenty to forty percent of US patenting.[23] The public companies commonly used in empirical asset pricing studies are therefore important to technological progress.

Conversely, technologically innovative firms are important to the standard CRSP sample of US-based firms traded on the three major exchanges. Each year on June 30 we classify firms as "innovators" or "non-innovators" based on whether they received a patent in the prior 12-month period.[24] Figure 1, Panels C-F show the importance

[20] `https://patentsview.org/download/data-download-tables`.

[21] `https://github.com/KPSS2017/Measuring-Technological-Innovation-Over-the-Long-Run-Replication-Kit`.

[22] `https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Replication-Kit`.

[23] Toward the end of the sample, the difference between all CRSP assignees and US-based CRSP assignees is due to growing importance of cross-listed foreign firms that receive patents in the United States.

[24] The USPTO publishes its Official Gazette every Tuesday with information on patents granted that day, so patent information is immediately observable. See `https://www.uspto.gov/learning-and`

of technological innovators to the CRSP universe of publicly traded firms over the past century. The innovators' share by firm count (Panels C-D) ranges from twenty to fifty percent. Their share by market capitalization (Panels E-F) ranges from fifty to seventy-five percent. We use value-weighted portfolios, so the large and stable market-capitalization weighted shares of innovators are most relevant.

2.1. Patent intensity definition

On June 30 of every year, for each CRSP firm we define patent intensity (PI) as the ratio of patents received in the prior twelve months divided by current CRSP market capitalization. This measure reflects several deliberate choices. We use twelve months of patent issuance in the numerator, a flow, rather than attempt to accumulate the stock of patents. This choice for our baseline specification prevents any mechanical overlap in different years' portfolios. More importantly, as patents age, uncertainty resolves and expected growth on average turns into actual growth. PI thus emphasizes the most recent flow of patents, to capture the cohort with the greatest unresolved uncertainty and potential to impact future growth.[25] Our empirical work tracks the portfolios as they age, and shows expected growth converting to actual growth, investment, and profitability.

The PI measure also uses simple patent counts in the numerator. Many possible refinements, such as citations, are not observable in real time. Kogan, Papanikolaou, Seru, and Stoffman (2017, KPSS) create a measure of patent value using three-day announcement returns following patent issuance. The information content of this measure depends on the market's ability to quickly infer the ultimate impacts of technological innovations. This is plausible especially for cases like the "inside" innovators of Akcigit and Kerr (2018), which focus on enhancing known and valuable existing product

`-resources/official-gazette`. Links from patent assignees to CRSP firms are reliable, but linking assignees to pre-IPO firms is more challenging. We therefore drop firms from our analysis that have less than a twelve-month CRSP history.

[25]Because of the persistence of patenting, high PI portfolios also strongly predict patenting in future years, which is another reason they should capture expected growth.

markets. Using a simple count in the numerator captures the idea of a lottery-like and highly unpredictable claim, as undertaken by the "outside" innovators of Akcigit and Kerr (2018). The measure thus reflects high uncertainty about the long-run payoffs of some innovations, which may take many years to resolve (Scherer, 1965, 1998, Pakes, 1986). Scaling by market capitalization is also a deliberate choice. Purchasing equity in high-PI firms maximizes, per dollar invested, exposure to recent patenting activity, and aligns with theories of investment heterogeneity, in which firms innovate differently depending whether or not they have valuable existing assets (Klepper, 1996, Akcigit and Kerr, 2018). This choice mirrors the book-to-market ratio, which can be thought of as a measure of asset intensity, as well as R&D to market, as considered in Chan, Lakonishok, and Sougiannis (2001) and Hou, Mo, Xue, and Zhang (2021). With these choices, patent intensity requires no accounting variables. Patent intensity thus provides a simple but economically important measure.

To address concerns that some other innovation-related sorting variable might be preferable, we further discuss our use of patent intensity and its role in our findings. First, from a purely asset pricing point of view, no particular sort is more valid than another. An asset pricing model should price all claims, and if we were to begin from a premise that only certain types of sorts are legitimate, we would likely lose important information. Second, one objective of our paper is to enhance and extend prior literature showing that the traditional Fama-French factors cannot accurately capture the returns of technological innovators, but we do not rely only on the PI sorts to make this point. In Section 4.1, we use the most primitive starting point of a sort into patenters versus non-patenters. The traditional FF3 and FF5 models persistently and statistically significantly fail to capture the returns of these basic portfolios over ten year horizons. Further, sorts on traditional value, investment, and profitability characteristics *within* these basic innovator/non-innovator portfolios produce very different return spreads and persistently cannot be priced by the FF3 and FF5 factors. Thus, our documentation of the inability of the traditional Fama-French factors to capture innovator returns is much broader than the PI portfolios, expanding on and further explaining evidence from prior literature. Third, the most important and original contribution of our paper is to develop evidence of life-cycle risk dynamics for certain types of innovative firms, and the PI portfolios are the ideal choice for this purpose. Again, high-PI firms have low valuations relative to their innovative outputs, hence the role of valuable and stable assets-in-place in this portfolio is likely small. As in the outside innovators of Akcigit and Kerr (2018), such firms should concentrate on the earliest stage of the innovation life-cycle, before finding significant product market success. A central motivation of our paper is to understand how these firms' risk dynamics evolve compared to other firms, and explain their long-run returns. Patent intensity is therefore economically simple, new to the literature, available from 1926 with no requirement for accounting data, and ideally suited to demonstrating the life-cycle dynamics of innovative firms.[26]

2.2. Summary statistics and characteristic dynamics

Each year, we sort firms into three groups by PI. Non-innovators (group 0) have no patents in the prior twelve month period. Low- and high-intensity innovators (groups 1 and 2) are obtained by dividing all innovators at the median PI break point, forming two equal-sized groups by firm count. Table 1 provides descriptive statistics. Panel A shows the average shares of each group according to firm count, market capitalization, past patenting, and future patenting. Most firms (68% on average) are non-patenters. Nonetheless, the 32% of patenting firms contribute the majority of market capitalization, 65% in an average year. The concentration of market capitalization is even stronger across the high- and low-PI groups. The low-PI group, while only 16% by firm count, contributes 54% of total market capitalization. The high-PI group, again 16% by firm count, contributes only 11% of total market capitalization. The high PI group has small market capitalization, but is nonetheless economically important. This group owns on

[26]The Internet Appendix shows that related innovation sorts, such as scaling patents by book value, produce positive but smaller returns and milder risk dynamics. To address concerns that some particular aspect of high-PI firms unrelated to innovation drives our results, we also create matched samples of non-innovative firms (by size, B/M, and prior returns), and show that the returns, alphas, and risk dynamics of high-PI firms are moderated but continue to hold relative to these matched samples.

average 62.5% of the patents created by public firms in the prior year. Moreover, their patenting activity is persistent. The high-PI group contributes 60% of patents granted to the sample in the following year, 58% in the next three years, and 57% in the next five years. Standard measures of patent quality further confirm economic importance. Forward citations, the influential-patent indicator of Kelly, Papanikolaou, Seru, and Taddy (2021), and indicators for the top ten and one percent of citations all indicate close to sixty percent of impactful patents belonging to the high-PI group. Thus, with 11% of total market capitalization, an investor can purchase equity interest in the majority of not only recent but also future public-market patents, including high-quality patents, and the rents that accompany these technological innovations.

Firm characteristics, shown in Table 1, Panel B, further distinguish the PI groups. High-PI firms are younger than low-PI firms, consistent with firm life cycle. Interestingly, non-innovators are slightly younger still than the high-PI firms. To understand this, note that death rate is an important contributor to average age, and the panel shows that average exit rates (delisting rates) are highest for non-innovators. Considering valuations, non-innovators have the highest B/M ratio, the traditional measure of "value". In the other direction, the lowest B/M ratios ("growth") correspond to the low-PI group, while high-intensity innovators have intermediate B/M ratios. At the same time, high-PI firms show both the lowest current investment and the lowest current profitability. Patent intensity thus has a complex relationship with the traditional firm fundamentals considered by factor models, and firm dynamics are therefore likely to play an important role in understanding valuation and return differences across patent-intensity groups.

Asset composition, shown in Panel B, further illuminates differences across the groups. Non-innovators and low-intensity innovators both have higher levels of physical capital ($PPE \approx 30\%$) than high-intensity innovators ($\approx 23\%$). Intangibles are largest among low-intensity innovators (10.5%), consistent with prior acquisitions, versus 7.3% for the other two groups. Finally, high-intensity innovators have the highest levels of current assets (62%) as well as cash (21%), which can help to fund risky innovation and the exercise of growth options. Again, these facts suggests differences in dynamics across the groups going forward.

One natural way to measure firm dynamics is by changes in characteristics. Figure 2 shows the evolution of different fundamentals for ten years following each initial sort, value weighting the characteristics in each group in each year. The panels also show a neutral benchmark that combines all firms into one group. The neutral benchmark reflects the dynamics expected from earlier investigations of broad cross-sections of firms.[27] In particular, for the neutral benchmark, investment decreases as firms age (Panels A and B), profitability increases (Panels C and D), market-to-book increases (Panel E), and beta modestly declines (Panel F). In the same panels, the life-cycle dynamics of PI-sorted groups show important differences from one another and from the neutral benchmark. Panels A and B show using two different measures that investment becomes more aggressive in the high-PI group over time, rather than decreasing. Panels C and D show that profitability improves more rapidly for high-PI firms than others. Panel E shows that market-to-book grows most rapidly for the high-PI group, converging over time to the low-PI group, while non-innovators maintain persistently low valuations. Finally, in Panel F market betas show remarkably persistent differences across innovator types. These results reflect only univariate portfolio characteristics, but suggest fundamental and long-lasting differences between PI portfolios that are likely to be important for asset pricing.

We conclude that patent intensity captures important and persistent differences across firms. The non-innovator archetype is a modestly sized, shorter-lived value firm with moderate investment and profitability. Low-intensity innovators are large and long-lived, with significant investments, high profitability, and low B/M ratios. High-intensity innovators are young and small, have intermediate B/M measures, invest less and have low profitability, but produce a disproportionately large share of technological innovation. Because of these important differences, we anticipate the pricing of PI

[27]See, for example, Jovanovic (1982), Dunne, Roberts, and Samuelson (1989), Sutton (1997), and Caves (1998).

portfolios to be a meaningful challenge for traditional asset-pricing factors such as size, value, investment, and profitability.

3. Returns, Risk, and Long-Run Dynamics

This section shows return, risk, and alpha dynamics of patent-intensity portfolios following the initial sort date. We use standard portfolio formation methods, value-weighting monthly,[28] but expand on much of the prior literature by following the portfolios for ten years rather than a single year following formation. Portfolios are formed annually at the end of June, beginning in 1926. After an initial burn-in period of ten years, at any point in time from July 1, 1935 onward we have a full complement of ten different cohorts of aged portfolios. We refer to these as "K-aged" portfolios, where $K = 1, ..., 10$ represents the Kth year relative to portfolio formation. The existence of the patent intensity measure from 1926 helps to enable our long-run analysis, because it ensures that by 1963 (all Fama-French factors available) or 1967 (all $q5$ factors available), our results incorporate the full set of ten aged patent-intensity portfolios.

3.1. Returns and Fama-French factors

Table 2 shows the returns and performance, according to the CAPM and Fama-French factors, of patent-intensity sorts in the first year following portfolio formation. The left-hand side of the table is based on the full sample beginning in July 1926, and the right-hand side begins in July, 1963. In the full sample, the portfolios are exactly as in the prior section: non-innovators (no patents, denoted portfolio 0), low-intensity innovators (lower half of PI sort, portfolio 1), and high-intensity innovators (upper half of PI sort, portfolio 2). In the post-1963 sample, we sort innovators into four groups with equal numbers of firms, and label these portfolios 1-4. Thus, portfolio

[28]We carefully account for delisting returns as in Hou, Xue, and Zhang (2020) and confirm that a slightly simpler approach from Shumway (1997) and Shumway and Warther (1999) gives practically the same results.

zero always corresponds to non-innovators (PI = 0), and positive-numbered portfolios are innovators of increasing PI. Portfolio HL is a zero-cost portfolio, short the non-innovator portfolio and long the highest PI portfolio. The table shows value-weighted monthly excess returns (Panel A), CAPM regressions (Panel B), Fama-French three-factor regressions (Panel C), and Fama-French five-factor regressions (Panel D).

In Panel A, the annualized average excess returns (monthly returns multiplied by twelve) increase monotonically across portfolios in the full sample from 7.58% for the non-patenting portfolio 0 to 11.64% for the high-PI stocks. The sample starting in 1963 confirms the increasing average excess returns. The HL portfolio earns economically and statistically significant returns of about 4.1% over the full sample and 6.7% over the post-1963 sample. CAPM regressions (Panel B) show that market betas slightly increase with PI, but not sufficiently to explain returns. The CAPM alphas of the HL portfolio decrease relative to raw returns (to 2.4% in the full sample and 5.0% post-1963), but remain statistically significant. Controlling for FF3 factors (Panel C) does not substantially change the long-short alphas relative to the CAPM. Among innovators, higher PI is associated with larger size loadings and somewhat more value than growth. Focusing particular attention on the value-growth factor, we observe only modest variations in HML loadings across the portfolios, with the largest (value) loading belonging to the non-innovator portfolio. Thus, the three-factor Fama-French model, and in particular the value-growth factor, does not help to explain the returns of patent-intensity portfolios.

The FF5 model (Panel D) adds investment and profitability factors, and deepens the difficulties reconciling realized returns. The profitability loadings align negatively with PI, opposite the direction needed to explain PI-sorted returns since the profitability factor earns a positive premium. Investment loadings increase with PI, but are only marginally statistically significant. The net effect is a stronger alpha sort than the CAPM or three-factor models, with a highly significant HL alpha of 6.5%.[29]

[29]The Internet Appendix shows that including a momentum factor as in Fama and French (2018) has little effect on our results since momentum loadings on the PI-sorted portfolios are small. We thank Mihail Velikov for providing a report on the patent-intensity signal with additional sorting methodologies

Table 3 shows the full set of ten years of dynamics for returns as well as alphas according to the CAPM, FF3, and FF5 models, again considering the full sample (Panel A) and the sample beginning in 1963 (Panel B). The results are striking. In Panel A, the raw-return differences of the HL portfolio begin at about 7% annually, and slowly decline over the following decade, exceeding 3% annually every year but one, with statistical significance at least at the five percent level for the full decade. This basic result of large, persistent differences in returns is important. Many of the anomalies documented in prior literature are short-lived, giving the appearance that long-term discount rates are not very different across firms (Keloharju, Linnainmaa, and Nyberg, 2021).[30] In contrast, the patent intensity portfolios show statistically significant return differences for ten years following portfolio formation. Furthermore the magnitudes are economically important. Using the simple approximation of compounding average returns, cumulative ten-year discount rates for innovators versus non-innovators are approximately 320% versus 215%, nearly 1.5 times larger.

Cochrane (2011) makes the point that long-term effects on required returns should connect to persistent fundamentals. In the Internet Appendix, we show that patent-intensity sorts are considerably more persistent (i.e., exhibit less mean reversion in transition probabilities) than a comparable value-growth sort. Consistent with Arrow's intuition, innovation deeply connects to firm primitives and costs of capital, and patent intensity correspondingly captures long-lasting differences in both fundamentals and required returns.

The additional rows of Panel A show the effects of CAPM and FF3 risk adjustment. The CAPM does help to reconcile some of the return differences in the HL portfolio, reducing the magnitude as well as the statistical significance of persistence in the alpha to two years. The additional factors of the FF3 model do not provide much additional help, with magnitudes mostly the same or larger, and marginal statistical significance of the HL alpha extending to three years.

and benchmarks, following Novy-Marx and Velikov (2023) (https://sites.psu.edu/assayinganomalies/).

[30] Baba-Yara, Boons, and Tamoni (2024) provide evidence of variation across anomalies.

Panel B shows the shorter post-1963 sample, which enables use of the full set of FF5 factors. The raw return differences are comparable in magnitude to the full sample, although their statistical significance is less uniform. This shows the usefulness of having the longer sample to improve statistical power, while also reassuring that the raw return differences in the two samples are comparable. The CAPM and FF3 risk adjustments also have comparable effects to the full sample, showing two and three years of statistical significance respectively, with slighly larger magnitudes than the full sample. Adding investment and profitability with the FF5 factors not only increases the magnitudes and significance of alphas in the year following portfolio formation, as already shown in Table 2, but these effects are highly persistent. The negative alphas of the non-innovator portfolio are highly significant for ten years following portfolio formation, and the positive alphas of the high-PI portfolio are significant at the ten percent level in eight of ten years. The HL alpha is significant at the one percent level for all ten years, with magnitudes ranging from a high of 7.7% to a low of 3.5%. Thus, the FF5 model dramatically overestimates the realized long-term returns of non-innovators while persistently underestimating high-PI returns. In Section 4.1 we return to further explain why the traditional value, investment, and profitability factors do not help to explain the long-run returns of patent-intensity portfolios.

3.2. Reconciling the long-term: Expected growth and life-cycle

Our multiple-horizon return-based analysis provides direct observation of dynamics in returns, alphas, and risk loadings. In this subsection, we show a fundamentals-based factor model, the $q5$ model, that accurately captures the long-lived differences in patent-intensity portfolio returns. In order to reflect how patent-intensity realized returns evolve over time, the empirical model estimates dynamically changing risk loadings that capture key economic features of how innovation drives changes in expected growth, investment, and profitability.

We apply the $q5$ model to the full set of aged patent intensity portfolios, for the sample beginning in 1967. Table 4 shows the alphas for all portfolios. These are nearly all statistically indistinguishable from zero, with only one of sixty significant at the five percent level, and three additional at the ten percent level. The $q5$ model thus captures the realized returns of patent-intensity portfolios, whereas FF5 is inaccurate for a full decade following portfolio formation. Many studies of factor models combine information from hundreds of anomalies at shorter monthly or annual horizons, making economic interpretation of model distinctions difficult. A long-run perspective gives a different impression by focusing on persistent anomalies with the greatest potential to impact prices and real investment decisions (Cochrane, 2011, Binsbergen and Opp, 2019). Patent-intensity portfolios show highly significant and economically important long-run distinctions between the $q5$ and FF5 factor models, which are typically viewed as close competitors.

The $q5$ loading dynamics, shown in Table 5, are essential to the model's accurate reflection of expected return dynamics. These reveal a compelling economic story of innovative-firm dynamics. Loading differences on the market factor are initially larger for the high-PI portfolio than for non-innovators, with a difference of 0.16 that is statistically significant at the one percent level. This loading difference remains fairly stable for the full ten years, with statistical significance at the five percent level or better in every year. Considering size loadings, we expect these to gradually decline over time as firms mature. Non-innovator size loadings change gradually, while the decline for high-PI firms is much larger, consistent with their faster growth over the decade.

The key investment, profitability, and expected growth loading dynamics are shown in the remaining rows of Table 5. For investment, the non-innovator loading initially begins at 0.22 ($t = 5.21$) and modestly increases over the decade to become more "conservative". In contrast, the high-PI portfolio is initially neutral at -0.01 and statistically indistinguishable from zero, but goes in the opposite direction becoming "aggressive" over time. As a consequence, the HL investment loading begins at -0.24, insignificantly negative, but nearly triples over the decade to -0.73 ($t = -5.69$). Rather than differences converging over time to become more neutral, the investment loadings of the HL portfolio therefore diverge. For profitability, the non-innovator loadings are slightly positive and mostly stable over the decade, ranging from 0.06 to 0.10. The high-PI loadings are much more dynamic, beginning at a very negative level (-0.59, $t = -6.07$) and becoming less negative (more "robust") over time, more than halving by the end of the decade (-0.27, $t = -2.76$). Finally, the loadings on expected growth are modestly negative and statistically significant for non-innovators for the entire decade. The high-PI expected growth loadings are strongly positive initially with modest decline over time. These findings are displayed in plots in Figure 3 for the full range of patent-intensity portfolios. Taken together, these loadings on the market, size, investment, profitability, and expected growth factors drive a compelling economic story. High-intensity innovators develop growth options, which they take advantage of through investments in assets, gradually leading to improved profitability and larger size. All factors earn strong premia, and combine to capture the complex risk and return dynamics of innovative firms.

These dynamics are confirmed in Table 6, which shows differences of year 2-10 loadings relative to year 1. The key findings are the economically and statistically significant loading dynamics required to accurately price the high-PI portfolio: steady size increases, increasingly aggressive investment, improving profitability, and gradually diminishing expected growth.

A natural question is whether these changes in risk dynamics are also reflected in changes to firm fundamentals. Cochrane (1991) shows that realized investment returns, which approximate stock returns, should be roughly proportional to changes in investment.[31] Hou, Mo, Xue, and Zhang (2021) build on this insight in a cross-sectional setting. Using asset growth as a standard proxy for investment from the empirical asset pricing literature, they measure firm-level "expected growth" using fitted values from regressions of changes in asset growth, at horizons up to three years, on firm fundamentals.[32] We use their framework, but beyond asset growth, consider changes in

[31]See Cochrane (1991) p. 217.

[32]See Hou, Mo, Xue, and Zhang (2021) Section 3.1, pp. 7-11.

additional firm fundamentals including a different measure of investment, investment-to-assets (CAPX/PPENT), two profitability measures (ROE and ROA), sales growth, and employment growth. We evaluate forecasting horizons up to ten years, and in addition to the predictor variables used by HMXZ, add patent intensity as the primary predictor of interest.

Table 7 shows estimated coefficients on patent intensity for all forecasting horizons. For each of the fundamentals, patent intensity positively predicts improvements, and the magnitudes increase with the horizon K for at least several years. Specifically, high patent intensity predicts increases in rates of asset growth, investment, and profitability, as well as acceleration of employment and sales growth. Thus, these changes in fundamentals predicted by patent intensity are broadly consistent with the dynamics of risk loadings for patent-intensity portfolios shown previously in Tables 5 and 6.

The results of this subsection show how the concept of life-cycle, of widespread importance in both economics and finance, can connect to empirical asset pricing through the dynamics of fundamentals-based factor loadings, opening new lines of research. For example, innovation theories can be evaluated by seeking to match the persistent dynamics of returns, fundamentals, and risk loadings that we have documented. Additionally, time-varying risk loadings are necessary for conditional asset pricing to have meaningful effects,[33] and we have demonstrated economically large and statistically significant risk dynamics driven by the key economic fundamental of innovation. Finally, the $q5$ model directly connects to the concept of expected growth, originally distinguished from current growth and shown to have opposite return implications in Cochrane (1991).

[33] See, e.g., Jagannathan and Wang (1996), Lewellen and Nagel (2006), Boguth, Carlson, Fisher, and Simutin (2011), Choi (2013), Cederburg and O'Doherty (2016), and Chernov, Lochstoer, and Lundeby (2022).

4. Sources of Pricing Differences and Alternatives

This section traces the key difference between the FF5 and $q5$ models, which is that the traditional value, investment, and profitability factors do not apply equally to non-innovative versus innovative firms. In particular, the value, investment, and profitability anomalies are substantially weakened or reversed among portfolios of innovators. This causes persistent and highly significant FF3 and FF5 alphas even for the coarsest sort into patenters versus non-patenters. We then discuss alternative pricing approaches that incorporate innovation directly into traditional factors such as value, investment, or profitability. These approaches aim to accommodate the unique aspects of innovative firms in different ways, and we discuss their similarities and differences relative to expected growth.

4.1. Value, investment, and profitability

To better understand why the Fama-French models do not explain, and can even worsen the pricing of PI-sorted portfolios, we further examine the roles of the value, investment, and profitability anomalies. Our approach is to sort *within* the groups of all innovators ($PI > 0$ and three or more patents in last three years) and all non-innovators (all other firms) on the value, investment, and profitability characteristics. For each characteristic, we sort into quintiles in the direction that in prior literature produces a positive return spread (i.e., positively for B/M and profitability, and negatively for investment), and take the long-short portfolio as the difference between highest and lowest quintiles. We then ask whether the characteristics earn similar return spreads within the groups of innovators and non-innovators, and compare alphas after controlling for the FF5 factors.

Table 8 shows the results. For the B/M anomaly (Panel A), the return spread for non-innovators is positive, economically large, and highly statistically significant (7.15%, $t = 4.39$), while the return spread for innovators is considerably smaller (3.38%, $t = 1.8$). The difference in these average return spreads is large and statistically significant (non-innovator minus innovator HL difference equals 3.78, $t = 2.1$). These disparities in average returns are not explained by the Fama-French factors. Among non-innovators, value earns a significantly positive FF5 alpha, while "growth" (low B/M) shows a significantly negative alpha, combining to produce a large, significant alpha for the HL portfolio (5.54%, $t = 4.57$). In the final row of the panel, all of the FF5 loadings on the difference between non-innovator and innovator HL portfolios are negative, indicating stronger covariation with FF5 factors in the innovator HL portfolio than for the non-innovator HL portfolio, despite the larger return spread for non-innovators. As a consequence, the alpha difference in the HL portfolios is economically larger and more statistically significant (6.08%, $t = 3.52$) than the original return difference. Thus, the traditional value anomaly is much stronger among non-innovators than innovators, and FF5 risk adjustment does not capture these differences in value sorts across non-innovators and innovators.

Panels B and C show differences between non-innovators and innovators in the investment and profitability anomalies. For the investment anomaly (Panel B), the HL return spread for non-innovators is positive and statistically significant, indicating that lower investment predicts higher returns, which is the traditional finding in the literature. The HL return spread for innovators is also positive, but the magnitude is lower and not statistically significant. The difference in the HL return spreads for non-innovators and innovators cannot be statistically distinguished from zero. Controlling for the FF5 factors, however, the alpha difference becomes significantly positive (4.94%, $t = 2.74$), with a key contributor being the negative loading on investment. Specifically, innovators have a wider spread in investment loadings than non-innovators, but earn a lower return spread, contributing to the significantly positive alpha difference. Profitability sorts (Panel C) show a different but equally interesting contrast between the two groups. Non-innovators have the familiar positive HL return spread (5.25%, $t = 2.34$). To the contrary, among innovators the return spread is *negative* (-1.37%) although not significant. The HL return spread difference is both economically large and statistically significant (-6.62%, $t = -3.03$). Further, controlling for the FF5 factors the long-short alpha for non-innovators is close to zero and insignificant, but for innovators the long-short alpha is negative and significant (-5.04%, $t = -2.89$). The negative long-short alpha for innovators occurs in large part because profitability does not earn a positive return spread among innovators but the portfolio still covaries strongly with the profitability factor (HL loading equals 1.62, $t = 12.72$).

These findings explain the inability of the Fama-French factors to price portfolios related to innovation. Non-innovators earn strong positive return spreads after sorts that follow familiar patterns from aggregate data (i.e., we sort positively on B/M and profitablity and negatively on investment). Sorting in the same way within the subset of all innovators produces similar or stronger variation in factor loadings, but the associated return spreads for innovators are weaker or even in the opposite direction from traditional findings. As a consequence, benchmarking with value, investment, and profitability factors in the FF5 model drives a large wedge in the alphas of patent-intensity sorted portfolios, and more generally causes difficulties for the traditional Fama-French factors in pricing portfolio sorts related to innovation.

To further emphasize these findings, we carry out an even simpler sort, separating the entire group of innovators from the entire group of non-innovators. Table 9 shows average returns and alphas according to the CAPM, FF3, FF5, and $q5$ models for each of the two groups, as well as their difference, for ten years following portfolio formation. We use a sample period beginning in 1963 for all panels, except the $q5$ panel which begins in 1967.[34] In Panel A, returns of innovators are modestly higher than non-innovators for all ten years, about one percent annually, but the differences are not statistically significant. The CAPM alphas in Panel B are slightly negative for non-innovators and positive for innovators, in the latter case statistically significant for all $K > 1$. Most interestingly, the FF3 alphas in Panel C are significantly negative for non-innovators and positive for innovators in all years. These combine to produce HL alphas that exceed two percent every year for ten years, significant at the one-percent level at

[34] Results are similar for the sample beginning in 1926 in Panels A-C, as well as for the shorter post-1967 sample in Panels A-D.

every horizon, with virtually no decay. These alpha differences demonstrate persistent inability of FF3 to accurately capture the long-run realized returns of either innovators or non-innovators. The FF5 alphas (Panel D) are similar in economic magnitude, persistence, and statistical significance, again with minimal decay. In contrast, the $q5$ alphas (Panel E) are uniformly closer to zero and less significant. Thus, the simplest sorts into innovators versus non-innovators confirm the persistent inability of the FF3 and FF5 models to capture the long-run returns of portfolios related to innovation.

The results of this subsection help to explain the difficulty of capturing the long-run returns of innovators versus non-innovators using the traditional Fama-French factors. Sorts on B/M, investment, and profitability produce very different return spreads within groups of innovators and non-innovators, and these differences are not captured, or are even exacerbated, by controlling for exposures to the FF5 factors (Table 8). The FF3 model alone introduces persistent inaccuracies in matching the long-run returns of the broadest sort into innovators versus non-innovators (Table 9). The investment and profitability factors of the FF5 model create even larger persistent alphas for patent-intensity sorts, as demonstrated previously in Tables 2 and 3. Thus, the value, investment, and profitability anomalies have different implications for innovative versus non-innovative firms, and each contribute to the difficulties of the FF3 and FF5 models in accurately capturing the long-run returns of patent-intensity portfolios.

The empirical methods in this subsection have not relied on patent intensity, and are instead based upon the most basic sort into innovators versus non-innovators. The findings therefore help to generalize and more broadly explain prior findings of the inability of the Fama-French factors to price other innovation-related portfolios.[35]

[35]In the Internet Appendix, we show the long-run inability of the Fama-French factors to capture the returns of other innovation-related sorts, some of which have been shown at shorter horizons in prior literature.

4.2. Alternative approaches to pricing innovation

In this subsection, we explain alternative approaches to pricing innovative firms, and how these relate to our main results. The logic of the expected growth approach (Hou, Mo, Xue, and Zhang, 2021) is to replace the traditional value factor, which is largely subsumed by investment and profitability,[36] with a factor that captures the concept of expected growth developed in Cochrane (1991). The traditional investment and profitability factors capture static aspects of firm valuation, as emphasized in Fama and French (2015) and Hou, Xue, and Zhang (2015), while expected growth reflects anticipated future changes. The primary alternative approaches that have been considered in the literature are to instead modify one or more of the traditional value, investment, and profitability factors. For example, building on Eisfeldt and Papanikolaou (2013), Eisfeldt, Kim, and Papanikolaou (2022) create an "intangible value" factor based on including intangibles in a modified B/M ratio, and Ball, Gerakos, Linnainmaa, and Nikolaev (2016) measure profitability based on cash-based profitability.[37] We first make a clarifying point about the relation between the different pricing approaches, and then discuss how they relate to our central point about the long-run returns and life-cycle risk dynamics of technological innovators.

To better understand what drives the ability to price patent-intensity portfolios, we first focus on cash-based profitability, introduced by Ball, Gerakos, Linnainmaa, and Nikolaev (2016) in a general study, and applied to portfolios of innovators in Goyal and Wahal (2024). We define cash-based operating profitability (CP/BE) as revenue minus cost-of-goods-sold, minus selling, general, and administrative expense, minus accruals, all scaled by book equity.[38] The most important difference of this definition of cash

[36]Fama and French (2015) state in their abstract (p. 1), "With the addition of profitability and investment factors, the value factor of the FF three-factor model becomes redundant for describing average returns in the sample we examine." Hou, Xue, and Zhang (2015) similarly show that their $q4$ model which includes investment and profitability factors but not a value factor prices value-growth portfolios as well as models that do include a value factor.

[37]See also Gulen, Li, Peters, and Zekhnini (2024) and Goyal and Wahal (2024).

[38]Ball, Gerakos, Linnainmaa, and Nikolaev (2016) scale by book value of assets, whereas Goyal and Wahal (2024) follow the Fama-French approach of scaling operating profitability by book equity, which we also follow.

profitability relative to the Fama-French definition of operating profitability is deducting accruals, or non-cash expenses, from profitability.[39] This key difference between cash profitability and operating profitability aligns with accruals being the distinguishing feature of cash profitability. However, there is another essential difference in how both Ball, Gerakos, Linnainmaa, and Nikolaev (2016) and Goyal and Wahal (2024) define cash profitability, which is that they do not include R&D in expenses, effectively adding back R&D to their cash profitability measures. Fama and French (2018) draw specific attention to this difference in treatment of R&D.[40] We want to understand the distinct roles of 1) accruals and 2) treatment of R&D, in pricing patent-intensity portfolios. We therefore carry out factor regressions using CP/BE as defined above, which only deducts accruals, and an additional version that adds back R&D expense, as in Ball, Gerakos, Linnainmaa, and Nikolaev (2016) and Goyal and Wahal (2024). In both cases, we follow the Fama-French procedures for forming factors, but replace their operating profitability measure with either cash-profitability (CP/BE) or an analogous version that adds back R&D expenses in the numerator(CP+R&D).[41]

Table 10 shows results, revealing that the treatment of R&D plays a crucial role. Panel A is based on cash-profitability (CP/BE), which only subtracts accruals from operating profitability. This reduces alphas somewhat relative to Table 2, but the HL portfolio that is long high-patent intensity firms and short non-innovators still has an alpha of approximately 4.5% annually, significant at the five-percent level. Panel B shows results when R&D expenses are added back to create CP+R&D.[42] In this case, all portfolio alphas are statistically indistinguishable from zero. The decisive element is therefore the treatment of R&D. Adjusting for accruals alone does not cause the

[39]Another minor difference is that Fama and French subtract interest expense from operating profitability, which has small effects, and our approach of not deducting interest expense follows Ball, Gerakos, Linnainmaa, and Nikolaev (2016) and Goyal and Wahal (2024).

[40]They write, "In previous drafts, we follow Ball et al. (2016) and measure operating and cash profitability before research and development (R&D) expense. This is equivalent to treating R&D as an infinitely lived asset (which means it should be added to investment). Here, we follow the Financial Accounting Standards Board and measure profitability net of R&D." (page 237).

[41]The definition of accruals and the factor construction (equivalent to 3×2 sorts by profitability and size as in FF5) are in appendix A.1.

[42]We take the simplest approach of assuming that missing R&D values are zero.

factor model to accurately capture the returns of patent-intensity portfolios, while the inclusion or exclusion of R&D expense plays an essential role. We see this result as natural, since R&D and patenting are highly correlated, and directly incorporating some measure of innovation into one or more factors should help to realign the pricing of innovative firms.

The prior comparison facilitates discussion of the mechanical and economic relationships between the expected growth and cash-based profitability approaches. As discussed by HMXZ, the construction of the expected growth factor uses cash-based profitability as one of three forecasting variables for expected growth, so the treatment of R&D embedded in cash-based profitability is also included in the expected growth factor.[43] Despite this mechanical relationship, there is also a more meaningful economic relationship. Cash-based profitability, due to its treatment of R&D, is a strong forecaster of expected growth as previously shown by HMXZ. Further, the broad economic idea that innovation predicts improvements in growth is also consistent with our findings for patent intensity in Table 7. Thus, despite expected growth and cash-based profitability having very different initial motivations, in production-based asset pricing versus accounting respectively, the two approaches are connected, both mechanically and economically.

Despite their strong connection, the expected growth and cash-based profitability approaches do have practical differences in implementation, which can be traced to their different motivations, and therefore their decompositions of risk. In Table 10 Panel A, which subtracts accruals but does not add back R&D expenses, the cash profitability loadings monotonically decline with patent-intensity. This pattern is consistent with both the FF5 loadings in Table 2 and the $q5$ loadings in Table 5 and Figure 3, which all show profitability loadings declining with patent intensity. This pattern of low profitability associated with patent intensity is also consistent with standard measures of profitability (Table 1) as well as both life-cycle theory and empirical evidence that high-PI firms are those without established, profitable product markets, but which have

[43]Goyal and Wahal (2024) also emphasize this point.

an objective to develop innovations that can drive future valuations. The CP+R&D loadings in Table 10, Panel B show a very different pattern, as they increase with patent intensity. This occurs because the profitability measures in Panel B add back R&D expenses, and R&D activity and patenting are highly correlated. Since R&D is more or less a direct measure of investments in innovation, the profitability loadings in Panel B add together two effects: traditional profitability, which is negatively related to patent intensity, and R&D, which is positively related to patent intensity. The profitability loadings estimated in Panel B net these two effects out, showing neither individually, but only the sum. In contrast, the $q5$ loadings from Table 5 provide these effects separately through negative profitability loadings, but very strong positive loadings on expected growth, which is associated with innovation.

These differences between the expected growth and cash-based profitability approaches carry over to risk dynamics. Table 11 shows loading dynamics of patent-intensity portfolios for the five-factor specification with cash profitability plus R&D. Most notably, the HL loadings on CP+R&D are more or less stable over the decade. From prior tables, we know that the traditional profitability loadings are negative but increase over time, whereas the R&D component, which is related to expected growth, is initially positive but declines over time. These two effects cancel out leading to the stable CP+R&D exposures. The CP+R&D formulation thus masks within a single factor an important aspect of life cycle. As exposures to innovation (R&D, or alternately expected growth in the $q5$ model) decline, covariance with traditional profitability improves.[44] Thus, both approaches can effectively price patent-intensity portfolios over time, but the differences in their decompositions of risk give different views of firm dynamics.

Fama and French (2018) raise a related critique, which is the desirability of an internally consistent framework of factors. Their central point is that if R&D is not

[44]The value and investment loadings in Table 11 do change over time, but the economic interpretation is more limited. Most notably, the value loadings of the HL portfolio decrease, indicating improving valuation (higher M/B). However, the impetus for these dynamics in value loadings is difficult to associate with innovation, because R&D is only one component within cash profitability.

included in expenses, as occurs if it is added back to profitability, then it should appear as an asset, with corresponding impacts on the investment and value factors.[45] In line with the thinking that innovation can appear in different factors, Eisfeldt, Kim, and Papanikolaou (2022) propose a five-factor model that replaces the traditional value factor with a measure of value that includes intangibles.[46] Gulen, Li, Peters, and Zekhnini (2024) build on and help to unify these approaches by creating an internally consistent treatment of intangibles within a complete factor model. This produces a seven-factor framework, where intangible expenses are added back to profitability, as with the treatment of R&D in the cash-based profitability approach of Ball, Gerakos, Linnainmaa, and Nikolaev (2016), and two new factors are added in order to distinguish between tangible and intangible versions of value and investment.

Table 12 shows the dynamics of PI alphas and risk for this seven-factor specification. The model is effective in capturing realized returns, with only two of sixty alphas significant at the five-percent level, and an additional four significant at the ten-percent level. The risk loadings also show some interesting dynamics. While there is some noisiness in the factor loadings from year to year, likely due to more challenging identification in a seven-factor model, we do see some clear patterns. First, off-balance-sheet investment is at first very negative (aggressive) while the traditional CMA loading is very positive (conservative), and both revert towards neutral over time. For value, the off-balance-sheet loading begins at a very positive level (value), while the traditional loading begins at a very negative loading (growth), and both decline over time indicating improving valuations (i.e., lower B/M). The seven-factor model thus accurately captures long-run returns of patent-intensity portfolios, while risk dynamics display a strong initial tilt towards intangibles that decays over time.

This subsection has shown two additional approaches that accurately capture the long-run returns of patent-intensity portfolios, and explains how these findings relate to our central results. Cash-based profitability as defined by (Ball, Gerakos, Linnainmaa,

[45] See their page 237.

[46] In untabulated results, we find that while this approach leaves significant alphas in patent intensity portfolios.

and Nikolaev, 2016) differs from traditional measures of profitability by subtracting accruals and by adding back R&D expenses. We show that adding back R&D expenses plays a central role in the accurate pricing of patent-intensity portfolios, and discuss how this adjustment of profitability is mechanically and economically related to the incorporation of expected growth in the $q5$ model. Gulen, Li, Peters, and Zekhnini (2024) develop a seven-factor model, motivated by providing an internally consistent framework that incorporates tangible and intangible assets in value, investment, and profitability factors. Consistent with theories of heterogeneous innovation, high-PI firms innovate intensively and lack valuable assets in place, producing strong life-cycle risk dynamics. The three approaches – $q5$ model, cash-based profitability adjustment, and seven-factor intangible assets model – provide different perspectives on these risk dynamics.

5. Conclusion

We propose that patent intensity, patents granted divided by market capitalization, relates to theories of investment heterogeneity (Akcigit and Kerr, 2018). High-PI portfolios concentrate innovative activity by firms that do not have valuable assets-in-place, and these portfolios possess strong life-cycle dynamics in their characteristics. Patent intensity also produces strong variation in long-run returns that is not captured by standard fundamentals-based factor models. We find large alphas that are highly significant for a decade following portfolio formation, but are resolved by the $q5$ model based on expected growth, as well as related approaches that capture intangibles in factors.

We more broadly explain the inability of traditional factor models to capture portfolios sorts related to innovation. Using the coarsest classification into patenters and non-patenters, each representing significant proportions of market capitalization, we show much weaker or reversed return spreads for value, investment, and profitability among innovators versus non-innovators. As a consequence, this basic sort produces significant FF3 and FF5 alphas that persist for ten years with virtually no decay; innovator alphas are persistently positive, while non-innovator alphas are persistently negative. Expected growth again resolves these difficulties, with alphas moving toward zero and becoming less significant.

Recent literature emphasizes the potential of a long-run perspective to discipline the factor zoo (e.g., Cochrane, 2011). We show that patent-intensity portfolios and more broadly the basic sorts into innovators versus non-innovators generate clear long-run distinctions between factor models. Further, accurately capturing the returns of patent-intensity portfolios requires strong dynamics in factor loadings. We find large but declining loadings on expected growth, increasing investment, and improving profitability. In future work, these life-cycle dynamics can be used to guide and calibrate production-based theories that incorporate innovation.

A. Appendix

Variable definitions

CRSP age: calculated from the stock's first appearance in CRSP.

Investment: total assets (Compustat item AT) for the fiscal year ending in $t-1$, divided by total assets for fiscal year ending in $t-2$ minus one.

Profitability: total revenue (REVT) minus cost of goods sold (COGS, zero if missing), minus selling general and administrative expenses (XSGA, zero if missing), minus interest expense (XINT, zero if missing), divided by book equity, all for fiscal year ending in $t-1$. We require at least one of COGS, XSGA, and XINT to be non-missing. Book equity is stockholders' book equity plus deferred taxes and investment credits (TXDITC), if available, minus book equity of preferred stock. Stockholders' equity is Compustat item SEQ, if available. If not, we use book value of common equity (CEQ) plus value of preferred stocks (PSTK). Otherwise, we use the book value of total assets (AT) minus book value of total liabilities (LT). For the value of preferred stocks, we use redemption (PSTKRV), liquidating (PSTKL), or par value (PSTK) depending on availability and in this order.

BM: book-to-market ratio with book equity from fiscal year ending in year $t-1$ divided by the firm market capitalization from the end of December $t-1$. Book equity is as in Profitability, but we further complement it with historical book-equity data from Davis, Fama, and French (2000) to allow time series back to 1926.

PPE: property, plant and equipment.

Intangibles: defined in Compustat as "item consists almost exclusively of the excess of cost over equity acquired in assets of purchased subsidiaries which are still unamortized or not eliminated by a direct charge to a capital account", i.e., intangibles recognized through acquisitions.

ROA: net income (IB) divided by total assets (AT).

Sales growth: $Sale_t/Sale_{t-1} - 1$.

Market beta: CAPM beta estimated at the end of June year t by regressing a stock's monthly excess returns on market excess returns and a constant, using returns over the last 60 months, requiring a minimum of 36 months.

$CAPX_t/PPENT_{t-1}$: based on the respective variables from Compustat.

A.1. Definitions of profitability factors.

The operating profitability (OP/BE) is defined as revenue (Compustat item revt) minus cost of goods sold (cogs) minus selling, general and administrative expensess (xsga), all divided by book equity in the same year.

The operating profitability plus R&D ((OP+R&D)/BE) is similar as operating profitability OP/BE, but it substracts R&D expense from the selling, general and administrative expense (xsga-xrd), i.e., it adds it back to the numerator of OP/BE: $(OP + R\&D)/BE = OP/BE + \frac{R\&D}{BE}$.

The cash-based operating profitability (CP/BE) adjusts the operating profitability (OP/BE) for accruals. This "cash correction" is the one-year difference in receivables (rect), inventories (invt) and prepaid expenses (xpp) minus the one year difference in current deferred revenue (drc), long-term deferred revenue (drlt), accounts payable (ap) and accrued expenses (xacc). The cash-based operating profitability is then $CP/BE = OP/BE + \frac{\Delta[rect+invt+xpp]-\Delta[drc+drlt+ap+xacc]}{BE}$.

The cash-based operating profitability plus R&D ((CP+R&D)/BE) is cash-based operating profitability with R&D expense added back: $(CP + R\&D)/BE = CP/BE + \frac{R\&D}{BE}$.

The book equity is defined above, and we use only stocks with positive book equity. The profitability factors are constructed from sorting firms independently into three portfolios by the selected profitability measure based on 30^{th} and 70^{th} percentile and two portfolios sorted by size (market capitalization) based on 50^{th} percentile breakpoint. The breakpoints are calculated from stocks listed on NYSE only. From these two sorts, we construct six underlying value-weighted portfolios: LowSmall, MediumSmall, HighSmall, LowBig, MediumBig, HighBig (ProfitabilitySize). The profitability factor is: $\frac{1}{2}(HighSmall\ +\ HighBig) - \frac{1}{2}(LowSmall\ +\ LowBig)$.

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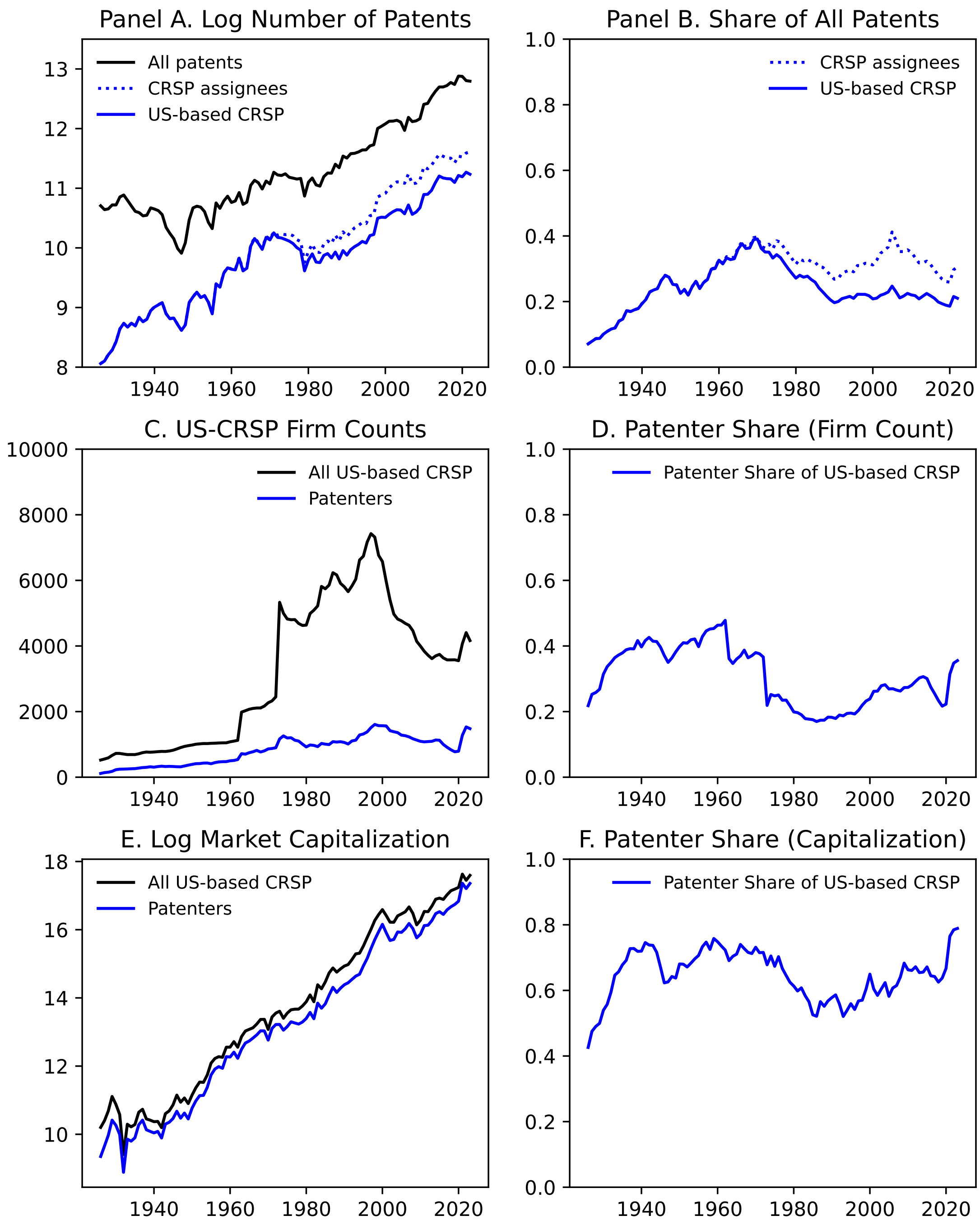

Figure 1: Patenting and Public Firms. Panel A shows the log number of patents per calendar year of patent assignees (all, CRSP, and US-based CRSP). CRSP assignee is any CRSP firm assigned a patent in current year, and US-based CRSP assignees are US-incorporated firms with common stock (shrcd 10 or 11). Panel B shows the patent shares of CRSP assignees and US-based CRSP assignees. Panel C shows the count of all US-based CRSP firms (shrcd 10 or 11) and the subset of technological innovators, which are firms with at least one patent in a given year, using June year-ends. Panel D shows the technological innovators' share of US-based CRSP firms by firm count. Panel E plots the log market capitalization of all US-based CRSP firms and the technological innovator subsample. Panel F shows the technological innovators' market capitalization share relative to all US-based CRSP firms. All stocks or firms refer to firms traded on NYSE, NASDAQ or AMEX.

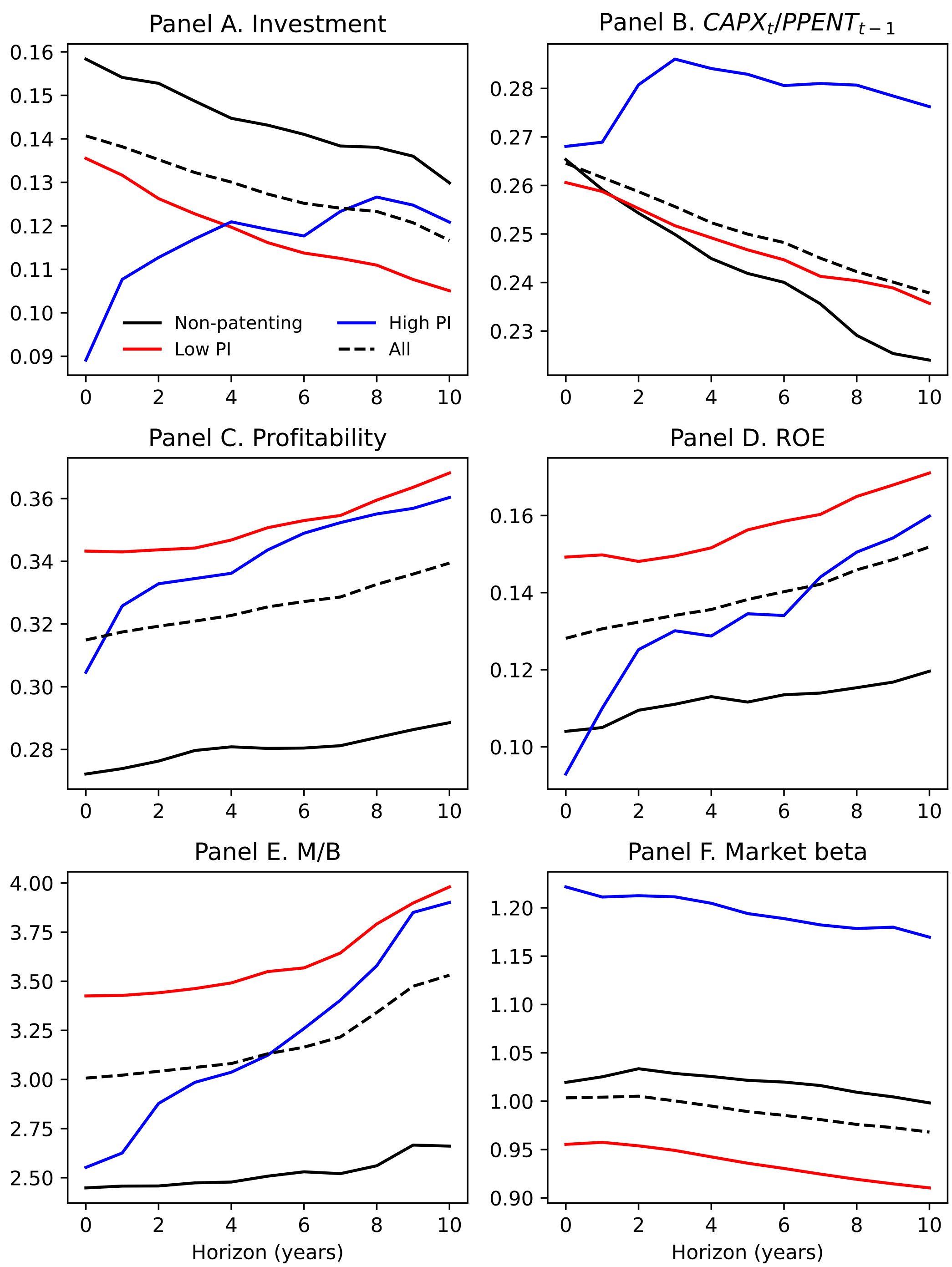

Figure 2: Dynamics of Patent-Intensity Portfolio Characteristics. This figure shows dynamics of variables indicated in the panel headings for aged PI-sorted portfolios. Characteristic and market-beta definitions are given in the Appendix. Characteristics are measured by the calendar year of their fiscal year-end, allocated to portfolios formed the following June, and market betas are measured at the end of June. Firms are initially sorted every year at the end of June into three portfolios. The first consists of non-patenting firms (PI=0). Remaining firms are split equally into two portfolios, low- and high-PI. The stocks are held in the portfolios over horizon of 10 years. Portfolio formation begins in 1963 and ends ten years before the end of our sample. For all portfolios, we first calculate the annual value-weighted average at the specified horizon and then average across years. The dotted line shows value-weighted statistics for all firms.

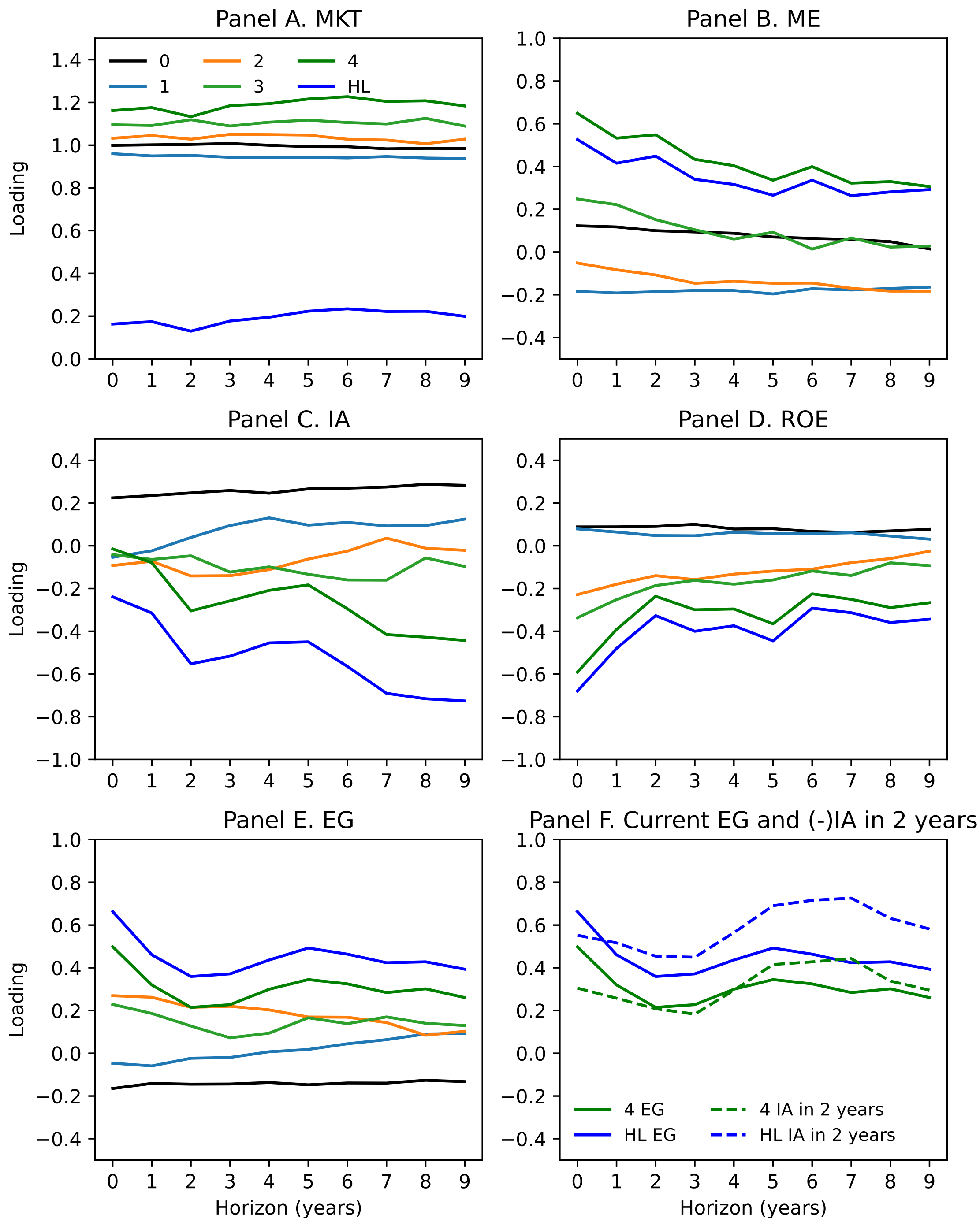

Figure 3: Aged Patent-Intensity Portfolios, $q5$ Loading Dynamics. The figure shows dynamics of $q5$ loadings for aged PI-sorted portfolios, as indicated in headings of panels A-E. Panel F shows HL and high-PI expected growth (EG) loadings overlaid with (negative) investment (IA) loadings two years ahead. The investment loadings are plotted negatively to facilitate comparison. Portfolio construction follows the description in Section 3 and the aged portfolios are value-weighted and rebalanced monthly. The sample begins in 1967 to accommodate availability of the $q5$ factors.

Table 1: Patent Intensity (PI) and Firm Characteristics. This table shows characteristics of firms sorted on patent intensity. Non-patenting firms have PI=0, and the remaining firms are split into two equal groups by firm count. Panel A shows portfolio shares of each variable as indicated. Citations are based on 5-year forward citations adjusted for technology section and year of grant. Breakthrough patents are based on the text-based measure of Kelly, Papanikolaou, Seru, and Taddy (2021), indicating the top ten percent by category. Top 10% and 1% indicators are based on 5-year forward adjusted citations. The data starts from 1926, except for citation-based shares, which start from 1947 due to data availability. Panel B shows the mean and median firm characteristics, exit probabilities and asset types. The firms characteristics are defined in the Appendix and start from 1963 except for CRSP age and BM, which start from 1926. Exit probabilities start from 1926, and asset types start from 1963. For all numbers, we first calculate the annual percentages (or mean and median as indicated) and then average across years from beginning of the data to 2023.

Panel A. Portfolio shares of (columns sum to 1)			
	Non-patenting	Low PI	High PI
Firms	0.681	0.16	0.159
Market capitalization	0.346	0.541	0.113
Patents		0.374	0.626
Patents (next year)	0.012	0.391	0.597
Patents (next 3 years)	0.016	0.405	0.58
Patents (next 5 years)	0.019	0.417	0.564
Citations		0.4	0.6
Breakthrough patents (KPST)		0.414	0.586
Patents in top 10%		0.416	0.584
Patents in top 1%		0.44	0.56

Panel B. Firm characteristics						
	Non-patenting		Low PI		High PI	
	Mean	Median	Mean	Median	Mean	Median
CRSP age	13.434	11.757	20.419	17.763	15.497	12.994
BM	1.574	1.000	0.797	0.657	1.136	0.911
Investment	0.129	0.069	0.157	0.087	0.077	0.036
CAPX/PPE	0.318	0.202	0.316	0.224	0.302	0.210
Profitability	0.143	0.204	0.233	0.253	0.020	0.138
Return on equity	-0.030	0.086	0.062	0.114	-0.151	0.026
Exit probabilities						
Exits in 1 year	0.055		0.026		0.041	
Exits in 5 years	0.268		0.161		0.218	
Asset composition (share of total assets)						
PPE	0.297	0.279	0.290	0.324	0.231	0.252
Intangibles	0.073	0.048	0.105	0.052	0.073	0.042
Current assets	0.513	0.519	0.517	0.520	0.625	0.625
Cash	0.131	0.131	0.160	0.142	0.210	0.172

Table 2: Patent-Intensity Sorts and Performance, Fama-French Factors. The table shows the average excess returns of PI-sorted portfolios in Panel A and regressions of excess portfolio returns (in excess of the risk-free rate) on a constant and market excess returns (Panel B), the Fama-French three factors (Panel C), and the Fama-French five factors (Panel D). Portfolio 0 consists of non-patenting firms and the remaining portfolios are sorted by PI annually into equal groups by firm count. HL is a zero-cost portfolio, long the highest-numbered portfolio and short portfolio 0. Stocks are sorted at the end of June. The time period of each panel is indicated in the headings. In this and remanining tables (unless stated differently), the portfolios are value-weighted, rebalanced monthly. The underlying portfolio returns are at monthly frequency, and the estimates of the average excess returns and constants (alphas) are annualized by multiplying by twelve. t-statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses and the standard errors in brackets. */**/*** indicate significance level at 10, 5, and 1%, respectively. Significance stars are omitted for the average excess returns and the Mkt-RF loadings of the long portfolios.

	1926-2023				1963-2023					
	0	1	2	HL	0	1	2	3	4	HL
Panel A. Excess returns										
Ex. ret.	7.58	8.35	11.64	4.06***	6.49	6.21	8.5	9.37	13.18	6.69***
	(3.79)	(4.41)	(4.73)	(3.81)	(2.94)	(3.18)	(3.88)	(3.77)	(4.02)	(3.32)
Panel B. CAPM										
Constant	-0.5	0.55*	1.85**	2.35**	-0.32	-0.1	1.63**	1.62	4.66**	4.98**
	(-1.03)	(1.78)	(2.31)	(2.4)	(-0.47)	(-0.2)	(2.43)	(1.57)	(2.49)	(2.56)
Mkt-RF	1.0	0.96	1.21	0.21***	1.01	0.93	1.01	1.14	1.26	0.25***
	[0.01]	[0.01]	[0.03]	(7.75)	[0.02]	[0.01]	[0.02]	[0.03]	[0.05]	(5.45)
R^2	0.95	0.97	0.89	0.14	0.93	0.94	0.90	0.82	0.67	0.07
Panel C. Fama-French 1993										
Constant	-0.97**	0.83***	1.5*	2.46**	-1.37***	0.51	1.95***	1.28	3.57**	4.94**
	(-2.35)	(3.2)	(1.89)	(2.47)	(-2.8)	(1.24)	(2.87)	(1.24)	(2.11)	(2.56)
Mkt-RF	0.96	0.99	1.15	0.19***	1.02	0.96	1.01	1.09	1.13	0.11*
	[0.01]	[0.01]	[0.03]	(5.9)	[0.01]	[0.01]	[0.02]	[0.03]	[0.05]	(1.88)
SMB	0.08***	-0.12***	0.26***	0.18*	0.1**	-0.19***	-0.01	0.31***	0.72***	0.62***
	(2.58)	(-9.39)	(3.62)	(1.82)	(2.31)	(-15.2)	(-0.4)	(3.61)	(5.78)	(3.82)
HML	0.14***	-0.07***	0.06	-0.09	0.23***	-0.11***	-0.07**	0.02	0.11*	-0.11
	(6.07)	(-5.0)	(1.21)	(-1.44)	(8.13)	(-5.71)	(-2.39)	(0.37)	(1.82)	(-1.46)
R^2	0.96	0.98	0.90	0.18	0.95	0.96	0.90	0.85	0.76	0.24
Panel D. Fama-French 2015										
Constant					-1.73***	0.32	2.26***	2.02*	4.78***	6.51***
					(-3.46)	(0.74)	(3.3)	(1.94)	(2.8)	(3.31)
Mkt-RF					1.01	0.96	1.01	1.09	1.14	0.13**
					[0.01]	[0.01]	[0.02]	[0.03]	[0.04]	(2.45)
SMB					0.14***	-0.18***	-0.06*	0.23***	0.6***	0.46***
					(5.43)	(-13.81)	(-1.84)	(3.95)	(7.67)	(4.79)
HML					0.22***	-0.08***	-0.09**	-0.09	-0.1	-0.31***
					(6.55)	(-3.58)	(-2.26)	(-1.33)	(-1.07)	(-2.78)
CMA					-0.03	0.0	0.06	0.16*	0.26*	0.3*
					(-0.82)	(0.13)	(1.16)	(1.8)	(1.89)	(1.83)
RMW					0.11***	0.04*	-0.11***	-0.26***	-0.42***	-0.53***
					(2.84)	(1.9)	(-3.18)	(-3.27)	(-2.9)	(-3.09)
R^2					0.96	0.96	0.90	0.86	0.78	0.30

Table 3: Patent Intensity Long-run Returns and Alphas, Fama-French Factors. The table shows average excess and abnormal returns (alphas) of aged PI-sorted portfolios. At the end of June of year t, stocks are sorted into five K-aged portfolios based on the patent-intensity sort from the end of June of year $t-K$. All portfolios are rebalanced monthly based on market capitalization at the end of the prior month. The sample period begins in 1926 in Panel A and in 1963 in Panel B and ends in 2023 for both panels. Portfolio 0 consists of non-patenting firms and the remaining portfolios are sorted by PI. HL is a zero-cost portfolio with a long position in portfolio 4 and a short position in portfolio 0. Portfolios 1-3 are not shown for brevity. The first two columns indicate the portfolio and, if applicable, the benchmark model for alphas. The estimates of the average excess returns and constants (alphas) are annualized by multiplying by twelve. t-statistics from Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses. */**/*** indicate significance level at 10, 5, and 1%. Significance stars are omitted for the average excess returns of the long portfolios.

		Horizon (K years)									
Portfolio	Model	1	2	3	4	5	6	7	8	9	10
Panel A. 1926-											
		Excess returns									
0		7.58	7.55	7.56	7.09	7.56	7.66	8.98	7.93	7.95	7.84
		(3.79)	(3.74)	(3.72)	(3.5)	(3.74)	(3.8)	(4.49)	(4.42)	(4.46)	(4.4)
4		14.61	14.51	12.24	10.26	10.34	11.49	13.78	11.59	11.89	11.45
		(4.79)	(4.86)	(4.25)	(3.49)	(3.67)	(3.97)	(4.76)	(4.44)	(4.5)	(4.44)
HL		7.02***	6.96***	4.68***	3.17**	2.78**	3.83***	4.8***	3.66**	3.95**	3.6**
		(4.34)	(4.36)	(3.08)	(2.08)	(1.96)	(2.67)	(3.2)	(2.41)	(2.51)	(2.28)
		Alphas									
HL	CAPM	3.92***	3.97***	2.1	0.57	0.25	0.89	1.46	0.68	0.98	0.94
		(2.86)	(2.72)	(1.46)	(0.41)	(0.19)	(0.69)	(1.06)	(0.46)	(0.64)	(0.59)
HL	FF3	3.44**	3.8***	2.33*	0.78	0.41	1.01	2.06	1.77	2.37	2.63*
		(2.54)	(2.76)	(1.73)	(0.59)	(0.32)	(0.81)	(1.56)	(1.26)	(1.64)	(1.75)
Panel B. 1963-											
		Excess returns									
0		6.49	6.51	6.62	6.37	6.45	6.24	6.29	6.51	6.31	6.18
		(2.94)	(2.97)	(3.03)	(2.94)	(3.0)	(2.91)	(2.94)	(3.07)	(3.02)	(2.96)
4		13.18	13.61	11.3	9.26	9.1	9.44	10.48	10.39	10.07	10.38
		(4.02)	(4.23)	(3.69)	(2.99)	(3.02)	(3.09)	(3.31)	(3.26)	(3.15)	(3.24)
HL		6.69***	7.11***	4.67**	2.89	2.66	3.19*	4.19**	3.87*	3.75*	4.2*
		(3.32)	(3.5)	(2.4)	(1.52)	(1.49)	(1.83)	(2.21)	(1.9)	(1.79)	(1.94)
		Alphas									
HL	CAPM	4.98**	5.29***	2.86	0.88	0.73	1.15	1.95	1.61	1.41	1.96
		(2.56)	(2.58)	(1.41)	(0.45)	(0.4)	(0.67)	(1.06)	(0.79)	(0.68)	(0.91)
HL	FF3	4.94**	5.89***	4.04**	2.01	1.72	2.35	3.4*	3.41*	3.24*	3.84**
		(2.56)	(3.21)	(2.29)	(1.15)	(1.04)	(1.43)	(1.95)	(1.82)	(1.7)	(1.98)
0	FF5	-1.73***	-1.76***	-1.71***	-1.95***	-1.7***	-1.83***	-1.75***	-1.49***	-1.58***	-1.66***
		(-3.46)	(-3.65)	(-3.45)	(-3.98)	(-3.46)	(-3.74)	(-3.6)	(-3.08)	(-3.27)	(-3.34)
4		4.78***	5.9***	4.39***	2.3*	1.76	2.06	3.27**	3.73**	3.52**	4.2**
		(2.8)	(3.66)	(2.78)	(1.66)	(1.35)	(1.57)	(2.26)	(2.23)	(2.11)	(2.49)
HL		6.51***	7.67***	6.09***	4.24***	3.46**	3.88**	5.02***	5.22***	5.09***	5.86***
		(3.31)	(4.22)	(3.38)	(2.62)	(2.21)	(2.52)	(2.97)	(2.69)	(2.63)	(2.95)

Table 4: Patent Intensity Long-run Alphas, $q5$ Factors. The table shows the abnormal returns (alphas) relative to $q5$-factor model (Hou, Mo, Xue, and Zhang, 2021) of PI-sorted portfolios (indicated in rows) for holding period of one-year at different investment horizons (indicated in columns). Details of the portfolio construction and investment horizons are described in the Table 3 notes. The sample period begins in 1967, to accommodate the q-factors, and ends in 2023. The estimates of the alphas are annualized by multiplying by twelve. t-statistics from Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses. */**/*** indicate significance level at 10, 5, and 1%.

	Horizon (K years)									
	1	2	3	4	5	6	7	8	9	10
0	-0.65	-0.86	-0.73	-1.11**	-0.84	-0.96*	-0.9	-0.58	-1.01*	-1.0*
	(-1.18)	(-1.49)	(-1.28)	(-2.0)	(-1.51)	(-1.76)	(-1.61)	(-1.04)	(-1.82)	(-1.7)
1	0.5	0.56	0.48	0.2	-0.37	0.14	0.03	-0.52	-0.63	-0.28
	(1.05)	(1.11)	(0.97)	(0.38)	(-0.69)	(0.24)	(0.06)	(-0.97)	(-1.1)	(-0.51)
2	0.75	0.88	0.37	0.79	0.51	0.18	0.2	0.12	1.2	0.34
	(1.06)	(1.16)	(0.51)	(0.97)	(0.69)	(0.22)	(0.29)	(0.17)	(1.58)	(0.46)
3	1.29	0.47	0.34	1.05	1.43	0.9	1.05	0.95	-0.37	0.16
	(1.08)	(0.4)	(0.31)	(0.91)	(1.29)	(0.79)	(0.92)	(0.98)	(-0.37)	(0.16)
4	1.94	3.47	2.5	0.44	-0.69	-0.45	0.27	1.68	1.48	2.41
	(1.23)	(1.49)	(1.13)	(0.28)	(-0.46)	(-0.31)	(0.16)	(0.93)	(0.81)	(1.3)
HL	2.59	4.32	3.24	1.55	0.15	0.52	1.17	2.26	2.49	3.41
	(1.41)	(1.62)	(1.28)	(0.82)	(0.08)	(0.31)	(0.62)	(1.08)	(1.17)	(1.56)

Table 5: Patent Intensity Risk Dynamics, $q5$ Factors. The table shows the loadings on the $q5$ model's factors of PI-sorted portfolios (indicated in rows) for holding period of one-year at different investment horizons (indicated in columns). Details of the portfolio construction and investment horizons are described in the Table 3 notes. Portfolios 1-3 are not shown for brevity. The sample period begins in 1967, to accommodate the q-factors, and ends in 2023. t-statistics from Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses and the standard errors in brackets. */**/*** indicate significance level at 10, 5, and 1%. Significance stars are omitted for the Market (MKT) loadings of the long portfolios.

	Horizon (K years)									
	1	2	3	4	5	6	7	8	9	10
Market (MKT)										
0	1.0	1.0	1.0	1.01	1.0	0.99	0.99	0.98	0.99	0.98
	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]
4	1.16	1.18	1.13	1.18	1.19	1.22	1.23	1.2	1.21	1.18
	[0.05]	[0.03]	[0.05]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.05]	[0.05]
HL	0.16***	0.17***	0.13**	0.18***	0.19***	0.22***	0.23***	0.22***	0.22***	0.2***
	(2.87)	(4.05)	(2.31)	(3.59)	(3.98)	(4.28)	(4.56)	(4.04)	(3.92)	(3.15)
Size (ME)										
0	0.12**	0.12**	0.1*	0.09*	0.09*	0.07*	0.06	0.06	0.05	0.01
	(2.38)	(2.37)	(1.95)	(1.91)	(1.91)	(1.68)	(1.29)	(1.32)	(1.19)	(0.32)
4	0.65***	0.53***	0.55***	0.43***	0.4***	0.34***	0.4***	0.32***	0.33***	0.31***
	(5.2)	(6.16)	(4.51)	(4.86)	(5.35)	(3.9)	(4.24)	(3.08)	(3.29)	(2.93)
HL	0.53***	0.42***	0.45***	0.34***	0.32***	0.27**	0.34**	0.26*	0.28**	0.29**
	(3.08)	(3.26)	(2.69)	(2.61)	(2.88)	(2.19)	(2.47)	(1.85)	(2.1)	(2.04)
Investment (IA)										
0	0.22***	0.24***	0.25***	0.26***	0.25***	0.27***	0.27***	0.28***	0.29***	0.28***
	(5.21)	(5.08)	(5.57)	(5.49)	(5.57)	(7.33)	(6.87)	(7.06)	(8.09)	(7.57)
4	-0.01	-0.08	-0.3**	-0.26***	-0.21***	-0.18**	-0.3***	-0.42***	-0.43***	-0.44***
	(-0.12)	(-0.56)	(-2.14)	(-2.85)	(-2.6)	(-2.2)	(-3.61)	(-3.97)	(-4.12)	(-4.25)
HL	-0.24	-0.31*	-0.55***	-0.52***	-0.45***	-0.45***	-0.56***	-0.69***	-0.72***	-0.73***
	(-1.64)	(-1.75)	(-3.12)	(-4.17)	(-4.11)	(-4.35)	(-5.23)	(-5.29)	(-5.65)	(-5.69)
Profitability (ROE)										
0	0.09**	0.09**	0.09**	0.1***	0.08**	0.08**	0.07	0.06	0.07*	0.08**
	(2.44)	(2.39)	(2.36)	(2.63)	(2.08)	(2.21)	(1.64)	(1.58)	(1.93)	(2.06)
4	-0.59***	-0.39***	-0.24**	-0.3***	-0.3***	-0.37***	-0.22***	-0.25***	-0.29***	-0.27***
	(-6.07)	(-4.18)	(-2.19)	(-3.93)	(-3.44)	(-3.71)	(-2.84)	(-3.05)	(-2.91)	(-2.76)
HL	-0.68***	-0.48***	-0.33**	-0.4***	-0.37***	-0.45***	-0.29***	-0.31***	-0.36***	-0.34***
	(-5.58)	(-4.1)	(-2.49)	(-4.28)	(-3.58)	(-3.78)	(-2.82)	(-2.93)	(-2.93)	(-2.92)
Expected-growth (EG)										
0	-0.16***	-0.14***	-0.14***	-0.14***	-0.14***	-0.15***	-0.14***	-0.14***	-0.13***	-0.13***
	(-4.44)	(-3.52)	(-3.78)	(-3.52)	(-3.4)	(-3.96)	(-3.6)	(-3.81)	(-3.46)	(-3.44)
4	0.5***	0.32**	0.21*	0.23**	0.3***	0.34***	0.32***	0.28**	0.3***	0.26**
	(4.76)	(2.35)	(1.78)	(2.09)	(2.99)	(3.75)	(3.38)	(2.53)	(2.68)	(2.4)
HL	0.66***	0.46***	0.36**	0.37***	0.44***	0.49***	0.46***	0.42***	0.43***	0.39***
	(5.34)	(2.81)	(2.43)	(2.72)	(3.41)	(4.2)	(3.85)	(3.1)	(3.12)	(2.96)

Table 6: Changes in $q5$ Factor Loadings. The table shows the changes in the loadings on the $q5$ model's factors of PI-sorted portfolios (indicated in rows) over different horizons (indicated in columns). The change in the loading is the difference in the loadings of one-year holding period portfolio returns at the indicated investment horizon and the portfolio returns at one-year horizon (immediate after sorting). Details of the portfolio construction and investment horizons are described in the Table 3 notes. Portfolios 1-3 are not shown for brevity. The sample period begins in 1967, to accommodate the q-factors, and ends in 2023. t-statistics from Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses and the standard errors in brackets. */**/*** indicate significance level at 10, 5, and 1%. Significance stars are omitted for the Market (MKT) loadings of the long portfolios.

	Horizon (K years)									
	1	2	3	4	5	6	7	8	9	10
Market (MKT)										
0	-	0.0	0.0	0.01	0.0	-0.01	-0.01	-0.02	-0.01	-0.01
	-	[0.0]	[0.0]	[0.0]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
4	-	0.01	-0.03	0.02	0.03	0.05	0.07	0.04	0.05	0.02
	-	[0.04]	[0.05]	[0.04]	[0.03]	[0.04]	[0.04]	[0.04]	[0.04]	[0.05]
HL	-	0.01	-0.03	0.01	0.03	0.06	0.07*	0.06	0.06	0.04
	-	(0.31)	(-0.64)	(0.35)	(0.9)	(1.62)	(1.67)	(1.24)	(1.3)	(0.74)
Size (ME)										
0	-	-0.01	-0.02***	-0.03***	-0.04***	-0.05***	-0.06***	-0.06***	-0.07***	-0.11***
	-	(-0.88)	(-3.81)	(-4.18)	(-3.04)	(-3.61)	(-4.84)	(-4.5)	(-4.24)	(-7.88)
4	-	-0.12	-0.1	-0.22***	-0.25***	-0.31***	-0.25***	-0.33***	-0.32***	-0.34***
	-	(-1.32)	(-1.29)	(-2.6)	(-2.61)	(-4.17)	(-3.47)	(-4.25)	(-4.37)	(-4.83)
HL	-	-0.11	-0.08	-0.19**	-0.21**	-0.26***	-0.19**	-0.26***	-0.25***	-0.23***
	-	(-1.21)	(-0.98)	(-2.17)	(-2.08)	(-3.06)	(-2.51)	(-3.09)	(-2.96)	(-3.11)
Investment (IA)										
0	-	0.01	0.02**	0.03***	0.02	0.04***	0.05**	0.05***	0.06***	0.06***
	-	(1.09)	(2.47)	(2.74)	(1.28)	(3.26)	(2.49)	(3.2)	(3.3)	(2.84)
4	-	-0.06	-0.29**	-0.24**	-0.19*	-0.17*	-0.28***	-0.4***	-0.41***	-0.43***
	-	(-0.52)	(-2.13)	(-2.24)	(-1.89)	(-1.88)	(-2.83)	(-3.35)	(-3.37)	(-3.46)
HL	-	-0.08	-0.31**	-0.28**	-0.22**	-0.21**	-0.33***	-0.45***	-0.48***	-0.49***
	-	(-0.58)	(-2.3)	(-2.57)	(-2.08)	(-2.2)	(-3.2)	(-3.69)	(-3.76)	(-3.83)
Profitability (ROE)										
0	-	0.0	0.0	0.01	-0.01	-0.01	-0.02	-0.03	-0.02	-0.01
	-	(0.05)	(0.3)	(1.55)	(-0.85)	(-0.79)	(-1.29)	(-1.5)	(-1.06)	(-0.65)
4	-	0.2**	0.36***	0.29***	0.3***	0.23***	0.37***	0.34***	0.3***	0.32***
	-	(2.07)	(2.85)	(3.53)	(4.01)	(3.02)	(4.35)	(4.26)	(3.81)	(4.07)
HL	-	0.2**	0.35***	0.28***	0.31***	0.23***	0.39***	0.37***	0.32***	0.34***
	-	(2.0)	(2.8)	(3.34)	(4.01)	(2.92)	(4.24)	(4.17)	(3.67)	(3.95)
Expected-growth (EG)										
0	-	0.02**	0.02*	0.02*	0.03	0.02	0.03	0.03	0.04*	0.03
	-	(2.43)	(1.87)	(1.65)	(1.63)	(1.21)	(1.64)	(1.53)	(1.92)	(1.56)
4	-	-0.18	-0.28**	-0.27**	-0.2*	-0.15	-0.17	-0.21	-0.2	-0.24*
	-	(-1.33)	(-2.2)	(-2.1)	(-1.68)	(-1.45)	(-1.43)	(-1.55)	(-1.46)	(-1.77)
HL	-	-0.2	-0.3**	-0.29**	-0.23*	-0.17	-0.2	-0.24*	-0.24*	-0.27*
	-	(-1.46)	(-2.35)	(-2.24)	(-1.85)	(-1.53)	(-1.62)	(-1.71)	(-1.7)	(-1.96)

Table 7: Forecasting Changes in Growth and Other Fundamentals with Patent Intensity. This table shows the coefficients on patent intensity for annual Fama and MacBeth (1973) cross-sectional regressions of the dependent variables indicated in the left-most column, at horizons up to ten years. The dependent variables are changes from the most recent observation to the observation at horizon K, indicated by the columns, as in Hou, Mo, Xue, and Zhang (2021) Section 3.1. Control variables (not reported) are log Tobin's q, cash-based operating profitability, and change in ROE, all following the procedures and definitions in HMXZ. t-statistics from Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses. The sample period is from 1963 to 2023.

Dependent variable,	Horizon (K years)									
K-year change in	1	2	3	4	5	6	7	8	9	10
$log\,(A_t/A_{t-1})$	0.152***	0.285***	0.342***	0.341***	0.349***	0.415***	0.435***	0.4***	0.426***	0.429***
	(3.93)	(3.76)	(3.68)	(3.98)	(3.47)	(3.33)	(3.45)	(3.32)	(3.15)	(3.14)
$log\,(CAPX_t/PPENT_{t-1})$	0.07***	0.138***	0.177***	0.231***	0.212***	0.243***	0.25***	0.215***	0.228***	0.22***
	(3.8)	(3.87)	(3.57)	(3.71)	(3.32)	(3.16)	(3.2)	(3.11)	(2.95)	(2.86)
ROE_t	0.029	0.165***	0.188**	0.203**	0.21**	0.233**	0.309***	0.266**	0.289**	0.303***
	(0.77)	(3.1)	(2.25)	(2.29)	(2.39)	(2.39)	(2.87)	(2.25)	(2.49)	(2.6)
ROA_t	0.035**	0.071***	0.08**	0.094***	0.086***	0.097***	0.121***	0.1**	0.109***	0.119***
	(2.41)	(3.42)	(2.56)	(2.58)	(2.66)	(2.86)	(2.96)	(2.52)	(2.64)	(2.58)
$log\,(Sales_t/Sales_{t-1})$	0.108***	0.187***	0.218***	0.218***	0.259***	0.256***	0.312***	0.276***	0.276***	0.231**
	(2.92)	(3.9)	(3.76)	(3.3)	(3.32)	(3.56)	(3.19)	(3.22)	(2.99)	(2.41)
$log\,(Emp_t/Emp_{t-1})$	0.108***	0.196***	0.22***	0.239***	0.252***	0.284***	0.301***	0.294***	0.297***	0.306***
	(3.98)	(3.86)	(3.91)	(3.93)	(3.69)	(3.28)	(3.46)	(3.25)	(3.04)	(3.15)

Table 8: Characteristics Sorts for Innovative vs. Non-innovative Firms. The table shows average excess returns, alphas, and risk loadings for portfolios sorted on B/M (Panel A), investment (Panel B), and profitability (Panel C) within subsamples of innovative and non-innovative firms. Stocks are labeled as innovators or non-innovators at the end of June in each year t and then sorted into five portfolios within the two groups. Innovative firms are firms that have at least one patent in the last year and three patents over the last three years. The remaining firms are treated as non-innovative. The table shows the returns of the bottom portfolio Quintile 1, top portfolio Quintile 5, and the HL portfolio, defined as long Quintile 5 and short Quintile 1. B/M, investment and profitability are defined in the Appendix. For each characteristic, we sort in the direction that would produce a positive HL return spread based on findings from prior literature (i.e., positively for B/M and profitability, and negatively for investment). Following Hou, Xue, and Zhang (2020), we discard stocks with negative book equity. The sample period is 1963-2023. The estimates of the average excess returns and constants (alphas) are annualized by multiplying by twelve. t-statistics from Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses and the standard errors in brackets. */**/*** indicate significance level at 10, 5, and 1%. Significance stars are omitted for the average excess returns and the Mkt-RF loadings of the long portfolios.

Portfolio	Ex. ret.	Alpha	Mkt-RF	SMB	HML	CMA	RMW
Panel A. B/M							
				Non-innovative			
Quintile 5 (value)	11.89	2.4***	1.02	0.35***	0.62***	-0.04	-0.08
	(4.98)	(2.63)	[0.03]	(10.34)	(8.11)	(-0.46)	(-1.52)
Quintile 1 (growth)	4.73	-3.14***	1.09	0.2***	-0.21***	-0.05	0.24***
	(1.94)	(-3.86)	[0.02]	(5.62)	(-4.09)	(-0.93)	(4.36)
HL (Q5 - Q1)	7.15***	5.54***	-0.07**	0.15***	0.83***	0.02	-0.33***
	(4.39)	(4.57)	(-1.98)	(2.87)	(7.89)	(0.13)	(-3.72)
				Innovative			
Quintile 5 (value)	10.45	1.49	1.07	0.17***	0.68***	-0.07	-0.21***
	(4.29)	(1.37)	[0.02]	(4.25)	(10.63)	(-0.87)	(-2.59)
Quintile 1 (growth)	7.07	2.02***	0.98	-0.19***	-0.33***	-0.11**	0.11***
	(3.23)	(2.67)	[0.02]	(-8.84)	(-10.24)	(-2.07)	(3.33)
HL (Q5 - Q1)	3.38*	-0.54	0.09***	0.36***	1.01***	0.04	-0.32***
	(1.8)	(-0.4)	(2.61)	(8.39)	(16.28)	(0.38)	(-3.86)
				Difference (Non-innovative - Innovative)			
HL difference	3.78**	6.08***	-0.16***	-0.21***	-0.18	-0.02	-0.0
	(2.1)	(3.52)	(-2.96)	(-3.15)	(-1.33)	(-0.12)	(-0.04)

Table 8: Characteristic Sorts – Continued.

Portfolio	Ex. ret.	Alpha	Mkt-RF	SMB	HML	CMA	RMW
Panel B. Investment							
	Non-innovative						
Quintile 5 (conservative)	9.01	-1.62*	1.09	0.42***	0.09	0.53***	0.03
	(3.75)	(-1.91)	[0.02]	(11.59)	(1.63)	(7.38)	(0.44)
Quintile 1 (aggressive)	4.5	-2.86***	1.14	0.32***	0.02	-0.44***	0.06
	(1.66)	(-3.47)	[0.02]	(8.2)	(0.33)	(-7.92)	(0.99)
HL (Q5 - Q1)	4.51***	1.23	-0.05**	0.1**	0.07	0.97***	-0.03
	(3.24)	(1.14)	(-2.27)	(2.48)	(1.53)	(11.87)	(-0.58)
	Innovative						
Quintile 5 (conservative)	8.94	-0.22	1.07	0.06	-0.19***	0.78***	-0.07
	(4.0)	(-0.21)	[0.02]	(1.54)	(-3.65)	(10.6)	(-1.15)
Quintile 1 (aggressive)	7.05	3.48***	1.05	-0.11***	-0.19***	-0.65***	-0.14***
	(2.67)	(3.71)	[0.02]	(-3.77)	(-4.2)	(-8.8)	(-3.02)
HL (Q5 - Q1)	1.89	-3.7***	0.02	0.17***	-0.0	1.44***	0.07
	(1.08)	(-3.0)	(0.65)	(3.72)	(-0.06)	(18.71)	(0.99)
	Difference (Non-innovative - Innovative)						
HL difference	2.62	4.94***	-0.07*	-0.07	0.07	-0.47***	-0.1
	(1.54)	(2.74)	(-1.79)	(-1.01)	(0.79)	(-3.61)	(-0.98)
Panel C. Profitability							
	Non-innovative						
Quintile 5 (robust)	7.94	-1.58**	1.08	0.24***	0.12***	-0.1**	0.45***
	(3.43)	(-2.5)	[0.02]	(7.4)	(3.12)	(-2.19)	(10.47)
Quintile 1 (weak)	2.69	-0.57	1.13	0.41***	-0.15**	-0.33***	-1.13***
	(0.8)	(-0.36)	[0.03]	(5.97)	(-2.4)	(-3.15)	(-11.86)
HL (Q5 - Q1)	5.25**	-1.02	-0.06	-0.17**	0.27***	0.23*	1.58***
	(2.34)	(-0.61)	(-1.45)	(-2.5)	(4.27)	(1.91)	(18.45)
	Innovative						
Quintile 5 (robust)	8.36	1.61***	0.96	-0.13***	-0.16***	0.04	0.3***
	(4.28)	(3.09)	[0.01]	(-6.36)	(-6.07)	(0.91)	(9.19)
Quintile 1 (weak)	9.72	6.65***	1.06	0.48***	-0.52***	0.27*	-1.32***
	(2.77)	(3.72)	[0.04]	(5.96)	(-5.58)	(1.79)	(-8.98)
HL (Q5 - Q1)	-1.37	-5.04***	-0.1***	-0.61***	0.36***	-0.24	1.62***
	(-0.51)	(-2.89)	(-2.68)	(-8.08)	(4.04)	(-1.61)	(12.72)
	Difference (Non-innovative - Innovative)						
HL difference	6.62***	4.03	0.05	0.44***	-0.09	0.46**	-0.04
	(3.03)	(1.56)	(0.93)	(4.27)	(-0.75)	(2.27)	(-0.23)

Table 9: Innovator vs. Non-innovator Portfolios, Long-run Returns and Alphas. The table shows average excess and abnormal returns for portfolios of innovators, non-innovators, and their difference. Firms are classified at the end of June of year t based on patent grants over twelve months prior. Firms with no patents are assigned to portfolio 0 and firms with at least one patent are assigned to portfolio 1. The portfolios are rebalanced monthly based on market capitalization at the end of the prior month, and followed for ten years following portfolio formation. The portfolio HL is a zero-cost portfolio long portfolio 1 and short portfolio 0. The sample period begins in 1963 in Panels A-D and in 1967 in Panel E, to accommodate the $q5$ factors, and ends in 2023 for all panels. The panel headings indicate the benchmark model for alphas. The estimates of the average excess returns and constants (alphas) are annualized by multiplying by twelve. t-statistics from Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses. */**/*** indicate significance level at 10, 5, and 1%. Significance stars are omitted for the average excess returns of the long portfolios.

	Horizon (K years)									
Portfolio	1	2	3	4	5	6	7	8	9	10
Panel A. Excess returns										
0	6.49	6.51	6.62	6.37	6.45	6.24	6.29	6.51	6.31	6.18
	(2.94)	(2.97)	(3.03)	(2.94)	(3.0)	(2.91)	(2.94)	(3.07)	(3.02)	(2.96)
1	7.18	7.24	7.2	7.25	7.23	7.3	7.33	7.2	7.24	7.3
	(3.53)	(3.58)	(3.59)	(3.62)	(3.64)	(3.7)	(3.76)	(3.69)	(3.71)	(3.79)
HL	0.69	0.73	0.58	0.87	0.79	1.05	1.03	0.69	0.92	1.12
	(0.73)	(0.78)	(0.62)	(0.92)	(0.87)	(1.2)	(1.21)	(0.8)	(1.07)	(1.36)
Panel B. CAPM alphas										
0	-0.32	-0.27	-0.13	-0.38	-0.27	-0.4	-0.34	-0.05	-0.21	-0.31
	(-0.47)	(-0.4)	(-0.2)	(-0.55)	(-0.4)	(-0.62)	(-0.54)	(-0.07)	(-0.32)	(-0.49)
1	0.53	0.62*	0.62*	0.7*	0.72**	0.8**	0.89**	0.77**	0.83**	0.93**
	(1.5)	(1.73)	(1.71)	(1.93)	(2.01)	(2.24)	(2.49)	(2.16)	(2.28)	(2.46)
HL	0.85	0.89	0.75	1.08	0.99	1.2	1.23	0.81	1.04	1.24
	(0.84)	(0.88)	(0.75)	(1.07)	(1.03)	(1.31)	(1.39)	(0.91)	(1.17)	(1.45)
Panel C. FF3 alphas										
0	-1.37***	-1.34***	-1.2**	-1.48***	-1.36***	-1.46***	-1.46***	-1.17**	-1.32***	-1.36***
	(-2.8)	(-2.76)	(-2.47)	(-3.02)	(-2.75)	(-3.09)	(-3.17)	(-2.45)	(-2.78)	(-2.86)
1	0.96***	1.03***	1.02***	1.11***	1.07***	1.12***	1.21***	1.07***	1.12***	1.18***
	(3.55)	(3.7)	(3.56)	(3.89)	(3.73)	(3.84)	(4.1)	(3.63)	(3.67)	(3.64)
HL	2.33***	2.37***	2.23***	2.59***	2.43***	2.58***	2.67***	2.24***	2.43***	2.54***
	(3.15)	(3.2)	(2.97)	(3.5)	(3.31)	(3.62)	(3.85)	(3.18)	(3.45)	(3.53)
Panel D. FF5 alphas										
0	-1.73***	-1.76***	-1.71***	-1.95***	-1.7***	-1.83***	-1.75***	-1.49***	-1.58***	-1.66***
	(-3.46)	(-3.65)	(-3.45)	(-3.98)	(-3.46)	(-3.74)	(-3.6)	(-3.08)	(-3.27)	(-3.34)
1	0.92***	0.94***	0.89***	0.87***	0.69**	0.71**	0.67**	0.49*	0.45	0.46
	(3.44)	(3.44)	(3.13)	(3.15)	(2.44)	(2.41)	(2.38)	(1.69)	(1.48)	(1.47)
HL	2.64***	2.7***	2.59***	2.82***	2.39***	2.53***	2.42***	1.97***	2.03***	2.12***
	(3.55)	(3.69)	(3.43)	(3.82)	(3.23)	(3.41)	(3.34)	(2.73)	(2.77)	(2.85)
Panel E. $q5$ alphas										
0	-0.65	-0.86	-0.73	-1.11**	-0.84	-0.96*	-0.9	-0.58	-1.01*	-1.0*
	(-1.18)	(-1.49)	(-1.28)	(-2.0)	(-1.51)	(-1.76)	(-1.61)	(-1.04)	(-1.82)	(-1.7)
1	0.39	0.37	0.21	0.29	0.03	0.08	-0.06	-0.26	-0.19	-0.19
	(1.26)	(1.13)	(0.64)	(0.89)	(0.09)	(0.24)	(-0.17)	(-0.73)	(-0.5)	(-0.47)
HL	1.04	1.22	0.95	1.4*	0.87	1.04	0.85	0.32	0.81	0.81
	(1.24)	(1.4)	(1.09)	(1.68)	(1.04)	(1.27)	(1.02)	(0.38)	(0.97)	(0.94)

Table 10: Pricing Patent-Intensity Portfolios with Cash-based Profitability. The table shows the abnormal returns (alphas) and factor loadings from regressions of excess portfolio returns (in excess of the risk-free rate) on a constant, four factors from Fama-French five factor model (market excess return, SMB, HML, and CMA) and cash-based operating profitability factor (CP/BE in Panel A and (CP+R&D)/BE in Panel B). Portfolios are sorted by the PI variable as described in notes of Table 2. The cash-based operating profitability (CP/BE) and cash-based operating profitability plus R&D ((CP+R&D)/BE) factors are defined in Appendix A.1. The time period is from 1976-2023, to accommodate the R&D data. All portfolios are value-weighted and rebalanced monthly. The underlying portfolio returns are at monthly frequency, and the estimates of the constants (alphas) are annualized by multiplying by twelve. t-statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses and the standard errors in brackets. */**/*** indicate significance level at 10, 5, and 1%, respectively. Significance stars are omitted for the Mkt-RF loadings of the long portfolios.

	0	1	2	3	4	HL
Panel A. FF4 and cash-based operating profitability						
Constant	-0.85	-0.22	1.64**	2.07*	3.62*	4.47**
	(-1.53)	(-0.41)	(2.07)	(1.72)	(1.76)	(1.99)
Mkt-RF	1.0	0.97	1.02	1.09	1.16	0.16***
	[0.01]	[0.01]	[0.02]	[0.04]	[0.05]	(2.64)
SMB	0.11***	-0.16***	-0.08*	0.23***	0.62***	0.51***
	(2.96)	(-10.16)	(-1.86)	(2.65)	(5.29)	(3.42)
HML	0.27***	-0.08***	-0.16***	-0.17*	-0.22*	-0.49***
	(6.47)	(-3.12)	(-3.77)	(-1.95)	(-1.7)	(-3.08)
CMA	-0.12**	0.0	0.19***	0.29**	0.49**	0.61**
	(-2.29)	(0.1)	(2.69)	(2.11)	(2.32)	(2.44)
CP/BE	0.03	0.07***	-0.1**	-0.19***	-0.28**	-0.31**
	(1.22)	(2.96)	(-2.52)	(-2.83)	(-2.4)	(-2.37)
R^2	0.96	0.96	0.90	0.84	0.75	0.29
Panel B. FF4 and cash-based operating profitability plus R&D						
Constant	0.28	-0.19	0.42	-0.04	0.81	0.53
	(0.51)	(-0.37)	(0.52)	(-0.03)	(0.45)	(0.28)
Mkt-RF	0.99	0.97	1.03	1.12	1.2	0.21***
	[0.01]	[0.01]	[0.02]	[0.04]	[0.06]	(3.22)
SMB	0.07*	-0.17***	-0.03	0.32***	0.75***	0.67***
	(1.7)	(-11.63)	(-0.57)	(3.19)	(5.16)	(3.65)
HML	0.24***	-0.06**	-0.15***	-0.15	-0.2	-0.44**
	(5.72)	(-2.23)	(-2.95)	(-1.59)	(-1.36)	(-2.5)
CMA	-0.08*	0.0	0.15**	0.23	0.41*	0.49*
	(-1.75)	(0.15)	(2.07)	(1.59)	(1.87)	(1.94)
(CP+R&D)/BE	-0.11***	0.06***	0.06	0.08	0.09	0.2**
	(-4.47)	(2.67)	(1.56)	(1.49)	(1.08)	(2.13)
R^2	0.96	0.96	0.90	0.84	0.74	0.27

Table 11: PI Alpha and Risk Dynamics, Cash-based Profitability Plus R&D. The table shows the abnormal returns (alphas in Panel A) relative to the FF5-factor model with cash-based profitability and the loadings on the model's factors (Panel B) of PI-sorted portfolios (indicated in rows) for holding period of one-year at different investment horizons (indicated in columns). Details of the portfolio construction and investment horizons are described in the Table 3 notes. Loadings of portfolios 1-3 are not shown for brevity. The sample period begins in 1976, to accommodate the cash-based profitability factor based on R&D, and ends in 2023. The estimates of the alphas are annualized by multiplying by twelve. t-statistics from Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses. */**/*** indicate significance level at 10, 5, and 1%. Significance stars are omitted for the Mkt-RF loadings of the long portfolios.

	Horizon (K years)									
Portfolio	1	2	3	4	5	6	7	8	9	10
Panel A. Alphas										
0	0.28	0.15	0.25	0.08	0.34	0.09	0.27	0.35	0.12	-0.07
	(0.51)	(0.26)	(0.45)	(0.16)	(0.68)	(0.17)	(0.52)	(0.65)	(0.21)	(-0.13)
1	-0.19	-0.36	-0.05	-0.37	-0.93	-0.45	-0.5	-0.67	-0.81	-0.6
	(-0.37)	(-0.68)	(-0.1)	(-0.68)	(-1.57)	(-0.71)	(-0.87)	(-1.21)	(-1.51)	(-1.08)
2	0.42	1.14	0.18	0.51	0.42	0.44	0.14	-0.2	0.97	0.6
	(0.52)	(1.42)	(0.22)	(0.6)	(0.53)	(0.54)	(0.18)	(-0.29)	(1.34)	(0.82)
3	-0.04	-0.8	-0.74	0.08	0.59	0.22	0.88	0.73	-0.74	-0.48
	(-0.03)	(-0.73)	(-0.72)	(0.08)	(0.54)	(0.21)	(0.71)	(0.71)	(-0.73)	(-0.46)
4	0.81	2.99	1.18	-1.02	-1.33	-1.39	-0.23	1.38	0.65	1.49
	(0.45)	(1.55)	(0.67)	(-0.6)	(-0.82)	(-0.81)	(-0.12)	(0.68)	(0.31)	(0.75)
HL	0.53	2.84	0.93	-1.1	-1.67	-1.48	-0.5	1.03	0.53	1.57
	(0.28)	(1.38)	(0.47)	(-0.58)	(-0.89)	(-0.78)	(-0.25)	(0.45)	(0.22)	(0.67)
Panel B. Loadings										
Mkt-RF										
0	0.99	1.0	1.0	1.0	0.99	0.99	0.99	0.98	0.98	0.98
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
4	1.2	1.21	1.16	1.23	1.22	1.24	1.26	1.23	1.23	1.22
	[0.06]	[0.04]	[0.04]	[0.04]	[0.04]	[0.05]	[0.05]	[0.05]	[0.05]	[0.05]
HL	0.21***	0.22***	0.16***	0.23***	0.23***	0.25***	0.27***	0.25***	0.25***	0.24***
	(3.22)	(5.12)	(3.44)	(4.69)	(4.35)	(4.51)	(5.18)	(4.57)	(4.33)	(3.97)
SMB										
0	0.07*	0.07	0.05	0.04	0.04	0.02	0.0	0.01	0.0	-0.03
	(1.7)	(1.59)	(1.13)	(1.02)	(1.2)	(0.59)	(0.12)	(0.29)	(0.04)	(-0.82)
4	0.75***	0.63***	0.66***	0.51***	0.48***	0.43***	0.48***	0.42***	0.44***	0.4***
	(5.16)	(8.5)	(5.62)	(5.27)	(5.76)	(4.77)	(5.38)	(4.11)	(4.55)	(4.0)
HL	0.67***	0.56***	0.61***	0.46***	0.44***	0.41***	0.47***	0.4***	0.44***	0.44***
	(3.65)	(5.33)	(3.99)	(3.65)	(4.16)	(3.57)	(4.05)	(3.22)	(3.69)	(3.35)
HML										
0	0.24***	0.25***	0.25***	0.28***	0.27***	0.25***	0.28***	0.26***	0.27***	0.28***
	(5.72)	(5.78)	(5.55)	(6.64)	(6.68)	(6.53)	(7.55)	(7.09)	(7.74)	(7.02)
4	-0.2	-0.3***	-0.3**	-0.27***	-0.22**	-0.3***	-0.29***	-0.35***	-0.36***	-0.39***
	(-1.36)	(-2.69)	(-2.42)	(-2.83)	(-2.36)	(-2.73)	(-3.29)	(-3.92)	(-3.59)	(-3.7)
HL	-0.44**	-0.55***	-0.55***	-0.54***	-0.49***	-0.55***	-0.57***	-0.62***	-0.63***	-0.67***
	(-2.5)	(-3.77)	(-3.55)	(-4.2)	(-4.1)	(-4.03)	(-4.92)	(-5.28)	(-5.12)	(-5.09)
CMA										
0	-0.08*	-0.07	-0.06	-0.09**	-0.1**	-0.06	-0.1**	-0.07*	-0.07*	-0.09**
	(-1.75)	(-1.48)	(-1.32)	(-2.11)	(-2.53)	(-1.36)	(-2.49)	(-1.68)	(-1.7)	(-2.02)
4	0.41*	0.36**	0.13	0.1	0.14	0.28	0.16	0.08	0.08	0.08
	(1.87)	(2.34)	(0.66)	(0.66)	(0.95)	(1.61)	(1.2)	(0.54)	(0.47)	(0.43)
HL	0.49*	0.42**	0.19	0.19	0.24	0.34*	0.26	0.15	0.16	0.17
	(1.94)	(2.36)	(0.87)	(1.05)	(1.4)	(1.67)	(1.62)	(0.82)	(0.77)	(0.77)
(CP+R&D)/BE										
0	-0.11***	-0.1***	-0.09***	-0.09***	-0.08***	-0.09***	-0.1***	-0.09***	-0.08***	-0.08***
	(-4.47)	(-3.35)	(-3.62)	(-3.77)	(-2.95)	(-2.94)	(-3.59)	(-3.39)	(-3.12)	(-2.86)
4	0.09	-0.0	0.06	-0.02	0.02	0.01	0.07	-0.02	0.02	0.06
	(1.08)	(-0.03)	(0.55)	(-0.22)	(0.2)	(0.13)	(0.67)	(-0.17)	(0.21)	(0.6)
HL	0.2**	0.09	0.16	0.07	0.11	0.1	0.17	0.08	0.1	0.14
	(2.13)	(0.63)	(1.21)	(0.6)	(0.86)	(0.9)	(1.54)	(0.67)	(0.94)	(1.33)

Table 12: PI Alpha and Risk Dynamics, Intangible Factors. The table shows the abnormal returns (alphas in Panel A) relative to the seven-factor model of Gulen, Li, Peters, and Zekhnini (2024) and the loadings on the model's factors (Panel B) of PI-sorted portfolios (indicated in rows) for holding period of one-year at different investment horizons (indicated in columns). Details of the portfolio construction and investment horizons are described in the Table 3 notes. Loadings of portfolios 1-3 are not shown for brevity. The sample period begins in 1977, to accommodate the factors based on R&D, and ends in 2023. The estimates of the alphas are annualized by multiplying by twelve. t-statistics from Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses. */**/*** indicate significance level at 10, 5, and 1%. Significance stars are omitted for the Mkt-RF loadings of the long portfolios.

	Horizon (K years)									
Portfolio	1	2	3	4	5	6	7	8	9	10
Panel A. Alphas										
0	-0.64	-0.77*	-0.8*	-0.96**	-0.69	-0.69	-0.69	-0.64	-0.75	-0.91*
	(-1.38)	(-1.67)	(-1.65)	(-2.11)	(-1.47)	(-1.4)	(-1.45)	(-1.29)	(-1.51)	(-1.76)
1	0.43	0.24	0.51	0.39	0.01	0.13	0.12	0.18	-0.29	0.03
	(0.83)	(0.49)	(0.98)	(0.73)	(0.02)	(0.23)	(0.22)	(0.35)	(-0.55)	(0.06)
2	0.36	1.19	0.41	0.35	0.17	0.47	0.47	-0.03	1.4**	1.02
	(0.43)	(1.63)	(0.55)	(0.45)	(0.24)	(0.67)	(0.65)	(-0.04)	(2.0)	(1.49)
3	0.77	-0.1	-0.15	1.17	1.64	1.27	0.99	1.23	-0.08	-0.15
	(0.66)	(-0.09)	(-0.15)	(1.05)	(1.42)	(1.11)	(0.87)	(1.13)	(-0.07)	(-0.14)
4	0.51	3.04	1.89	0.16	-0.82	-1.42	0.67	0.88	0.79	2.29
	(0.32)	(1.64)	(1.09)	(0.1)	(-0.51)	(-0.85)	(0.38)	(0.5)	(0.43)	(1.25)
HL	1.14	3.81*	2.69	1.13	-0.12	-0.73	1.37	1.52	1.54	3.2
	(0.7)	(1.95)	(1.44)	(0.63)	(-0.07)	(-0.4)	(0.7)	(0.78)	(0.75)	(1.54)

Table 12: PI with Intangible Factors – continued.

Portfolio	Horizon (K years)									
	1	2	3	4	5	6	7	8	9	10
Panel B. Loadings										
Mkt-RF										
0	1.03***	1.03***	1.03***	1.03***	1.02***	1.02***	1.02***	1.01***	1.0***	1.01***
	(77.24)	(70.25)	(75.12)	(85.51)	(78.28)	(78.49)	(79.59)	(82.31)	(81.96)	(74.11)
4	1.12***	1.15***	1.09***	1.19***	1.17***	1.19***	1.21***	1.19***	1.19***	1.18***
	(21.83)	(34.39)	(23.64)	(27.81)	(29.23)	(25.4)	(25.12)	(25.81)	(26.65)	(24.6)
HL	0.09	0.12***	0.06	0.16***	0.15***	0.18***	0.2***	0.19***	0.19***	0.17***
	(1.62)	(3.53)	(1.17)	(3.37)	(3.33)	(3.53)	(3.93)	(3.6)	(3.76)	(3.25)
SMB										
0	0.16***	0.15***	0.14***	0.12***	0.11***	0.09***	0.06**	0.06**	0.05*	0.02
	(6.51)	(6.14)	(5.36)	(4.98)	(4.55)	(3.66)	(2.53)	(2.51)	(1.92)	(0.8)
4	0.42***	0.4***	0.45***	0.38***	0.31***	0.23***	0.32***	0.29***	0.31***	0.27***
	(5.14)	(7.45)	(6.05)	(5.31)	(4.12)	(3.33)	(4.67)	(3.83)	(4.08)	(3.67)
HL	0.26***	0.25***	0.32***	0.26***	0.2**	0.15*	0.25***	0.23***	0.27***	0.25***
	(2.72)	(4.62)	(3.81)	(3.21)	(2.45)	(1.92)	(3.42)	(2.81)	(3.21)	(3.09)
HML										
0	0.26***	0.27***	0.27***	0.29***	0.28***	0.27***	0.29***	0.28***	0.29***	0.28***
	(10.0)	(9.5)	(9.43)	(10.54)	(9.51)	(9.34)	(10.65)	(9.52)	(9.53)	(9.12)
4	-0.06	-0.16**	-0.22**	-0.2***	-0.16**	-0.2**	-0.17**	-0.21***	-0.2**	-0.31***
	(-0.68)	(-2.0)	(-2.29)	(-2.77)	(-2.02)	(-2.48)	(-2.04)	(-2.88)	(-2.52)	(-3.64)
HL	-0.32***	-0.43***	-0.49***	-0.49***	-0.45***	-0.47***	-0.46***	-0.48***	-0.49***	-0.59***
	(-3.53)	(-4.95)	(-5.11)	(-6.0)	(-5.09)	(-5.16)	(-5.41)	(-6.37)	(-5.93)	(-6.53)
HML OBS										
0	-0.13***	-0.12***	-0.12***	-0.09***	-0.09***	-0.09***	-0.06**	-0.05*	-0.05**	-0.06**
	(-4.67)	(-4.05)	(-4.62)	(-3.62)	(-3.38)	(-3.15)	(-2.2)	(-1.87)	(-1.97)	(-2.2)
4	0.65***	0.46***	0.42***	0.26***	0.38***	0.4***	0.27**	0.25**	0.22**	0.22**
	(5.69)	(5.08)	(5.26)	(2.66)	(4.45)	(4.89)	(2.5)	(2.47)	(2.32)	(2.28)
HL	0.77***	0.58***	0.54***	0.36***	0.46***	0.49***	0.33***	0.3***	0.27***	0.28***
	(6.84)	(6.66)	(5.94)	(3.33)	(5.05)	(5.86)	(2.99)	(2.83)	(2.58)	(2.61)
CMA										
0	-0.14***	-0.09*	-0.08*	-0.13***	-0.11**	-0.1*	-0.16***	-0.1**	-0.11**	-0.13**
	(-2.71)	(-1.76)	(-1.8)	(-2.74)	(-2.21)	(-1.79)	(-3.29)	(-1.99)	(-2.12)	(-2.52)
4	0.38	0.24	-0.07	-0.18	-0.02	0.24	0.14	0.08	0.07	0.01
	(1.57)	(1.29)	(-0.26)	(-0.98)	(-0.15)	(1.37)	(0.82)	(0.43)	(0.34)	(0.06)
HL	0.52**	0.33	0.02	-0.05	0.09	0.33*	0.3	0.18	0.17	0.14
	(1.99)	(1.63)	(0.06)	(-0.23)	(0.49)	(1.83)	(1.62)	(0.92)	(0.84)	(0.62)
CMA OBS										
0	0.15***	0.12***	0.12***	0.13***	0.11***	0.1**	0.11***	0.08**	0.07*	0.09**
	(3.58)	(2.98)	(3.01)	(3.33)	(2.86)	(2.54)	(2.65)	(1.99)	(1.68)	(2.4)
4	-0.54**	-0.33**	-0.2	0.03	-0.11	-0.28**	-0.29	-0.25	-0.24	-0.11
	(-2.18)	(-2.31)	(-0.95)	(0.2)	(-0.77)	(-2.06)	(-1.61)	(-1.31)	(-1.26)	(-0.53)
HL	-0.69**	-0.45***	-0.33	-0.1	-0.22	-0.38***	-0.4**	-0.32	-0.31	-0.2
	(-2.54)	(-2.85)	(-1.39)	(-0.52)	(-1.43)	(-2.62)	(-2.04)	(-1.59)	(-1.52)	(-0.92)
RMW Total										
0	0.1***	0.12***	0.13***	0.13***	0.11***	0.09**	0.09***	0.09***	0.07**	0.08***
	(3.16)	(3.19)	(4.19)	(3.69)	(3.54)	(2.5)	(2.78)	(2.81)	(2.42)	(2.6)
4	-0.25**	-0.3*	-0.26*	-0.36***	-0.26**	-0.26**	-0.23*	-0.25**	-0.29**	-0.32***
	(-2.18)	(-1.95)	(-1.82)	(-3.12)	(-1.99)	(-2.39)	(-1.94)	(-2.08)	(-2.51)	(-2.81)
HL	-0.35***	-0.42**	-0.39**	-0.49***	-0.37**	-0.35***	-0.32**	-0.34***	-0.36***	-0.4***
	(-2.92)	(-2.39)	(-2.43)	(-3.71)	(-2.58)	(-2.88)	(-2.5)	(-2.6)	(-2.93)	(-3.46)

Internet Appendix to:

Patent Intensity, Firm Life Cycle, and the Long-Run Return and Risk Dynamics of Technological Innovators

IA1. Supplementary Results

Persistence of patent intensity: Table IA1, Panel A, shows average transition and exit probabilities across the three PI-groups, at horizons of one and five years. For comparison, Panel B shows similar probabilities for the B/M ratio, with break points set on a year-by-year basis identical to the percentiles of the PI sorts. The break points in Panel B are calculated conditional on not having a negative or missing book value. Missing or negative book values are not trivial, 10% of the sample on average across years, a general difficulty for accounting-based characteristics that does not apply to patent intensity. One key finding from Table IA1 is that non-innovators exit at a much higher rate than innovators. At all horizons, non-innovators exit at about twice the rate of low-intensity innnovators, and 30-50% more frequently than high-intensity innovators. The exit rates of non-innovators are large even in comparison with the value firms in Panel B (6.0 vs. 4.5% and 24.1 vs. 20.9% at one and five years), despite the strong link between value and distress (Garlappi and Yan, 2011). The high exit rate of non-innovators helps to explain their low average age. Many delistings are negative events, which affects stock performance (Shumway, 1997). Table IA1 also shows that PI sorts are highly persistent. At every horizon, high-intensity innovators have a greater probability of remaining within their category than do growth firms, low-intensity innovators have higher staying probabilities than neutral firms, and non-innovators have higher staying probabilities than value firms. Patent intensity is a fundamental and persistent characteristic that can potentially drive long-lasting differences in firm returns.

Patent composition: Table IA2 illustrates the composition of patent-intensity portfolios, classified into product and process innovations. This classification follows the methodology of Bena and Simintzi (2024), which uses the preambles of patent claims to calculate the ratio of process claims to total claims, defining the firm-level share of process innovations. According to Klepper (1996), firms with established, valuable assets (incumbents) are more inclined toward process improvements, while new entrants, lacking such valuable assets, are more likely to emphasize product innovations. Consistent with this intuition, the table reveals a monotonic decrease in the share of process claims from portfolio 1 to portfolio 4, indicating that the importance of process innovation diminishes (and non-process innovation increases) with higher patent intensity. This trend is particularly pronounced in the pre-2000 sample. In the post-2000 sample, the share of process claims remains nearly constant across portfolios with varying patent intensity. This shift reflects the changing nature of patentable process innovations, following the landmark decision on the Amazon's 1-Click patent, granted in 1999, which expanded the patentable subject matter to include business methods and software innovations.[47]

Additional pricing models (FF5+momentum and q4): Table IA3 shows alphas adjusting for FF5 plus momentum. The PI-sorted portfolios have negligible loading on momentum and adding this factor has little impact on alphas. Table IA4 shows the dynamics of alphas controlling for FF5 plus momentum, which are similar to the FF5 results shown in the paper. Table IA5 shows the dynamics of alphas under the q4 model, which are also persistently different from zero similar to the FF5 results in the paper.

Alpha dynamics of B/M portfolios: Table IA6 shows alpha dynamics for B/M sorted portfolios under the FF5 model. Unlike patent intensity, these are mostly close to zero and insignificant for ten years following portfolio formation.

Matched portfolios (by size, B/M, and prior returns): We match firms in the high-PI portfolio to non-innovators by each of size, B/M, and prior 36-month return. Table IA7 summarizes one-year pricing for the high-PI portfolio relative to each of the matched portfolios, and Tables IA10 to IA13 show the dynamics of returns, alphas, and loadings relative to each matched portfolio. The results show that persistence in returns remains relative to matches, the Fama-French factors are still unable to capture long-run returns, and the dynamics of the q5 risk loadings are somewhat reduced but still present.

Related sorts (Patents/Book, PI within Fama-French 10 industries, KPSS/M, R&D/M): Tables IA14 to IA21 show return, alpha, and loading dynamics for sorts related to patent intensity. In general, the return differences are still significant and persistent, but lower in duration and magnitude than for patent intensity. The Fama-French factors persistently cannot capture the realized returns of these sorts, as with

[47] See `https://www.wilmerhale.com/en/insights/publications/the-effects-of-the-one-click-patent-and-reversal-of-the-amazon-com-decision-what-does-it-mean-for-business-method-patents-april-2001` and `https://knowledge.wharton.upenn.edu/podcast/knowledge-at-wharton-podcast/amazons-1-click-goes-off-patent/`.

patent intensity. The $q5$ model improves alphas, reducing their magnitude, significance, and persistence, although some significant abnormal performance remains. The risk loadings of these portfolios under the $q5$ model generally show similar or weaker dynamics than patent intensity. The sample period for R&D/Market begins in 1976 for portfolio one, and increases by $K - 1$ for each of the K-aged portfolios.

Patents/R&D: Table IA22 shows the performance, alphas, and loadings for portfolios sorted by number of patents received over the last twelve months divided by R&D expenditures in previous fiscal year.

Operating profitability plus R&D: For comparison with Table 10, Table IA23 shows pricing of patent intensity sorts using operating profitability and operating profitability plus R&D. Again, the inclusion or exclusion of R&D expenses from profitability is decisive in whether the alphas are significant.

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Table IA1: Transition Probabilities of PI- vs. B/M-sorted Portfolios. Panel A shows the transition probabilities over one and five years between portfolios of stocks sorted by PI as described in the notes of Table 1 in the main paper. Rows specify the initial portfolio and columns the ending portfolio, with "out" designating a stock that leaves the sample. Entries indicate the conditional probability of moving from the initial portfolio (rows) to the destination portfolio (columns), and sum to one across columns. Panel B shows equivalent transition probabilities for book-to-market (B/M) sorts, where "Missing" denotes firms with negative or missing book-to-market ratios. To improve comparison, the B/M sorts are based on the same percentiles as the PI sorts: Each year, we calculate the percentages of firms in each of the three PI-sorted portfolios and use these percentages to categorize stocks by B/M. The unconditional probabilities (shares) of non-patenting, low-PI, and high-PI portfolios are 68.2%, 15.9% and 15.9%, respectively (see Table 1 in the main paper). These probabilities apply also to the B/M-sorted portfolios for stocks with non-missing B/M (89.9% of stocks have non-missing B/M). Accordingly, the unconditional probabilities of the three B/M-sorted portfolios are: 68.2%·89.9%=61.3% (high B/M or value), 15.9%·89.9%=14.3% (medium B/M or neutral), and 15.9%·89.9%=14.3% (low B/M or growth). Transition probabilities are calculated annually from 1926 to 2021. The presented transition probabilities are time-series averages.

Panel A. PI-sorted portfolios

	Transition probabilities over 1 year				Transition probabilities over 5 years			
	Non-pat.	Low PI	High PI	Out	Non-pat.	Low PI	High PI	Out
Non-pat.	86.7	4.6	2.7	6.0	67.5	5.5	2.9	24.1
Low PI	17.6	67.1	12.7	2.6	17.0	53.7	16.8	12.5
High PI	12.7	12.0	71.2	4.1	12.9	16.4	52.4	18.4

Panel B. B/M-sorted portfolios

	Transition probabilities over 1 year					Transition probabilities over 5 years				
	Value	Neutral	Growth	Out	Missing	Value	Neutral	Growth	Out	Missing
Value	85.6	6.6	1.6	4.5	1.6	65.6	7.8	3.5	20.9	2.2
Neutral	34.6	43.6	16.4	3.5	1.8	44.8	22.3	13.7	16.9	2.3
Growth	9.9	19.8	62.9	3.6	3.8	25.5	18.4	35.2	17.2	3.6
Missing	11.1	2.8	7.1	15.3	63.7	19.9	5.7	6.6	37.6	30.3

Table IA2: Patent Composition, Process vs. Product. The table shows the percentage shares of process claims of all firm's patents granted over the last twelve months, for portfolios sorted on patenting intensity PI. Portfolios are sorted on PI at the end of June each year. The shares are calculated for each year as average shares across the firms in each portfolio, equal or value weighted as indicated. The reported numbers are time-series averages of the shares calculated each year from 1926 to 2022 (or as indicated). The data for process claims is from Ganglmair, Robinson, and Seeligson (2022).

	0	1	2	3	4
Equal-weighted					
Process claims	-	0.30	0.26	0.23	0.21
until 1980	-	0.25	0.20	0.15	0.11
until 2000	-	0.26	0.22	0.18	0.15
since 2001	-	0.44	0.40	0.41	0.41
Value-weighted					
Process claims	-	0.33	0.29	0.27	0.24
until 1980	-	0.27	0.23	0.19	0.15
until 2000	-	0.29	0.25	0.23	0.19
since 2001	-	0.45	0.40	0.42	0.43

Table IA3: Patent-Intensity Sorts, Fama-French Factors with Momentum. The table shows regressions of excess portfolio returns (in excess of the risk-free rate) of PI-sorted portfolios on a constant, Fama-French five factors and the momentum factor. Portfolio 0 consists of non-patenting firms and the remaining portfolios are sorted by PI annually into equal groups by firm count. HL is a zero-cost portfolio, long portfolio 4 and short portfolio 0. Stocks are sorted at the end of June. All portfolios are value-weighted and rebalanced monthly. The underlying portfolio returns are at monthly frequency, and the estimates of the constants (alphas) are annualized by multiplying by twelve. t-statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses and the standard errors in brackets. */**/*** indicate significance level at 10, 5, and 1%, respectively. Significance stars are omitted for the Mkt-RF loadings of the long portfolios. The time period of the sample is 1963-2023.

	0	1	2	3	4	HL
Constant	-1.51***	0.2	2.41***	2.97***	5.87***	7.38***
	(-3.19)	(0.45)	(3.38)	(2.77)	(3.6)	(4.07)
Mkt-RF	1.01***	0.96***	1.01***	1.07***	1.11***	0.1**
	(81.69)	(94.86)	(66.38)	(37.02)	(27.16)	(2.13)
SMB	0.13***	-0.19***	-0.05	0.23***	0.6***	0.47***
	(5.6)	(-13.87)	(-1.62)	(3.94)	(7.64)	(4.87)
HML	0.2***	-0.08***	-0.1**	-0.14**	-0.14	-0.35***
	(6.75)	(-3.26)	(-2.3)	(-2.01)	(-1.59)	(-3.2)
CMA	-0.03	0.0	0.09	0.17**	0.26*	0.29*
	(-0.86)	(0.03)	(1.52)	(2.02)	(1.84)	(1.8)
RMW	0.11***	0.03*	-0.11***	-0.26***	-0.42***	-0.53***
	(2.9)	(1.72)	(-2.94)	(-2.96)	(-2.63)	(-2.87)
Mom	-0.02	0.01	-0.03	-0.1***	-0.09	-0.07
	(-1.27)	(0.94)	(-1.37)	(-2.68)	(-1.4)	(-0.92)
R^2	0.960	0.960	0.900	0.860	0.780	0.310

Table IA4: Patent Intensity Long-run Alphas, FF5+Momentum. The table shows the abnormal returns (alphas) relative to FF5 model with momentum of PI-sorted portfolios (indicated in rows) for holding period of one-year at different investment horizons (indicated in columns). Details of the portfolio construction and investment horizons are described in the Table 3 notes in the main paper. The sample period begins in 1963, to accommodate the FF5 factors, and ends in 2023. The estimates of the alphas are annualized by multiplying by twelve. t-statistics from Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses. */**/*** indicate significance level at 10, 5, and 1%.

	Horizon (K years)									
	1	2	3	4	5	6	7	8	9	10
0	-1.51***	-1.58***	-1.52***	-1.69***	-1.62***	-1.53***	-1.36***	-1.19***	-1.4***	-1.4***
	(-3.19)	(-3.36)	(-3.21)	(-3.64)	(-3.5)	(-3.31)	(-3.07)	(-2.68)	(-3.12)	(-3.0)
1	0.2	0.21	0.34	0.03	0.05	0.35	0.23	0.2	-0.04	0.37
	(0.45)	(0.48)	(0.78)	(0.08)	(0.1)	(0.74)	(0.52)	(0.48)	(-0.09)	(0.84)
2	2.41***	2.6***	1.68**	1.92***	1.33**	0.89	1.13*	0.64	1.53**	0.71
	(3.38)	(3.76)	(2.53)	(2.68)	(2.07)	(1.43)	(1.9)	(1.07)	(2.52)	(1.21)
3	2.97***	1.75*	1.47*	2.0**	2.4***	2.48***	1.69*	2.26***	0.95	1.46*
	(2.77)	(1.79)	(1.67)	(2.15)	(2.65)	(2.67)	(1.88)	(2.65)	(1.01)	(1.72)
4	5.87***	6.36***	4.73***	3.14**	2.41*	2.7**	3.44**	3.3**	3.54**	4.11***
	(3.6)	(3.55)	(2.68)	(2.24)	(1.89)	(2.03)	(2.35)	(2.28)	(2.49)	(2.93)
HL	7.38***	7.94***	6.25***	4.83***	4.03***	4.23***	4.79***	4.49***	4.94***	5.5***
	(4.07)	(4.0)	(3.17)	(3.0)	(2.68)	(2.83)	(2.93)	(2.77)	(3.04)	(3.39)

Table IA5: Patent Intensity Long-run Alphas, $q4$ Factors. The table shows the abnormal returns (alphas) relative to $q4$-factor model (Hou, Xue, and Zhang, 2015) of PI-sorted portfolios (indicated in rows) for holding period of one-year at different investment horizons (indicated in columns). Details of the portfolio construction and investment horizons are described in the Table 3 notes in the main paper. The sample period begins in 1963, to accommodate the $q4$-factors, and ends in 2023. The estimates of the alphas are annualized by multiplying by twelve. t-statistics from Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses. */**/*** indicate significance level at 10, 5, and 1%.

	Horizon (K years)									
	1	2	3	4	5	6	7	8	9	10
0	-2.02***	-2.04***	-1.94***	-2.31***	-1.98***	-2.19***	-2.06***	-1.75***	-2.06***	-2.11***
	(-3.2)	(-3.32)	(-3.09)	(-3.63)	(-3.29)	(-3.79)	(-3.27)	(-2.86)	(-3.51)	(-3.3)
1	0.11	0.07	0.28	0.03	-0.31	0.29	0.4	0.01	0.12	0.49
	(0.24)	(0.14)	(0.62)	(0.06)	(-0.54)	(0.5)	(0.74)	(0.02)	(0.24)	(0.91)
2	2.99***	3.07***	2.17***	2.62***	2.2***	1.59**	1.61**	1.32**	1.91***	1.2*
	(3.95)	(4.01)	(2.94)	(3.04)	(2.79)	(2.04)	(2.23)	(2.02)	(3.0)	(1.79)
3	3.2***	2.02*	1.41	1.65*	2.21**	2.28**	2.2*	2.37**	0.8	1.25
	(2.6)	(1.79)	(1.46)	(1.67)	(2.21)	(2.22)	(1.94)	(2.29)	(0.77)	(1.3)
4	6.1***	6.13***	4.29**	2.34	1.81	2.43	2.97*	4.04**	3.99**	4.59**
	(3.28)	(3.12)	(2.12)	(1.55)	(1.28)	(1.61)	(1.78)	(2.12)	(2.11)	(2.33)
HL	8.12***	8.17***	6.24***	4.65**	3.79**	4.62**	5.04**	5.79**	6.06***	6.69***
	(3.6)	(3.52)	(2.6)	(2.5)	(2.19)	(2.54)	(2.47)	(2.53)	(2.66)	(2.79)

Table IA6: B/M Portfolios Long-run Alphas, FF5 Model. The table shows the abnormal returns (alphas) relative to the FF5 model Fama and French (2015) of B/M-sorted portfolios (indicated in rows) for holding period of one-year at different investment horizons (indicated in columns). At the end of June of year t, stocks are sorted into five K-aged portfolios based on the Book-to-Market ratio (defined in the Appendix in the main paper) from the end of December prior to year $t-K$. The breakpoints percentiles of the portfolio sorts correspond to the percentiles of the breakpoints of the PI-sorted portfolios each year. All portfolios are rebalanced monthly based on market capitalization at the end of the prior month. HL is a zero-cost portfolio with a long position in portfolio 4 and a short position in portfolio 0. The sample period begins in 1963, to accommodate the FF5 factors, and ends in 2023. The estimates of the alphas are annualized by multiplying by twelve. t-statistics from Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses. */**/*** indicate significance level at 10, 5, and 1%.

	Horizon (K years)									
	1	2	3	4	5	6	7	8	9	10
0	0.02	0.15	-0.1	-0.34*	-0.34*	-0.27	-0.23	-0.16	-0.2	-0.17
	(0.17)	(1.04)	(-0.63)	(-1.84)	(-1.72)	(-1.16)	(-1.04)	(-0.82)	(-1.01)	(-0.75)
1	-0.51	1.23	0.14	-0.75	-0.35	-0.2	-1.46	-0.13	0.65	-0.21
	(-0.7)	(1.38)	(0.16)	(-0.69)	(-0.38)	(-0.17)	(-1.39)	(-0.11)	(0.56)	(-0.18)
2	-0.01	-0.05	1.13	1.28	-0.86	0.2	0.92	-1.01	-0.56	-0.53
	(-0.01)	(-0.06)	(1.12)	(1.3)	(-0.7)	(0.16)	(0.85)	(-0.95)	(-0.45)	(-0.48)
3	0.9	-0.89	0.7	0.96	0.74	-2.88**	-0.35	0.0	-0.61	-1.7
	(0.95)	(-0.81)	(0.63)	(0.83)	(0.6)	(-2.54)	(-0.28)	(0.0)	(-0.53)	(-1.25)
4	-1.72	1.63	0.37	0.91	-0.5	-0.65	-1.31	-1.94	-2.77*	-4.36***
	(-1.24)	(1.05)	(0.27)	(0.64)	(-0.34)	(-0.43)	(-0.88)	(-1.33)	(-1.66)	(-2.76)
HL	-1.74	1.47	0.48	1.25	-0.15	-0.38	-1.09	-1.77	-2.57	-4.2**
	(-1.26)	(0.93)	(0.33)	(0.84)	(-0.1)	(-0.24)	(-0.68)	(-1.16)	(-1.49)	(-2.56)

Table IA7: High PI and Matched Portfolios, Fama-French Factors. The table shows the average excess returns, abnormal returns (alphas), and the Fama-French factor loadings of high-PI portfolios, the portfolios of non-patenting stocks matched by the variables indicated in the headings, and the difference between the high PI and the non-patenting matched portfolios. At the end of June, stocks are sorted into five portfolios based on the patent intensity. The high PI portfolio consists of the stocks in the highest sort. To construct the matched portfolios, for each stock in the high PI portfolio we select non-patenting stocks with the lowest distance in the matching variable indicated in the headings. The returns of the high PI portfolios vary slightly across the matching variables as only high-PI stocks with a valid match are included, and stocks are matched in June at the time of portfolio formation without replacing delisting high PI stocks or their matches during the holding period until next June. Portfolios are value-weighted and rebalanced monthly. The time period is from 1963 to 2023 due to availability of the FF5 factors. H-M is a zero-cost portfolio with a long position in the high PI portfolio and a short position in the Matched portfolio. The underlying portfolio returns are at monthly frequency, and the estimates of the average excess returns and constants (alphas) are annualized by multiplying by twelve. t-statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses and the standard errors in brackets. */**/*** indicate significance level at 10, 5, and 1%, respectively. Significance stars are omitted for the average excess returns and the Mkt-RF loadings of the long portfolios.

	Size			3-year return			B/M		
	High PI	Matched	H-M	High PI	Matched	H-M	High PI	Matched	H-M
Panel A. Excess returns									
Ex. ret.	13.18	6.72	6.69***	13.16	6.13	6.67***	13.2	6.97	6.71***
	(4.02)	(3.07)	(3.32)	(4.02)	(2.58)	(3.31)	(4.04)	(3.18)	(3.33)
Panel B. CAPM									
Constant	4.66**	0.08	4.98**	4.64**	-0.77	4.96**	4.68**	0.34	5.0***
	(2.49)	(0.08)	(2.56)	(2.48)	(-0.66)	(2.55)	(2.51)	(0.38)	(2.58)
Mkt-RF	1.26	0.98	0.25***	1.26	1.02	0.25***	1.26	0.98	0.25***
	[0.05]	[0.03]	(5.45)	[0.05]	[0.03]	(5.43)	[0.05]	[0.02]	(5.43)
R^2	0.670	0.800	0.070	0.670	0.820	0.070	0.670	0.850	0.070
Panel C. Fama-French 1993									
Constant	3.57**	-1.2	4.94**	3.54**	-2.22**	4.91**	3.62**	-0.94	4.99***
	(2.11)	(-1.26)	(2.56)	(2.09)	(-2.43)	(2.55)	(2.13)	(-1.25)	(2.59)
Mkt-RF	1.13	0.97	0.11*	1.13	1.01	0.11*	1.13	0.99	0.11*
	[0.05]	[0.02]	(1.88)	[0.05]	[0.02]	(1.89)	[0.05]	[0.02]	(1.88)
SMB	0.72***	0.22***	0.62***	0.72***	0.23***	0.62***	0.71***	0.12***	0.62***
	(5.78)	(5.75)	(3.82)	(5.77)	(5.29)	(3.81)	(5.73)	(2.72)	(3.78)
HML	0.11*	0.25***	-0.11	0.11*	0.29***	-0.11	0.1*	0.27***	-0.12
	(1.82)	(5.98)	(-1.46)	(1.84)	(5.9)	(-1.45)	(1.7)	(6.21)	(-1.56)
R^2	0.760	0.830	0.240	0.760	0.860	0.240	0.760	0.880	0.240
Panel D. Fama-French 2015									
Constant	4.78***	-1.21	6.51***	4.76***	-2.33***	6.49***	4.84***	-1.45*	6.57***
	(2.8)	(-1.18)	(3.31)	(2.79)	(-2.63)	(3.3)	(2.84)	(-1.91)	(3.35)
Mkt-RF	1.14	0.98	0.13**	1.14	1.02	0.13**	1.14	1.0	0.13**
	[0.04]	[0.02]	(2.45)	[0.04]	[0.02]	(2.45)	[0.04]	[0.02]	(2.45)
SMB	0.6***	0.22***	0.46***	0.6***	0.23***	0.46***	0.59***	0.16***	0.46***
	(7.67)	(5.81)	(4.79)	(7.66)	(5.52)	(4.78)	(7.64)	(4.65)	(4.75)
HML	-0.1	0.2***	-0.31***	-0.09	0.22***	-0.31***	-0.1	0.22***	-0.32***
	(-1.07)	(4.22)	(-2.78)	(-1.04)	(3.87)	(-2.76)	(-1.17)	(4.35)	(-2.86)
CMA	0.26*	0.05	0.3*	0.26*	0.08	0.29*	0.27*	0.06	0.3*
	(1.89)	(0.81)	(1.83)	(1.88)	(1.07)	(1.81)	(1.93)	(1.02)	(1.86)
RMW	-0.42***	-0.02	-0.53***	-0.42***	-0.01	-0.53***	-0.42***	0.09	-0.53***
	(-2.9)	(-0.32)	(-3.09)	(-2.89)	(-0.17)	(-3.08)	(-2.96)	(1.56)	(-3.14)
R^2	0.780	0.830	0.300	0.780	0.860	0.300	0.780	0.880	0.300

Table IA8: High-PI and B/M Matched Portfolios Long-run Returns and Alphas, Fama-French Factors. The table shows average excess and abnormal returns (alphas) of the high PI and non-patenting B/M matched portfolios. At the end of June of year t, stocks are sorted into five K-aged portfolios based on the patent-intensity sort from the end of June of year $t-K$. For each firm in the highest PI sort, we search for the closest match (minimum absolute distance) by the Book-to-Market ratio (defined in the Appendix in the main paper) from the end of December prior to year $t-K$ and form the Matched portfolio. The high PI portfolio are stocks in the highest PI sort with a valid match. All portfolios are rebalanced monthly based on market capitalization at the end of the prior month. The sample period begins in 1927 in Panel A and in 1963 in Panel B and ends in 2023 for both panels. H-M is a zero-cost portfolio with a long position in the high PI portfolio and a short position in the Matched portfolio. The first two columns indicate the portfolio and, if applicable, the benchmark model for alphas. The estimates of the average excess returns and constants (alphas) are annualized by multiplying by twelve. t-statistics from Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses. */**/*** indicate significance level at 10, 5, and 1%. Significance stars are omitted for the average excess returns of the long portfolios.

		Horizon (K years)									
Portfolio	Model	1	2	3	4	5	6	7	8	9	10
Panel A. 1926-											
		Excess returns									
High PI		14.65	14.57	11.88	10.68	10.99	12.87	11.99	11.79	11.71	10.9
		(4.77)	(4.85)	(4.11)	(3.65)	(3.92)	(4.49)	(4.53)	(4.52)	(4.44)	(4.24)
Matched		8.47	7.67	8.16	7.61	8.84	8.01	7.93	8.87	8.81	8.21
		(4.07)	(3.72)	(3.8)	(3.6)	(4.05)	(3.66)	(4.1)	(4.53)	(4.79)	(4.2)
H-M		6.18***	6.9***	3.72**	3.07*	2.15	4.86***	4.06**	2.92*	2.9*	2.69
		(3.67)	(3.96)	(2.4)	(1.94)	(1.41)	(3.25)	(2.5)	(1.79)	(1.78)	(1.56)
		Alphas									
H-M	CAPM	3.2**	3.83**	1.46	0.47	-0.14	1.89	1.13	0.37	-0.07	0.34
		(2.22)	(2.42)	(1.01)	(0.32)	(-0.1)	(1.33)	(0.7)	(0.22)	(-0.04)	(0.19)
H-M	FF3	2.88**	3.58**	1.88	0.47	0.21	2.66*	2.43	2.03	1.63	2.21
		(2.02)	(2.4)	(1.38)	(0.34)	(0.15)	(1.92)	(1.57)	(1.31)	(1.06)	(1.34)
Panel B. 1963-											
		Excess returns									
High PI		13.2	13.69	11.39	9.34	9.17	9.38	10.47	10.38	10.09	10.4
		(4.04)	(4.26)	(3.72)	(3.01)	(3.04)	(3.07)	(3.3)	(3.26)	(3.16)	(3.24)
Matched		6.97	7.84	7.73	7.06	7.5	4.64	6.41	8.32	7.1	6.48
		(3.18)	(3.57)	(3.54)	(3.11)	(3.51)	(2.14)	(2.83)	(3.6)	(3.26)	(2.82)
H-M		6.23***	5.85***	3.67*	2.28	1.67	4.74**	4.05*	2.06	2.98	3.92*
		(2.9)	(2.8)	(1.84)	(1.17)	(0.83)	(2.35)	(1.86)	(0.94)	(1.37)	(1.7)
		Alphas									
H-M	CAPM	4.34**	3.95*	1.8	0.24	-0.49	2.54	1.54	-0.06	0.6	1.8
		(2.13)	(1.9)	(0.89)	(0.12)	(-0.25)	(1.3)	(0.71)	(-0.03)	(0.28)	(0.77)
H-M	FF3	4.56**	4.54**	2.96	1.38	0.53	4.01**	3.37	2.24	2.5	3.71*
		(2.25)	(2.35)	(1.63)	(0.74)	(0.29)	(2.12)	(1.6)	(1.1)	(1.24)	(1.78)
High PI	FF5	4.84***	5.97***	4.47***	2.4*	1.87	2.06	3.26**	3.74**	3.55**	4.23**
		(2.84)	(3.7)	(2.82)	(1.72)	(1.43)	(1.57)	(2.25)	(2.22)	(2.12)	(2.5)
Matched		-1.45*	-0.12	-0.07	-1.08	-1.15	-4.1***	-2.36**	-0.13	-0.76	-1.46
		(-1.91)	(-0.17)	(-0.09)	(-1.2)	(-1.41)	(-4.65)	(-2.12)	(-0.13)	(-0.87)	(-1.49)
H-M		6.29***	6.09***	4.54**	3.48*	3.02*	6.17***	5.62***	3.88*	4.31**	5.69***
		(3.01)	(3.24)	(2.5)	(1.95)	(1.81)	(3.7)	(2.78)	(1.83)	(2.1)	(2.59)

Table IA9: High-PI and B/M Matched Portfolios Alpha Risk Dynamics, $q5$ Factors. The table shows the abnormal returns (alphas in Panel A) and the loadings on the $q5$ model's factors (Panel B) of the high PI and non-patenting B/M matched portfolios (indicated in rows) for holding period of one-year at different investment horizons (indicated in columns). Details of the portfolio construction and investment horizons are described in the Table IA8 notes. The sample period begins in 1967, to accommodate the q-factors, and ends in 2023. t-statistics from Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses and the standard errors in brackets. */**/*** indicate significance level at 10, 5, and 1%. Significance stars are omitted for the Market (MKT) loadings of the long portfolios.

	Horizon (K years)									
Portfolio	1	2	3	4	5	6	7	8	9	10
Panel A. Alphas										
High PI	2.02	3.48	2.53	0.54	-0.57	-0.44	0.21	1.62	1.44	2.4
	(1.28)	(1.49)	(1.13)	(0.34)	(-0.37)	(-0.31)	(0.13)	(0.89)	(0.78)	(1.29)
Matched	-1.29	0.33	0.31	-0.05	-1.13	-3.43***	-1.89	0.09	0.14	-1.24
	(-1.36)	(0.39)	(0.33)	(-0.05)	(-1.13)	(-2.78)	(-1.47)	(0.06)	(0.14)	(-1.02)
H-M	3.32	3.15	2.22	0.59	0.56	2.99	2.1	1.53	1.3	3.64
	(1.61)	(1.18)	(0.93)	(0.29)	(0.28)	(1.45)	(0.9)	(0.6)	(0.6)	(1.42)
Panel B. Loadings										
Market (MKT)										
High PI	1.16	1.18	1.14	1.19	1.2	1.22	1.23	1.21	1.21	1.18
	[0.05]	[0.03]	[0.05]	[0.04]	[0.04]	[0.04]	[0.04]	[0.05]	[0.05]	[0.05]
Matched	0.99	0.98	0.99	1.0	0.98	0.97	0.96	1.02	0.97	1.01
	[0.02]	[0.02]	[0.02]	[0.02]	[0.03]	[0.02]	[0.03]	[0.04]	[0.03]	[0.03]
H-M	0.18***	0.2***	0.14***	0.19***	0.21***	0.24***	0.27***	0.19***	0.24***	0.17**
	(3.07)	(4.42)	(2.58)	(3.35)	(3.94)	(4.5)	(4.67)	(2.68)	(4.17)	(2.51)
Size (ME)										
High PI	0.65***	0.53***	0.54***	0.43***	0.39***	0.33***	0.39***	0.32***	0.33***	0.3***
	(5.17)	(6.09)	(4.45)	(4.67)	(5.14)	(3.73)	(4.11)	(3.0)	(3.21)	(2.88)
Matched	0.17***	0.17***	0.13**	0.08	0.14*	0.15***	0.15*	0.1	0.08	0.02
	(2.91)	(3.71)	(2.55)	(1.21)	(1.86)	(2.66)	(1.87)	(1.41)	(1.51)	(0.21)
H-M	0.48***	0.36***	0.42***	0.35**	0.26*	0.18	0.25	0.22	0.25*	0.29*
	(2.77)	(3.03)	(2.64)	(2.39)	(1.87)	(1.35)	(1.51)	(1.31)	(1.82)	(1.74)
Investment (IA)										
High PI	-0.02	-0.08	-0.31**	-0.26***	-0.21***	-0.18**	-0.29***	-0.41***	-0.42***	-0.44***
	(-0.17)	(-0.55)	(-2.16)	(-2.88)	(-2.59)	(-2.22)	(-3.52)	(-3.88)	(-4.04)	(-4.24)
Matched	0.3***	0.21***	0.2***	0.25***	0.3***	0.32***	0.37***	0.37***	0.28***	0.35***
	(4.63)	(4.49)	(4.4)	(3.95)	(4.38)	(4.72)	(4.46)	(4.5)	(4.54)	(4.49)
H-M	-0.32**	-0.28*	-0.5***	-0.51***	-0.51***	-0.51***	-0.66***	-0.78***	-0.71***	-0.79***
	(-2.01)	(-1.65)	(-3.03)	(-3.87)	(-4.05)	(-4.29)	(-4.75)	(-5.12)	(-5.23)	(-5.54)
Profitability (ROE)										
High PI	-0.59***	-0.39***	-0.23**	-0.3***	-0.3***	-0.37***	-0.23***	-0.25***	-0.29***	-0.26***
	(-6.03)	(-4.15)	(-2.14)	(-3.92)	(-3.47)	(-3.71)	(-2.83)	(-3.05)	(-2.88)	(-2.71)
Matched	0.06	0.03	0.07*	0.08*	0.11**	0.12**	0.12*	0.0	-0.01	0.08
	(1.14)	(0.63)	(1.73)	(1.67)	(2.03)	(2.2)	(1.7)	(0.03)	(-0.19)	(1.38)
H-M	-0.65***	-0.42***	-0.3**	-0.38***	-0.41***	-0.49***	-0.35***	-0.26**	-0.28**	-0.35***
	(-5.17)	(-3.57)	(-2.52)	(-4.1)	(-3.88)	(-3.89)	(-2.93)	(-2.27)	(-2.2)	(-3.11)
Expected growth (EG)										
High PI	0.5***	0.32**	0.22*	0.23**	0.3***	0.34***	0.33***	0.29**	0.3***	0.26**
	(4.76)	(2.37)	(1.79)	(2.08)	(2.91)	(3.67)	(3.41)	(2.56)	(2.68)	(2.4)
Matched	-0.08	-0.08**	-0.09*	-0.16***	-0.05	-0.13*	-0.11	-0.06	-0.1	-0.13**
	(-1.43)	(-1.97)	(-1.68)	(-2.6)	(-0.99)	(-1.93)	(-1.45)	(-1.03)	(-1.58)	(-2.26)
H-M	0.58***	0.4***	0.31**	0.39***	0.35***	0.47***	0.44***	0.35**	0.4***	0.39***
	(4.39)	(2.62)	(2.1)	(2.6)	(2.61)	(3.56)	(2.97)	(2.34)	(2.9)	(2.76)

Table IA10: High-PI and Size Matched Portfolios Long-run Returns and Alphas, Fama-French Factors. The table shows average excess and abnormal returns (alphas) of the high PI and non-patenting size matched portfolios. At the end of June of year t, stocks are sorted into five K-aged portfolios based on the patent-intensity sort from the end of June of year $t-K$. For each firm in the highest PI sort, we search for the closest match (minimum absolute distance) by the market capitalization at the time of sorting and form the Matched portfolio. The high PI portfolio are stocks in the highest PI sort with a valid match. All portfolios are rebalanced monthly based on market capitalization at the end of the prior month. The sample period begins in 1926 in Panel A and in 1963 in Panel B and ends in 2023 for both panels. H-M is a zero-cost portfolio with a long position in the high PI portfolio and a short position in the Matched portfolio. The first two columns indicate the portfolio and, if applicable, the benchmark model for alphas. The estimates of the average excess returns and constants (alphas) are annualized by multiplying by twelve. t-statistics from Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses. */**/*** indicate significance level at 10, 5, and 1%. Significance stars are omitted for the average excess returns of the long portfolios.

		Horizon (K years)									
Portfolio	Model	1	2	3	4	5	6	7	8	9	10
Panel A. 1926-											
		Excess returns									
High PI		14.61	14.51	12.24	10.26	10.34	11.49	13.78	11.59	11.89	11.45
		(4.79)	(4.86)	(4.25)	(3.49)	(3.67)	(3.97)	(4.76)	(4.44)	(4.5)	(4.44)
Matched		8.33	8.23	8.75	7.08	8.31	8.78	10.83	7.49	6.86	8.09
		(3.64)	(3.47)	(3.77)	(3.19)	(3.68)	(3.85)	(5.14)	(3.77)	(3.35)	(3.95)
H-M		6.28***	6.28***	3.49**	3.18**	2.04	2.71	2.95*	4.1***	5.03***	3.36**
		(4.02)	(4.18)	(2.37)	(2.04)	(1.37)	(1.63)	(1.75)	(2.66)	(2.92)	(2.05)
		Alphas									
H-M	CAPM	4.11***	3.99***	1.59	0.42	-0.09	-0.06	0.0	1.62	2.13	0.98
		(2.9)	(2.71)	(1.12)	(0.3)	(-0.07)	(-0.04)	(0.0)	(1.08)	(1.23)	(0.57)
H-M	FF3	4.4***	4.28***	2.13	0.55	0.35	0.21	0.71	2.72*	3.76**	2.94*
		(3.13)	(2.94)	(1.51)	(0.4)	(0.26)	(0.13)	(0.47)	(1.82)	(2.31)	(1.78)
Panel B. 1963-											
		Excess returns									
High PI		13.18	13.61	11.3	9.26	9.1	9.44	10.48	10.39	10.07	10.38
		(4.02)	(4.23)	(3.69)	(2.99)	(3.02)	(3.09)	(3.31)	(3.26)	(3.15)	(3.24)
Matched		6.72	5.99	6.74	6.07	6.72	7.25	8.58	5.8	5.14	6.2
		(3.07)	(2.43)	(2.73)	(2.6)	(2.89)	(3.04)	(3.89)	(2.56)	(2.1)	(2.66)
H-M		6.46***	7.62***	4.56**	3.19*	2.38	2.19	1.9	4.58**	4.92**	4.18*
		(3.07)	(3.85)	(2.4)	(1.68)	(1.22)	(1.1)	(0.88)	(2.23)	(2.19)	(1.87)
		Alphas									
H-M	CAPM	4.58**	5.93***	3.05	1.3	0.68	0.16	-0.36	2.37	2.76	2.11
		(2.3)	(2.96)	(1.57)	(0.71)	(0.35)	(0.08)	(-0.18)	(1.19)	(1.2)	(0.92)
H-M	FF3	4.76**	6.46***	3.87**	2.52	1.96	1.85	0.92	3.82*	5.04**	4.32**
		(2.41)	(3.36)	(2.16)	(1.48)	(1.07)	(0.96)	(0.45)	(1.91)	(2.46)	(2.04)
High PI	FF5	4.78***	5.9***	4.39***	2.3*	1.76	2.06	3.27**	3.73**	3.52**	4.2**
		(2.8)	(3.66)	(2.78)	(1.66)	(1.35)	(1.57)	(2.26)	(2.23)	(2.11)	(2.49)
Matched		-1.21	-1.08	-0.79	-2.22**	-1.71	-1.78*	0.34	-1.95*	-4.31***	-2.75***
		(-1.18)	(-1.11)	(-0.78)	(-2.01)	(-1.58)	(-1.72)	(0.32)	(-1.9)	(-3.81)	(-2.83)
H-M		6.0***	6.98***	5.18***	4.52***	3.47**	3.84**	2.93	5.69***	7.82***	6.95***
		(2.88)	(3.67)	(2.82)	(2.74)	(1.96)	(2.12)	(1.56)	(2.79)	(3.74)	(3.29)

Table IA11: High-PI and Size Matched Portfolios Alpha and Risk Dynamics, $q5$ Factors. The table shows the abnormal returns (alphas in Panel A) the loadings on the $q5$ model's factors (Panel B) of the high PI and non-patenting size matched portfolios (indicated in rows) for holding period of one-year at different investment horizons (indicated in columns). Details of the portfolio construction and investment horizons are described in the Table IA10 notes. The sample period begins in 1967, to accommodate the q-factors, and ends in 2023. t-statistics from Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses and the standard errors in brackets. */**/*** indicate significance level at 10, 5, and 1%. Significance stars are omitted for the Market (MKT) loadings of the long portfolios.

	Horizon (K years)									
Portfolio	1	2	3	4	5	6	7	8	9	10
Panel A. Alphas										
High PI	1.94	3.47	2.5	0.44	-0.69	-0.45	0.27	1.68	1.48	2.41
	(1.23)	(1.49)	(1.13)	(0.28)	(-0.46)	(-0.31)	(0.16)	(0.93)	(0.81)	(1.3)
Matched	-1.23	-0.78	0.49	-1.05	0.55	-0.38	0.69	-0.46	-3.68**	-1.25
	(-1.1)	(-0.67)	(0.4)	(-0.8)	(0.47)	(-0.32)	(0.58)	(-0.41)	(-2.41)	(-1.07)
H-M	3.17	4.25*	2.01	1.49	-1.24	-0.07	-0.42	2.14	5.16**	3.67
	(1.53)	(1.65)	(0.85)	(0.76)	(-0.61)	(-0.03)	(-0.19)	(1.0)	(2.04)	(1.51)
Panel B. Loadings										
Market (MKT)										
High PI	1.16	1.18	1.13	1.18	1.19	1.22	1.23	1.2	1.21	1.18
	[0.05]	[0.03]	[0.05]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.05]	[0.05]
Matched	0.96	0.96	0.98	1.01	1.01	0.98	0.95	0.96	1.01	0.97
	[0.02]	[0.02]	[0.02]	[0.03]	[0.03]	[0.03]	[0.02]	[0.03]	[0.03]	[0.03]
H-M	0.2***	0.22***	0.15***	0.17***	0.19***	0.24***	0.28***	0.25***	0.2***	0.21***
	(3.38)	(5.22)	(3.14)	(3.63)	(3.76)	(4.5)	(5.5)	(4.58)	(3.3)	(3.21)
Size (ME)										
High PI	0.65***	0.53***	0.55***	0.43***	0.4***	0.34***	0.4***	0.32***	0.33***	0.31***
	(5.2)	(6.16)	(4.51)	(4.86)	(5.35)	(3.9)	(4.24)	(3.08)	(3.29)	(2.93)
Matched	0.23***	0.28***	0.23***	0.11*	0.1	0.21***	0.29***	0.1*	0.18***	0.18***
	(4.88)	(6.32)	(5.22)	(1.73)	(1.44)	(3.9)	(7.59)	(1.82)	(2.58)	(3.8)
H-M	0.42***	0.25***	0.32***	0.33***	0.3**	0.12	0.11	0.22	0.14	0.13
	(2.74)	(3.4)	(2.87)	(2.78)	(2.52)	(0.98)	(1.19)	(1.56)	(0.93)	(0.98)
Investment (IA)										
High PI	-0.01	-0.08	-0.3**	-0.26***	-0.21***	-0.18**	-0.3***	-0.42***	-0.43***	-0.44***
	(-0.12)	(-0.56)	(-2.14)	(-2.85)	(-2.6)	(-2.2)	(-3.61)	(-3.97)	(-4.12)	(-4.25)
Matched	0.24***	0.08	0.06	0.3***	0.28***	0.34***	0.22***	0.17***	0.35***	0.34***
	(3.5)	(1.59)	(1.09)	(4.62)	(3.46)	(5.94)	(3.86)	(2.81)	(3.81)	(4.69)
H-M	-0.25*	-0.16	-0.37***	-0.56***	-0.49***	-0.53***	-0.51***	-0.58***	-0.78***	-0.78***
	(-1.66)	(-1.1)	(-2.77)	(-5.09)	(-4.0)	(-5.03)	(-4.92)	(-4.49)	(-4.84)	(-5.39)
Profitability (ROE)										
High PI	-0.59***	-0.39***	-0.24**	-0.3***	-0.3***	-0.37***	-0.22***	-0.25***	-0.29***	-0.27***
	(-6.07)	(-4.18)	(-2.19)	(-3.93)	(-3.44)	(-3.71)	(-2.84)	(-3.05)	(-2.91)	(-2.76)
Matched	-0.05	-0.07	0.05	0.07	0.06	0.04	0.1*	0.14***	0.11	0.09*
	(-1.14)	(-1.43)	(1.03)	(1.13)	(0.94)	(0.75)	(1.89)	(2.7)	(1.4)	(1.93)
H-M	-0.54***	-0.32***	-0.29***	-0.37***	-0.36***	-0.41***	-0.33***	-0.39***	-0.4***	-0.36***
	(-4.4)	(-3.39)	(-2.65)	(-3.26)	(-4.21)	(-3.94)	(-2.87)	(-3.61)	(-2.8)	(-3.24)
Expected growth (EG)										
High PI	0.5***	0.32**	0.21*	0.23**	0.3***	0.34***	0.32***	0.28**	0.3***	0.26**
	(4.76)	(2.35)	(1.78)	(2.09)	(2.99)	(3.75)	(3.38)	(2.53)	(2.68)	(2.4)
Matched	-0.02	-0.07	-0.19***	-0.21***	-0.28***	-0.15**	-0.1*	-0.24***	-0.1	-0.22***
	(-0.29)	(-1.01)	(-2.83)	(-3.19)	(-3.66)	(-2.05)	(-1.8)	(-4.22)	(-1.06)	(-3.23)
H-M	0.52***	0.39***	0.4***	0.43***	0.58***	0.49***	0.43***	0.53***	0.4**	0.48***
	(4.01)	(2.82)	(3.34)	(3.7)	(4.06)	(3.68)	(3.46)	(3.86)	(2.25)	(3.61)

Table IA12: High-PI and Prior Returns Matched Portfolios Long-run Returns and Alphas, Fama-French Factors. The table shows average excess and abnormal returns (alphas) of the high PI and non-patenting prior return matched portfolios. At the end of June of year t, stocks are sorted into five K-aged portfolios based on the patent-intensity sort from the end of June of year $t-K$. For each firm in the highest PI sort, we search for the closest match (minimum absolute distance) by the cumulative return over 36 month window ending in June of year $t-K$ and form the Matched portfolio. The high PI portfolio are stocks in the highest PI sort with a valid match. All portfolios are rebalanced monthly based on market capitalization at the end of the prior month. The sample period begins in 1927 in Panel A and in 1963 in Panel B and ends in 2023 for both panels. H-M is a zero-cost portfolio with a long position in the high PI portfolio and a short position in the Matched portfolio. The first two columns indicate the portfolio and, if applicable, the benchmark model for alphas. The estimates of the average excess returns and constants (alphas) are annualized by multiplying by twelve. t-statistics from Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses. */**/*** indicate significance level at 10, 5, and 1%. Significance stars are omitted for the average excess returns of the long portfolios.

		Horizon (K years)									
Portfolio	Model	1	2	3	4	5	6	7	8	9	10
Panel A. 1926-											
		Excess returns									
High PI		14.58	14.54	11.85	10.66	10.94	12.92	11.99	11.79	11.75	10.91
		(4.74)	(4.82)	(4.08)	(3.64)	(3.9)	(4.5)	(4.53)	(4.51)	(4.44)	(4.25)
Matched		7.78	8.3	7.17	8.21	8.24	9.82	7.35	8.5	9.12	8.51
		(3.27)	(3.57)	(3.07)	(3.61)	(3.66)	(4.1)	(3.7)	(4.16)	(4.54)	(4.2)
H-M		6.8***	6.24***	4.68***	2.46*	2.69*	3.1**	4.64***	3.29*	2.62	2.41
		(4.42)	(4.02)	(3.13)	(1.67)	(1.72)	(2.09)	(2.94)	(1.95)	(1.47)	(1.37)
		Alphas									
H-M	CAPM	4.62***	3.82**	2.65*	0.22	0.33	0.7	1.91	0.73	-0.08	0.1
		(3.27)	(2.56)	(1.75)	(0.15)	(0.21)	(0.49)	(1.23)	(0.43)	(-0.04)	(0.06)
H-M	FF3	4.79***	4.0***	3.23**	0.78	0.98	1.5	3.25**	2.55	2.03	2.06
		(3.37)	(2.83)	(2.35)	(0.58)	(0.67)	(1.07)	(2.13)	(1.63)	(1.2)	(1.21)
Panel B. 1963-											
		Excess returns									
High PI		13.16	13.64	11.31	9.26	9.09	9.44	10.48	10.39	10.07	10.38
		(4.02)	(4.24)	(3.69)	(2.99)	(3.01)	(3.09)	(3.31)	(3.26)	(3.15)	(3.24)
Matched		6.13	7.7	6.26	6.71	6.53	6.33	5.93	6.24	7.54	7.89
		(2.58)	(3.14)	(2.71)	(2.88)	(2.8)	(2.73)	(2.71)	(2.58)	(3.19)	(3.24)
H-M		7.03***	5.94***	5.05**	2.56	2.56	3.1	4.55**	4.15*	2.53	2.49
		(3.47)	(2.91)	(2.54)	(1.34)	(1.27)	(1.61)	(2.11)	(1.88)	(1.04)	(1.03)
		Alphas									
H-M	CAPM	5.41***	4.42**	3.25	0.68	0.39	1.09	2.18	1.94	0.33	0.31
		(2.77)	(2.13)	(1.56)	(0.34)	(0.19)	(0.58)	(1.04)	(0.86)	(0.13)	(0.12)
H-M	FF3	5.76***	5.32***	4.59**	2.28	1.96	2.77	3.9*	4.05**	2.86	2.51
		(2.93)	(2.84)	(2.45)	(1.28)	(1.05)	(1.57)	(1.85)	(1.97)	(1.34)	(1.12)
High PI	FF5	4.76***	5.93***	4.41***	2.3*	1.75	2.06	3.27**	3.74**	3.52**	4.2**
		(2.79)	(3.68)	(2.79)	(1.66)	(1.34)	(1.57)	(2.26)	(2.23)	(2.11)	(2.49)
Matched		-2.33***	-0.93	-2.07**	-2.47***	-2.16**	-2.35**	-2.54**	-2.09*	-1.73	-1.08
		(-2.63)	(-1.03)	(-2.06)	(-2.99)	(-2.34)	(-2.25)	(-2.41)	(-1.95)	(-1.64)	(-0.84)
H-M		7.09***	6.85***	6.48***	4.77***	3.91**	4.41**	5.8***	5.82***	5.25**	5.28**
		(3.42)	(3.61)	(3.38)	(2.89)	(2.29)	(2.57)	(2.94)	(2.73)	(2.47)	(2.32)

Table IA13: High-PI and Prior Return Matched Portfolios Alpha and Risk Dynamics, $q5$ Factors. The table shows the abnormal returns (alphas in Panel A) the loadings on the $q5$ model's factors (Panel B) of the high PI and non-patenting past return matched portfolios (indicated in rows) for holding period of one-year at different investment horizons (indicated in columns). Details of the portfolio construction and investment horizons are described in the Table IA12 notes. The sample period begins in 1967, to accommodate the q-factors, and ends in 2023. t-statistics from Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses and the standard errors in brackets. */**/*** indicate significance level at 10, 5, and 1%. Significance stars are omitted for the Market (MKT) loadings of the long portfolios.

	Horizon (K years)									
Portfolio	1	2	3	4	5	6	7	8	9	10
Panel A. Alphas										
High PI	1.93	3.51	2.52	0.44	-0.71	-0.44	0.27	1.68	1.48	2.41
	(1.23)	(1.51)	(1.14)	(0.27)	(-0.47)	(-0.31)	(0.17)	(0.93)	(0.81)	(1.3)
Matched	-1.56	0.1	-1.74	-1.54	-1.06	-1.45	-1.41	-0.8	-0.83	0.73
	(-1.41)	(0.1)	(-1.48)	(-1.63)	(-0.84)	(-1.28)	(-1.17)	(-0.68)	(-0.66)	(0.57)
H-M	3.49*	3.41	4.26	1.98	0.35	1.01	1.68	2.48	2.32	1.68
	(1.65)	(1.27)	(1.53)	(0.98)	(0.16)	(0.53)	(0.75)	(1.07)	(0.97)	(0.7)
Panel B. Loadings										
Market (MKT)										
High PI	1.16	1.18	1.13	1.18	1.19	1.22	1.23	1.2	1.21	1.18
	[0.05]	[0.03]	[0.05]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.05]	[0.05]
Matched	1.0	1.03	0.98	1.01	0.96	0.99	0.96	0.96	1.02	0.98
	[0.02]	[0.03]	[0.03]	[0.03]	[0.03]	[0.03]	[0.03]	[0.03]	[0.03]	[0.03]
H-M	0.16***	0.15***	0.15**	0.17***	0.24***	0.22***	0.26***	0.24***	0.19***	0.2***
	(2.93)	(3.13)	(2.52)	(2.84)	(4.39)	(4.2)	(4.33)	(4.6)	(3.12)	(3.2)
Size (ME)										
High PI	0.65***	0.53***	0.55***	0.43***	0.4***	0.34***	0.4***	0.32***	0.33***	0.31***
	(5.21)	(6.16)	(4.5)	(4.86)	(5.35)	(3.9)	(4.24)	(3.08)	(3.29)	(2.93)
Matched	0.25***	0.23***	0.25***	0.22**	0.2***	0.17***	0.16*	0.18***	0.1	0.07
	(4.74)	(4.55)	(4.29)	(2.48)	(3.79)	(2.77)	(1.77)	(3.98)	(1.35)	(0.99)
H-M	0.4**	0.3**	0.3*	0.21	0.21*	0.16	0.24	0.14	0.23	0.23
	(2.5)	(2.45)	(1.78)	(1.33)	(1.87)	(1.22)	(1.44)	(1.1)	(1.45)	(1.46)
Investment (IA)										
High PI	-0.02	-0.08	-0.31**	-0.26***	-0.21***	-0.18**	-0.29***	-0.42***	-0.43***	-0.44***
	(-0.14)	(-0.57)	(-2.15)	(-2.86)	(-2.6)	(-2.2)	(-3.61)	(-3.97)	(-4.12)	(-4.25)
Matched	0.28***	0.26***	0.17***	0.3***	0.34***	0.35***	0.29***	0.27***	0.42***	0.38***
	(4.48)	(4.12)	(2.68)	(3.52)	(4.3)	(4.85)	(3.63)	(4.15)	(4.58)	(4.64)
H-M	-0.3**	-0.34*	-0.47***	-0.55***	-0.55***	-0.53***	-0.59***	-0.69***	-0.85***	-0.82***
	(-2.01)	(-1.85)	(-2.66)	(-3.57)	(-4.17)	(-4.1)	(-4.23)	(-4.67)	(-5.4)	(-5.66)
Profitability (ROE)										
High PI	-0.59***	-0.39***	-0.24**	-0.3***	-0.3***	-0.36***	-0.22***	-0.25***	-0.29***	-0.27***
	(-6.08)	(-4.18)	(-2.2)	(-3.93)	(-3.44)	(-3.71)	(-2.84)	(-3.05)	(-2.91)	(-2.76)
Matched	-0.06	-0.0	0.07	0.06	0.12*	0.02	0.14**	-0.04	0.11	0.06
	(-0.97)	(-0.06)	(1.39)	(0.8)	(1.7)	(0.24)	(2.03)	(-0.73)	(1.43)	(0.94)
H-M	-0.53***	-0.39***	-0.31**	-0.36***	-0.42***	-0.38***	-0.37***	-0.21*	-0.4***	-0.33***
	(-4.55)	(-3.1)	(-2.36)	(-3.3)	(-3.41)	(-2.74)	(-3.18)	(-1.92)	(-2.73)	(-2.83)
Expected growth (EG)										
High PI	0.5***	0.32**	0.22*	0.23**	0.3***	0.34***	0.32***	0.28**	0.3***	0.26**
	(4.75)	(2.35)	(1.78)	(2.1)	(2.99)	(3.75)	(3.38)	(2.53)	(2.68)	(2.4)
Matched	-0.07	-0.1*	-0.05	-0.1	-0.18**	-0.11*	-0.18**	-0.11	-0.15*	-0.2***
	(-1.24)	(-1.82)	(-0.76)	(-1.55)	(-2.04)	(-1.86)	(-2.43)	(-1.44)	(-1.75)	(-2.58)
H-M	0.56***	0.42***	0.27	0.33**	0.48***	0.46***	0.51***	0.39**	0.45***	0.46***
	(4.46)	(2.7)	(1.58)	(2.41)	(2.98)	(3.74)	(3.39)	(2.52)	(2.71)	(3.09)

Table IA14: Patents/B Long-run Returns and Alphas, Fama-French Factors. The table shows average excess and abnormal returns (alphas) of aged Patents/B-sorted portfolios. At the end of June of year t, stocks are sorted into five K-aged portfolios based on the patents/B sort from the end of June of year $t-K$. All portfolios are rebalanced monthly based on market capitalization at the end of the prior month. The sample period begins in 1926 in Panel A and in 1963 in Panel B and ends in 2023 for both panels. Portfolio 0 consists of non-patenting firms and the remaining portfolios are sorted by patents/B. HL is a zero-cost portfolio with a long position in portfolio 4 and a short position in portfolio 0. Portfolios 1-3 are not shown for brevity. Patents/B is defined as number of patents in 12 month window prior to the end of June divided by book equity from fiscal year ending in calendar year prior to June. Definition of the book equity is in the Appendix in the main paper (definition of BM). The first two columns indicate the portfolio and, if applicable, the benchmark model for alphas. The estimates of the average excess returns and constants (alphas) are annualized by multiplying by twelve. t-statistics from Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses. */**/*** indicate significance level at 10, 5, and 1%. Significance stars are omitted for the average excess returns of the long portfolios.

		Horizon (K years)									
Portfolio	Model	1	2	3	4	5	6	7	8	9	10
Panel A. 1926-											
		Excess returns									
0		7.59	7.54	7.5	7.11	7.58	7.68	8.94	7.92	7.85	7.88
		(3.81)	(3.75)	(3.71)	(3.52)	(3.76)	(3.82)	(4.47)	(4.4)	(4.39)	(4.4)
4		10.85	10.15	9.11	8.63	9.15	9.98	11.79	10.95	10.95	10.86
		(4.24)	(3.94)	(3.48)	(3.35)	(3.59)	(3.92)	(4.91)	(4.87)	(4.78)	(4.7)
HL		3.26***	2.62**	1.61	1.52	1.56	2.3*	2.86**	3.04**	3.11**	2.98**
		(2.61)	(2.04)	(1.18)	(1.07)	(1.21)	(1.69)	(2.32)	(2.36)	(2.25)	(2.16)
		Alphas									
HL	CAPM	1.23	0.6	-0.39	-0.25	-0.16	0.56	0.99	1.3	1.34	1.25
		(1.01)	(0.48)	(-0.29)	(-0.17)	(-0.13)	(0.41)	(0.79)	(0.99)	(0.93)	(0.87)
HL	FF3	2.14*	1.51	0.61	0.79	0.79	1.62	2.02*	2.82**	3.34***	3.44***
		(1.92)	(1.32)	(0.5)	(0.61)	(0.68)	(1.34)	(1.75)	(2.4)	(2.64)	(2.59)
Panel B. 1963-											
		Excess returns									
0		6.5	6.51	6.61	6.41	6.51	6.27	6.29	6.47	6.3	6.22
		(2.94)	(2.97)	(3.02)	(2.95)	(3.02)	(2.92)	(2.94)	(3.04)	(2.99)	(2.97)
4		9.52	8.89	7.55	7.65	7.72	8.34	9.06	9.95	9.65	9.88
		(3.4)	(3.19)	(2.66)	(2.68)	(2.76)	(3.01)	(3.42)	(3.57)	(3.39)	(3.44)
HL		3.02*	2.38	0.94	1.24	1.21	2.07	2.76*	3.48**	3.35*	3.66*
		(1.84)	(1.42)	(0.52)	(0.64)	(0.69)	(1.15)	(1.69)	(1.96)	(1.79)	(1.95)
		Alphas									
HL	CAPM	1.46	0.81	-0.65	-0.21	-0.28	0.63	1.42	2.06	1.82	2.17
		(0.84)	(0.46)	(-0.33)	(-0.1)	(-0.15)	(0.33)	(0.84)	(1.14)	(0.94)	(1.12)
HL	FF3	3.93***	3.36**	1.97	2.65*	2.37	3.26**	3.8***	4.5***	4.42***	4.7***
		(2.86)	(2.38)	(1.33)	(1.7)	(1.61)	(2.23)	(2.76)	(3.04)	(2.75)	(2.84)
0	FF5	-1.73***	-1.78***	-1.74***	-1.93***	-1.63***	-1.8***	-1.75***	-1.54***	-1.6***	-1.63***
		(-3.49)	(-3.73)	(-3.54)	(-4.01)	(-3.42)	(-3.76)	(-3.66)	(-3.24)	(-3.33)	(-3.35)
4		4.0***	3.7***	2.66**	3.35***	2.92**	3.13***	3.3***	4.06***	4.7***	4.92***
		(3.4)	(3.17)	(2.27)	(2.85)	(2.54)	(2.63)	(2.72)	(3.34)	(3.38)	(3.39)
HL		5.73***	5.49***	4.4***	5.28***	4.54***	4.92***	5.04***	5.59***	6.29***	6.56***
		(4.01)	(3.84)	(3.04)	(3.59)	(3.19)	(3.31)	(3.38)	(3.79)	(3.79)	(3.73)

Table IA15: Patents/B Portfolios Alpha and Risk Dynamics, $q5$ Factors. The table shows the abnormal returns (alphas in Panel A) relative to $q5$-factor model Hou, Mo, Xue, and Zhang (2021) and the loadings on the model's factors (Panel B) of Patents/B-sorted portfolios (indicated in rows) for holding period of one-year at different investment horizons (indicated in columns). Details of the portfolio construction and investment horizons are described in the Table IA14 notes. Loadings of portfolios 1-3 are not shown for brevity. The sample period begins in 1967, to accommodate the q-factors, and ends in 2023. The estimates of the alphas are annualized by multiplying by twelve. t-statistics from Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses and the standard errors in brackets. */**/*** indicate significance level at 10, 5, and 1%. Significance stars are omitted for the Market (MKT) loadings of the long portfolios.

	Horizon (K years)									
Portfolio	1	2	3	4	5	6	7	8	9	10
Panel A. Alphas										
0	-0.63	-0.85	-0.74	-1.13**	-0.8	-0.93*	-0.88	-0.58	-0.94*	-0.9
	(-1.17)	(-1.49)	(-1.3)	(-2.03)	(-1.46)	(-1.72)	(-1.59)	(-1.05)	(-1.71)	(-1.56)
1	0.2	0.34	0.23	0.85	0.22	0.96	0.87	0.33	0.24	0.5
	(0.33)	(0.57)	(0.42)	(1.42)	(0.35)	(1.4)	(1.34)	(0.52)	(0.38)	(0.7)
2	0.16	-0.24	-0.39	-0.7	-1.38**	-2.21***	-2.17***	-1.66**	-1.35*	-1.51**
	(0.24)	(-0.35)	(-0.57)	(-0.98)	(-2.07)	(-2.9)	(-3.2)	(-2.53)	(-1.91)	(-1.99)
3	0.38	0.98	1.13	0.53	1.83*	1.96*	1.22	0.06	-0.37	-0.41
	(0.39)	(1.13)	(1.17)	(0.57)	(1.96)	(1.81)	(1.34)	(0.06)	(-0.41)	(-0.46)
4	2.88*	2.07	1.29	1.76	0.78	0.97	1.12	2.17	3.12**	3.16*
	(1.65)	(1.36)	(0.82)	(1.05)	(0.5)	(0.64)	(0.76)	(1.52)	(1.99)	(1.92)
HL	3.52*	2.92	2.03	2.88	1.58	1.9	2.0	2.75	4.06**	4.06**
	(1.68)	(1.56)	(1.04)	(1.43)	(0.84)	(1.03)	(1.11)	(1.57)	(2.12)	(2.03)
Panel B. Loadings										
Market (MKT)										
0	1.0	1.0	1.0	1.01	1.0	0.99	0.99	0.98	0.99	0.99
	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]
4	1.14	1.14	1.14	1.11	1.12	1.13	1.12	1.12	1.09	1.1
	[0.03]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]
HL	0.14***	0.14***	0.13**	0.1*	0.12**	0.14***	0.13***	0.14***	0.1*	0.11**
	(3.15)	(2.66)	(2.37)	(1.9)	(2.56)	(2.73)	(2.6)	(2.71)	(1.77)	(1.97)
Size (ME)										
0	0.12**	0.12**	0.1**	0.1**	0.09**	0.08*	0.07	0.07	0.05	0.02
	(2.41)	(2.42)	(2.0)	(1.97)	(2.11)	(1.88)	(1.47)	(1.5)	(1.39)	(0.41)
4	0.13*	0.15*	0.11	0.1	0.15*	0.08	0.12*	0.13	0.19	0.13
	(1.83)	(1.83)	(1.28)	(1.09)	(1.68)	(1.08)	(1.7)	(1.59)	(1.63)	(1.2)
HL	0.0	0.03	0.01	0.01	0.05	0.01	0.05	0.07	0.14	0.11
	(0.02)	(0.21)	(0.07)	(0.05)	(0.42)	(0.06)	(0.45)	(0.55)	(0.89)	(0.74)
Investment (IA)										
0	0.22***	0.23***	0.24***	0.26***	0.24***	0.26***	0.26***	0.26***	0.28***	0.28***
	(5.16)	(5.01)	(5.5)	(5.45)	(5.54)	(7.19)	(6.79)	(6.89)	(7.87)	(7.39)
4	-0.51***	-0.57***	-0.55***	-0.63***	-0.58***	-0.5***	-0.47***	-0.46***	-0.62***	-0.53***
	(-4.28)	(-5.6)	(-5.17)	(-6.25)	(-7.04)	(-6.45)	(-6.76)	(-6.58)	(-6.04)	(-5.43)
HL	-0.73***	-0.8***	-0.79***	-0.88***	-0.82***	-0.75***	-0.73***	-0.73***	-0.89***	-0.81***
	(-4.84)	(-5.73)	(-5.55)	(-6.26)	(-7.08)	(-7.24)	(-7.66)	(-7.48)	(-7.0)	(-6.51)
Profitability (ROE)										
0	0.09**	0.09**	0.09**	0.1***	0.08**	0.08**	0.07*	0.07*	0.07**	0.08**
	(2.47)	(2.43)	(2.4)	(2.67)	(2.12)	(2.35)	(1.75)	(1.72)	(2.02)	(2.04)
4	-0.2**	-0.19**	-0.28***	-0.3***	-0.28***	-0.24***	-0.19***	-0.17**	-0.26***	-0.26***
	(-2.35)	(-2.37)	(-3.08)	(-3.54)	(-3.19)	(-2.78)	(-2.59)	(-2.26)	(-3.25)	(-3.12)
HL	-0.29***	-0.28***	-0.38***	-0.4***	-0.36***	-0.32***	-0.26***	-0.24**	-0.34***	-0.34***
	(-2.6)	(-2.65)	(-3.14)	(-3.49)	(-3.15)	(-2.9)	(-2.63)	(-2.3)	(-3.12)	(-3.05)
Expected growth (EG)										
0	-0.17***	-0.14***	-0.15***	-0.15***	-0.14***	-0.15***	-0.14***	-0.15***	-0.13***	-0.14***
	(-4.48)	(-3.56)	(-3.83)	(-3.56)	(-3.46)	(-4.09)	(-3.75)	(-4.03)	(-3.69)	(-3.55)
4	0.17*	0.21**	0.23**	0.26**	0.31***	0.3***	0.31***	0.28***	0.29***	0.29***
	(1.69)	(2.4)	(2.33)	(2.39)	(3.15)	(3.02)	(3.88)	(3.11)	(3.0)	(2.9)
HL	0.34***	0.35***	0.37***	0.41***	0.45***	0.45***	0.46***	0.43***	0.43***	0.42***
	(2.63)	(3.04)	(2.99)	(2.9)	(3.49)	(3.57)	(4.29)	(3.68)	(3.48)	(3.31)

Table IA16: PI Portfolios Within Fama-French 10 Industries Long-run Returns and Alphas, Fama-French Factors. The table shows average excess and abnormal returns (alphas) of aged PI-sorted portfolios within the Fama-French 10 industries. At the end of June of year t, stocks are sorted into five K-aged portfolios based on the patent-intensity sort within industries from the end of June of year $t - K$. All portfolios are rebalanced monthly based on market capitalization at the end of the prior month. The sample period begins in 1926 in Panel A and in 1963 in Panel B and ends in 2023 for both panels. Portfolio 0 consists of non-patenting firms. The remaining stocks are sorted by PI within each of the Fama-French 10 industries, and portfolios are formed from stocks with the same within-industry sort. HL is a zero-cost portfolio with a long position in portfolio 4 and a short position in portfolio 0. Portfolios 1-3 are not shown for brevity. The first two columns indicate the portfolio and, if applicable, the benchmark model for alphas. The estimates of the average excess returns and constants (alphas) are annualized by multiplying by twelve. t-statistics from Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses and the standard errors in brackets. */**/*** indicate significance level at 10, 5, and 1%. Significance stars are omitted for the average excess returns of the long portfolios.

		Horizon (K years)									
Portfolio	Model	1	2	3	4	5	6	7	8	9	10
Panel A. 1926-											
		Excess returns									
0		7.58	7.55	7.55	7.08	7.53	7.67	8.98	7.94	7.94	7.83
		(3.79)	(3.74)	(3.72)	(3.49)	(3.73)	(3.8)	(4.49)	(4.42)	(4.44)	(4.38)
4		12.87	13.13	10.89	9.64	9.88	10.46	12.56	11.18	9.91	9.82
		(4.54)	(4.73)	(3.98)	(3.4)	(3.62)	(3.83)	(4.65)	(4.75)	(4.33)	(4.43)
HL		5.29***	5.58***	3.34***	2.56*	2.35*	2.79**	3.58***	3.24***	1.97*	1.99*
		(3.81)	(4.07)	(2.61)	(1.74)	(1.8)	(2.15)	(2.83)	(2.75)	(1.67)	(1.78)
		Alphas									
HL	CAPM	2.63**	3.16**	1.33	0.45	0.32	0.56	0.97	1.16	0.0	0.4
		(2.2)	(2.49)	(1.14)	(0.33)	(0.25)	(0.47)	(0.85)	(1.04)	(0.0)	(0.36)
HL	FF3	2.16*	2.92**	1.32	0.51	0.35	0.56	1.21	1.61	0.69	1.01
		(1.85)	(2.4)	(1.15)	(0.38)	(0.29)	(0.48)	(1.09)	(1.44)	(0.61)	(0.9)
Panel B. 1963-											
		Excess returns									
0		6.49	6.5	6.62	6.37	6.44	6.24	6.3	6.51	6.31	6.17
		(2.94)	(2.97)	(3.03)	(2.93)	(2.99)	(2.91)	(2.94)	(3.07)	(3.01)	(2.96)
4		10.88	11.05	9.03	8.33	8.57	8.31	9.1	9.67	8.02	8.2
		(3.85)	(3.87)	(3.25)	(2.79)	(2.92)	(2.92)	(3.23)	(3.51)	(3.03)	(3.15)
HL		4.39***	4.55***	2.4	1.96	2.13	2.07	2.8*	3.16**	1.72	2.02
		(2.81)	(2.82)	(1.63)	(1.05)	(1.28)	(1.29)	(1.84)	(2.05)	(1.12)	(1.38)
		Alphas									
HL	CAPM	3.13**	3.22**	1.13	0.55	0.61	0.63	1.34	1.95	0.48	0.93
		(2.01)	(1.96)	(0.75)	(0.28)	(0.36)	(0.4)	(0.89)	(1.29)	(0.31)	(0.63)
HL	FF3	3.18*	3.6**	1.62	1.47	1.35	1.38	2.22	2.83*	1.55	1.8
		(1.96)	(2.27)	(1.14)	(0.85)	(0.85)	(0.88)	(1.53)	(1.93)	(1.08)	(1.22)
0	FF5	-1.73***	-1.77***	-1.71***	-1.95***	-1.71***	-1.83***	-1.75***	-1.49***	-1.58***	-1.66***
		(-3.46)	(-3.65)	(-3.45)	(-4.0)	(-3.48)	(-3.75)	(-3.58)	(-3.08)	(-3.28)	(-3.35)
4		2.84**	3.16**	1.51	1.52	0.92	0.86	1.27	2.29*	0.84	0.74
		(2.1)	(2.41)	(1.18)	(1.08)	(0.64)	(0.61)	(0.93)	(1.71)	(0.66)	(0.53)
HL		4.56***	4.93***	3.22**	3.47**	2.63*	2.69*	3.02**	3.77**	2.43	2.4
		(2.88)	(3.32)	(2.29)	(2.17)	(1.67)	(1.7)	(2.0)	(2.47)	(1.6)	(1.49)

Table IA17: PI Portfolios Within Fama-French 10 Industries Alpha and Risk Dynamics, $q5$ Factors. The table shows the abnormal returns (alphas in Panel A) relative to $q5$-factor model (Hou, Mo, Xue, and Zhang, 2021) and the loadings on the model's factors (Panel B) of within-industries PI-sorted portfolios (indicated in rows) for holding period of one-year at different investment horizons (indicated in columns). Details of the portfolio construction and investment horizons are described in the Table IA16 notes. The sample period begins in 1967, to accommodate the q-factors, and ends in 2023. The estimates of the alphas are annualized by multiplying by twelve. t-statistics from Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses and the standard errors in brackets. */**/*** indicate significance level at 10, 5, and 1%. Significance stars are omitted for the Market (MKT) loadings of the long portfolios.

	Horizon (K years)									
Portfolio	1	2	3	4	5	6	7	8	9	10
Panel A. Alphas										
0	-0.65	-0.86	-0.74	-1.12**	-0.85	-0.96*	-0.89	-0.58	-1.01*	-1.0*
	(-1.19)	(-1.5)	(-1.29)	(-2.01)	(-1.52)	(-1.76)	(-1.59)	(-1.04)	(-1.82)	(-1.71)
1	-0.08	0.29	-0.36	-0.09	-0.5	-0.72	-1.09*	-1.3**	-0.89	-0.67
	(-0.15)	(0.57)	(-0.66)	(-0.17)	(-0.83)	(-1.22)	(-1.93)	(-2.21)	(-1.41)	(-1.09)
2	1.5**	0.63	1.13	1.03	0.48	1.3*	1.11	0.45	1.18	0.52
	(2.26)	(0.85)	(1.58)	(1.55)	(0.68)	(1.86)	(1.52)	(0.63)	(1.61)	(0.64)
3	0.71	1.42	1.15	0.83	1.27	1.05	1.83*	2.23**	0.58	0.56
	(0.61)	(1.32)	(1.08)	(0.77)	(1.01)	(1.03)	(1.66)	(2.05)	(0.65)	(0.6)
4	2.67*	2.38	1.7	2.07	1.21	1.53	1.55	2.49	1.22	1.44
	(1.9)	(1.4)	(0.98)	(1.28)	(0.81)	(0.89)	(1.01)	(1.52)	(0.87)	(0.98)
HL	3.33**	3.24	2.43	3.19*	2.05	2.49	2.44	3.07	2.23	2.44
	(1.98)	(1.61)	(1.24)	(1.71)	(1.21)	(1.27)	(1.37)	(1.64)	(1.32)	(1.43)
Panel B. Loadings										
Market (MKT)										
0	1.0	1.0	1.0	1.01	1.0	0.99	0.99	0.98	0.99	0.98
	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]
4	1.14	1.16	1.13	1.12	1.17	1.14	1.17	1.09	1.08	1.1
	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]
HL	0.14***	0.16***	0.12***	0.11**	0.17***	0.14***	0.17***	0.11**	0.1**	0.11**
	(2.72)	(3.58)	(2.84)	(2.12)	(4.22)	(3.08)	(4.26)	(2.12)	(1.99)	(2.56)
Size (ME)										
0	0.12**	0.12**	0.1*	0.09*	0.09*	0.07*	0.06	0.06	0.05	0.01
	(2.38)	(2.37)	(1.95)	(1.91)	(1.91)	(1.67)	(1.29)	(1.32)	(1.19)	(0.31)
4	0.29***	0.26***	0.21***	0.2**	0.1*	0.12**	0.07	0.19**	0.17*	0.01
	(2.73)	(3.15)	(2.91)	(2.06)	(1.66)	(2.43)	(1.33)	(2.12)	(1.95)	(0.13)
HL	0.17	0.15	0.12	0.11	0.02	0.05	0.01	0.13	0.13	-0.0
	(1.1)	(1.19)	(1.04)	(0.77)	(0.23)	(0.69)	(0.12)	(1.03)	(1.03)	(-0.08)
Investment (IA)										
0	0.22***	0.24***	0.25***	0.26***	0.25***	0.27***	0.27***	0.28***	0.29***	0.28***
	(5.23)	(5.08)	(5.57)	(5.5)	(5.57)	(7.34)	(6.88)	(7.06)	(8.08)	(7.6)
4	0.17*	0.17*	0.07	-0.08	0.01	-0.01	0.04	-0.02	-0.06	0.01
	(1.91)	(1.68)	(0.68)	(-0.75)	(0.19)	(-0.14)	(0.48)	(-0.22)	(-0.77)	(0.15)
HL	-0.06	-0.07	-0.18	-0.33**	-0.23**	-0.28***	-0.23**	-0.29***	-0.34***	-0.27***
	(-0.49)	(-0.51)	(-1.33)	(-2.49)	(-2.43)	(-2.73)	(-2.36)	(-2.61)	(-3.62)	(-3.07)
Profitability (ROE)										
0	0.09**	0.09**	0.09**	0.1***	0.08**	0.08**	0.07*	0.06	0.07*	0.08**
	(2.46)	(2.4)	(2.37)	(2.65)	(2.09)	(2.22)	(1.65)	(1.58)	(1.94)	(2.07)
4	-0.42***	-0.28***	-0.2*	-0.23**	-0.13	-0.27***	-0.12	-0.16*	-0.12	-0.03
	(-4.15)	(-3.13)	(-1.93)	(-2.47)	(-1.58)	(-2.68)	(-1.37)	(-1.72)	(-1.54)	(-0.38)
HL	-0.5***	-0.37***	-0.29**	-0.33***	-0.21**	-0.35***	-0.18*	-0.22*	-0.19*	-0.11
	(-4.06)	(-3.26)	(-2.46)	(-2.99)	(-2.14)	(-3.0)	(-1.79)	(-1.89)	(-1.88)	(-1.22)
Expected growth (EG)										
0	-0.16***	-0.14***	-0.14***	-0.14***	-0.14***	-0.15***	-0.14***	-0.14***	-0.13***	-0.13***
	(-4.45)	(-3.52)	(-3.78)	(-3.53)	(-3.42)	(-3.97)	(-3.61)	(-3.81)	(-3.47)	(-3.44)
4	0.14	0.08	-0.04	-0.07	-0.08	-0.01	-0.04	0.01	-0.05	-0.1
	(1.6)	(0.77)	(-0.47)	(-0.73)	(-0.88)	(-0.1)	(-0.51)	(0.11)	(-0.61)	(-1.31)
HL	0.3***	0.22*	0.1	0.08	0.06	0.14	0.1	0.15	0.08	0.03
	(2.93)	(1.69)	(0.9)	(0.67)	(0.57)	(1.46)	(1.05)	(1.5)	(0.81)	(0.38)

Table IA18: KPSS/M Portfolios Long-run Return and Alphas, Fama-French Factors. The table shows average excess and abnormal returns (alphas) of aged KPSS/M-sorted portfolios. At the end of June of year t, stocks are sorted into five K-aged portfolios based on the KPSS/M sort from the end of June of year $t-K$. All portfolios are rebalanced monthly based on market capitalization at the end of the prior month. The sample period begins in 1926 in Panel A and in 1963 in Panel B and ends in 2023 for both panels. Portfolio 0 consists of non-patenting firms and the remaining portfolios are sorted by KPSS/M. HL is a zero-cost portfolio with a long position in portfolio 4 and a short position in portfolio 0. Portfolios 1-3 are not shown for brevity. The KPSS/M is defined as the sum of the nominal value estimates of patents Kogan, Papanikolaou, Seru, and Stoffman (2017) granted to the firm in the 12-month window prior to end June divided by the firm market capitalization at the end of June. The first two columns indicate the portfolio and, if applicable, the benchmark model for alphas. The estimates of the average excess returns and constants (alphas) are annualized by multiplying by twelve. t-statistics from Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses. */**/*** indicate significance level at 10, 5, and 1%. Significance stars are omitted for the average excess returns of the long portfolios.

		Horizon (K years)									
Portfolio	Model	1	2	3	4	5	6	7	8	9	10
Panel A. 1926-											
		Excess returns									
0		7.54	7.57	7.56	7.09	7.56	7.66	8.98	7.93	7.95	7.84
		(3.77)	(3.75)	(3.72)	(3.5)	(3.74)	(3.8)	(4.49)	(4.42)	(4.46)	(4.4)
4		10.22	9.26	8.7	8.62	8.82	8.93	10.19	9.21	9.19	9.02
		(4.68)	(4.7)	(4.49)	(4.35)	(4.57)	(4.56)	(5.36)	(5.32)	(5.32)	(5.27)
HL		2.68***	1.68*	1.15	1.53*	1.26	1.27	1.22	1.27	1.24	1.18
		(2.69)	(1.94)	(1.38)	(1.72)	(1.5)	(1.53)	(1.46)	(1.55)	(1.49)	(1.47)
		Alphas									
HL	CAPM	2.03**	1.79**	1.34	1.75*	1.64*	1.5*	1.64*	1.41*	1.48*	1.4*
		(2.23)	(2.03)	(1.59)	(1.96)	(1.96)	(1.8)	(1.94)	(1.69)	(1.73)	(1.7)
HL	FF3	2.44***	2.56***	2.23***	2.71***	2.56***	2.41***	2.44***	2.25***	2.55***	2.54***
		(2.87)	(3.33)	(3.04)	(3.48)	(3.53)	(3.27)	(3.25)	(3.06)	(3.47)	(3.47)
Panel B. 1963-											
		Excess returns									
0		6.43	6.54	6.62	6.37	6.45	6.24	6.29	6.51	6.31	6.18
		(2.9)	(2.99)	(3.03)	(2.94)	(3.0)	(2.91)	(2.94)	(3.07)	(3.02)	(2.96)
4		7.68	7.46	7.5	7.4	7.47	7.36	7.66	7.54	7.35	7.3
		(3.76)	(3.66)	(3.76)	(3.69)	(3.77)	(3.73)	(3.9)	(3.85)	(3.74)	(3.71)
HL		1.25	0.93	0.88	1.02	1.02	1.12	1.37	1.03	1.04	1.13
		(1.13)	(0.83)	(0.81)	(0.92)	(0.96)	(1.06)	(1.31)	(0.98)	(1.0)	(1.12)
		Alphas									
HL	CAPM	1.45	1.17	1.12	1.3	1.32	1.39	1.65	1.31	1.29	1.36
		(1.25)	(0.99)	(0.98)	(1.12)	(1.18)	(1.28)	(1.54)	(1.22)	(1.2)	(1.31)
HL	FF3	3.01***	2.84***	2.79***	3.02***	3.02***	2.98***	3.27***	2.89***	2.85***	2.86***
		(3.42)	(3.19)	(3.23)	(3.47)	(3.47)	(3.47)	(3.84)	(3.32)	(3.25)	(3.25)
0	FF5	-1.57***	-1.61***	-1.71***	-1.95***	-1.7***	-1.83***	-1.75***	-1.49***	-1.58***	-1.66***
		(-3.32)	(-3.44)	(-3.45)	(-3.98)	(-3.46)	(-3.74)	(-3.6)	(-3.08)	(-3.27)	(-3.34)
4		1.64***	1.37***	1.34***	1.18***	1.11**	0.78*	1.08**	0.94*	0.7	0.59
		(3.49)	(2.97)	(3.11)	(2.62)	(2.33)	(1.7)	(2.19)	(1.91)	(1.38)	(1.14)
HL		3.21***	2.98***	3.05***	3.13***	2.81***	2.61***	2.83***	2.43***	2.28**	2.25**
		(3.64)	(3.4)	(3.51)	(3.58)	(3.16)	(2.94)	(3.15)	(2.7)	(2.49)	(2.46)

Table IA19: KPSS/M Portfolios Alpha and Risk Dynamics, $q5$ Factors. The table shows the abnormal returns (alphas in Panel A) relative to $q5$-factor model (Hou, Mo, Xue, and Zhang, 2021) and the loadings on the model's factors (Panel B) of KPSS/M-sorted portfolios (indicated in rows) for holding period of one-year at different investment horizons (indicated in columns). Details of the portfolio construction and investment horizons are described in the Table IA18 notes. The sample period begins in 1967, to accommodate the q-factors, and ends in 2023. The estimates of the alphas are annualized by multiplying by twelve. t-statistics from Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses and the standard errors in brackets. */**/*** indicate significance level at 10, 5, and 1%. Significance stars are omitted for the Market (MKT) loadings of the long portfolios.

	Horizon (K years)									
Portfolio	1	2	3	4	5	6	7	8	9	10
Panel A. Alphas										
0	-0.69	-0.77	-0.73	-1.11**	-0.84	-0.96*	-0.9	-0.58	-1.01*	-1.0*
	(-1.26)	(-1.36)	(-1.28)	(-2.0)	(-1.51)	(-1.76)	(-1.61)	(-1.04)	(-1.82)	(-1.7)
1	1.03	1.29	0.71	0.89	-0.56	0.75	0.47	-0.72	0.22	0.14
	(1.23)	(1.61)	(0.87)	(1.05)	(-0.76)	(0.65)	(0.62)	(-0.83)	(0.26)	(0.17)
2	1.19	1.45	0.85	0.71	0.42	1.68**	1.5*	0.08	0.97	1.77
	(1.28)	(1.56)	(0.94)	(0.91)	(0.44)	(2.09)	(1.66)	(0.08)	(0.9)	(1.18)
3	-0.28	0.16	0.29	1.46**	1.11	1.53*	-0.27	1.45	0.03	0.38
	(-0.33)	(0.19)	(0.38)	(2.15)	(1.52)	(1.91)	(-0.25)	(1.33)	(0.03)	(0.42)
4	0.59	0.13	0.07	-0.08	-0.09	-0.4	-0.16	-0.47	-0.59	-0.66
	(1.12)	(0.25)	(0.13)	(-0.16)	(-0.16)	(-0.74)	(-0.27)	(-0.79)	(-0.97)	(-1.03)
HL	1.29	0.9	0.8	1.03	0.75	0.56	0.74	0.11	0.42	0.34
	(1.27)	(0.9)	(0.79)	(1.04)	(0.75)	(0.57)	(0.74)	(0.11)	(0.41)	(0.32)
Panel B. Loadings										
Market (MKT)										
0	1.0	1.0	1.0	1.01	1.0	0.99	0.99	0.98	0.99	0.98
	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]
4	1.02	1.01	1.01	1.01	1.01	1.01	1.0	1.0	1.0	1.0
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
HL	0.02	0.01	0.01	0.0	0.01	0.01	0.01	0.01	0.01	0.01
	(0.72)	(0.44)	(0.34)	(0.15)	(0.35)	(0.48)	(0.35)	(0.54)	(0.45)	(0.51)
Size (ME)										
0	0.12**	0.12**	0.1*	0.09*	0.09*	0.07*	0.06	0.06	0.05	0.01
	(2.24)	(2.32)	(1.95)	(1.91)	(1.91)	(1.68)	(1.29)	(1.32)	(1.19)	(0.32)
4	-0.17***	-0.17***	-0.17***	-0.18***	-0.19***	-0.18***	-0.18***	-0.18***	-0.18***	-0.19***
	(-7.27)	(-7.55)	(-9.63)	(-11.0)	(-12.1)	(-9.95)	(-9.94)	(-10.1)	(-11.21)	(-12.14)
HL	-0.29***	-0.29***	-0.27***	-0.28***	-0.28***	-0.25***	-0.24***	-0.23***	-0.23***	-0.21***
	(-3.9)	(-4.05)	(-4.16)	(-4.53)	(-5.05)	(-4.57)	(-3.96)	(-4.2)	(-4.61)	(-4.06)
Investment (IA)										
0	0.17***	0.21***	0.25***	0.26***	0.25***	0.27***	0.27***	0.28***	0.29***	0.28***
	(3.53)	(4.41)	(5.57)	(5.49)	(5.57)	(7.33)	(6.87)	(7.06)	(8.09)	(7.57)
4	-0.1***	-0.08**	-0.06**	-0.07**	-0.05**	-0.03	-0.03	-0.01	-0.01	0.0
	(-2.98)	(-2.44)	(-2.21)	(-2.46)	(-2.05)	(-1.15)	(-0.95)	(-0.47)	(-0.21)	(0.1)
HL	-0.27***	-0.29***	-0.31***	-0.33***	-0.3***	-0.3***	-0.3***	-0.29***	-0.29***	-0.28***
	(-3.55)	(-3.78)	(-4.55)	(-4.78)	(-4.89)	(-5.71)	(-5.56)	(-5.56)	(-5.52)	(-5.26)
Profitability (ROE)										
0	0.07*	0.08**	0.09**	0.1***	0.08**	0.08**	0.07	0.06	0.07*	0.08**
	(1.82)	(2.14)	(2.36)	(2.63)	(2.08)	(2.21)	(1.64)	(1.58)	(1.93)	(2.06)
4	-0.1***	-0.09***	-0.08***	-0.06**	-0.06**	-0.05**	-0.04*	-0.05**	-0.04*	-0.03
	(-3.62)	(-3.39)	(-3.2)	(-2.54)	(-2.4)	(-2.1)	(-1.82)	(-2.16)	(-1.74)	(-1.19)
HL	-0.17***	-0.17***	-0.17***	-0.16***	-0.13**	-0.13**	-0.11**	-0.11**	-0.11**	-0.11**
	(-2.73)	(-2.81)	(-2.9)	(-2.8)	(-2.38)	(-2.42)	(-1.96)	(-2.15)	(-2.23)	(-2.11)
Expected growth (EG)										
0	-0.13***	-0.13***	-0.14***	-0.14***	-0.14***	-0.15***	-0.14***	-0.14***	-0.13***	-0.13***
	(-3.33)	(-3.24)	(-3.78)	(-3.52)	(-3.4)	(-3.96)	(-3.6)	(-3.81)	(-3.46)	(-3.44)
4	0.19***	0.21***	0.2***	0.2***	0.21***	0.21***	0.22***	0.24***	0.22***	0.22***
	(5.79)	(6.3)	(6.81)	(6.87)	(6.82)	(6.81)	(6.63)	(6.93)	(6.82)	(6.12)
HL	0.31***	0.34***	0.35***	0.35***	0.35***	0.36***	0.36***	0.38***	0.35***	0.35***
	(4.87)	(5.13)	(5.58)	(5.4)	(5.53)	(6.16)	(5.89)	(6.18)	(5.84)	(5.76)

Table IA20: R&D/M Portfolios Long-run Return and Alphas, Fama-French Factors, 1976-2023 (Unbalanced). The table shows average excess and abnormal returns (alphas) of aged R&D/M-sorted portfolios. At the end of June of year t, stocks are sorted into five K-aged portfolios based on the R&D/M sort from the end of June of year $t - K$. All portfolios are rebalanced monthly based on market capitalization at the end of the prior month. The sample period begins in 1976 for $K = 0$-aged portfolio (horizon one year) and an additional year later for each subsequent-horizon portfolio due to availability of reliable data for R&D. The sample period ends in 2023 for all portfolios, resulting in unbalanced portfolio-return time-series across differently aged portfolios (horizons). Portfolio 0 consists of firms with missing or zero R&D, and the remaining portfolios are sorted by R&D/M into equal groups by firm count. HL is a zero-cost portfolio with a long position in portfolio 4 and a short position in portfolio 0. Portfolios 1-3 are not shown for brevity. R&D/M is defined as R&D expenses in fiscal year ending in calendar year prior to June divided by market capitalization in December prior to June. The first two columns indicate the portfolio and, if applicable, the benchmark model for alphas. The estimates of the average excess returns and constants (alphas) are annualized by multiplying by twelve. t-statistics from Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses. */**/*** indicate significance level at 10, 5, and 1%. Significance stars are omitted for the average excess returns of the long portfolios.

		Horizon (K years)									
Portfolio	Model	1	2	3	4	5	6	7	8	9	10
		Excess returns									
0		7.84***	7.91***	8.08***	8.13***	8.08***	7.94***	8.72***	7.77***	8.37***	7.81***
		(3.45)	(3.42)	(3.45)	(3.43)	(3.38)	(3.28)	(3.55)	(3.2)	(3.43)	(3.15)
4		12.36***	9.72***	8.2**	8.62**	11.89***	11.38***	12.29***	13.08***	11.74***	11.67***
		(3.44)	(2.67)	(2.15)	(2.28)	(3.11)	(2.96)	(3.19)	(3.27)	(3.06)	(3.14)
HL		4.52*	1.81	0.12	0.5	3.8	3.44	3.57	5.32*	3.36	3.86
		(1.94)	(0.78)	(0.05)	(0.22)	(1.54)	(1.42)	(1.52)	(1.92)	(1.28)	(1.45)
		Alphas									
HL	CAPM	2.31	-0.87	-3.05	-2.61	0.76	0.39	-0.31	2.12	-0.08	0.67
		(1.04)	(-0.38)	(-1.32)	(-1.22)	(0.32)	(0.17)	(-0.14)	(0.82)	(-0.03)	(0.25)
HL	FF3	2.49	-0.04	-1.8	-1.33	2.53	2.3	1.61	4.53**	2.01	2.48
		(1.23)	(-0.02)	(-0.89)	(-0.73)	(1.28)	(1.16)	(0.82)	(1.96)	(0.9)	(1.09)
0	FF5	-1.72***	-1.8***	-1.84***	-1.86***	-1.96***	-2.11***	-1.98***	-2.12***	-1.85***	-1.97***
		(-3.46)	(-3.63)	(-3.57)	(-3.6)	(-3.82)	(-4.04)	(-3.65)	(-3.8)	(-3.44)	(-3.65)
4		4.18**	1.75	-0.09	0.25	4.11***	2.77*	2.52	5.48***	3.1*	3.04
		(2.39)	(1.12)	(-0.05)	(0.16)	(2.61)	(1.76)	(1.62)	(2.62)	(1.65)	(1.48)
HL		5.9***	3.55**	1.75	2.11	6.08***	4.89***	4.5**	7.6***	4.95**	5.01**
		(3.06)	(2.11)	(0.96)	(1.24)	(3.42)	(2.91)	(2.51)	(3.18)	(2.27)	(2.1)

Table IA21: R&D/M Portfolios Alpha and Risk Dynamics, $q5$ Factors, 1976-2023 (Unbalanced). The table shows the abnormal returns (alphas in Panel A) relative to $q5$-factor model (Hou, Mo, Xue, and Zhang, 2021) and the loadings on the model's factors (Panel B) of R&D/M-sorted portfolios (indicated in rows) for holding period of one-year at different investment horizons (indicated in columns). Details of the portfolio construction and investment horizons are described in the Table IA20 notes. The sample period begins in 1976 due to availability of reliable data for R&D and ends in 2023. The estimates of the alphas are annualized by multiplying by twelve. t-statistics from Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses and the standard errors in brackets. */**/*** indicate significance level at 10, 5, and 1%. Significance stars are omitted for the Market (MKT) loadings of the long portfolios.

	Horizon (K years)									
Portfolio	1	2	3	4	5	6	7	8	9	10
Panel A. Alphas										
0	-0.92	-1.16*	-1.18*	-1.29**	-1.32**	-1.48**	-1.48**	-1.56**	-1.58**	-1.72**
	(-1.54)	(-1.93)	(-1.9)	(-2.09)	(-2.07)	(-2.34)	(-2.24)	(-2.29)	(-2.3)	(-2.51)
1	1.22	0.97	0.64	0.12	0.28	1.11	0.04	0.43	-0.84	-0.71
	(1.38)	(1.2)	(0.72)	(0.14)	(0.32)	(1.18)	(0.06)	(0.45)	(-0.91)	(-0.74)
2	0.75	1.52*	1.48	1.38	1.08	0.97	1.89**	-0.05	0.52	0.75
	(0.76)	(1.68)	(1.56)	(1.49)	(1.29)	(1.14)	(2.14)	(-0.04)	(0.52)	(0.85)
3	0.62	1.94	1.21	3.52***	3.73***	-0.16	-0.5	1.69	1.96	1.51
	(0.45)	(1.55)	(0.95)	(2.76)	(3.0)	(-0.13)	(-0.38)	(1.22)	(1.34)	(1.04)
4	4.25**	1.86	-1.38	-0.67	2.07	0.48	1.56	4.33**	2.25	1.9
	(2.52)	(0.91)	(-0.81)	(-0.41)	(1.24)	(0.29)	(1.0)	(2.17)	(1.14)	(0.88)
HL	5.17***	3.02	-0.2	0.63	3.39*	1.97	3.04	5.89**	3.83	3.63
	(2.67)	(1.32)	(-0.1)	(0.35)	(1.7)	(1.01)	(1.58)	(2.5)	(1.64)	(1.38)
Panel B. Loadings										
Market (MKT)										
0	0.99***	0.99***	0.99***	0.99***	0.99***	1.0***	0.99***	0.99***	0.99***	0.99***
	(54.7)	(54.28)	(52.77)	(54.64)	(55.22)	(57.26)	(55.47)	(53.68)	(54.1)	(52.17)
4	1.1***	1.14***	1.19***	1.2***	1.19***	1.23***	1.25***	1.18***	1.18***	1.18***
	(24.24)	(28.9)	(32.17)	(33.76)	(32.31)	(38.11)	(28.39)	(24.58)	(23.33)	(24.47)
HL	0.11**	0.15***	0.2***	0.21***	0.2***	0.23***	0.25***	0.18***	0.19***	0.19***
	(2.0)	(3.11)	(4.39)	(4.86)	(4.3)	(5.9)	(5.01)	(3.27)	(3.13)	(3.22)
Size (ME)										
0	0.01	0.0	-0.01	-0.02	-0.02	-0.04	-0.04	-0.05	-0.05	-0.07
	(0.16)	(0.02)	(-0.2)	(-0.25)	(-0.36)	(-0.55)	(-0.64)	(-0.77)	(-0.81)	(-0.98)
4	0.52***	0.45***	0.51***	0.37***	0.39***	0.31***	0.24***	0.29***	0.23***	0.22***
	(4.62)	(7.81)	(8.02)	(6.33)	(7.58)	(5.51)	(4.5)	(4.24)	(2.64)	(3.73)
HL	0.51***	0.44***	0.52***	0.39***	0.41***	0.34***	0.28***	0.34***	0.28**	0.29***
	(3.01)	(4.48)	(4.68)	(4.92)	(3.88)	(3.62)	(3.02)	(2.83)	(1.98)	(2.59)
Investment (IA)										
0	0.33***	0.34***	0.35***	0.35***	0.35***	0.36***	0.36***	0.37***	0.37***	0.37***
	(6.3)	(6.47)	(6.51)	(6.64)	(6.77)	(6.95)	(6.69)	(6.64)	(6.66)	(6.49)
4	0.06	-0.08	-0.19***	-0.15*	-0.25***	-0.12	-0.28***	-0.45***	-0.38***	-0.38***
	(0.63)	(-0.78)	(-2.77)	(-1.74)	(-3.15)	(-1.54)	(-3.09)	(-3.49)	(-3.15)	(-3.12)
HL	-0.27**	-0.42***	-0.53***	-0.51***	-0.61***	-0.48***	-0.64***	-0.81***	-0.76***	-0.75***
	(-2.18)	(-3.0)	(-5.94)	(-4.82)	(-5.62)	(-4.82)	(-5.53)	(-5.21)	(-4.75)	(-4.81)
Profitability (ROE)										
0	0.16***	0.16***	0.17***	0.18***	0.18***	0.2***	0.2***	0.2***	0.2***	0.21***
	(3.7)	(3.7)	(3.84)	(4.13)	(4.14)	(4.76)	(4.58)	(4.61)	(4.59)	(4.54)
4	-0.64***	-0.53***	-0.47***	-0.5***	-0.55***	-0.44***	-0.45***	-0.46***	-0.46***	-0.36***
	(-6.91)	(-6.16)	(-5.94)	(-6.05)	(-7.8)	(-5.11)	(-4.65)	(-5.11)	(-5.45)	(-3.49)
HL	-0.8***	-0.69***	-0.65***	-0.68***	-0.73***	-0.64***	-0.65***	-0.67***	-0.66***	-0.56***
	(-6.42)	(-6.08)	(-7.07)	(-6.73)	(-7.7)	(-6.66)	(-5.96)	(-6.71)	(-6.31)	(-4.35)
Expected growth (EG)										
0	-0.17***	-0.17***	-0.17***	-0.17***	-0.17***	-0.18***	-0.17***	-0.17***	-0.17***	-0.18***
	(-3.58)	(-3.34)	(-3.43)	(-3.32)	(-3.24)	(-3.34)	(-3.13)	(-2.99)	(-2.88)	(-3.0)
4	0.19*	0.13	0.26***	0.27***	0.41***	0.38***	0.31***	0.37***	0.33***	0.31***
	(1.9)	(0.99)	(2.72)	(2.66)	(4.16)	(3.93)	(3.05)	(3.69)	(2.73)	(2.93)
HL	0.37***	0.3*	0.44***	0.44***	0.58***	0.56***	0.49***	0.54***	0.5***	0.49***
	(2.83)	(1.78)	(3.58)	(3.38)	(4.3)	(4.31)	(3.58)	(3.99)	(2.97)	(3.27)

Table IA22: Patents/R&D Portfolios and Performance, Fama-French and $q5$ Factors. The table shows the average excess returns of patents/R&D-sorted portfolios in panel A and regressions of excess portfolio returns (in excess of the risk-free rate) on a constant and market excess returns (Panel B), the Fama-French three factors (Panel C), the Fama-French five factors (Panel D), and the $q5$ factors (Panel E). Patents/R&D is defined as the number of patents granted during the previous twelve months divided by R&D expenditures in fiscal year ending in previous calendar year. Portfolio 0 consists of firms without patents or with zero (or missing) R&D, and the remaining portfolios are sorted by patents/R&D annually into equal groups by firm count. HL is a zero-cost portfolio, long portfolio 4 and short portfolio 0. Stocks are sorted at the end of June. The time period is (due to availability of reliable R&D data) from 1976 to 2023. The portfolios are value-weighted, rebalanced monthly. The underlying portfolio returns are at monthly frequency, and the estimates of the average excess returns and constants (alphas) are annualized by multiplying by twelve. t-statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses and the standard errors in brackets. */**/*** indicate significance level at 10, 5, and 1%, respectively. Significance stars are omitted for the average excess returns and the Market (Mkt-RF and MKT) loadings of the long portfolios.

	0	1	2	3	4	HL
Panel A. Excess returns						
Ex. ret.	7.87	7.76	9.83	9.23	7.99	0.12
	(3.42)	(3.28)	(3.9)	(3.87)	(3.16)	(0.09)
Panel B. CAPM						
Constant	0.06	0.04	1.62	1.22	-0.52	-0.58
	(0.09)	(0.04)	(1.63)	(1.39)	(-0.44)	(-0.4)
Mkt-RF	0.97	0.96	1.03	1.0	1.06	0.09**
	[0.02]	[0.03]	[0.02]	[0.02]	[0.03]	(2.36)
R^2	0.94	0.84	0.86	0.88	0.82	0.02
Panel C. Fama-French 1993						
Constant	-0.84*	1.36	2.47***	1.45*	-0.6	0.25
	(-1.83)	(1.61)	(2.89)	(1.69)	(-0.51)	(0.19)
Mkt-RF	1.01	0.93	1.01	1.0	1.03	0.02
	[0.01]	[0.02]	[0.02]	[0.02]	[0.03]	(0.65)
SMB	0.01	-0.11***	-0.11**	-0.05*	0.19***	0.18***
	(0.34)	(-4.1)	(-2.41)	(-1.69)	(4.34)	(2.7)
HML	0.24***	-0.33***	-0.21***	-0.05*	-0.02	-0.26***
	(9.77)	(-10.77)	(-6.09)	(-1.81)	(-0.37)	(-4.51)
R^2	0.96	0.88	0.88	0.88	0.83	0.16

Table IA22 – Continued.

	0	1	2	3	4	HL
Panel D. Fama-French 2015						
Constant	-1.44***	2.05**	3.07***	0.52	-0.85	0.59
	(-3.09)	(2.34)	(3.54)	(0.6)	(-0.72)	(0.44)
Mkt-RF	1.01	0.93	1.02	1.03	1.04	0.03
	[0.01]	[0.02]	[0.02]	[0.02]	[0.03]	(0.97)
SMB	0.08***	-0.18***	-0.18***	-0.04	0.19***	0.12**
	(3.25)	(-6.46)	(-4.87)	(-1.44)	(4.28)	(2.12)
HML	0.24***	-0.3***	-0.19***	-0.15***	-0.1*	-0.34***
	(10.04)	(-7.92)	(-5.16)	(-4.98)	(-1.69)	(-5.31)
CMA	-0.04	0.01	0.05	0.23***	0.11	0.16
	(-1.43)	(0.08)	(0.96)	(4.35)	(1.1)	(1.39)
RMW	0.14***	-0.14***	-0.15***	0.06	-0.0	-0.14*
	(4.75)	(-3.41)	(-3.43)	(1.29)	(-0.01)	(-1.85)
R^2	0.97	0.89	0.89	0.88	0.83	0.17
Panel E. $q5$						
Constant	-0.65	1.32	1.4	0.04	-0.14	0.51
	(-1.22)	(1.38)	(1.62)	(0.04)	(-0.1)	(0.33)
MKT	0.99	0.95	1.04	1.03	1.03	0.04
	[0.02]	[0.02]	[0.02]	[0.02]	[0.03]	(0.88)
ME	0.05	-0.15***	-0.13***	-0.05	0.15***	0.1
	(0.9)	(-4.02)	(-2.73)	(-1.54)	(2.83)	(1.11)
IA	0.25***	-0.33***	-0.22***	0.06	0.01	-0.24**
	(5.78)	(-5.99)	(-5.41)	(1.18)	(0.09)	(-2.4)
ROE	0.13***	-0.12**	-0.26***	0.01	-0.02	-0.16*
	(3.71)	(-2.57)	(-5.96)	(0.16)	(-0.36)	(-1.86)
EG	-0.16***	0.14**	0.34***	0.09	-0.05	0.11
	(-4.22)	(2.35)	(7.08)	(1.54)	(-0.75)	(1.2)
R^2	0.95	0.87	0.90	0.88	0.83	0.08

Table IA23: Pricing Patent-Intensity Portfolios with Operating Profitability and R&D. The table shows the abnormal returns (alphas) and factor loadings from regressions of excess portfolio returns (in excess of the risk-free rate) on a constant, four factors from Fama-French five factor model (market excess return, SMB, HML, and CMA) and operating profitability factor (OP/BE in Panel A and (OP+R&D)/BE in Panel B). Portfolios are sorted by the PI variable as described in notes of Table 2 in the main paper. The operating profitability (OP/BE) and operating profitability plus R&D ((OP+R&D)/BE) factors are defined in Appendix A.1 in the main paper. The time period is from 1976-2023, to accomodate the R&D data. All portfolios are value-weighted and rebalanced monthly. The underlying portfolio returns are at monthly frequency, and the estimates of the average excess returns and constants (alphas) are annualized by multiplying by twelve. t-statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses and the standard errors in brackets. */**/*** indicate significance level at 10, 5, and 1%, respectively. Significance stars are omitted for the Mkt-RF loadings of the long portfolios.

	0	1	2	3	4	HL
Panel A. FF4 and operating profitability						
Constant	-1.14**	0.15	1.5*	1.91*	3.31*	4.46**
	(-2.24)	(0.31)	(1.95)	(1.68)	(1.68)	(2.08)
Mkt-RF	1.0	0.96	1.03	1.11	1.19	0.19***
	[0.01]	[0.01]	[0.02]	[0.04]	[0.05]	(3.21)
SMB	0.14***	-0.18***	-0.08**	0.21***	0.6***	0.46***
	(4.38)	(-10.47)	(-2.03)	(2.7)	(5.54)	(3.51)
HML	0.26***	-0.08***	-0.15***	-0.14*	-0.17	-0.43***
	(7.31)	(-3.17)	(-3.43)	(-1.86)	(-1.59)	(-3.23)
CMA	-0.1**	0.02	0.16**	0.23*	0.42**	0.52**
	(-2.45)	(0.65)	(2.47)	(1.94)	(2.22)	(2.45)
OP/BE	0.08***	0.03	-0.09***	-0.2***	-0.27***	-0.36***
	(3.6)	(1.27)	(-2.93)	(-3.36)	(-2.63)	(-3.03)
R^2	0.96	0.96	0.90	0.85	0.75	0.31
Panel B. FF4 and operating profitability plus R&D						
Constant	-0.42	0.23	0.62	0.41	1.11	1.53
	(-0.82)	(0.44)	(0.77)	(0.33)	(0.63)	(0.8)
Mkt-RF	1.0	0.96	1.03	1.11	1.19	0.19***
	[0.01]	[0.01]	[0.02]	[0.04]	[0.06]	(2.79)
SMB	0.09**	-0.19***	-0.03	0.31***	0.74***	0.64***
	(2.12)	(-11.69)	(-0.68)	(3.1)	(5.04)	(3.46)
HML	0.27***	-0.07***	-0.16***	-0.17*	-0.21	-0.48***
	(5.99)	(-2.92)	(-3.32)	(-1.75)	(-1.49)	(-2.72)
CMA	-0.11**	0.02	0.17**	0.25*	0.43**	0.54**
	(-2.13)	(0.64)	(2.3)	(1.76)	(2.01)	(2.16)
(OP+R&D)/BE	-0.02	0.01	0.04	0.03	0.06	0.08
	(-1.12)	(0.61)	(1.1)	(0.53)	(0.72)	(0.95)
R^2	0.96	0.96	0.90	0.84	0.74	0.27