Pricing Technological Innovators:
Patent Intensity and Life-Cycle Dynamics

Abstract

Technological innovators are priced differently than other firms, earning high stock returns controlling for standard factors, with less punishment for high capital investment and weak profitability. We create the persistent new firm variable patent intensity (PI), patents received divided by market capitalization, available from 1926. On average, high PI firms account for ten percent of CRSP market value but generate over half of five-year-forward public-market patenting. Aged portfolios and standard factors show economically and statistically significant alphas lasting more than a decade past formation. Adding an expected growth factor, alphas become insignificant at most horizons, and loadings show strong life-cycle dynamics: high but declining growth, aggressive and increasing investment, and weak but improving profitability.

Keywords: technological innovation, patent intensity, stock returns, firm life-cycle, risk dynamics.

JEL Classification: G12, E20.

1. Introduction

Innovation invigorates firms, unlocking new product markets, efficiencies, and possibilities for follow-on discovery, while simultaneously transforming the economy and propelling it forward (Schumpeter, 1911).[1] Because of positive externalities, financing innovation is societally important (Nelson, 1959, Arrow, 1962). Naturally high costs-of-capital have been hypothesized for innovators because of extremely uncertain outcomes (Scherer, 1998),[2] embedded real options that leverage risk (Berk, Green, and Naik, 2004), and financing frictions such as information asymmetry (Hall, 2007, Hall and Lerner, 2010). While innovation entails change, leading empirical models of expected returns invoke static or steady-state valuation models to motivate fundamental pricing factors based on market/book ratios (Tobin's q), capital investment, and profitability (Fama and French, 1993, 2015, Hou, Xue, and Zhang, 2015).[3] These models' foundations in steady-state valuation appear at odds with the dynamic nature of economically important innovative firms.

We provide new facts about the pricing of innovative firms. Motivated by life-cycle theories (e.g., Klepper, 1996, Klette and Kortum, 2004), we investigate the evolution of returns, characteristics, risk loadings, and abnormal performance (alpha) for both innovators and non-innovators. Consistent with the prior hypotheses of Hall and Lerner (2010), innovative firms do have high returns, lasting more than a decade after portfolio formation. Further, standard pricing models derived from static valuation (Fama and French, 2015, Hou, Xue, and Zhang, 2015) severely and persistently misprice innovators, producing larger alpha than raw-return spreads. We trace mispricing to innovators covarying with investment and profitability factors but not receiving commensurate returns: Investment and profitability anomalies are driven by non-innovative firms, and

[1] See also Solow (1957), Romer (1986, 1990), and Aghion and Howitt (1992).

[2] See also Arrow (1962), "*By the very definition of information, invention must be a risky process...*" (p. 616) and the surrounding discussion.

[3] See Fama and French (1995) equation 2, Fama and French (2015) equation 3, Hou, Xue, and Zhang (2015) equation 1. Berk (1995) provides a related valuation identity motivating size-related anomalies. The market/book ratio as a driver of investment is developed in Tobin (1958).

are not present among innovators. The expected growth factor of Hou, Mo, Xue, and Zhang (2021), built from forecasts of two-year asset growth using accounting variables, largely resolves innovator mispricing. Innovators load heavily on this factor for a full decade, consistent with innovation driving expected growth, as in Kogan, Papanikolaou, Seru, and Stoffman (2017). We thus provide a coherent empirical framework that connects technological innovation, expected growth, and expected returns as they evolve through the life-cycle of innovative firms. Our results highlight shortcomings as well as improvements in leading empirical asset pricing models while also providing new facts about technological-innovator expected returns, a question of long-standing interest and importance (Hall and Lerner, 2010).

Our analysis is based on a simple, new measure of technological innovation, patent intensity (PI), defined as the ratio of the number of patents received in the past twelve-month period divided by current market capitalization. The measure is easy to calculate, requires no accounting data, and extends back to 1926. From the point of view of a speculator or investor, PI ranks firms according to their patents produced per dollar invested. High-PI portfolios therefore give the cheapest way to purchase equity interest in the recently produced public-market patent stock and its stream of future rents. Given persistence of patenting at the firm level, high-PI portfolios also provide a crude approximation to the cheapest way to purchase equity interest in future public-market patenting activity.

We also relate the PI measure to theories of innovation heterogeneity and investment frictions. Innovation-heterogeneity theories (Klepper, 1996, Akcigit and Kerr, 2018) hold that firms with valuable existing assets should innovate differently from other firms, motivated by increasing the value of their existing assets through less risky "process" or "inside" innovations.[4] In contrast, firms without valuable existing assets should invest proportionally more in riskier new directions, for example to new product markets,

[4]Early work includes Utterback and Abernathy (1975) and Abernathy, Utterback, et al. (1978). Dasgupta and Stiglitz (1980) discuss how market structure influences the nature of innovation in a static setting. Bena, Garlappi, and Grüning (2016) examine incremental and radical innovations in a dynamic "horse race" setting.

consistent with empirical evidence (Cohen and Klepper, 1996). If we break technological innovators into two groups by patent intensity, we hypothesize that low-PI firms will be older, larger, with more-profitable and more-valuable assets-in-place, and engage in lower-risk types of innovation. By contrast, we hypothesize high-PI firms to be younger, smaller, with less valuable and less profitable assets-in-place, and engage in riskier types of innovation. The literature on frictions in innovation investment (Hall and Lerner, 2010) also yields predictions for the returns of low- and high-intensity innovators. Low PI firms are likely to have profitable and valuable assets-in-place, and therefore be more able to fund innovation investment from internal cash flows, reducing financing frictions. Patent intensity is therefore a simple and intuitive measure that captures key elements of both life-cycle theories of innovation heterogeneity and theories of investment frictions.

Patent-intensity sorted portfolios produce a significant spread in returns, approximately seven percent annually whether beginning in 1926 or starting later in 1963 to accommodate accounting-based risk factors. The average return spread declines in magnitude for ten years after portfolio formation, while remaining positive and statistically significant. Accounting for standard fundamentals-based factors, alphas are large and statistically significant for a full decade after portfolio formation. We trace these large and persistent alphas to the fact that innovators are not penalized for lack of profitability or high investment to the same degree as non-innovators. The most innovation-intensive firms tend to have high asset growth and low profitability risk loadings. Since they are not penalized for this covariation to the same extent as non-innovators, their alphas increase when benchmarked to the steady-state models.

Hou, Mo, Xue, and Zhang (2021, HMXZ) augment the Q4 model of HXZ with an expected growth factor, targeted at capturing influences on expected returns in a dynamic model that are not present in a static model.[5] This factor can potentially address technologically innovative firms and their life-cycle dynamics. We find that including the HMXZ expected growth factor eliminates abnormal returns of patent-intensity sorted portfolios, not only immediately after formation, but at nearly all

[5]See their equation 1.

of the ten-year horizon that we consider, and at which the static models fail. Our study therefore strongly supports the importance of expected growth for asset pricing, as proposed by HMXZ. Unlike standard characteristic-based factors, their expected growth factor is not built directly from simple ratios of a firm's own characteristics, but instead uses rolling forecasting regressions of growth rates on lagged variables.[6] The importance of their factor should spur further research on modeling expected growth, as well as additional applications to estimating costs of capital for societally important innovative firms.

Risk dynamics in the decade following formation further elaborate the technological innovator life-cycle. High PI firms load heavily on expected growth immediately following formation, and over time their expected growth loadings fall. Even a decade after formation, the growth loadings of innovators significantly exceed those of non-innovators. Investment loadings of innovators are initially aggressive, and become even more so for two to three years following portfolio formation. Investment loadings remain higher than non-innovators for a full decade. Finally, innovators show extremely weak profitability loadings immediately after formation, but strengthen substantially over the following decade. Thus, consistent with economic theory, technological innovators are severely mispriced by cross-sectional asset pricing models derived from steady-state valuation for a full ten years following formation, but augmenting these models with an expected growth factor resolves mispricing and shows risk-dynamics consistent with the life-cycle of innovators and their characteristics.

The explosion in variety of empirical asset pricing models has generated the critique of "too many" models (e.g., Cochrane, 2011). An important direction in research uses statistical techniques to select and combine predictors (e.g., Barillas and Shanken, 2018, Gu, Kelly, and Xiu, 2020). An equally important tradition founds empirical asset pricing models on internally consistent economic frameworks. Streams of work by Fama and French ("FF") and HXZ and their co-authors follow this approach (see footnotes 2

[6]HMXZ use panels of firm-year data to obtain linear forecasts with time-varying coefficients. The underlying variables used in their regressions are the market-to-book ratio, operating cash flows, and recent changes in return-on-equity.

and 4), and the connection of their factors to economically intuitive firm fundamentals likely explains the enduring popularity of these approaches. We add to this tradition by showing that technological innovators are severely mispriced using static versions of the HXZ and FF models, but that misspecification resolves when accounting for dynamics with expected growth. Further, the strong life-cycle profiles of innovators as they mature confirm that risk loadings from fundamentals-based models capture economically important phenomena.

We contribute to the broad literature on technological innovation and the stock market. Among these, a key contribution is Kogan, Papanikolaou, Seru, and Stoffman (2017, KPSS), who measure the stock price impact of patents in short windows following announcements. Following the literature on innovation heterogeneity (e.g., Klepper, 1996, Akcigit and Kerr, 2018), firms with valuable assets in place should engage in more certain "inside" innovation, while firms without valuable existing product markets must engage in riskier and harder to value "outside" innovation. Our research complements KPSS by showing the long-run as opposed to immediate effects of innovation on stock returns. Further, KPSS emphasize the relation of innovation to firm growth. We add additional evidence on the dynamics of expected growth loadings, and that accounting for expected growth is necessary to obtain accurate costs of capital for innovators within fundamentals-based pricing models. Relative to the broader literature on innovation and asset pricing,[7] we develop a new measure of innovation intensity based on patents, and show the dynamics of returns, characteristics, risk loadings, and alphas for fundamentals-based pricing models with and without expected growth. Prior literature hypothesizes naturally high and difficult to measure costs of capital for innovators (Arrow, 1962, Hall and Lerner, 2010). We provide robust evidence of the hypothesized

[7]Research emphasizing the roles of patenting and R&D includes Lev and Sougiannis (1996), Eberhart, Maxwell, and Siddique (2004), Gu (2005), Cohen, Diether, and Malloy (2013), Hirshleifer, Hsu, and Li (2013), Hirshleifer, Hsu, and Li (2018), Bena and Garlappi (2020), Kelly, Papanikolaou, Seru, and Taddy (2021), and Stoffman, Woeppel, and Yavuz (2022). 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), Kogan and Papanikolaou (2010, 2013, 2014), Kogan, Papanikolaou, and Stoffman (2020), Papanikolaou (2011), Garleanu, Panageas, and Yu (2012), Kung and Schmid (2015), Garlappi and Song (2017).

high costs of capital for innovators, in both raw returns and relative to standard benchmarks, and further show that accounting for expected growth is necessary to accurately estimate expected returns. We also show that an important property of innovation is its persistence. Portfolios formed on patent intensity have low turnover, and their return spread lasts ten full years following portfolio formation, presenting a significant challenge to asset pricing models.

Previous work has shown positive abnormal returns for R&D sorted portfolios Chan, Lakonishok, and Sougiannis (2001), Hou, Mo, Xue, and Zhang (2021). These studies exclude firms with missing or zero R&D, comprising on average half of firms by market capitalization, possibly because of uncertainty over how to interpret missing R&D data. Patent counts do not have missing data, and we categorize all firms with no patents in a single "non-innovator" category. Further, patent intensity does not rely on accounting data, and can be measured over a much longer sample beginning in 1926. We show however that patent intensity and R&D intensity are closely related over the period over which they can both be measured, and in particular patent-intensity prices R&D intensity, but the reverse does not hold. Future work should continue to investigate the relationship between R&D and patenting as in Hirshleifer, Hsu, and Li (2013).

Innovating firms have played an important role in the US stock market that can be measured over almost a full century. While the firms and industries that dominated the innovative landscape have varied over time, from manufacturing firms in the mid-20th century to computer and information technology companies in the most recent two decades, the overall share of innovators in the US stock market has remained remarkably constant. Throughout the 1926-2021 sample period, innovators accounted for approximately 45-75% of total US-market capitalization, with no apparent secular trend. Therefore, the pricing of these firms is not only highly relevant for our understanding of asset pricing models, but also critical for economy-wide capital allocation and growth.

2. Technological Innovators and Patent Intensity

This section describes the patenting activity of publicly listed firms in the United States from 1926. We define our main variable, patent intensity (PI), and show the characteristics of more and less patent-intensive firms.

2.1. Patent Data and Innovative Firms

The United States Patent & Trademark Office (USPTO) is the source of complete data for all patents granted. The USPTO provides downloadable text data starting in 1976.[8] For the universe of all patents filed between 1926-1975, Kelly, Papanikolaou, Seru, and Taddy (2021) provide cleaned and tabulated patent data created from USPTO image files.[9] In combination, these two sources provide full coverage of all U.S. patents issued from 1926-2021. We link patents to publicly listed companies using CRSP permno-patent links from Kogan, Papanikolaou, Seru, and Stoffman (2017).[10]

U.S. firms with common stock traded on NYSE, AMEX, or Nasdaq are important contributors to overall U.S. patenting. Each calendar year, starting in 1926, we calculate the share of patents for all CRSP assignees (includes foreign firms), as well as the share of patents for all U.S. listed firms with common stock (CRSP shrcd is 10 or 11). Figure 1, Panel A shows the logarithm of the patent counts for each group (universe, all CRSP, and listed U.S. common stock). Panel B shows the shares of all CRSP assignees and U.S. listed common stock. The wedge between all CRSP assignees and U.S. listed common stock assignees toward the end of the sample is due to the growing importance of cross-listed foreign firms who receive U.S. patents. Patenters with U.S. listed common stock are important throughout the sample, with a share of overall patenting ranging from twenty to forty percent throughout most of the sample. These firms are key building blocks of empirical asset pricing studies. Publicly listed patenters are also economically

[8] `https://www.uspto.gov/patents/search`.

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

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

important because they provide a broad investor base access to equity in technological innovators, and because daily updated prices reflect a market view of the value of innovation.

From the standard CRSP sample of all common stock (shrcd is 10 or 11) traded on NYSE, AMEX, or Nasdaq, 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. The USPTO publishes its Official Gazette every Tuesday with information on patents granted that day, so patent information is immediately available to market participants.[11]

Relative to other measures of innovation such as accounting-based measures of R&D, a patent-based classification of innovators is appealing because it is based on a standardized and tangible legal claim. Patent data is not subject to the reporting practices of individual firms, and reporting cannot be missing or delayed. Patents measure the output of the innovation process, whereas R&D measures the input. Our choice of a twelve-month lookback period for measuring innovation is simple and convenient. Our results are robust to variations such as measuring patenting activity over the prior calendar year, or to using longer lookback periods, such as patents received over a three-year window. Choosing a one-year window for our main results ensures that our results about the persistence of patenting activity are not artificially driven by overlapping measurement windows. To avoid any inconsistencies with assigning patents to newly listed firms, we drop firms from our analysis that have less than a twelve month history in the CRSP data.[12]

Figure 1, Panels C-F show that despite some sharp fluctuations in the percentage of innovators versus non-innovators over time by firm count, the percentage of innovators by market capitalization is much slower moving, and appears mean-reverting. The share of innovators by number of firms (Panel D) ranges from about twenty to fifty percent throughout the sample. By market capitalization, the share of innovators generally

[11] `https://www.uspto.gov/learning-and-resources/official-gazette`.

[12] Links from patent assignees to CRSP firms are reliable, but linking assignees to firms before they become public is more challenging.

ranges from fifty to seventy-five percent, consistent with innovators being larger. All of our main results use value-weighted portfolios, so the more stable market-capitalization weighted shares of innovators versus non-innovators are most relevant.

A coarse example shows that the sector composition of innovative and non-innovative firms varies considerably through time. Each year we assign all CRSP firms to one of ten Fama-French industries, each of which can be thought of as a sector. Figure 2, Panel A shows sector allocations over time from the market-capitalization weighted portfolio of all innovative firms. Panel B shows the sector allocations for the market-capitalization weighted portfolio of all non-innovative firms. The sector allocations change considerably throughout the sample. For example, the importance of manufacturing and consumer durables in the innovator portfolio decreases over time, while the importance of business equipment and healthcare increases. Technological innovation concentrates in different sectors of the economy throughout our sample.

2.2. Patent Intensity

Starting in 1926, on June 30 of every year we calculate for every firm in the CRSP sample the ratio of patents received in the prior 12-month period divided by current CRSP market capitalization. This is our measure of patent intensity (PI). All results in the remainder of the paper are robust to reasonable alternative choices such as measuring patent intensity at the end of the prior calendar year, or over three year windows. We choose a one-year window because of its simplicity and because a one-year window does not generate mechanical persistence in the measure. Scaling by market capitalization is a natural choice and makes PI comparable to prior measures such as the book-to-market ratio, which can be thought of as a measure of asset intensity, or R&D to market capitalization. Conceptually, purchasing firms with high PI allows an investor to obtain the most concentrated exposure to recent patenting activity with the least dollar investment.

To begin our characterization of patent intensity, each year we sort firms into three groups. Group zero has no patents in the prior twelve month period, and are the "non-innovators" described previously. We note that unlike other variables, there is no issue of "missing data" with patents. For example, missing data is common in R&D data and many researchers (e.g., Chan, Lakonishok, and Sougiannis, 2001) discard from analysis firms with missing R&D data. Ambiguity caused by missing data is not an issue with patents. We distinguish between low- and high-intensity patenters, each year dividing all innovators at the median positive PI break point, forming two equal-sized groups by firm count.

Table 1 provides descriptive statistics for the three groups, showing important differences. Panel A shows the average contributions of each of the three groups to firm counts, total market capitalization, and to past 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 more noticeable if we look at the high- and low-PI groups. The low PI group, while only 16% of firm count, contributes 54% of market capitalization. The high-PI group is again 16% by firm count, but only 11% by market capitalization.

It would be a tremendous mistake to conclude that the high-PI group is inconsequential because of its small market capitalization. This group owns on average 62.5% of the universe of patents created by public firms in the prior year. The majority of innovation has occurred within this group. Moreover, this is not just *ex post* selection. The high-PI group also contributes 60% of the patents granted to public firms in the next year, 58% of patents granted in the next three years, and 56.5% of patents in the next five years. Patenting activity is very persistent, and with a relatively small allocation of equity capital (11.3% of total market capitalization), one can purchase the majority of not only recent but also future five-year ahead public market patenting activity.

Table 1, Panel B shows further characteristics of the three groups. Non-innovators are younger on average and by median than innovators. This may seem surprising given the stereotype of young firms as innovators, but average age also relates to death rate, which we explore further below. Among innovators, high-PI are younger than low-PI, consistent with intuition. The B/M ratio is a traditional measure of "value", and non-innovators have the highest B/M ratios. Interestingly, high-intensity innovators appear to be more value-like than low-intensity innovators. This should not be too surprising, since both PI and B/M have market capitalization in the denominator. We can usefully think of PI as a measure of technological-innovation value, or the most cost-efficient way to purchase patenting activity. Considering investment and profitability, low-intensity innovators have the highest investment rates in traditional assets, and the highest profitability. High-intensity innovators have both the lowest investment in traditional assets and the lowest profitability.

Table 1 thus shows that technological innovation intensity captures important differences across firms. The archetype of a non-innovator is a modestly sized, perhaps shorter-lived value firm with moderate investment and profitability. Low patent-intensity firms are larger, longer-lived firms who appear successful, investing in traditional assets and maintaining high profitability, and appearing as "growth" by low B/M. High-intensity innovators are young and small, somewhat counterintuitively appear as "value" by the B/M measure, invest the least in traditional assets and have the lowest profitability, but produce the lion's share of technological innovation among listed public firms. Because of the important differences across these categories of firms, we anticipate a meaningful challenge for traditional pricing factors such as size, value, investment, and profitability to price PI-sorted portfolios.

The NASDAQ exchange has a reputation as a listing place for technological innovators,[13] and Table 2 shows the importance of NASDAQ for patenting. Panel A shows that by firm count, most of the firms on NASDAQ are non-innovators. But by market capitalization, NASDAQ has been shifting more and more to be represented by low-intensity innovators. Panel B shows the contribution of NASDAQ firms to the PI-sorted portfolios. In recent years, more than fifty percent of the cap weight and forty percent of the patents of low-intensity innovators have come from NASDAQ. For high-intensity

[13] See for example Schwert (2002), Pástor and Veronesi (2006, 2009).

innovators, more than forty percent of both the cap weight and patents come recently from NASDAQ.

Finally, Table 3 shows in Panel A average transition probabilities across the three PI-sorted portfolios as well as exit, at horizons of one, three, and five years. For comparison, Panel B shows similar transition probabilities for the traditional measure of growth, the M/B ratio. To enhance comparison, we set the break points for the M/B sort in Panel B identically on a year-by-year basis to the breakpoints for the PI sorts in Panel A.[14]

One key message from Table 3 is the high exit rate of non-innovative firms. Comparing to the low-M/B firms in Panel B at one-, three-, and five-year horizons, the non-innovator versus low-M/B delisting rates are respectively 6.1 vs. 2.7%, 16.1 vs. 11.9%, and 24.1 vs. 19.6%. The high delisting rate of non-innovators helps to explain their low average age shown previously. Further, the majority of delistings are negative events, which is known to impact portfolio performance (Shumway, 1997).

A second key finding from Table 3 is the persistence of PI sorts. For every horizon, high-PI firms are considerably more likely to remain high-PI firms in the future than are high-M/B firms. Low-PI is similarly more persistent than medium M/B. Comparing non-patenters to the low M/B firms, persistence is modestly higher at all horizons, but given the higher exit rates of non-patenters this persistence is still noteable. Because of the persistence of the PI characteristic, we expect portfolio sorts to be relatively low-turnover.

2.3. The Life-Cycle of Innovative Firms

We document patterns in the life-cycle of innovators and non-innovators by documenting changes over time in firm characteristics. For each of the previously-formed portfolios of non-innovators, low-PI, and high-PI firms, we track the underlying firms for

[14]Transition probabilities in Panel B are calculated conditional on not having a negative or missing book value. Missing or negative book values are not trivial, 12% of the sample on average, which is a general difficulty for accounting-based characteristics that does not apply to patent intensity.

ten years following portfolio formation. Each year following formation we calculate the value-weighted average of a set of two measures of investment, two measures of profitability, sales growth, and market beta. The investment measures are the standard growth in assets as well as CAPX/PPENT, or capital expenditures divided by net property plant and equipment. We choose the latter measure which focuses on physical capital in both numerator and denominator because we show in the Appendix that innovators and non-innovators have different compositions of assets, with non-innovators having more focus on property, plant, and equipment, while innovators have a higher proportion of current assets such as cash, inventory, and receivables. CAPX/PPENT thus isolates investment in property, plant, and equipment and is not affected by differences in the composition of book assets. Our profitability measures are the equity profitability measure defined earlier as well as return on assets.

Figure 3 shows the life-cycle dynamics of firm-characteristics for each group of firms, as well as a neutral benchmark that combines all firms into one group. The characteristics of the aged portfolios are driven by both survivorship, as in the selection model of Jovanovic (1982), and dynamics in the characteristics of survivors. The neutral benchmark reflects intuitive changes expected from earlier investigations of broad cross-sections of firms.[15] In particular, as the neutral benchmark ages and the portfolio is composed of older firms, investment decreases (Panels A and B), profitability increases (Panels C and D), sales growth decreases (Panel E), and beta modestly declines (Panel F).

The life-cycle dynamics of innovators are markedly different than other firms. First considering investment, Panels A and B show that non-innovators and low-PI firms differ from the neutral benchmark mostly by a level shift. But high-PI firms are completely different, instead of their investment levels declining as they age, their investment increases, consistent with innovation creating growth options. Similarly considering profitability, non-innovators and low-PI firms differ from the benchmark primarily by a level shift. High-PI firms however show much greater increases in profitability,

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

consistent with innovation creating future rents that increase value. Sales growth similarly shows high-PI firms bucking the benchmark trend of growth declining with age. High-PI firms' sales growth increases with age while other firms are declining. Finally, market beta shows mostly level differences, with high-PI firms showing consistently larger market betas.

High patent intensity firms are far from the standard model of a firm in steady state. Innovators are different, both because innovators tend to be young firms, but also because the act of innovation provides its own form of rejuvenation, providing new product lines and profit opportunities, as in the models of Klette and Kortum (2004) and Akcigit and Kerr (2018). High-patent intensity firms reverse the trend of aged benchmark portfolios, showing increasing investment over time rather than decreasing, increasing sales growth over time rather than decreasing, and a sharper increase in profitability with aging than the benchmark.

3. Patent Intensity and Stock Returns

We compare the stock returns of innovators and non-innovators. Innovators have higher returns than non-innovators, both in raw returns and after controlling for common risk factors. We show similarities in sorts on R&D intensity and patenting intensity, and demonstrate that controlling for expected growth is crucial to explain the expected returns of innovative firms.

3.1. Stock Returns of Patent Intensity Portfolios

We use two samples in this subsection. The first, full sample, begins in July, 1926. The second sample begins in July, 1963 to accommodate performance analysis with the Fama-French five-factor model, whose investment and profitability factors begin that month.

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"). The 1963-2021 period eliminates early years with much smaller numbers of firms, so we sort innovators into bins of four bins with equal numbers of firms. We label these 1-4. The sorts thus appear numbered as tercile or quintile sorts, but portfolio zero always corresponds to non-innovators ($PI = 0$), and positive-numbered portfolios are innovators ($PI > 0$) sorted by PI into bins with equal numbers of firms. Portfolio HL is a zero-cost portfolio with a short position in the non-patenting portfolio "0" and a long position in the highest PI portfolio. Table 4 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). The left-hand side of the table shows full-sample results and the right-hand side shows the 1963-2021 sample.

In Table 4, Panel A, the annualized average excess returns (monthly returns multiplied by twelve) increase monotonically across portfolios in the full sample from 7.68% for the non-patenting portfolio 0 to 11.79% for the high-PI stocks. The sample starting in 1963 confirms the increasing average excess returns across the more granular sort into five portfolios. The pattern is again monotonic with the exception of portfolio 1 having a slightly lower return than non-patenting portfolio. The HL portfolio earns economically and statistically significant returns of 4.1% over the full sample and 6.97% over the post-1963 sample.

The CAPM regressions in Panel B show that market betas are slightly increasing across the PI-sorted portfolios, but not sufficiently to explain the excess returns of the high-PI portfolio. The HL alpha is 2.28% p.a. in the full-sample and 5.12% post-1963, both statistically significant. The FF3 regressions in Panel C show similar alphas – controlling for size and book-to-market factors does not substantially change our inference about portfolio performance. We do see that non-innovative firm loadings are consistent with small size and value. Among innovators, higher PI is associated with greater size loadings and somewhat more value than growth.

Despite the common description of the HML factor as value versus growth, the FF3 results could be consistent with HML playing dual contradictory roles for PI-sorted portfolios. Firms in the high-PI portfolio do a lot of patenting, which we naturally think of as a predictor of growth. At the same time, investors can acquire these firms with minimum employment of equity capital, which seems to indicate value. The value-growth paradigm faces the difficulty that value and growth do not seem to be opposites in a single dimension, but two distinct concepts. Value-growth can be effective in a low-dimensional factor model because it relates to and summarizes several other useful sources of variation, but in higher-dimensional models HML becomes less informative as those other sources of variation are parsed explicitly (Fama and French, 2015). This difficulty can be seen in the PI sorts. Despite the very large variation in the types of firms in the PI-sorted portfolios, we see surprisingly little variation in the HML loadings. The HML factor cannot help to explain the returns of technological innovators.

The FF5 regressions in Panel D, which add investment and profitability factors, cannot resolve the mispricing of technological innovators. In fact, if anything the difficulties deepen. The profitabality loadings align very strongly with the technological innovation sort, but in the opposite direction needed to explain the pattern of returns. High-PI firms have very negative profitability loadings, and non-innovators have positive profitability loadings. Higher profitability is supposed to earn a premium according to the profitability factor, but that pattern is reversed in the PI sorts. Investment loadings are not statistically significant, but align in the right direction to help explain returns. The net effect is that the five-factor model produces a stronger alpha-sort than the CAPM or three-factor models, with a highly statitically significant HL alpha of 6.7%.

One other item of note from Panel D is the abnormal negative five-factor performance of non-innovators (portfolio 0). This portfolio can be formed with a simple indicator variable, whether a firm received a patent in the last year or not. Though the magnitude of the alpha is economically modest, -1.76% per year, it is highly statistically significant. Non-innovators earn negative abnormal returns according to very standard benchmark models (see also Panel C in both samples).

The results presented in this subsection are robust to including a momentum factor as in the Fama and French (2018) six-factor model, as shown in Table A4 in the appendix. Momentum loadings on the PI sorted portfolios are generally small and do not change alphas substantially.

3.2. Comparison with R&D Intensity

Research and development expenditures and patents both capture aspects of the innovation process. R&D expenditures are an input to technological innovation, whereas patents are an output. While the success of research and development is uncertain, prior literature (e.g., Bound, Cummins, Griliches, Hall, and Jaffe, 1982) shows that R&D expenses predict patenting. We therefore expect portfolios sorted on R&D to relate to portfolios sorted on patent intensity.

Following prior literature, we measure R&D intensity (RDI) on June 30 as the ratio of R&D expense (prior fiscal year) to CRSP market capitalization (calendar end of prior year) starting in 1975. Chan, Lakonishok, and Sougiannis (2001) first show a positive relationship between R&D expenses and returns. They scale R&D expense by market capitalization, and begin their sample in 1975. Although R&D data is available prior to 1975, in 1974 the FASB issued SFAS No. 2, which standardized and required accounting for R&D costs.[16] Hou, Mo, Xue, and Zhang (2021) confirm a positive relationship between R&D and abnormal returns with standard factors in a sample extended to 2016.

Our measure of R&D intensity (RDI) is identical to the R&D to market equity variable used in prior literature, but we make one important change to methodology in the treatment of missing or zero R&D expenses. Both Chan, Lakonishok, and Sougiannis (2001) and Hou, Mo, Xue, and Zhang (2021) include only stocks with positive R&D expenses, sorting into quintiles and deciles, respectively. Stocks with missing or zero R&D are excluded.[17] We treat stocks with missing R&D data in Compustat as having

[16]See *Statement of Financial Accounting Standard No. 2: Accounting for Research and Development Costs* at `https://fasb.org/referencelibrary`. The impact of this change has been studied in the accounting literature. See Elliott, Richardson, Dyckman, and Dukes (1984).

[17]See Chan, Lakonishok, and Sougiannis (2001) Table VI, p. 2449, and Hou, Xue, and Zhang (2020)

no R&D. Following the sorting methodology we use for patents, our portfolio zero comprises all stocks having zero or missing R&D expenses ("non-innovators"), and from the remaining firms with positive R&D expenses ("innovators") we sort into four bins by RDI with equal numbers of firms.

Our approach to missing or zero R&D data is different but informative. First, as Peters and Taylor (2017) explain, SFAS No. 2 gives us reasonable confidence that firms with missing R&D expenses in Compustat after 1974 typically did not incur such expenses, i.e. can be treated as zero. Second, the identical treatment of our R&D sort with our patent sort gives greater comparability of results. Third, the effects of our treatment of R&D expenses can be checked *ex post*. If our portfolio zero of non-innovators with R&D looks similar to our portfolio of non-innovators with patents, where there is no missing data, then this gives confidence that treating absence of R&D expenses as no R&D expenses is reasonable. Finally, including firms with zero or missing R&D expenses greatly expands the scope of our analysis. In the post-1975 period, firms with zero or missing R&D comprised 60-70% of the total universe by firm count, and 40-50% of the total universe by market capitalization, as shown in Figure 4. Including these firms in our analysis therefore gives a useful check of the relationship documented in earlier literature on a broader sample.

Table 5 shows results for return performance of the RDI portfolios. Panel A confirms that firms with high RDI have higher returns than firms with low RDI. The average annual excess returns of firms in the highest RDI quartile is approximately 6.41% higher than of those in the lowest quartile. The average excess return of firms with no research an development expenses, shown in portfolio "0", is slightly higher than that of firms in portfolio "1", but still substantially lower than the return of high RDI firms. Panel B shows risk-adjusted returns controlling for the Fama-French five factors. Here, the importance of separating low-R&D firms from no-R&D firms becomes evident. While low-R&D firms are correctly priced by the Fama-French five factor model, no-R&D firms have a statistically significant negative alpha of -1.06% per year. This finding

Appendix A.5.4, p. 2104. See also Cohen, Diether, and Malloy (2013).

mirrors the results for the low-patenting versus no-patenting portfolios shown in the previous section.

Table 6 compares the high-minus-low RDI portfolio with the high-minus-low PI portfolio. Columns 1 and 3 show FF5 regressions for PI and RDI, respectively. Both HL portfolios load similarly on the Fama-French five factors, for example loading very negatively on profitability (-0.64 and -0.71 for PI and RDI, respectively), somewhat negatively on value (-0.36 and -0.24), and positively on investment (0.41 and 0.32 implying conservative investment in traditional assets). These results confirm that the two portfolios have similar risk exposures and returns. In columns 2 and 4, we test whether the RDI portfolio spans the PI portfolio and vice versa. Column 2 shows that the PI portfolio loads strongly on RDI (loading of 0.61), and the regression R^2 increases from 0.34 in column 1 to 0.56 in column 2. Alpha falls by approximately one half from column 1 to column 2, leaving a significant abnormal return of 2.92% unexplained. Column 4 similarly shows that the PI portfolio explains significant variation in the RDI portfolio, and about two-thirds of the RDI alpha is eliminated with the remainder being statistically indistinguishable from zero.

The overriding takeaway from this analysis is that patenting intensity and R&D intensity, both measures of technological innovation, capture similar variations in risk and expected returns. Of less interest to us is a "horse race" between the two measures, since in theory both are important. While our current interest is the similarity between PI and RDI, future research may want to explore their differences, particularly as they should capture different phases of the innovation process. One practical difference between PI and RDI is the considerably longer sample period permitted by patent intensity. Standardized R&D data begins only in 1975, whereas our current study calculates patent intensity for the entire 95 years of available CRSP data. Since reliable patent data goes back even further, until 1790, the only limitation preventing further historical analysis of patent intensity is comprehensive linking to stock return data. A final advantage of the patent data is lack of ambiguity about the definition of portfolio "0" for PI sorts, as non-patenting firms can be clearly identified from the data. The close resemblance of the RDI portfolio “0” and the PI portfolio “0” serves as a robustness check for the treatment of missing values in the R&D data.

3.3. Pricing Patent Intensity with q-Factors

Hou, Xue, and Zhang (2015) develop their original q-factor model motivated by the first-order conditions of the static optimization problem of a profit-maximizing firm, suggesting investment and profitability as characteristics related to firm returns.[18] Their q-factor model has four factors, with market and size in addition to investment and profitability.

The q-factor model is sometimes presented as in competition with the five-factor model of Fama and French (2015),[19] but for our purposes the similarities between the two models are more relevant. Fama and French (2015) also have market, size, investment, and profitability factors, and acknowledge that their value factor is redundant after accounting for the first four factors. Further, the characteristics for size and investment are identical in both approaches. If the value factor is removed, the remaining differences between the two approaches relate to how profitability is defined, and the sorting procedures used for combining factors.[20] Like HXZ, FF have consistently emphasized using simple economic theory to discipline the factors, favoring a static return decomposition (see for example equation 3 in Fama and French (2015) and equation 2 in Fama and French (1995)). While the q-factor model and the FF5 model may certainly have meaningful empirical differences in specific cases, the economic motivation and content of the models is similar, and we expect them to present a consistent overall picture of technological innovators.

A much more import distinction is the $q5$ model of Hou, Mo, Xue, and Zhang

[18]See their equation 4. Earlier literature documents the anomalies related to investment (Titman, Wei, and Xie, 2004, Cohen, Diether, and Malloy, 2013) and profitability (e.g., Novy-Marx (2013)).

[19]See for example Hou, Xue, and Zhang (2020).

[20]Fama and French (2015) define profitability as operating profitability scaled by annually updated book equity while Hou, Xue, and Zhang (2015) use earnings before extraordinary items scaled by quarterly updated book equity. FF use bivariate sorts on size and profitability and size and investment to form those factors, while HXZ use a trivariate sort of all three characteristics.

(2021), which adds an expected growth factor. Expected growth fits into the paradigm of appearing in the first order conditions of an optimizing firm, once extended to a multiperiod setting (see HMXZ equation 1). One can also see that growth matters in the accounting identity of Fama and French (2015), allowing for variation in future quantities (see their equation 3). Technological innovation should naturally be expected to load on expected growth. Innovation creates new products or reduces costs, raising the marginal product of future investments in traditional assets, and adding to expected growth. Correspondingly, HMXZ demonstrate the importance of expected growth for R&D sorted portfolios.

We show that the expected growth factor also plays an essential role in pricing patent intensity portfolios. This complements the findings of HMXZ by using a different but related measure of technological innovation. Further, our sample is nine years longer, limited only by the availability of q-factors before 1967. Finally, our methodology uses a broader cross-section of firms, including the portfolio zero of non-innovators.

We first apply the original q-factor model with four factors. Panel A in table 7 shows that this model leads to similar or even stronger mispricing across the portfolios than the FF5 model. The alphas increase monotonically from -2.03% in portfolio zero to 6.79% in portfolio 4, generating abnormal return of 8.82% for the HL portfolio. In unreported results, we confirm that the stronger mispricing result relative to the FF5 model is not driven by the slightly later start of the q-factor data in 1967.

The q-factor loadings of the PI-sorted portfolios closely resemble the loadings on the five Fama-French factors discussed in the previous section. In particular, the loadings on the profitability factor (ROE) decrease almost monotonically across the portfolios from slightly positive but insignificant value for non-patenting firms to significantly negative value of -0.48 for high-PI firms. This lowers the q-factor model implied expected returns for high-PI portfolios, further adding to the already higher excess returns of these portfolios. Although the q-factor model is based on an appealing investment asset pricing framework, its empirical factors share some key characteristics of the FF5 factors, and hence lead to a similar amplification of the mispricing of the PI-sorted portfolios.

Panel B shows q5-regressions, which include the expected growth factor (EG). The loadings show a strong relationship between patenting intensity and expected growth. Non-patenting firms have a negative loading of -0.18 on EG, which monotonically increases with PI to 0.64 for high-patent intensity firms, generating a loading spread of 0.82 in the long-short portfolio. Including EG further amplifies the negative loadings on the investment and profitability factors, which decrease to -0.42 and -0.79 from -0.27 and -0.52, respectively. The inclusion of the EG factor is crucial to explain the returns of the PI-sorted portfolio. While q5-factor alphas are still monotonically increasing, resulting in a long-short alpha of 2.26%, the remaining long-short alpha is statistically indistinguishable from zero. The results show that the q5 model is able to price technological innovators, in particular relative to non-innovating firms.

In unreported robustness checks, we find that the statistical significance of the q5 results are sensitive to the exact specification of patenting activity. For example, when measuring patent intensity as the number of patents over last 36 months (instead of 12 months in the main specification) divided by the firm's market capitalization, the high-PI portfolio still earns a statistically significant q5-alpha, resulting in a significant alpha of the HL portfolio as well. Nonetheless, what remains robust across all checks is a very strong sort on the expected growth loading and a large reduction in mispricing. These are the key economic findings that we focus on.

3.4. Build-up or Resolution?

A different lens through which to understand the performance of technological innovators is the methodology of Binsbergen, Boons, Opp, and Tamoni (2021), which proposes to determine whether an anomaly is due to "build-up" or "resolution" of misvaluation. They generate an empirical pricing kernel by assuming that the market portfolio is priced correctly on average over the sample period, given realized cash flows (dividends) over a fifteen year period and the terminal value of the portfolio in year fifteen.

Other portfolios, such as the market at other horizons or any anomaly portfolio at any horizon, can be valued using this pricing kernel. Assets are therefore priced by their covariation with realized market returns, as in the CAPM. We apply this methodology to our patent-intensity portfolios.

Starting in 1963, we estimate the fair market value of anomaly portfolios, including PI-portfolios, using the Binsbergen, Boons, Opp, and Tamoni (2021) dividend discount model and CAPM-SDF. For greater comparability with their results, we form our last portfolios in 2002 (final cash flows in 2017). Portfolios are therefore formed in June of every year from 1963 to 2002. The price wedge of a portfolio is the difference between the actual price of the portfolio and the imputed fair market value from the model. In addition to the price wedge at the time of portfolio formation, we track the portfolios through time until 15 years after portfolio formation. Importantly, we track the same group of stocks throughout the 15 years and keep the endpoint constant, forcing the price wedge to be equal to zero after 15 years. We carry out this methodology for not only the PI-portfolios but also the market and anomalies related to size, value, investment, and profitability.

Figure 5 shows estimated price wedges. The top left panel shows the benchmark market portfolio, and long-short portfolios formed on size, value, investment, and profitability. This reveals an important consideration in interpreting the reported price wedges: The market itself is "misvalued" in the years after portfolio formation as it ages. We point this out not to critique the methodology, but to make clear that the pattern observed in the market is the benchmark by which we may want to evaluate other portfolios.[21] The long-short portfolios in the top left corner should not be as strongly affected by this benchmark issue, since it affects both the long and short sides. Consistent with the results of Binsbergen, Boons, Opp, and Tamoni (2021), the profitability anomaly is a "build-up" anomaly, and the other anomalies considered are "resolution" or reduction of existing mispricing.

[21] The apparent misvaluation of the market at intermediate horizons could be due to autocorrelations in market returns, or to dropping years of data at the sample beginning in the aged portfolios. For example, the one-year aged portfolio drops from the valuation of the market all of the 1963 data.

The top right panel of Figure 5 shows price wedges for the long and short sides separately of each of the traditional anomalies. To avoid the benchmark issue shown for the market portfolio, we display price-wedge differences, the difference between the price wedge of each portfolio and the price wedge of the market portfolio (if we did not subtract the price wedge of the market portfolio, all long-only portfolios would have this as a common component of their price wedges). Undervaluation appears to play a modestly more important role than overvaluation. We also see differences in the speed of misvaluation resolution. For example, small stocks have a small undervaluation wedge that dissipates quickly.

The bottom two panels of Figure 5 show price wedge dynamics of the PI-sorted portfolios, with the long-short portfolio in the left-hand panel and the price wedge differences (relative to market) of the long and short sides separately on the right-hand side. According to the benchmark model, the long-short portfolio is initially undervalued by a little less than twenty percent, with all of this coming from undervaluation of patent-intensive firms.

These results help to interpret the CAPM results shown in Table 4. According to the CAPM, non-innovators (the short side of the PI long-short portfolio) are not mispriced, and the price wedge shows no long-run mispricing either. On the other hand, patent-intensive firms earn postive abnormal returns, and the bottom right-hand panel of Figure 5 says that this should be interpreted as undervaluation that takes several years to resolve. The results thus conform well with early discussions in the literature of undervaluation of technological innovation by investors, perhaps because of short-sightedness or misunderstanding the value of innovation (Hall, 1993, Hall and Hall, 1993).

A natural question to follow this analysis is why does adding additional "standard" factors to the CAPM, such as investment and profitability, worsen the mispricing of technological innovators (Table 4, Panel D)? Further, is this additional mispricing short-lived or long-lived? We turn to these questions in the next section.

4. Life-Cycle Dynamics and Innovation Mispricing

We show risk and alpha dynamics of patent-intensity sorted portfolios for a decade following the initial sort date. We also investigate the roles of different factors, and show that for innovative firms high investment and weak profitability are not punished to the same extent as in non-innovative firms.

4.1. Risk and Alpha Dynamics of Aged Portfolios

To form our aged portfolios, at the end of June of year t we use the PI sort from year $t - K$ and form value-weighted portfolios, for lags $K = 0, 1, ..., 10$. The sorts do not depend on time-t information, and any stocks from the $t - K$ sort that are no longer present at date t are simply omitted from the aged portfolio. The value weights depend on values at the end of June of year t. The K-aged portfolio returns are identical to the returns one would receive if forming the portfolios at year $t - K$, rebalancing each year to current value weights based on the stocks remaining from the original portfolio sort, and reinvesting any dividends or delisting returns at the same value weights. In other words, we study portfolios of firms that were classified as high-PI or non-patenting K years ago. The analysis reveals the evolution of risk and performance of the initially sorted portfolios over time.

Table 8 shows FF5 alpha dynamics of the aged portfolios in the 1963-2021 sample period. The results are striking. FF5 abnormal performance for non-innovators is significantly negative for a full eleven years after formation (cohorts 0 to 10), and the high-PI portfolio remains significantly positive for a full ten years. The long-short portfolio alpha is highly statistically significant exceeding 5% annually in the 10th year after formation (cohort 9). The persistence of performance is remarkable.

Table 9 shows long-short returns and alphas for CAPM, FF3, and FF5, for the full sample and post-1963 sample. For the CAPM and FF3 models, positive abnormal returns remain statistically significant for only two to three years. The addition of the investment and profitability factors in the FF5 portfolios not only makes abnormal performance larger, but also substantially more persistent. As discussed by Binsbergen and Opp (2019), persistence in abnormal performance, or significant inaccuracy in costs-of-capital over long-periods of time, can imply highly inefficient real investment. If the FF5 model accurately captures the market-required return on equity capital, technological innovators face too-high costs of capital for long horizons, and are therefore likely to significantly underinvest. Meanwhile, non-innovator costs-of-capital would be too low, implying overinvestment. Appendix Tables A5 and A6 show similar results respectively for FF6 alphas (adds momentum) and $q4$ alphas.

Table 10 shows that the expected growth factor of the $q5$ model again remarkably resolves these difficulties for nearly all portfolios and horizons. To understand the role played by expected growth, Figure 6 shows the dynamics of factor loadings in the $q5$ model. (Appendix Figures A1 and A2 show similar loadings for FF5 and $q4$ models.) Table 7, Panel B previously showed a very high contemporaneous loading of the long-short PI portfolio on expected growth, but what does such a high level of expected growth imply for the risk dynamics of technological innovator loadings?

The factor loading dynamics reveal a compelling economic story. First we consider expected growth itself. The initial spread is very strong and monotonic, with the high-PI loading exceeding 0.6, the non-innovator loading approaching -0.2, and the net long-short loading exceeding 0.8. Over time, we should always anticipate loadings with a strong initial sort to mean-revert. The growth loadings mostly do so, but with a twist. In particular, the four innovator portfolio loadings appear to mean revert to a common mean, and all are in-between 0.1 and 0.2 in the 10th year, while the non-innovator loading stays negative and statistically significant throughout the decade. The long-short growth loading is 0.31 with a t-statistic exceeding 2 in the 10th year. Innovator growth and non-innovator growth appear to revert to different means, and innovator growth loadings are persistently higher.

The loadings on investment also show a strong distinction between innovators and non-innovators. The non-innovator investment loading is in the range of 0.25 to 0.3 (conservative) and highly statistically significant throughout the decade. Innovator loadings are initially negative (aggressive) and bunched (-0.06 to -0.17), but then diverge. Low-intensity innovators become more conservative in their investment loadings and high-intensity innovators become more aggressive. High-intensity innovators particularly shift toward aggressive investment in the two years following portfolio formation. To explore the relation between expected growth and investment further, Panel F (bottom right) plots growth loadings and two-year forward investment loadings on the same axes. The overlap is remarkably strong. Expected growth loadings predict future investment loadings for technological innovators.

The final piece of the economic story is profitability loadings. Once again the initial sort is strong and monotonic, with non-innovators loading slightly positively on profitability (0.1, t=2.7) and high-intensity innovators loading negatively (-0.69, t=-6.8). Over time mean-reversion occurs, but slowly and mostly among the most innovation-intense firms. In the 10th year the loading sort is still monotonic, with non-innovators still loading positively (0.08, t=1.9) and high-intensity innovators still loading negatively (-0.26, t=2.7). Over the ten year period, non-innovator profitability very modestly weakens (year 10 minus year 0 profitability loading equals -0.04, t=-2.36, Appendix Table A10, Panel D). Meanwhile the most intense innovators move strongly towards more robust profitability (year 10 minus year 0 profitability loading equals 0.4, t=4.9).

These three elements, growth, investment, and profitability, drive a compelling economic story. High-intensity innovators develop growth options, which they take advantage of through increasingly heavy investment, gradually leading to improved profitability. All three factors earn strong premia, and all are needed to explain the complex risk and return dynamics of innovative firms.

Though not as central to the economic story, the dynamics of size loadings are also interesting. Naturally, we expect *ex ante* that size loadings should decrease, as the firms in the aged portfolios are not replaced by new firms. Most of the portfolios follow a pattern of gradual decrease in size loadings, but size loadings drop most dramatically for the most innovation intensive, consistent with these firms growing fastest.

4.2. Investment and Profitability

We show that variations in investment and profitability for innovative firms do not earn the same premia as for non-innovative firms. Our approach is to sort *within* the groups of all non-innovators ($PI = 0$, portfolio 0) and all innovators ($PI > 0$, portfolios 1-4) on the FF5 characteristics: market, size, B/M, profitability, and investment. For simplicity, the long-short portfolios are always long the quintile with the highest value of the sorting variable and short the quintile with the lowest value, irrespective of which side earns the higher return traditionally. We 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 11 shows results. For beta, size, and B/M the return spreads and alphas are largely unremarkable. The value spreads are positive and significant among both innovators and non-innovators, but their difference is not, and none of the alphas is significant controlling for standard factors. The raw size spread is larger for innovators than non-innovators, but the alpha difference is insignificant controlling for standard factors. The raw beta spreads are insignificantly different from zero, as are the within-group alphas, but the alpha is mildly larger for innovators than non-innovators (beta earns more of a premium for innovators than non-innovators). These results do not appear central to explaining the pricing of innovative versus non-innovative firms.

The results for investment and profitability are more noteworthy. The raw return spread for non-innovators shows the familiar negative sign and is statistically significant, whereas the return spread for innovators is negative, but of lower magnitude and not significant. The difference in spreads is not significant. Controlling for FF5 factors, however, the difference in alpha becomes significantly positive, with a magnitude of 4.5% p.a. (t=2.36) driven by a very negative loading on investment (innovators have a much wider spread in investment loadings than non-innovators). The difference for profitability is even stronger. In raw returns, among non-innovators the most profitable quintile earns the familiar higher return than the least profitable quintile, with a return spread of 6% p.a. (t=2.34). To the contrary, among non-innovators the return spread is *negative* (-3.5% p.a.) but not significant. The return spread difference is very large, -9.6% p.a. (t=-3.4). Controlling for the FF5 factors has predictable results. The alpha for non-innovators is statistically indistinguishable from zero, but the alpha for innovators is -6.2% p.a. (t=-2.7). The alpha difference is economically meaningful at -7.8% p.a., and statistically significant.

The explanation for mispricing when using the FF5 model for innovative firms is now clear. In the aggregate data, the return spreads earned for investment and profitability are driven primarily by non-innovators. Innovators have strong variation in these characteristics, but the return spreads are weaker or even opposite to the overall data.

Why does the $q5$ model help to price portfolios of innovators, and can it further solve the challenging problem of characteristic sort mispricing *within* groups of innovators and non-innovators? Table 12 sheds light on these questions, showing mixed results. For investment sorts, the alpha difference between innovators and non-innovators falls by more than 50% to approximately 2% p.a. and a t-statistic less than one. The improvement in pricing is driven by a strong positive loading on expected growth (0.36, raising the benchmark required return) that partially compensates for the large negative investment loading (-0.74, decreasing the benchmark required return). This is the classic omitted variables problem. Heavy investors who are innovators are expected to grow faster than heavy investors who are non-innovators, and failing to account for this correlation causes mispricing. Turning to profitability sorts, the $q5$ model eliminates the statistical significance of the difference in alpha between innovators and non-innovators, but leaves a strong and statistically significant negative alpha (-7.2%, t=-2.4) for the sort within innovators. In other words, innovators still earn surprisingly low returns for profitability (according to the $q5$ model), even after accounting for the expected growth factor.

Overall, these results shed further light on differences in pricing for innovators and non-innovators. The raw investment and profitability anomalies are stronger in non-innovators than innovators, and innovators show abnormal performance for exposure to these factors using standard FF5 or $q4$ models. The expected growth factor of the $q5$ model realigns pricing of investment because heavy investors who are innovators also tend to have high growth loadings. The pricing of profitability sorts among innovators remains a challenge even for the $q5$ model. We note that the construction of the expected growth factor in the $q5$ model specifically targets investment growth. But fundamental valuation suggests that different types of growth can be relevant, for example, not just investment growth but also profitability growth or revenue growth. We leave these issues for future research.

5. Conclusion

Over the past century, approximately a quarter of US-publicly listed firms could be classified as technological innovators by their patenting activity. Since the 1930's, innovators accounted for more than half of the total market capitalization at any point in time. Despite being long proposed as a key driver of economic growth, leading factor models only implicitly take into account technological innovation. Our paper proposes a simple patent-based measure of innovation intensity that allows us to study the role of technological innovation for stock returns.

Technological innovators earn higher returns than non-innovators, and do not incur the same punishment for high capital investment and low profitability as non-innovators. In particular, a portfolio of firms with high patenting intensity earns significant abnormal returns for a full decade after portfolio formation, according to standard pricing models. We unite our findings with the recent literature on the role of expected growth in stock returns (Hou, Mo, Xue, and Zhang, 2021). Over time, firms with high patenting intensity invest more in physical capital and gradually improve their profitability as they age. An expected growth factor is crucial to explain the returns of innovating firms.

Our study highlights strongly predictable patterns in the risk dynamics of innovative firms. The results suggest more formally linking theory to the evolution of firm risk, providing stronger tests of pricing models. Since our measure does not rely on accounting data, empirical studies can use long samples, even beyond the nearly full century of data that we study. This is particularly important in the context of technology and growth, which shape the behavior of firms and the development of economies for decades into the future.

References

Abernathy, William J, James M Utterback, et al., 1978, Patterns of industrial innovation, *Technology review* 80, 40–47.

Aghion, Philippe, and Peter Howitt, 1992, A model of growth through creative destruction, *Econometrica* 60, 323–351.

Akcigit, Ufuk, and William R Kerr, 2018, Growth through heterogeneous innovations, *Journal of Political Economy* 126, 1374–1443.

Arrow, Kenneth, 1962, Economic welfare and the allocation of resources for invention, in *The rate and direction of inventive activity: Economic and social factors* . pp. 609–626 (Princeton University Press).

Barillas, Francisco, and Jay Shanken, 2018, Comparing asset pricing models, *The Journal of Finance* 73, 715–754.

Bena, Jan, and Lorenzo Garlappi, 2020, Corporate innovation and returns, *Review of Corporate Finance Studies* 9, 340–383.

——— , and Patrick Grüning, 2016, Heterogeneous innovation, firm creation and destruction, and asset prices, *The Review of Asset Pricing Studies* 6, 46–87.

Berk, Jonathan B, 1995, A critique of size-related anomalies, *The Review of Financial Studies* 8, 275–286.

——— , Richard C Green, and Vasant Naik, 2004, Valuation and return dynamics of new ventures, *The review of financial studies* 17, 1–35.

Binsbergen, Jules H., Martijn Boons, Christian C. Opp, and Andrea Tamoni, 2021, Dynamic asset (mis)pricing: Build-up vs. resolution anomalies, Discussion paper, SSRN.

Binsbergen, Jules H., and Christian C. Opp, 2019, Real anomalies, *Journal of Finance* 74, 1659–1706.

Bound, John, Clint Cummins, Zvi Griliches, Bronwyn H. Hall, and Adam B. Jaffe, 1982, Who does R&D and who patents?, Discussion paper, National Bureau of Economic Research.

Caves, Richard E, 1998, Industrial organization and new findings on the turnover and mobility of firms, *Journal of economic literature* 36, 1947–1982.

Chan, Louis K.C., Josef Lakonishok, and Theodore Sougiannis, 2001, The stock market valuation of research and development expenditures, *Journal of Finance* 56, 2431–2456.

Cochrane, John H, 2011, Presidential address: Discount rates, *The Journal of finance* 66, 1047–1108.

Cohen, Lauren, Karl Diether, and Christopher Malloy, 2013, Misvaluing innovation, *Review of Financial Studies* 26, 635–666.

Cohen, Wesley M, and Steven Klepper, 1996, Firm size and the nature of innovation within industries: the case of process and product r&d, *The review of Economics and Statistics* pp. 232–243.

Dasgupta, Partha, and Joseph Stiglitz, 1980, Industrial structure and the nature of innovative activity, *The Economic Journal* 90, 266–293.

Dunne, Timothy, Mark J Roberts, and Larry Samuelson, 1989, The growth and failure of us manufacturing plants, *The Quarterly Journal of Economics* 104, 671–698.

Eberhart, Allan C., William F Maxwell, and Akhtar R. Siddique, 2004, An examination of long-term abnormal stock returns and operating performance following R&D increases, *Journal of Finance* 59, 623–650.

Elliott, John, Gordon Richardson, Thomas Dyckman, and Roland Dukes, 1984, The impact of SFAS No. 2 on firm expenditures on research and development: Replications and extensions, *Journal of Accounting Research* 22, 85–102.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

——— , 1995, Size and book-to-market factors in earnings and returns, *Journal of Finance* 50, 131–155.

——— , 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116, 1–22.

——— , 2018, Choosing factors, *Journal of Financial Economics* 128, 234–252.

Garlappi, Lorenzo, and Zhongzhi Song, 2017, Capital utilization, market power, and the pricing of investment shocks, *Journal of Financial Economics* 126, 447–470.

Garleanu, Nicolae, Stavros Panageas, and Jianfeng Yu, 2012, Technological growth and asset pricing, *The Journal of Finance* 67, 1265–1292.

Greenwood, Jeremy, and Boyan Jovanovic, 1999, The information-technology revolution and the stock market, *American Economic Review* 89, 116–122.

Gu, Feng, 2005, Innovation, future earnings, and market efficiency, *Journal of Accounting, Auditing & Finance* 20, 385–418.

Gu, Shihao, Bryan Kelly, and Dacheng Xiu, 2020, Empirical asset pricing via machine learning, *The Review of Financial Studies* 33, 2223–2273.

Hall, Bronwyn, 1993, The stock market's valuation of R&D investment during the 1980's, *American Economic Review* 83, 259–264.

——— , 2007, Measuring the returns to r&d: The depreciation problem, .

——— , and Robert Hall, 1993, The value and performance of US corporations, *Brookings Papers on Economic Activity* 1993, 1–49.

Hall, Bronwyn, and Josh Lerner, 2010, The financing of r&d and innovation, in *Handbook of the Economics of Innovation*vol. 1 . pp. 609–639 (Elsevier).

Hirshleifer, David, Po-Hsuan Hsu, and Dongmei Li, 2013, Innovative efficiency and stock returns, *Journal of Financial Economics* 107, 632–654.

——— , 2018, Innovative originality, profitability, and stock returns, *Review of Financial Studies* 31, 2553–2605.

Hobijn, Bart, and Boyan Jovanovic, 2001, The information-technology revolution and the stock market: Evidence, *American Economic Review* 91, 1203–1220.

Hou, Kewei, Haitao Mo, Chen Xue, and Lu Zhang, 2021, An augmented q-factor model with expected growth, *Review of Finance* 25, 1–41.

Hou, Kewei, Chen Xue, and Lu Zhang, 2015, Digesting anomalies: An investment approach, *Review of Financial Studies* 28, 650–705.

——— , 2020, Replicating anomalies, *Review of Financial Studies* 33, 2019–2133.

Jovanovic, Boyan, 1982, Selection and the evolution of industry, *Econometrica: Journal of the econometric society* pp. 649–670.

Kelly, Bryan, Dimitris Papanikolaou, Amit Seru, and Matt Taddy, 2021, Measuring technological innovation over the long run, Discussion Paper, 3.

Klepper, Steven, 1996, Entry, exit, growth, and innovation over the product life cycle, *The American economic review* pp. 562–583.

Klette, Tor Jakob, and Samuel Kortum, 2004, Innovating firms and aggregate innovation, *Journal of political economy* 112, 986–1018.

Kogan, Leonid, and Dimitris Papanikolaou, 2010, Growth opportunities and technology shocks, *American Economic Review Papers and Proceedings* 100, 532–536.

——— , 2013, Firm characteristics and stock returns: The role of investment-specific shocks, *The Review of Financial Studies* 26, 2718–2759.

——— , 2014, Growth opportunities, technology shocks, and asset prices, *The journal of finance* 69, 675–718.

——— , Amit Seru, and Noah Stoffman, 2017, Technological innovation, resource allocation, and growth, *Quarterly Journal of Economics* 132, 665–712.

Kogan, Leonid, Dimitris Papanikolaou, and Noah Stoffman, 2020, Left behind: Creative destruction, inequality, and the stock market, *Journal of Political Economy* 128, 855–906.

Kung, Howard, and Lukas Schmid, 2015, Innovation, growth, and asset prices, *Journal of Finance* 70, 1001–1037.

Lev, Baruch, and Theodore Sougiannis, 1996, The capitalization, amortization, and value-relevance of R&D, *Journal of Accounting and Economics* 21, 107–138.

Nelson, Richard R, 1959, The simple economics of basic scientific research, *Journal of political economy* 67, 297–306.

Novy-Marx, Robert, 2013, The other side of value: The gross profitability premium, *Journal of Financial Economics* 108, 1–28.

Papanikolaou, Dimitris, 2011, Investment shocks and asset prices, *Journal of Political Economy* 119, 639–685.

Pástor, L'uboš, and Pietro Veronesi, 2006, Was there a nasdaq bubble in the late 1990s?, *Journal of Financial Economics* 81, 61–100.

——— , 2009, Technological revolutions and stock prices, *American Economic Review* 99, 1451–83.

Peters, Ryan H., and Lucian A. Taylor, 2017, Intangible capital and the investment-q relation, *Journal of Financial Economics* 123, 251–272.

Romer, Paul, 1986, Increasing returns and long-run growth, *Journal of Political Economy* 94, 1002–1007.

——— , 1990, Endogenous technological change, *Journal of Political Economy* 98, S71–S102.

Scherer, Frederic M, 1998, The size distribution of profits from innovation, *Annales d'Économie et de Statistique* pp. 495–516.

Schumpeter, Joseph, 1911, *The Theory of Economic Development* (Harvard University Press).

Schwert, G. William, 2002, Stock volatility in the new millennium: how wacky is Nasdaq?, *Journal of Monetary Economics* 49, 3–26.

Shumway, Tyler, 1997, The delisting bias in CRSP data, *Journal of Finance* 52, 327–340.

Solow, Robert, 1957, Technical change and the aggregate production function, *Review of Economics and Statistics* 39, 312–320.

Stoffman, Noah, Michael Woeppel, and Deniz Yavuz, 2022, Small innovators: No risk, no return, *Journal of Accounting and Economics* pp. 1—28.

Sutton, John, 1997, Gibrat's legacy, *Journal of economic literature* 35, 40–59.

Titman, Sheridan, K.C. John Wei, and Feixue Xie, 2004, Capital investments and stock returns, *Journal of Financial and Quantitative Analysis* 39, 677–700.

Tobin, James, 1958, Estimation of relationships for limited dependent variables, *Econometrica* pp. 24–36.

Utterback, James M, and William J Abernathy, 1975, A dynamic model of process and product innovation, *Omega* 3, 639–656.

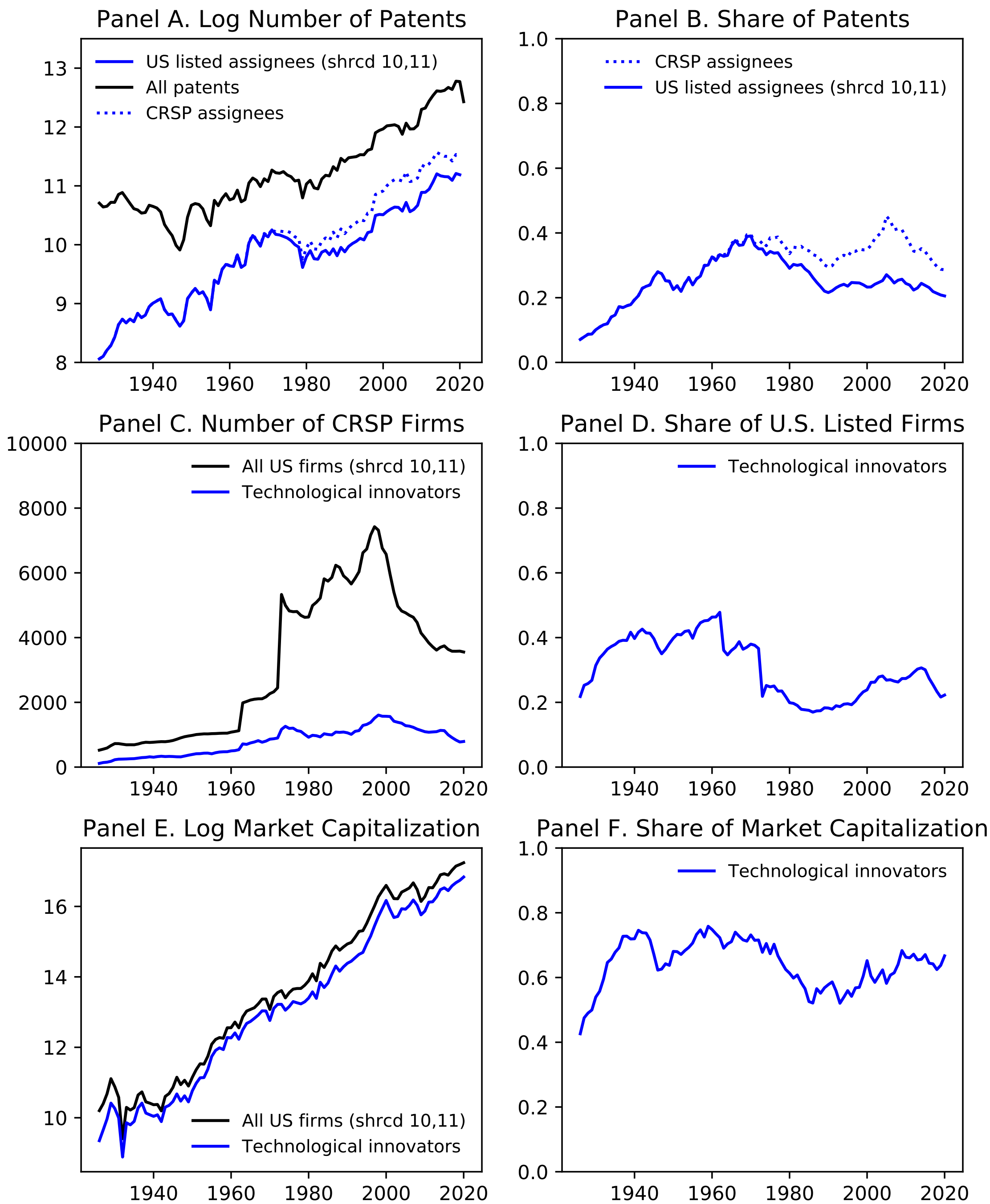

Figure 1: Patents, US Listed Firms, Technological Innovators and Market Capitalization. Panel A shows the log number of patents per year (calendar year) of all, CRSP, and US listed assignees. Panel B shows the share of patents of CRSP assignees and US listed assignees. CRSP assignee is any firm in the CRSP data with a patent and US listed assignees are US-incorporated firms with common stock (shrcd 10 or 11) with a patent. Panel C shows the total number of all US firms (shrcd 10 or 11) and the number of technological innovators, which are firms with at least one patent in a given year (year end in June). Panel D shows the percentage of technological innovators. Panel E plots the log market capitalization of all US firms (shrcd 10 or 11) and technological innovators. Panel F shows the market capitalization share of technological innovators. All stocks or firms refer to firms traded on NYSE, NASDAQ or AMEX.

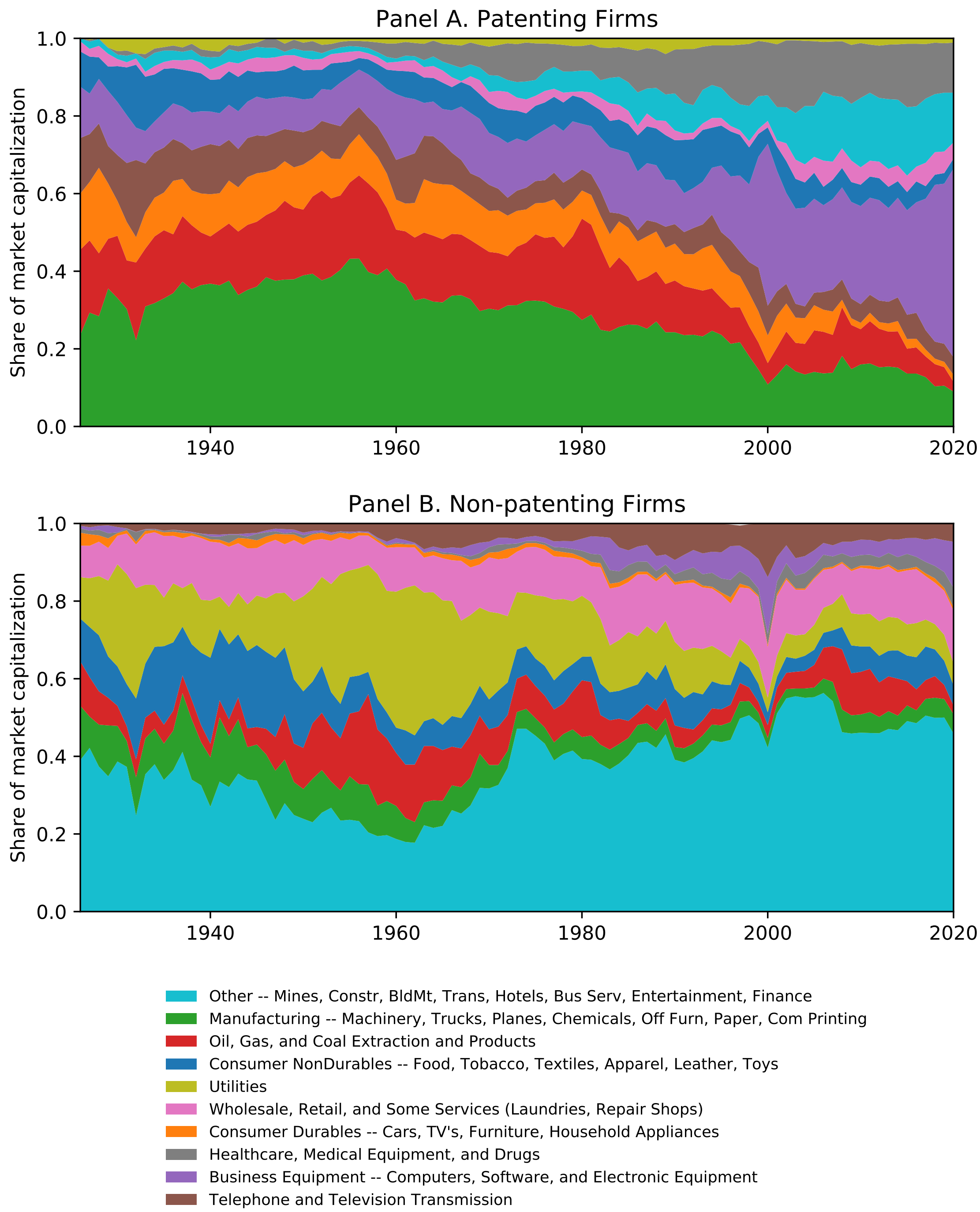

Figure 2: Sector Composition of Patenting and Non-patenting Firms. Panel A shows sectors' market capitalization shares of total market capitalization of patenting firms. For each sector, we calculate the market capitalization of patenting firms in the sector and divide by the total market capitalization of patenting firms in all sectors. Panel B shows the equivalent for non-patenting firms. Patenting firm is a firm with at least one patent in a year. Sectors are defined by Fama-French 10 industries.

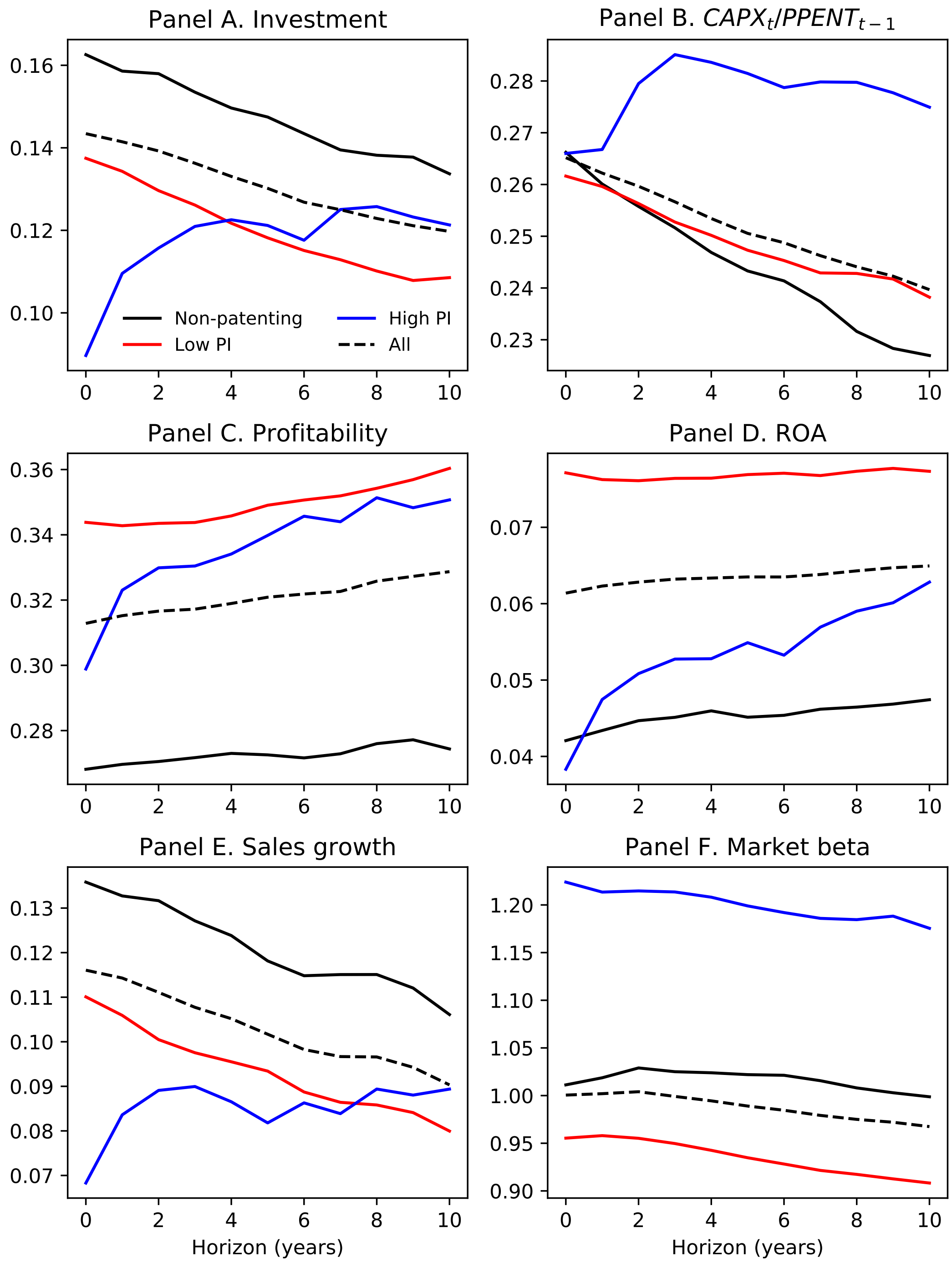

Figure 3: Aged Patent-Intensity Portfolios, Characteristics, 1963-2020. The figure shows the dynamics of variables of PI-sorted aged portfolios as indicated in the panel headings. Investment is growth rate in total assets between $t-1$ and t, Profitability is sales minus (sum of cogs, sga and interest expenses) divided by book equity. ROA is net income divided by total assets. Sales growth is $Sale_t/Sale_{t-1} - 1$. Firms are sorted every year at the end of June into three portfolios. The first portfolio 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. The time period is from 1963 to 2020. For all portfolios, we first calculate the annual value-weighted average at the specific horizon and then average across years from 1963 to 2010 (i.e., 2020 minus the 10-year horizon). The dotted line shows value-weighted statistics for all firms.

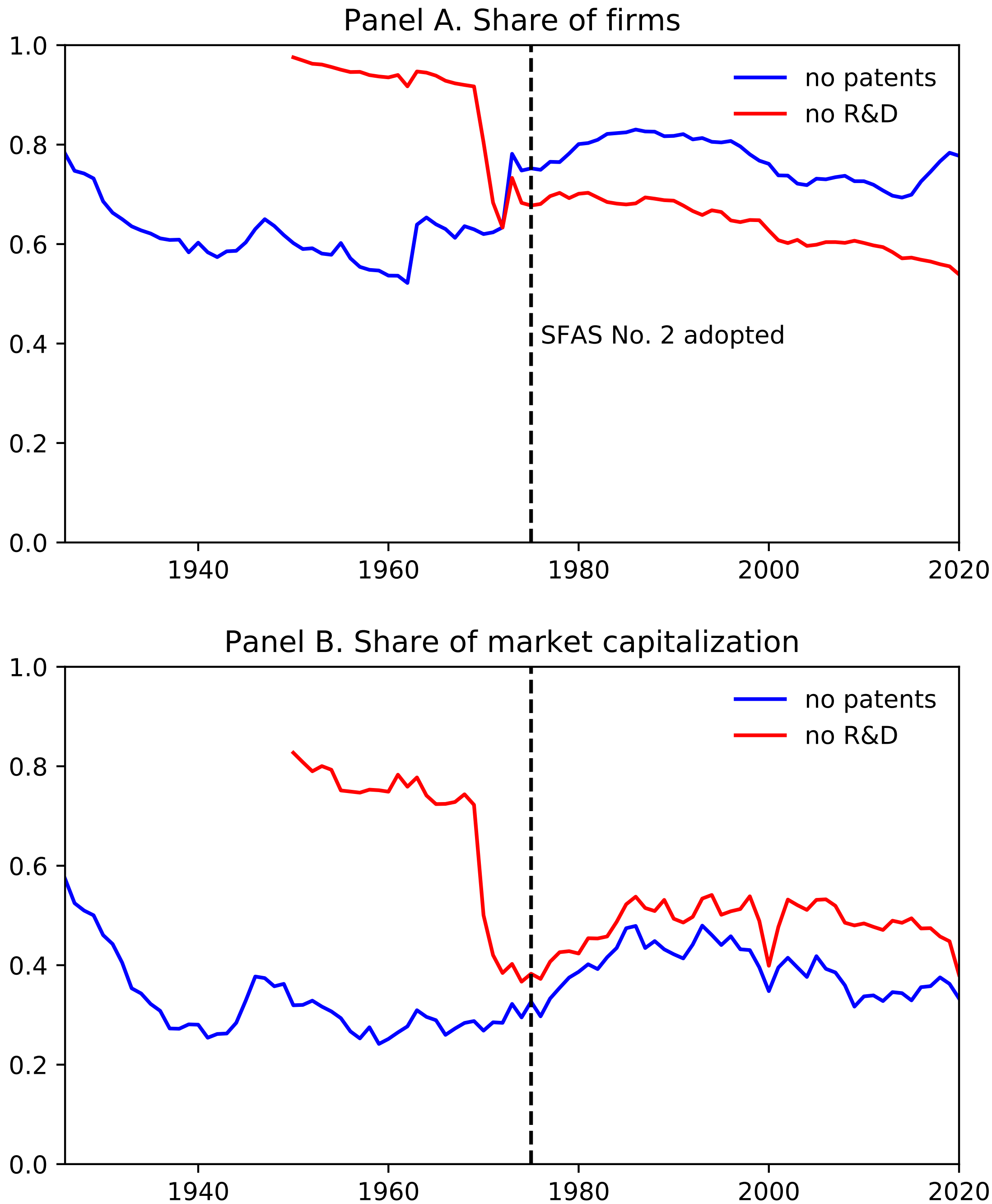

Figure 4: Fraction of non-R&D and non-patenting Firms. The left panel shows the fraction of CRSP firms no patenting activity as well as zero or missing R&D activity. The right panel shows the fraction of the total CRSP market capitalization that belongs to these firms. The sample of firm is identical to the sample in Figure 1.

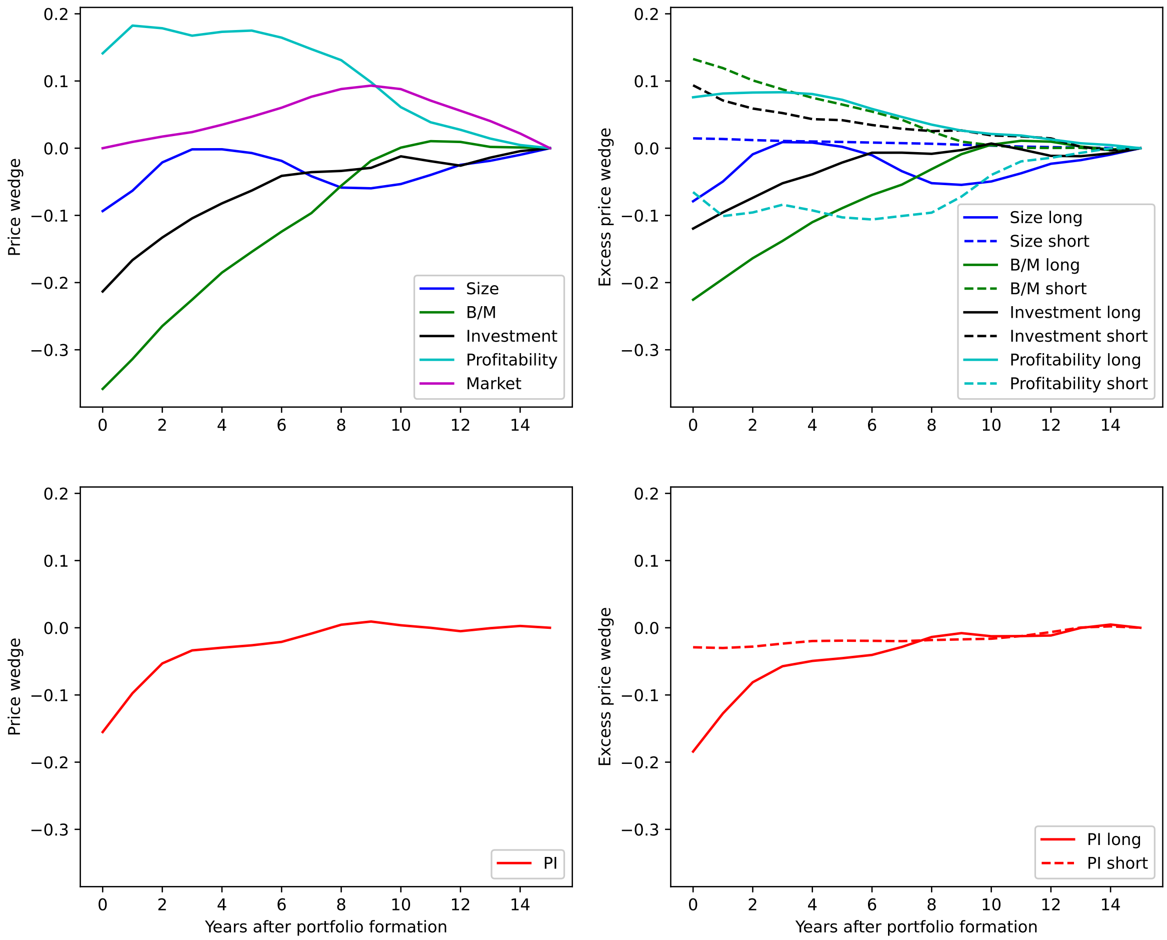

Figure 5: Price Wedge Dynamics. The figure shows price wedge dynamics for portfolios sorted on size, book-to-market, investment, and profitability in the top row and portfolios sorted on PI in the bottom row. Price wedges are calculated as the difference between observed and the fair market value suggested by a 15-year dividend discount model using CAPM SDF as suggested by Binsbergen, Boons, Opp, and Tamoni (2021). The top-left panel plots the price wedge for a long-short portfolio, where the long side is the quartile portfolio with the highest (lowest) value of b/m or profitability (size or investment) and the short side is the quartile portfolio with the lowest (highest) value. *Market* is the estimated price wedge of the market portfolio. The top-right panel plots the price wedges of the individual legs of the aforementioned long-short portfolios. The bottom-left panel plots the price wedge of a portfolio that goes long high PI firms (portfolio "4") and short low PI firms (portfolio "0"). The bottom-right panel shows the wedges of the two portfolios separately.

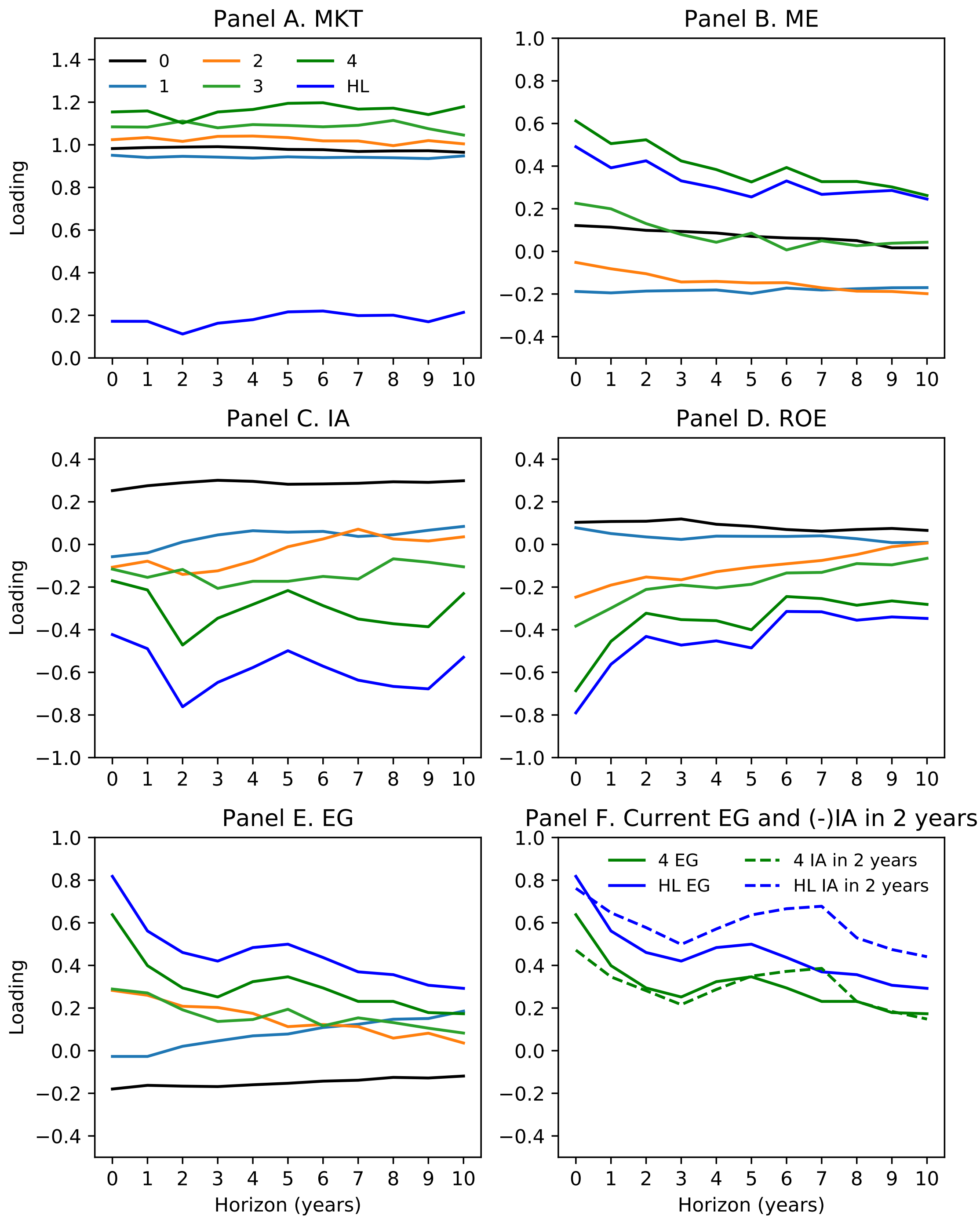

Figure 6: Aged Patent-Intensity Portfolios, Q5-Factor Loading Dynamics, 1967-2021. The figure shows the dynamics of loadings of PI-sorted aged portfolios on the Q5 factors as indicated in headings of panels A-E. Panel F shows the loadings of the HL and high-PI portfolios on the expected growth factor (EG) overlaid with the negative loadings on the investment factor (-IA) of the respective portfolios aged by additional two years, i.e., lead (EG factor) - lagged (negative IA). The investment factor (IA) is plotted negatively to facilitate comparison. The construction of the underlying portfolios is described in detail in notes to table 8. The time period of the sample is given by availability of the Q-factors, i.e., 1967-2021.

Table 1: Patent Intensity (PI) and Firm Characteristics. This table shows descriptive statistics and characteristics of firms sorted on patent intensity PI, patents received in the prior year divided by market capitalization. Firms are sorted every year at the end of June into three groups. The first group consists of non-patenting firms ($PI = 0$). Remaining firms are split equally into two groups, low and high PI. In panel A, share of firms is the portfolio's percentage of all companies, share of cap is the portfolio's share of total market capitalization and share of patents is the portfolio's share of all patents at the time of sorting or as indicated. Panel B shows descriptive statistics based on information available at the time of sorting. Mean and median indicate whether the value is from cross-sectional mean or median, respectively, before averaging across years. Age is calculated from the stock's first appearance in CRSP. Investment and profitability are available only since 1963. For all numbers, we first calculate the annual percentages (or mean and median as indicated) and then average across years from 1926 to 2021, or as indicated.

	Non-patenting	Low PI	High PI
Panel A. Portfolio shares			
Share of firms	0.682	0.159	0.159
Share of cap	0.349	0.538	0.113
Share of patents	0.000	0.375	0.625
Share of patents (next year)	0.012	0.391	0.597
Share of patents (next 3 years)	0.014	0.405	0.580
Share of patents (next 5 years)	0.017	0.418	0.565
Panel B. Portfolio variables			
CRSP age mean	13.313	20.283	15.422
CRSP age median	11.711	17.685	12.998
BM mean	1.573	0.801	1.130
BM median	0.998	0.662	0.909
Investment mean since 1963	0.137	0.164	0.090
Investment median since 1963	0.075	0.091	0.043
Profitability mean since 1963	0.164	0.257	0.095
Profitability median since 1963	0.210	0.264	0.165

Table 2: Technological Innovators on NASDAQ. This table reports the portfolio shares and composition of NASDAQ-listed companies across portfolios of non-patenting, low-PI and high-PI firms as defined in notes of table 1. The share of NASDAQ firms in panel A is the portfolio's average percentage of all NASDAQ-listed companies in the specified time period. The share of NASDAQ cap and the share of NASDAQ patents are equivalently portfolio's average percentages for market capitalization and patents, respectively, of NASDAQ listed companies. Firms from NASDAQ in panel B shows the average percentage of the firms in the portfolio over the indicated time period that are listed on NASDAQ. Cap and patents from NASDAQ are defined equivalently for market capitalization and patents, respectively, of NASDAQ-listed companies. For all numbers, we first calculate the annual percentages and then average across the indicated time period.

	Non-patenting	Low PI	High PI
Panel A. NASDAQ Composition (columns add to one)			
Share of NASDAQ firms since 1973	0.797	0.074	0.129
Share of NASDAQ firms since 2000	0.720	0.108	0.171
Share of NASDAQ firms since 2015	0.732	0.105	0.164
Share of NASDAQ cap since 1973	0.552	0.361	0.087
Share of NASDAQ cap since 2000	0.309	0.548	0.143
Share of NASDAQ cap since 2015	0.252	0.621	0.127
Share of NASDAQ patents since 1973		0.303	0.697
Share of NASDAQ patents since 2000		0.343	0.657
Share of NASDAQ patents since 2015		0.412	0.588
Panel B. NASDAQ Shares of Column (1-entry is non-NASDAQ)			
Firms from NASDAQ since 1973	0.606	0.352	0.604
Firms from NASDAQ since 2000	0.598	0.471	0.742
Firms from NASDAQ since 2015	0.587	0.472	0.732
Cap from NASDAQ since 1973	0.219	0.155	0.205
Cap from NASDAQ since 2000	0.229	0.277	0.371
Cap from NASDAQ since 2015	0.262	0.407	0.441
Patents from NASDAQ since 1973		0.185	0.218
Patents from NASDAQ since 2000		0.356	0.360
Patents from NASDAQ since 2015		0.517	0.407

Table 3: Transition Probabilities of PI- vs. M/B-sorted Portfolios. Panel A shows the transition probabilities between portfolios of stocks sorted by PI as described in notes of table 1 over 1, 3, and 5 years. Rows specify the initial portfolio and columns the portfolio of the stock after the indicated time period. Column "out" reports the probability of a stock to disappear from the data. The probabilities in each row are conditional, indicate the probability of moving from the initial portfolio (rows) to the destination portfolio in columns (or out), and sum up to 1 across the columns. Panel B shows the equivalent for market-to-book (M/B)-sorted portfolios and defines an additional "Missing" portfolio consisting of firms with negative or missing market-to-book ratio. To allow a fair comparison of the transition probabilities of the PI-sorted portfolios with the transition probabilities of M/B-sorted portfolio, the M/B-sorted portfolios are based on the same percentiles as PI-sorted portfolios: each year, we calculate the percentages of firms in each of the three PI-sorted portfolios and use these percentages to categorize stocks by M/B. 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). These probabilities apply also to the M/B-sorted portfolios for stocks with non-missing M/B. 88% of stocks have non-missing M/B, the remaining 12% have missing M/B. Accordingly, the unconditional probabilities of the four M/B-sorted portfolios are: 68%*88%=59.4% (low M/B), 15.9%*88%=14% (medium M/B), and 15.9%*88%=14% (high M/B). Transition probabilities are calculated annually over period from 1926 to 2020. The presented transition probabilities are time-series averages.

Panel A. PI-sorted portfolios					Panel B. M/B-sorted portfolios					
	Non-patenting	Low PI	High PI	Out		Low M/B	Medium M/B	High M/B	Missing	Out
Transition probabilities over 1 years										
Non-patenting	86.8	4.6	2.6	6.1	Low M/B	85.6	6.5	1.6	3.6	2.7
Low PI	17.7	67.0	12.7	2.6	Medium M/B	35.0	43.8	16.0	3.3	2.0
High PI	12.8	12.0	71.1	4.1	High M/B	9.8	19.9	63.0	5.2	2.1
					Missing	9.4	2.3	5.2	57.3	25.9
Transition probabilities over 3 years										
Non-patenting	75.9	5.2	2.8	16.1	Low M/B	73.6	7.7	3.0	3.8	11.9
Low PI	17.4	58.7	15.9	8.0	Medium M/B	43.6	28.1	15.2	3.7	9.4
High PI	13.2	15.0	60.0	11.8	High M/B	20.9	20.4	43.8	5.4	9.6
					Missing	14.9	4.2	5.6	39.0	36.2
Transition probabilities over 5 years										
Non-patenting	67.5	5.5	2.9	24.1	Low M/B	65.6	7.8	3.5	3.6	19.6
Low PI	17.1	53.6	16.7	12.5	Medium M/B	45.0	22.2	13.5	3.5	15.8
High PI	12.8	16.4	52.4	18.4	High M/B	25.5	18.5	35.1	4.8	16.1
					Missing	17.6	5.1	5.2	28.7	43.4

Table 4: Patent-Intensity Sorts and Performance, Fama-French Factors. The table shows the average excess returns of PI-sorted portfolios in panel A and results of regressing the portfolio returns on a constant and market excess returns, Fama-French 3 factors and Fama-French 5 factors in panels B, C, and D, respectively. Portfolio "0" consists of non-patenting firms and the remaining portfolios of patenting firms sorted by PI. HL is a zero-cost portfolio with a long position in the highest PI portfolio and a short position in portfolio "0". Stocks are sorted into portfolios each year at the end of June. All portfolios are value-weighted and rebalanced annually. The underlying portfolio returns are at monthly frequency, and the estimates of the average excess returns and constants are annualized. t-statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses. The time period of the sample is indicated in headings, i.e., 1926-2021 and 1963-2021. Data for Fama-French 5 factors is available from 1963. */**/*** indicate significance level at 10, 5, and 1%, respectively.

	1926-2021				1963-2021					
	0	1	2	HL	0	1	2	3	4	HL
Panel A. Excess returns										
Excess return	7.68***	8.41***	11.79***	4.1***	6.58***	6.18***	8.62***	9.56***	13.54***	6.97***
	(3.82)	(4.41)	(4.75)	(3.84)	(2.95)	(3.14)	(3.92)	(3.8)	(4.1)	(3.43)
Panel B. CAPM										
Constant	-0.44	0.5	1.83**	2.28**	-0.34	-0.24	1.59**	1.62	4.78**	5.12***
	(-0.93)	(1.62)	(2.29)	(2.32)	(-0.51)	(-0.46)	(2.32)	(1.55)	(2.52)	(2.61)
Mkt-RF	0.98***	0.95***	1.2***	0.22***	0.99***	0.92***	1.01***	1.14***	1.25***	0.26***
	(67.76)	(92.35)	(42.93)	(8.23)	(55.95)	(70.49)	(59.31)	(42.67)	(26.31)	(5.37)
R^2	0.95	0.97	0.89	0.16	0.93	0.94	0.9	0.82	0.67	0.07
Panel C. Fama-French 1993										
Constant	-0.89**	0.78***	1.45*	2.35**	-1.36***	0.41	1.83***	1.23	3.63**	4.99***
	(-2.23)	(2.96)	(1.84)	(2.35)	(-2.83)	(0.97)	(2.64)	(1.17)	(2.14)	(2.6)
Mkt-RF	0.94***	0.99***	1.15***	0.2***	1.0***	0.94***	1.0***	1.08***	1.12***	0.12*
	(86.04)	(122.77)	(42.37)	(6.24)	(68.43)	(96.36)	(52.54)	(31.78)	(20.54)	(1.9)
SMB	0.08**	-0.12***	0.25***	0.17*	0.09**	-0.2***	-0.01	0.3***	0.7***	0.61***
	(2.41)	(-9.47)	(3.62)	(1.79)	(2.06)	(-15.68)	(-0.26)	(3.73)	(5.78)	(3.84)
HML	0.14***	-0.06***	0.06	-0.09	0.22***	-0.1***	-0.06*	0.01	0.09	-0.13*
	(5.8)	(-4.38)	(1.2)	(-1.43)	(7.21)	(-5.48)	(-1.75)	(0.31)	(1.4)	(-1.67)
R^2	0.96	0.98	0.91	0.2	0.95	0.96	0.9	0.85	0.76	0.25
Panel D. Fama-French 2015										
Constant					-1.76***	0.13	2.11***	2.02**	4.94***	6.71***
					(-3.75)	(0.3)	(3.03)	(1.97)	(2.96)	(3.54)
Mkt-RF					1.0***	0.95***	1.01***	1.08***	1.12***	0.12**
					(76.92)	(93.56)	(64.84)	(33.85)	(23.2)	(2.29)
SMB					0.13***	-0.18***	-0.05*	0.22***	0.57***	0.44***
					(5.41)	(-14.08)	(-1.73)	(3.87)	(7.38)	(4.71)
HML					0.21***	-0.08***	-0.08**	-0.08	-0.1	-0.31***
					(6.57)	(-3.69)	(-1.99)	(-1.18)	(-1.08)	(-2.81)
CMA					-0.03	0.02	0.08	0.14	0.24	0.27
					(-0.81)	(0.58)	(1.37)	(1.55)	(1.58)	(1.6)
RMW					0.13***	0.05***	-0.12***	-0.28***	-0.45***	-0.58***
					(3.23)	(2.63)	(-3.38)	(-3.83)	(-3.11)	(-3.47)
R^2					0.96	0.96	0.9	0.86	0.77	0.32

Table 5: R&D-Intensity Sorts and Performance, Fama-French Factors. The table shows the average excess returns of R&D intensity-sorted portfolios in panel A and results of regressing the portfolio returns on a constant and Fama-French 5 factors in panel B. R&D intensity (RDI) is research and development expenses divided my the market value of equity. Portfolio "0" consists of firms with missing or no R&D expenditures and the remaining portfolios of firms are sorted by RDI. HL is a zero-cost portfolio with a long position in the highest RDI portfolio and a short position in portfolio "0". Stocks are sorted into portfolios each year at the end of June. All portfolios are value-weighted and rebalanced annually. The underlying portfolio returns are at monthly frequency, but the estimates of the average excess returns and constants are annualized. t-statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses. The sample period is 1975-2021. */**/*** indicate significance level at 10, 5, and 1%, respectively.

	0	1	2	3	4	HL
Panel A. Excess returns						
Average	8.459***	7.127***	9.890***	11.227***	13.538***	5.078**
	(3.55)	(3.08)	(3.92)	(4.18)	(3.64)	(2.23)
Panel B. Fama-French 2015						
Average	-1.056**	0.209	1.973**	3.082***	3.681**	4.737**
	(-2.46)	(0.25)	(2.17)	(2.79)	(2.07)	(2.46)
Mkt-RF	1.005***	0.951***	1.019***	1.022***	1.133***	0.129***
	(92.55)	(53.28)	(47.99)	(32.75)	(25.43)	(2.61)
SMB	0.051**	-0.180***	-0.028	0.156***	0.496***	0.445***
	(2.31)	(-5.91)	(-0.58)	(3.61)	(6.96)	(5.18)
HML	0.248***	-0.175***	-0.261***	-0.195***	0.009	-0.239**
	(10.38)	(-4.63)	(-5.34)	(-3.95)	(0.09)	(-2.13)
CMA	-0.080**	-0.006	0.123	0.180	0.245	0.324*
	(-2.31)	(-0.08)	(1.63)	(1.52)	(1.61)	(1.90)
RMW	0.118***	-0.042	-0.101	-0.302***	-0.590***	-0.707***
	(4.27)	(-0.66)	(-1.31)	(-3.19)	(-5.34)	(-5.57)
R^2	0.96	0.90	0.90	0.84	0.79	0.38

Table 6: Patent Intensity and R&D Intensity. The table shows the results of regressing PI- and RDI-sorted zero-cost portfolios onto the Fama-French 5 factors as well as the PI and RDI portfolios. PI is a zero-cost portfolio with a long position in the highest PI portfolio and a short position in PI portfolio "0". RDI is a zero-cost portfolio with a long position in the highest RDI portfolio and a short position in RDI portfolio "0". More details can be found in the descriptions of Tables 4 and 5. t-statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses. The sample period is 1975-2021. */**/*** indicate significance level at 10, 5, and 1%, respectively.

	PI	PI	RDI	RDI
Constant	5.826***	2.915**	4.737**	1.688
	(2.79)	(1.97)	(2.46)	(1.16)
Mkt-RF	0.140**	0.061	0.129***	0.055
	(2.45)	(1.25)	(2.61)	(1.31)
SMB	0.447***	0.174**	0.445***	0.211***
	(4.11)	(2.26)	(5.18)	(3.29)
HML	-0.355***	-0.208**	-0.239**	-0.053
	(-3.29)	(-2.45)	(-2.13)	(-0.56)
CMA	0.412**	0.212	0.324*	0.109
	(2.15)	(1.49)	(1.90)	(0.83)
RMW	-0.644***	-0.209*	-0.707***	-0.370***
	(-3.70)	(-1.84)	(-5.57)	(-5.08)
RDI		0.614***		
		(10.82)		
PI				0.523***
				(14.16)
R^2	0.34	0.56	0.38	0.58

Table 7: Patent Intensity and Q-Factors. The table shows the results of regressing the PI-sorted portfolio returns on a constant and the four Q-factors (Hou, Xue, and Zhang, 2015), i.e., market (MKT), size (ME), investment (IA), and profitability (ROE), in panel A, and additionally on fifth Q-factor (Hou, Mo, Xue, and Zhang, 2021), i.e., expected growth (EG), in panel B. Portfolio "0" consists of non-patenting firms and the remaining portfolios of patenting firms sorted by PI. HL is a zero-cost portfolio with a long position in the highest PI portfolio and a short position in portfolio "0". Stocks are sorted into portfolios each year at the end of June. All portfolios are value-weighted and rebalanced annually. The underlying portfolio returns are at monthly frequency, and the estimates of the constants are annualized. t-statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses. The time period of the sample is given by availability of the Q-factors, i.e., 1967-2021. */**/*** indicate significance level at 10, 5, and 1%, respectively.

	0	1	2	3	4	HL
Panel A. Q4-factors 1967-2021						
Constant	-2.04***	-0.04	2.83***	3.5***	6.79***	8.82***
	(-3.27)	(-0.08)	(3.75)	(2.87)	(3.69)	(3.96)
MKT	1.0***	0.95***	0.99***	1.05***	1.08***	0.08
	(50.36)	(86.86)	(53.28)	(28.13)	(19.58)	(1.11)
ME	0.14***	-0.19***	-0.08**	0.2**	0.55***	0.41**
	(2.68)	(-11.85)	(-2.07)	(2.56)	(4.44)	(2.43)
IA	0.22***	-0.06**	-0.05	-0.06	-0.05	-0.27*
	(4.52)	(-2.43)	(-1.25)	(-0.85)	(-0.39)	(-1.76)
ROE	0.04	0.07***	-0.15***	-0.29***	-0.48***	-0.52***
	(1.33)	(3.14)	(-3.6)	(-4.64)	(-5.02)	(-4.64)
R^2	0.95	0.96	0.9	0.86	0.78	0.28
Panel B. Q5-factors 1967-2021						
Constant	-0.59	0.18	0.57	1.18	1.67	2.26
	(-1.06)	(0.39)	(0.76)	(0.98)	(1.05)	(1.24)
MKT	0.98***	0.95***	1.02***	1.08***	1.15***	0.17***
	(55.85)	(86.26)	(60.46)	(29.18)	(23.18)	(2.85)
ME	0.12**	-0.19***	-0.05	0.23***	0.61***	0.49***
	(2.36)	(-12.25)	(-1.44)	(2.99)	(5.12)	(2.98)
IA	0.25***	-0.06**	-0.11***	-0.12*	-0.17	-0.42***
	(5.13)	(-2.15)	(-2.59)	(-1.7)	(-1.39)	(-2.8)
ROE	0.1***	0.08***	-0.25***	-0.38***	-0.69***	-0.79***
	(2.7)	(3.31)	(-5.57)	(-5.35)	(-6.84)	(-6.37)
EG	-0.18***	-0.03	0.28***	0.29***	0.64***	0.82***
	(-4.88)	(-0.9)	(5.54)	(3.8)	(5.92)	(6.52)
R^2	0.95	0.96	0.91	0.86	0.79	0.35

Table 8: Aged Patent-Intensity Portfolios, FF5 Alpha Dynamics, 1963-2021. The table shows the abnormal returns (alphas) relative to five-factor model (Fama and French 2015) of PI-sorted portfolios for holding period of one-year at different investment horizons (indicated in rows). Portfolio "0" consists of non-patenting firms and the remaining portfolios of patenting firms sorted by PI. HL is a zero-cost portfolio with a long position in the highest PI portfolio and a short position in portfolio "0". Stocks are sorted into portfolios at the end of June K years prior to the beginning of the holding period in July of year t. The holding period lasts for one year from July (end of June) in year t to the end of June in year $t+1$. Each portfolio consists of the stocks assigned to the portfolio K years ago that are still active as of the beginning of the holding period, i.e., end of June in year t. Portfolios are value weighted with weights as of the beginning of the holding period. The underlying portfolio returns are at monthly frequency, but the estimates of the alphas are annualized. t-statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses. The time period of the sample is given by availability of the FF5-factors, i.e., 1963-2021. */**/*** indicate significance level at 10, 5, and 1%, respectively.

Horizon (years)	0	1	2	3	4	HL
0	-1.76***	0.13	2.11***	2.02**	4.94***	6.71***
	(-3.75)	(0.3)	(3.03)	(1.97)	(2.96)	(3.54)
1	-1.78***	-0.13	2.57***	1.38	6.24***	8.03***
	(-3.9)	(-0.31)	(3.8)	(1.48)	(4.01)	(4.6)
2	-1.75***	0.0	1.55**	1.0	4.88***	6.63***
	(-3.71)	(0.01)	(2.5)	(1.2)	(3.19)	(3.83)
3	-2.0***	-0.13	1.53**	1.39	2.5*	4.5***
	(-4.26)	(-0.3)	(2.34)	(1.6)	(1.83)	(2.87)
4	-1.9***	-0.08	0.95	1.74*	1.92	3.82**
	(-4.07)	(-0.18)	(1.57)	(1.93)	(1.49)	(2.51)
5	-1.84***	0.18	0.44	1.73*	2.22*	4.07***
	(-3.99)	(0.38)	(0.72)	(1.94)	(1.71)	(2.71)
6	-1.82***	0.27	0.58	0.88	3.31**	5.13***
	(-3.98)	(0.59)	(1.02)	(0.94)	(2.33)	(3.15)
7	-1.55***	0.13	0.33	1.41*	2.97**	4.52***
	(-3.47)	(0.31)	(0.58)	(1.65)	(2.09)	(2.79)
8	-1.66***	-0.03	0.92	0.46	2.7*	4.36***
	(-3.7)	(-0.08)	(1.5)	(0.48)	(1.9)	(2.68)
9	-1.71***	0.27	0.35	0.76	3.55**	5.26***
	(-3.74)	(0.6)	(0.6)	(0.87)	(2.48)	(3.18)
10	-1.43***	0.24	-0.67	2.04**	1.44	2.86*
	(-3.09)	(0.5)	(-1.12)	(2.11)	(0.99)	(1.69)

Table 9: Aged Patent-Intensity Long-short Portfolio, Alpha Dynamics. The table shows the excess and abnormal return (indicated in columns) on PI-sorted long-short portfolios for holding period of one-year at different investment horizons (indicated in rows). The PI-sorted long-short portfolio consists of a long position in high-PI firms and a short position in non-patenting firms. In panel A, stocks are sorted into three portfolios (non-patenting, low-PI and high-PI), and in panel B into five portfolios (non-patenting, and the remaining patenting stocks into four portfolios by PI). Stocks are sorted into portfolios at the end of June K years prior to the beginning of the holding period in July of year t. The holding period lasts for one year from July (end of June) in year t to the end of June in year $t+1$. Each portfolio consists of the stocks assigned to the portfolio K years ago that are still active as of the beginning of the holding period, i.e., end of June in year t. Portfolios are value weighted with weights as of the beginning of the holding period. Excess return is average return of the long-short portfolio in excess of risk-free rate. CAPM alpha, FF3 alpha, and FF5 alpha indicate abnormal return relative to market model, Fama and French 1993, and Fama and French 2015, respectively. The underlying portfolio returns are at monthly frequency, but the estimates of the average excess returns and alphas are annualized. t-statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses. */**/*** indicate significance level at 10, 5, and 1%, respectively.

	Panel A. 1926-2021			Panel B. 1963-2021			
Horizon (years)	Excess return	CAPM alpha	FF3 alpha	Excess return	CAPM alpha	FF3 alpha	FF5 alpha
0	7.187***	3.914***	3.392**	6.968***	5.119***	4.99***	6.709***
	(4.423)	(2.852)	(2.505)	(3.431)	(2.605)	(2.604)	(3.543)
1	7.002***	3.88***	3.649***	7.213***	5.279**	5.849***	8.027***
	(4.362)	(2.651)	(2.648)	(3.507)	(2.535)	(3.202)	(4.604)
2	4.726***	2.056	2.201	4.736**	2.862	4.021**	6.628***
	(3.074)	(1.419)	(1.631)	(2.381)	(1.373)	(2.299)	(3.83)
3	3.169**	0.474	0.58	2.882	0.803	1.827	4.504***
	(2.05)	(0.337)	(0.436)	(1.495)	(0.402)	(1.039)	(2.874)
4	2.772*	0.156	0.221	2.7	0.736	1.638	3.822**
	(1.941)	(0.118)	(0.175)	(1.499)	(0.4)	(1.004)	(2.514)
5	3.976***	0.935	0.931	3.425*	1.321	2.369	4.067***
	(2.754)	(0.73)	(0.751)	(1.942)	(0.758)	(1.431)	(2.711)
6	5.019***	1.636	2.063	4.469**	2.218	3.406**	5.13***
	(3.356)	(1.197)	(1.584)	(2.367)	(1.204)	(1.997)	(3.149)
7	3.42**	0.484	1.309	3.483*	1.296	2.725	4.518***
	(2.381)	(0.345)	(1.004)	(1.823)	(0.674)	(1.61)	(2.79)
8	3.67**	0.731	1.847	3.324*	1.036	2.495	4.355***
	(2.45)	(0.501)	(1.373)	(1.677)	(0.522)	(1.437)	(2.681)
9	3.329**	0.726	2.137	3.823*	1.663	3.18*	5.26***
	(2.242)	(0.487)	(1.552)	(1.89)	(0.822)	(1.828)	(3.181)
10	1.8	-0.784	0.51	2.313	0.027	1.42	2.865*
	(1.24)	(-0.545)	(0.377)	(1.178)	(0.014)	(0.817)	(1.693)

Table 10: Aged Patent-Intensity Portfolios, Q-Factor Alpha Dynamics, 1963-2021. The table shows the abnormal returns (alphas) on PI-sorted portfolios for holding period of one-year at different investment horizons (indicated in rows) relative to the Q-factor model (Hou, Mo, Xue, and Zhang, 2021). Portfolio 0 consists of non-patenting firms and the remaining portfolios of patenting firms sorted by PI. HL is a zero-cost portfolio with a long position in the highest PI portfolio and a short position in portfolio 0. Stocks are sorted into portfolios at the end of June K years prior to the beginning of the holding period in July of year t. The holding period lasts for one year from July (end of June) in year t to the end of June in year $t+1$. Each portfolio consists of the stocks assigned to the portfolio K years ago that are still active as of the beginning of the holding period, i.e., end of June in year t. Portfolios are value weighted with weights as of the beginning of the holding period. The underlying portfolio returns are at monthly frequency, but the estimates of the alphas are annualized. t-statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses. The time period of the sample is given by availability of the Q-factors, i.e., 1967-2021. */**/*** indicate significance level at 10, 5, and 1%, respectively.

Horizon (years)	0	1	2	3	4	HL
0	-0.59	0.18	0.57	1.18	1.67	2.26
	(-1.06)	(0.39)	(0.76)	(0.98)	(1.05)	(1.24)
1	-0.76	0.27	0.69	0.11	3.57	4.33*
	(-1.31)	(0.54)	(0.86)	(0.1)	(1.56)	(1.65)
2	-0.65	0.01	0.22	0.05	2.9	3.56
	(-1.09)	(0.01)	(0.27)	(0.05)	(1.37)	(1.47)
3	-1.05*	-0.23	0.54	0.91	0.71	1.76
	(-1.85)	(-0.45)	(0.65)	(0.8)	(0.44)	(0.93)
4	-0.91	-0.5	0.15	1.28	-0.42	0.49
	(-1.62)	(-0.95)	(0.2)	(1.15)	(-0.27)	(0.27)
5	-0.94*	-0.3	0.22	0.76	-0.28	0.66
	(-1.68)	(-0.54)	(0.27)	(0.69)	(-0.19)	(0.38)
6	-0.95*	-0.35	0.12	0.51	0.45	1.4
	(-1.68)	(-0.62)	(0.17)	(0.46)	(0.27)	(0.71)
7	-0.65	-0.78	0.02	0.66	0.98	1.63
	(-1.17)	(-1.49)	(0.03)	(0.65)	(0.58)	(0.84)
8	-1.09**	-0.87	0.95	-0.47	0.88	1.97
	(-1.98)	(-1.4)	(1.2)	(-0.45)	(0.5)	(0.97)
9	-1.08*	-0.49	0.05	-0.01	2.08	3.16
	(-1.87)	(-0.84)	(0.07)	(-0.01)	(1.17)	(1.53)
10	-0.86	-0.96	-0.5	1.36	0.11	0.97
	(-1.41)	(-1.55)	(-0.63)	(1.16)	(0.06)	(0.46)

Table 11: Characteristics Sorts for Innovative vs. Non-innovative Firms. The table shows the average excess returns of innovative and non-innovative firms sorted on common firm characteristics as well as the results of regressing the portfolio returns on a constant and Fama-French 5 factors. Stocks are labeled as innovators and non-innovators at the end of June in each year and then sorted into five portfolios within the two groups. Innovative firms are firms that have at least three patents over the last three years and one patent over the last year at the time of portfolio formation. The table shows the returns of a long-short portfolio that goes long the highest quintile and short the lowest quintile. All portfolios are value-weighted and rebalanced annually. The five firm characteristics (beta, size, book-to-market equity ratio, investments, and profitability), shown in the first column of the table, follow the definitions from Ken French's website. The underlying portfolio returns are at monthly frequency, but constants are expressed in annualized percent. The time period of the sample is 1963-2021. */**/*** indicate significance level at 10, 5, and 1%, respectively.

		Ex. Ret.	Fama-French 2015						
		Constant	Constant	Mkt-RF	SMB	HML	CMA	RMW	R^2
Beta	Non-Inno	-1.237	-1.750	0.619***	-0.163***	0.140*	-0.762***	-0.372***	0.40
		(-0.49)	(-0.85)	(14.61)	(-2.68)	(1.72)	(-6.27)	(-4.42)	
	Inno	0.093	2.734	0.435***	-0.065	-0.233**	-0.751***	-0.645***	0.33
		(0.03)	(1.10)	(8.48)	(-0.88)	(-2.35)	(-5.10)	(-6.32)	
	Diff	1.330	4.484*	-0.183***	0.098	-0.374***	0.011	-0.273***	0.07
		(0.59)	(1.96)	(-3.87)	(1.45)	(-4.09)	(0.08)	(-2.91)	
Size	Non-Inno	-4.582*	-3.732*	0.225***	-1.148***	-0.320***	0.207*	0.257***	0.42
		(-1.82)	(-1.85)	(5.41)	(-19.25)	(-3.98)	(1.73)	(3.11)	
	Inno	-7.833***	-4.125**	-0.099**	-1.482***	-0.338***	0.070	0.421***	0.62
		(-2.67)	(-2.17)	(-2.52)	(-26.39)	(-4.47)	(0.62)	(5.41)	
	Diff	-3.251*	-0.393	-0.324***	-0.334***	-0.018	-0.137	0.164**	0.25
		(-1.73)	(-0.23)	(-9.15)	(-6.58)	(-0.27)	(-1.35)	(2.33)	
B/M	Non-Inno	3.792**	-0.217	0.004	0.184***	1.009***	0.136**	-0.202***	0.62
		(2.16)	(-0.19)	(0.19)	(5.47)	(22.23)	(2.02)	(-4.34)	
	Inno	5.965***	-0.794	0.157***	0.424***	0.976***	0.370***	-0.020	0.45
		(2.68)	(-0.46)	(4.39)	(8.27)	(14.13)	(3.60)	(-0.28)	
	Diff	2.173	-0.577	0.153***	0.240***	-0.033	0.234*	0.182**	0.05
		(1.10)	(-0.29)	(3.67)	(4.02)	(-0.40)	(1.95)	(2.21)	
Invest	Non-Inno	-4.168***	-0.786	0.007	-0.144***	-0.131***	-0.803***	0.020	0.52
		(-3.51)	(-0.91)	(0.37)	(-5.64)	(-3.81)	(-15.69)	(0.56)	
	Inno	-2.190	3.721**	-0.080**	-0.041	0.037	-1.631***	-0.002	0.48
		(-1.08)	(2.43)	(-2.54)	(-0.90)	(0.61)	(-18.02)	(-0.03)	
	Diff	1.978	4.507**	-0.087**	0.103*	0.168**	-0.827***	-0.022	0.10
		(1.03)	(2.36)	(-2.20)	(1.83)	(2.22)	(-7.33)	(-0.28)	
Profit	Non-Inno	6.048**	1.641	-0.092**	-0.335***	-0.268***	0.440***	1.572***	0.55
		(2.34)	(0.90)	(-2.47)	(-6.27)	(-3.72)	(4.11)	(21.33)	
	Inno	-3.538	-6.208***	-0.197***	-0.387***	0.243***	-0.284**	1.498***	0.47
		(-1.19)	(-2.71)	(-4.21)	(-5.74)	(2.68)	(-2.10)	(16.12)	
	Diff	-9.586***	-7.849***	-0.105*	-0.052	0.511***	-0.724***	-0.075	0.04
		(-3.40)	(-2.69)	(-1.77)	(-0.61)	-4.43	(-4.22)	(-0.63)	

Table 12: Pricing Characteristics-Sorted Portfolios in Innovative vs. Non-innovative Firms with the q5-Factor Model. The table shows the average excess returns of innovative and non-innovative firms sorted on common firm characteristics as well as the results of regressing the portfolio returns on a constant and HMXZ q5-factors. Stocks are labeled as innovators and non-innovators at the end of June in each year and then sorted into five portfolios within the two groups. Innovative firms are firms that have at least three patents over the last three years and one patent over the last year at the time of portfolio formation. The table shows the returns of a long-short portfolio that goes long the highest quintile and short the lowest quintile. The sample period is 1967-2021. More details can be found in the caption of table 11.

		Ex. Ret.	Hou, Mo, Xue, and Zhang 2021						
		Constant	Constant	MKT	ME	IA	ROE	EG	R^2
Beta	Non-Inno	-1.941	0.003	0.651***	-0.200***	-0.248**	-0.036	-0.444***	0.39
		(-0.73)	(0.00)	(14.33)	(-3.20)	(-2.41)	(-0.44)	(-3.64)	
	Inno	-0.706	1.969	0.529***	-0.151**	-0.822***	-0.410***	0.053	0.29
		(-0.23)	(0.66)	(9.51)	(-1.97)	(-6.51)	(-4.06)	(0.35)	
	Diff	1.235	1.967	-0.122**	0.049	-0.574***	-0.374***	0.496***	0.06
		(0.52)	(0.72)	(-2.41)	(0.71)	(-5.00)	(-4.07)	(3.65)	
Size	Non-Inno	-4.236	-8.669***	0.254***	-0.887***	0.138	0.753***	0.021	0.42
		(-1.61)	(-3.67)	(5.78)	(-14.69)	(1.38)	(9.42)	(0.18)	
	Inno	-7.544**	-9.464***	-0.039	-1.336***	0.027	0.788***	0.141	0.66
		(-2.46)	(-4.48)	(-0.99)	(-24.76)	(0.31)	(11.03)	(1.34)	
	Diff	-3.308*	-0.795	-0.292***	-0.450***	-0.110	0.035	0.120	0.29
		(-1.68)	(-0.41)	(-8.04)	(-9.00)	(-1.34)	(0.54)	(1.23)	
B/M	Non-Inno	4.283**	1.506	-0.024	0.174***	1.029***	-0.587***	0.173**	0.41
		(2.33)	(0.90)	(-0.78)	(4.10)	(14.64)	(-10.41)	(2.08)	
	Inno	5.290**	2.442	0.078*	0.337***	1.142***	-0.596***	0.011	0.33
		(2.28)	(1.09)	(1.87)	(5.91)	(12.12)	(-7.89)	(0.10)	
	Diff	1.006	0.936	0.102**	0.163***	0.113	-0.009	-0.162	0.05
		(0.49)	(0.40)	(2.33)	(2.72)	(1.14)	(-0.11)	(-1.38)	
Invest	Non-Inno	-4.556***	0.440	0.022	-0.194***	-0.847***	0.119***	-0.164***	0.47
		(-3.74)	(0.42)	(1.11)	(-7.27)	(-19.20)	(3.37)	(-3.14)	
	Inno	-2.679	2.524	0.005	-0.129***	-1.588***	0.033	0.192**	0.44
		(-1.30)	(1.39)	(0.14)	(-2.77)	(-20.72)	(0.54)	(2.12)	
	Diff	1.877	2.083	-0.017	0.066	-0.741***	-0.086	0.356***	0.10
		(0.96)	(0.95)	(-0.42)	(1.18)	(-8.04)	(-1.16)	(3.27)	
Profit	Non-Inno	6.225**	-1.737	-0.116***	-0.315***	0.232**	1.211***	0.099	0.47
		(2.35)	(-0.76)	(-2.74)	(-5.38)	(2.40)	(15.63)	(0.86)	
	Inno	-3.650	-7.176**	-0.213***	-0.541***	0.071	0.794***	0.134	0.31
		(-1.20)	(-2.39)	(-3.82)	(-7.06)	(0.56)	(7.82)	(0.89)	
	Diff	-9.876***	-5.439	-0.097	-0.227***	-0.161	-0.417***	0.035	0.03
		(-3.44)	(-1.63)	(-1.56)	(-2.66)	(-1.14)	(-3.70)	-0.21	

A. Appendix

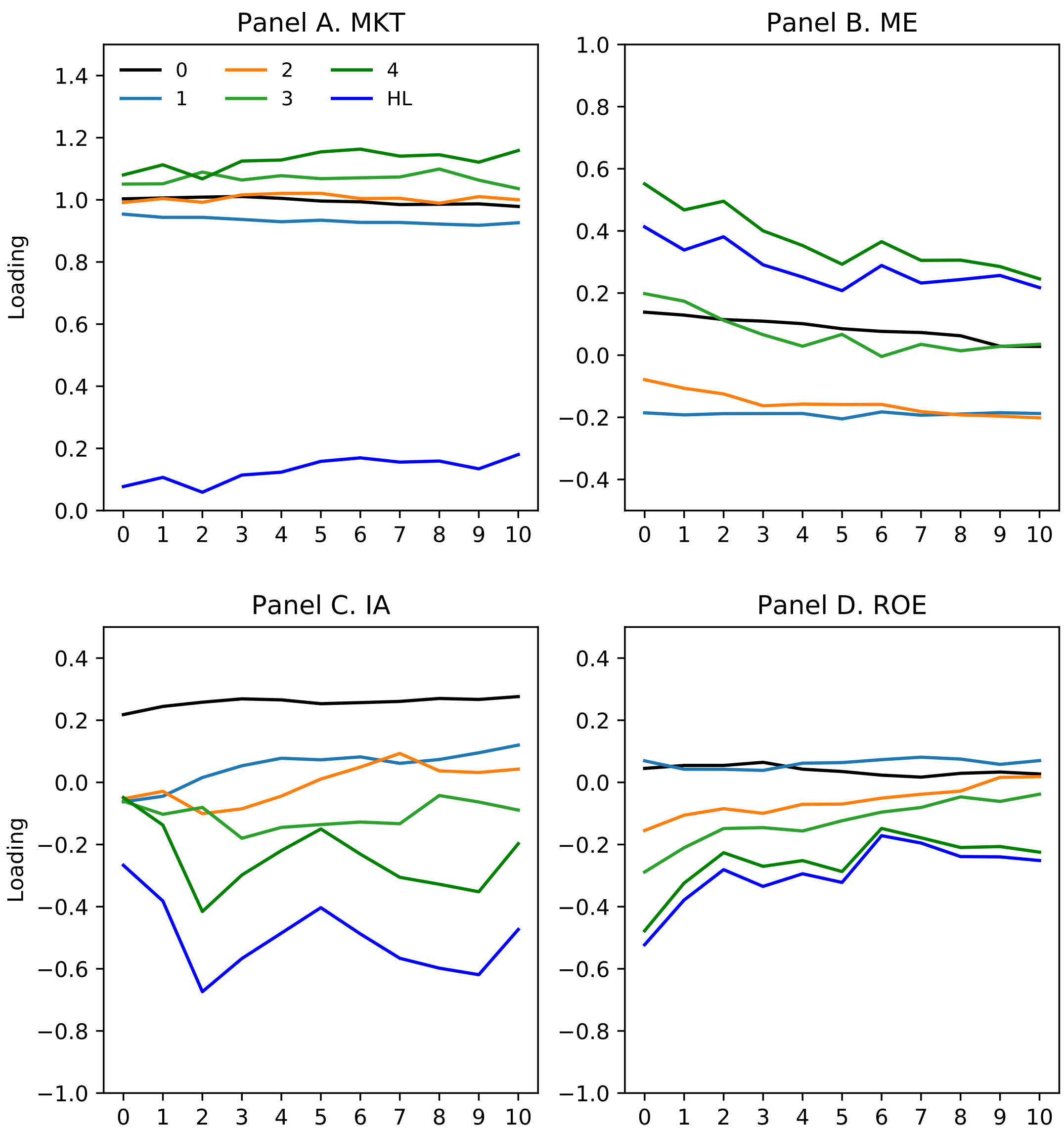

Figure A1: Aged Patent-Intensity Portfolios, Q4-Factor Loading Dynamics, 1967-2021. The figure shows the the dynamics of loadings of PI-sorted aged portfolios on the Q4 factors as indicated in headings of panels A-D. The construction of the underlying portfolios is described in detail in notes to table 8. The time period of the sample is given by availability of the Q-factors, i.e., 1967-2021.

Table A1: Asset Types. The table shows the percentage shares of different types of assets comprising the firm's total assets, i.e., PPE (property, plant and equipment, net), intangible assets, investments and advances, other assets and current assets, for portfolios sorted on patenting intensity PI. The indented rows show the percentage shares of the different types of current assets comprising the total current assets. 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. In panel A, the average shares in each year are simple averages (i.e., equal-weighted) across firms in each portfolio. In panel B, the average shares are value-weighted averages, i.e., weighted with firm's market capitalization. The reported numbers are time-series averages of the shares calculated each year from 1963 to 2020.

	0	1	2	3	4	Patenting	All
Panel A. Equal-weighted average shares							
PPE	0.30	0.32	0.27	0.25	0.22	0.26	0.29
Intangible assets	0.07	0.11	0.10	0.08	0.06	0.09	0.08
Investments and advances	0.07	0.05	0.04	0.03	0.03	0.04	0.06
Other assets	0.04	0.04	0.04	0.04	0.04	0.04	0.04
Current assets	0.51	0.48	0.56	0.60	0.65	0.57	0.53
Cash and equivalents	0.13	0.14	0.18	0.20	0.21	0.18	0.14
Receivables	0.22	0.16	0.18	0.19	0.20	0.18	0.21
Inventories	0.14	0.15	0.17	0.19	0.21	0.18	0.15
Other current assets	0.02	0.03	0.03	0.03	0.03	0.03	0.02
Panel B. Value-weighted average shares							
PPE	0.39	0.38	0.32	0.30	0.27	0.35	0.36
Intangible assets	0.08	0.10	0.10	0.09	0.09	0.10	0.09
Investments and advances	0.10	0.08	0.07	0.06	0.06	0.07	0.08
Other assets	0.05	0.05	0.05	0.06	0.06	0.05	0.05
Current assets	0.38	0.39	0.46	0.49	0.52	0.43	0.41
Cash and equivalents	0.09	0.11	0.13	0.13	0.14	0.12	0.11
Receivables	0.17	0.15	0.18	0.19	0.19	0.16	0.17
Inventories	0.10	0.10	0.13	0.15	0.16	0.12	0.11
Other current assets	0.02	0.02	0.03	0.03	0.03	0.03	0.02

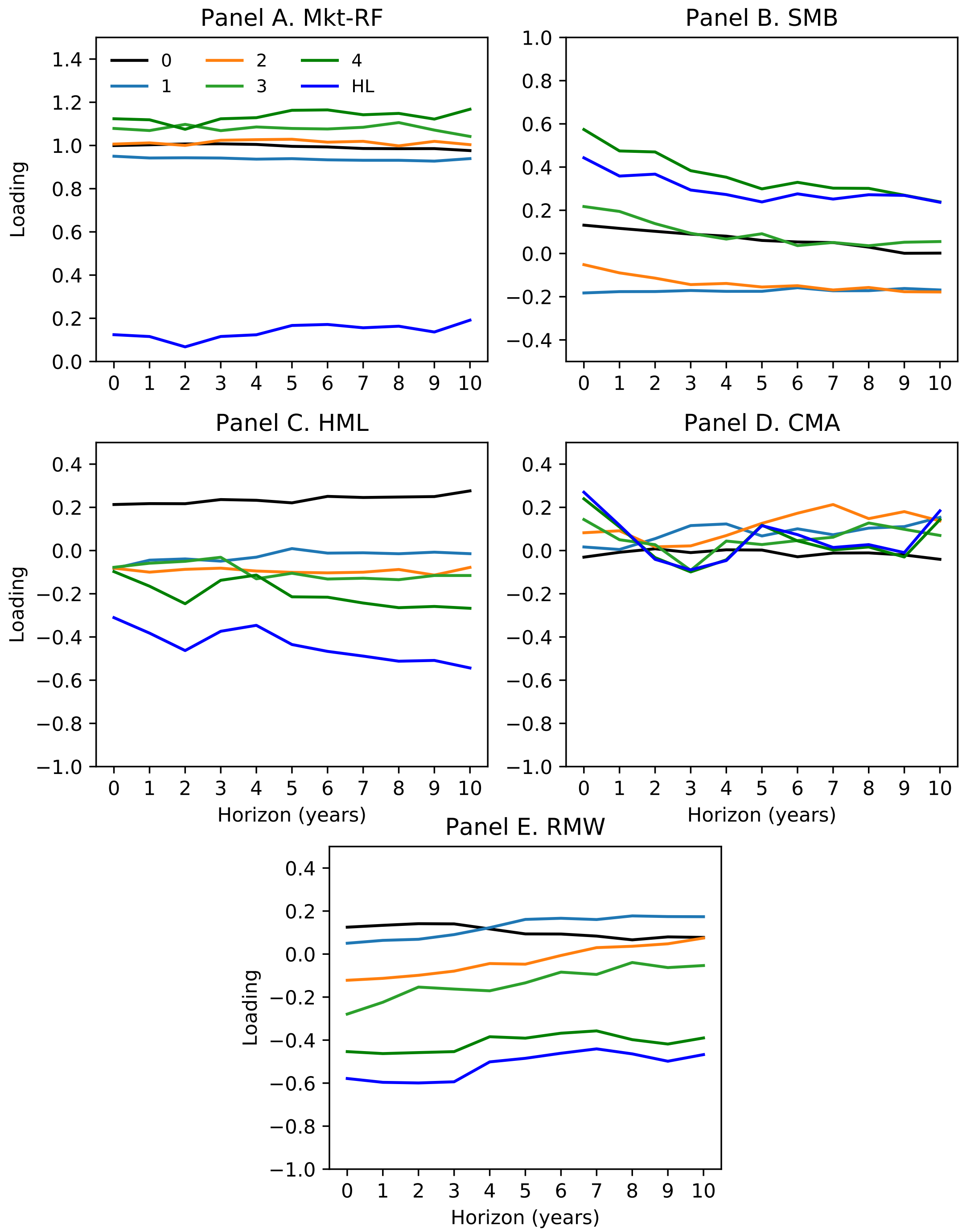

Figure A2: Aged Patent-Intensity Portfolios, FF5-Factor Loading Dynamics, 1963-2021. The figure shows the the dynamics of loadings of PI-sorted aged portfolios on the FF5 factors as indicated in headings of panels A-E. The construction of the underlying portfolios is described in detail in notes to table 8. The time period of the sample is given by availability of the FF5-factors, i.e., 1963-2021.

Table A2: Returns of PI-sorted Portfolios, 1926-1963. The table shows the average excess returns of PI-sorted portfolios in panel A and results of regressing the portfolio returns on a constant and market excess returns, and Fama-French 3 factors in panel B and C, respectively. Portfolio "0" consists of non-patenting firms and the remaining portfolios of patenting firms sorted by PI. HL is a zero-cost portfolio with a long position in the highest PI portfolio and a short position in portfolio "0". Stocks are sorted into portfolios each year at the end of June. All portfolios are value-weighted and rebalanced annually. The underlying portfolio returns are at monthly frequency, but the estimates of the average excess returns and constants are annualized. t-statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses. The time period of the sample is 1926-1963. */**/*** indicate significance level at 10, 5, and 1%, respectively.

	0	1	2	HL
Panel A. Excess returns				
Excess return	9.4**	10.69***	14.01***	4.61***
	(2.48)	(2.85)	(2.86)	(2.61)
Panel B. CAPM				
Constant	-0.64	0.75*	1.3	1.93
	(-0.97)	(1.7)	(1.14)	(1.4)
Mkt-RF	0.98***	0.97***	1.23***	0.26***
	(44.55)	(55.46)	(31.99)	(7.79)
R^2	0.96	0.98	0.95	0.36
Panel C. Fama-French 1993				
Constant	-0.85	0.9**	1.12	1.97
	(-1.34)	(2.04)	(1.01)	(1.43)
Mkt-RF	0.91***	1.01***	1.18***	0.27***
	(63.99)	(86.58)	(46.49)	(9.01)
SMB	0.08***	-0.08***	0.07*	-0.01
	(2.63)	(-3.99)	(1.68)	(-0.29)
HML	0.13***	-0.08***	0.1*	-0.03
	(4.55)	(-3.37)	(1.81)	(-0.45)
R^2	0.97	0.98	0.95	0.36

Table A3: Returns of PI-sorted (Equal-weighted) Portfolios. The table shows the average excess returns of PI-sorted, equal-weighted portfolios in panel A and results of regressing the portfolio returns on a constant and market excess returns, Fama-French 3 factors and Fama-French 5 factors in panels B, C, and D, respectively. Portfolio "0" consists of non-patenting firms and the remaining portfolios of patenting firms sorted by PI. HL is a zero-cost portfolio with a long position in the highest PI portfolio and a short position in portfolio "0". Stocks are sorted into portfolios each year at the end of June. All portfolios are equal-weighted and rebalanced annually. The underlying portfolio returns are at monthly frequency, but the estimates of the average excess returns and constants are annualized. t-statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses. The time period of the sample is indicated in headings, i.e., 1926-2021 and 1963-2021. Data for Fama-French 5 factors is available only from 1963. */**/*** indicate significance level at 10, 5, and 1%, respectively.

	1926-2021				1963-2021					
	0	1	2	HL	0	1	2	3	4	HL
Panel A. Excess returns										
Excess return	10.64***	10.14***	14.89***	4.25***	8.79***	7.85***	9.25***	11.07***	15.72***	6.92***
	(3.83)	(4.28)	(4.55)	(3.92)	(3.06)	(3.33)	(3.39)	(3.43)	(3.98)	(3.74)
Panel B. CAPM										
Constant	1.1	0.66	3.69**	2.58***	1.7	0.19	1.1	2.56	7.09***	5.38***
	(0.95)	(1.09)	(2.56)	(2.61)	(1.08)	(0.29)	(0.96)	(1.45)	(2.87)	(3.17)
Mkt-RF	1.15***	1.15***	1.35***	0.2***	1.01***	1.1***	1.17***	1.22***	1.23***	0.22***
	(24.4)	(59.19)	(29.69)	(12.01)	(30.69)	(88.15)	(44.11)	(36.46)	(26.04)	(7.28)
R^2	0.78	0.93	0.76	0.15	0.71	0.92	0.81	0.68	0.52	0.07
Panel C. Fama-French 1993										
Constant	-0.77*	0.21	2.16**	2.94***	-0.6	-0.02	0.24	1.2	5.13***	5.73***
	(-1.72)	(0.55)	(2.36)	(3.02)	(-0.98)	(-0.03)	(0.36)	(1.13)	(3.09)	(3.44)
Mkt-RF	0.92***	1.06***	1.11***	0.19***	0.88***	1.01***	1.01***	1.0***	0.95***	0.07
	(79.54)	(60.6)	(42.42)	(8.64)	(62.36)	(84.57)	(43.78)	(30.7)	(22.78)	(1.58)
SMB	0.86***	0.43***	1.1***	0.24**	0.88***	0.37***	0.75***	1.1***	1.45***	0.57***
	(39.87)	(9.41)	(11.68)	(2.28)	(23.52)	(14.99)	(16.88)	(12.26)	(10.83)	(3.71)
HML	0.41***	0.02	0.19***	-0.21***	0.32***	-0.05***	0.0	0.03	0.08	-0.24***
	(14.08)	(0.75)	(3.09)	(-3.69)	(12.37)	(-3.0)	(0.06)	(0.66)	(1.0)	(-2.8)
R^2	0.97	0.97	0.93	0.28	0.95	0.97	0.95	0.92	0.82	0.34
Panel D. Fama-French 2015										
Constant					-0.45	0.2	1.08*	2.57**	7.21***	7.66***
					(-0.74)	(0.45)	(1.94)	(2.46)	(4.2)	(4.36)
Mkt-RF					0.87***	1.02***	1.01***	0.99***	0.94***	0.07**
					(63.36)	(91.5)	(59.37)	(46.1)	(27.25)	(2.07)
SMB					0.88***	0.34***	0.69***	0.98***	1.27***	0.39***
					(29.9)	(22.3)	(26.47)	(21.83)	(18.66)	(5.45)
HML					0.16***	-0.15***	-0.15***	-0.2***	-0.25***	-0.41***
					(5.2)	(-8.25)	(-4.69)	(-3.29)	(-3.03)	(-4.66)
CMA					0.06	0.11***	0.13**	0.2**	0.33***	0.27**
					(1.49)	(3.01)	(2.22)	(2.41)	(2.69)	(2.37)
RMW					-0.03	-0.11***	-0.26***	-0.42***	-0.67***	-0.63***
					(-1.13)	(-4.42)	(-4.72)	(-4.39)	(-4.73)	(-4.02)
R^2					0.95	0.97	0.96	0.93	0.85	0.46

Table A4: Patent-Intensity Sorts and Performance, Fama-French Factors with Momentum, 1963-2021. The table shows the results of regressing the portfolio returns on a constant, Fama-French five factors and momentum factor. Portfolio "0" consists of non-patenting firms and the remaining portfolios of patenting firms sorted by PI. HL is a zero-cost portfolio with a long position in the highest PI portfolio and a short position in portfolio "0". Stocks are sorted into portfolios each year at the end of June. All portfolios are value-weighted and rebalanced annually. The underlying portfolio returns are at monthly frequency, but the estimates of the constant are annualized. t-statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses. The time period of the sample is 1963-2021. */**/*** indicate significance level at 10, 5, and 1%, respectively.

	0	1	2	3	4	HL
Constant	-1.58***	0.03	2.35***	2.85***	5.73***	7.31***
	(-3.38)	(0.06)	(3.33)	(2.71)	(3.58)	(4.15)
Mkt-RF	1.0***	0.95***	1.0***	1.06***	1.11***	0.11**
	(81.01)	(93.2)	(66.46)	(36.24)	(26.05)	(2.35)
SMB	0.13***	-0.18***	-0.05*	0.22***	0.58***	0.45***
	(5.72)	(-14.08)	(-1.66)	(3.9)	(7.4)	(4.74)
HML	0.2***	-0.08***	-0.1**	-0.13*	-0.15	-0.35***
	(6.85)	(-3.33)	(-2.29)	(-1.9)	(-1.57)	(-3.16)
CMA	-0.02	0.01	0.09	0.18**	0.27*	0.29*
	(-0.62)	(0.43)	(1.56)	(2.01)	(1.8)	(1.74)
RMW	0.13***	0.05**	-0.12***	-0.26***	-0.43***	-0.56***
	(3.38)	(2.55)	(-3.37)	(-3.14)	(-2.77)	(-3.15)
Mom	-0.02	0.01	-0.03	-0.1***	-0.09	-0.07
	(-1.33)	(0.95)	(-1.53)	(-2.84)	(-1.5)	(-1.0)
R^2	0.96	0.96	0.9	0.86	0.78	0.32

Table A5: Aged Patent-Intensity Portfolios, FF5+Momentum Alpha Dynamics, 1963-2021. The table shows the abnormal returns (alphas) relative to FF5 model with momentum (Fama and French 2015) of PI-sorted portfolios for holding period of one-year at different investment horizons (indicated in rows). Portfolio "0" consists of non-patenting firms and the remaining portfolios of patenting firms sorted by PI. HL is a zero-cost portfolio with a long position in the highest PI portfolio and a short position in portfolio "0". Stocks are sorted into portfolios at the end of June K years prior to the beginning of the holding period in July of year t. The holding period lasts for one year from July (end of June) in year t to the end of June in year $t+1$. Each portfolio consists of the stocks assigned to the portfolio K years ago that are still active as of the beginning of the holding period, i.e., end of June in year t. Portfolios are value weighted with weights as of the beginning of the holding period. The underlying portfolio returns are at monthly frequency, but the estimates of the alphas are annualized. t-statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses. The time period of the sample is given by availability of the FF5-factors, i.e., 1963-2021. */**/*** indicate significance level at 10, 5, and 1%, respectively.

Horizon (years)	0	1	2	3	4	HL
0	-1.58***	0.03	2.35***	2.85***	5.73***	7.31***
	(-3.38)	(0.06)	(3.33)	(2.71)	(3.58)	(4.15)
1	-1.61***	0.03	2.5***	1.63*	6.32***	7.93***
	(-3.48)	(0.07)	(3.64)	(1.73)	(3.67)	(4.15)
2	-1.56***	0.17	1.58**	1.38	4.67***	6.23***
	(-3.34)	(0.38)	(2.38)	(1.58)	(2.75)	(3.28)
3	-1.77***	-0.06	1.81**	1.96**	3.09**	4.86***
	(-3.87)	(-0.14)	(2.54)	(2.11)	(2.23)	(3.05)
4	-1.7***	-0.02	1.13*	2.39***	2.32*	4.02***
	(-3.71)	(-0.05)	(1.8)	(2.65)	(1.86)	(2.72)
5	-1.6***	0.27	0.77	2.25**	2.77**	4.37***
	(-3.48)	(0.56)	(1.23)	(2.46)	(2.1)	(2.93)
6	-1.47***	0.15	1.03*	1.51*	3.17**	4.64***
	(-3.37)	(0.34)	(1.76)	(1.67)	(2.18)	(2.85)
7	-1.29***	0.15	0.55	2.01**	2.98**	4.27***
	(-2.93)	(0.35)	(0.94)	(2.39)	(2.12)	(2.71)
8	-1.51***	-0.03	1.38**	0.8	3.27**	4.78***
	(-3.39)	(-0.07)	(2.24)	(0.85)	(2.35)	(3.01)
9	-1.47***	0.31	0.64	1.22	3.89***	5.36***
	(-3.17)	(0.7)	(1.1)	(1.46)	(2.84)	(3.39)
10	-1.22***	0.2	-0.15	2.33**	1.66	2.88*
	(-2.64)	(0.43)	(-0.24)	(2.52)	(1.12)	(1.7)

Table A6: Aged Patent-Intensity Portfolios, Q4 Alpha Dynamics, 1967-2021. The table shows the abnormal returns (alphas) relative to five-factor model (Fama and French 2015) of PI-sorted portfolios for holding period of one-year at different investment horizons (indicated in rows). Portfolio "0" consists of non-patenting firms and the remaining portfolios of patenting firms sorted by PI. HL is a zero-cost portfolio with a long position in the highest PI portfolio and a short position in portfolio "0". Stocks are sorted into portfolios at the end of June K years prior to the beginning of the holding period in July of year t. The holding period lasts for one year from July (end of June) in year t to the end of June in year $t+1$. Each portfolio consists of the stocks assigned to the portfolio K years ago that are still active as of the beginning of the holding period, i.e., end of June in year t. Portfolios are value weighted with weights as of the beginning of the holding period. The underlying portfolio returns are at monthly frequency, but the estimates of the alphas are annualized. t-statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses. The time period of the sample is given by availability of the Q-factors, i.e., 1967-2021. */**/*** indicate significance level at 10, 5, and 1%, respectively.

Horizon (years)	0	1	2	3	4	HL
0	-2.04***	-0.04	2.83***	3.5***	6.79***	8.82***
	(-3.27)	(-0.08)	(3.75)	(2.87)	(3.69)	(3.96)
1	-2.06***	0.05	2.78***	2.29**	6.77***	8.83***
	(-3.44)	(0.11)	(3.69)	(2.07)	(3.44)	(3.82)
2	-1.99***	0.17	1.89**	1.59*	5.26***	7.25***
	(-3.21)	(0.37)	(2.57)	(1.65)	(2.63)	(3.05)
3	-2.4***	0.14	2.17***	2.01**	2.73*	5.13***
	(-3.79)	(0.29)	(2.62)	(2.01)	(1.84)	(2.85)
4	-2.19***	0.06	1.55**	2.45**	2.18	4.37***
	(-3.76)	(0.12)	(2.19)	(2.45)	(1.56)	(2.6)
5	-2.17***	0.33	1.12	2.32**	2.5*	4.67***
	(-3.94)	(0.6)	(1.61)	(2.27)	(1.65)	(2.61)
6	-2.1***	0.52	1.11*	1.45	2.81*	4.91**
	(-3.42)	(0.99)	(1.69)	(1.43)	(1.67)	(2.41)
7	-1.77***	0.22	0.93	1.89*	2.83*	4.6**
	(-3.06)	(0.47)	(1.5)	(1.93)	(1.74)	(2.36)
8	-2.09***	0.31	1.42**	0.59	2.74*	4.83**
	(-3.78)	(0.62)	(2.2)	(0.55)	(1.7)	(2.5)
9	-2.11***	0.72	0.71	0.84	3.51**	5.62***
	(-3.51)	(1.37)	(1.14)	(0.91)	(2.04)	(2.71)
10	-1.81***	0.53	-0.21	2.03*	1.5	3.32
	(-2.95)	(1.0)	(-0.31)	(1.96)	(0.85)	(1.55)

Table A7: Characteristics-Sorted Portfolios in Innovative vs. Non-innovative Firms with Full-sample Breakpoints. The table shows the average excess returns of innovative and non-innovative firms sorted on common firm characteristics as well as the results of regressing the portfolio returns on a constant and Fama-French 5 factors. Stocks are labeled as innovators and non-innovators at the end of June in each year and independently sorted into five portfolios. Innovative firms are firms that have at least three patents over the last three years and one patent over the last year at the time of portfolio formation. The table shows the returns of a long-short portfolio that goes long the highest quintile and short the lowest quintile. More details can be found in the caption of table 11.

		Ex. Ret.	Fama-French 2015						
		Constant	Constant	Mkt-RF	SMB	HML	CMA	RMW	R^2
Beta	Non-Inno	-0.841	-1.713	0.641***	-0.039	0.118	-0.819***	-0.315***	0.43
		(-0.33)	(-0.83)	(15.04)	(-0.64)	(1.43)	(-6.69)	(-3.73)	
	Inno	-2.077	-1.069	0.576***	-0.371***	-0.099	-0.639***	-0.514***	0.33
		(-0.77)	(-0.45)	(11.74)	(-5.28)	(-1.05)	(-4.54)	(-5.28)	
	Diff	-1.236	0.644	-0.066	-0.332***	-0.217***	0.179	-0.199**	0.07
		(-0.66)	(0.33)	(-1.65)	(-5.82)	(-2.83)	(1.57)	(-2.52)	
Size	Non-Inno	-4.541*	-3.553*	0.200***	-1.131***	-0.301***	0.157	0.183**	0.41
		(-1.87)	(-1.81)	(5.02)	(-19.37)	(-3.98)	(1.35)	(2.26)	
	Inno	-5.517*	-4.409*	0.101**	-1.339***	-0.441***	0.134	0.673***	0.46
		(-1.77)	(-1.83)	(2.07)	(-18.70)	(-4.76)	(0.95)	(6.80)	
	Diff	-0.976	-0.856	-0.099***	-0.208***	-0.140**	-0.023	0.490***	0.18
		(-0.57)	(-0.52)	(-2.95)	(-4.24)	(-2.21)	(-0.23)	(7.24)	
B/M	Non-Inno	3.588*	-0.529	0.019	0.156***	1.131***	0.061	0.006	0.57
		(1.82)	(-0.39)	(0.70)	(3.89)	(21.73)	(0.76)	(0.10)	
	Inno	1.485	-3.142*	0.173***	0.298***	1.151***	0.104	-0.354***	0.44
		(0.61)	(-1.65)	(4.48)	(5.28)	(15.74)	(0.93)	(-4.53)	
	Diff	-2.104	-2.614	0.153***	0.142**	0.020	0.043	-0.359***	0.08
		(-0.94)	(-1.15)	(3.34)	(2.12)	(0.24)	(0.32)	(-3.87)	
Invest	Non-Inno	-3.607***	-1.192	0.039*	-0.138***	-0.068	-0.839***	0.158***	0.41
		(-2.69)	(-1.09)	(1.77)	(-4.25)	(-1.62)	(-13.11)	(3.53)	
	Inno	-2.378	2.944**	-0.038	-0.190***	-0.001	-1.433***	-0.070	0.47
		(-1.32)	(2.12)	(-1.36)	(-4.60)	(-0.03)	(-17.56)	(-1.23)	
	Diff	1.229	4.136**	-0.077**	-0.052	0.066	-0.594***	-0.228***	0.06
		(0.68)	(2.23)	(-2.06)	(-0.95)	(0.93)	(-5.45)	(-3.00)	
Profit	Non-Inno	5.653**	1.847	-0.113***	-0.203***	-0.112	0.226*	1.541***	0.46
		(2.17)	(0.92)	(-2.78)	(-3.42)	(-1.46)	(1.92)	(18.75)	
	Inno	-2.202	-3.421*	-0.145***	-0.691***	0.184**	-0.344***	1.478***	0.58
		(-0.76)	(-1.75)	(-3.69)	(-11.97)	(2.47)	(-3.01)	(18.52)	
	Diff	-7.854***	-5.268*	-0.033	-0.487***	0.297***	-0.570***	-0.063	0.07
		(-2.76)	(-1.83)	(-0.56)	(-5.75)	(2.70)	(-3.39)	(-0.54)	

Table A8: Characteristics-Sorted Portfolios in Innovative vs. Non-innovative Firms with the q5-Factor Model and Full-sample Breakpoints. The table shows the average excess returns of innovative and non-innovative firms sorted on common firm characteristics as well as the results of regressing the portfolio returns on a constant and q5-factors. Stocks are labeled as innovators and non-innovators at the end of June in each year and independently sorted into five portfolios. Innovative firms are firms that have at least three patents over the last three years and one patent over the last year at the time of portfolio formation. The table shows the returns of a long-short portfolio that goes long the highest quintile and short the lowest quintile. More details can be found in the caption of table 11.

		Ex. Ret.	q5						
		Constant	Constant	MKT	ME	IA	ROE	EG	R^2
Beta	Non-Inno	-1.493	0.922	0.665***	-0.121*	-0.353***	-0.012	-0.498***	0.43
		(-0.55)	-0.38	-14.71	(-1.96)	(-3.45)	(-0.15)	(-4.11)	
	Inno	-2.902	-1.092	0.643***	-0.416***	-0.454***	-0.237**	-0.132	0.31
		(-1.00)	(-0.38)	-12.1	(-5.72)	(-3.77)	(-2.46)	(-0.93)	
	Diff	-1.409	-2.014	-0.022	-0.295***	-0.101	-0.225***	0.367***	0.08
		(-0.71)	(-0.89)	(-0.52)	(-5.13)	(-1.06)	(-2.96)	-3.26	
Size	Non-Inno	-4.421*	-7.848***	0.238***	-0.875***	0.103	0.677***	0.009	0.41
		(-1.73)	(-3.40)	-5.55	(-14.73)	-1.07	-8.69	-0.08	
	Inno	-5.799*	-10.452***	0.177***	-1.181***	0.048	1.050***	0.071	0.51
		(-1.75)	(-3.84)	-3.51	(-16.90)	-0.42	-11.45	-0.53	
	Diff	-1.377	-2.604	-0.061*	-0.306***	-0.055	0.372***	0.063	0.19
		(-0.75)	(-1.35)	(-1.69)	(-6.15)	(-0.68)	-5.71	-0.66	
B/M	Non-Inno	3.920*	0.927	-0.009	0.121**	1.172***	-0.504***	0.104	0.34
		(1.89)	-0.47	(-0.25)	-2.38	-14.26	(-7.58)	-1.07	
	Inno	1.684	-0.223	0.124***	0.268***	1.136***	-0.842***	0.073	0.35
		(0.66)	(-0.09)	-2.74	-4.29	-11.19	(-10.24)	-0.61	
	Diff	-2.236	-1.15	0.133***	0.148**	-0.036	-0.337***	-0.031	0.08
		(-0.95)	(-0.43)	-2.7	-2.16	(-0.33)	(-3.76)	(-0.24)	
Invest	Non-Inno	-4.045***	-0.35	0.059**	-0.211***	-0.769***	0.266***	-0.201***	0.38
		(-2.93)	(-0.27)	-2.49	(-6.44)	(-14.46)	-6.19	(-3.21)	
	Inno	-2.875	0.831	0.045	-0.198***	-1.391***	0.097*	0.169**	0.43
		(-1.51)	-0.49	-1.43	(-4.56)	(-19.74)	-1.71	-2.04	
	Diff	1.170	1.181	-0.014	0.013	-0.623***	-0.169**	0.371***	0.08
		(0.62)	-0.55	(-0.35)	-0.24	(-6.98)	(-2.34)	-3.52	
Profit	Non-Inno	5.432**	-1.228	-0.095**	-0.256***	0.261**	1.081***	0.056	0.37
		(2.04)	(-0.49)	(-2.05)	(-4.00)	-2.51	-12.88	-0.46	
	Inno	-1.735	-3.424	-0.125**	-0.829***	0.219**	0.950***	-0.144	0.43
		(-0.58)	(-1.28)	(-2.53)	(-12.09)	-1.97	-10.56	(-1.10)	
	Diff	-7.168**	-2.196	-0.031	-0.574***	-0.042	-0.131	-0.2	0.07
		(-2.47)	(-0.67)	(-0.50)	(-6.77)	(-0.30)	(-1.17)	(-1.23)	

Table A9: Characteristics-Sorted Portfolios in Innovative vs. Non-innovative Firms with the q4-Factor Model and Full-sample Breakpoints. The table shows the average excess returns of innovative and non-innovative firms sorted on common firm characteristics as well as the results of regressing the portfolio returns on a constant and q4-factors. Stocks are labeled as innovators and non-innovators at the end of June in each year and independently sorted into five portfolios. Innovative firms are firms that have at least three patents over the last three years and one patent over the last year at the time of portfolio formation. The table shows the returns of a long-short portfolio that goes long the highest quintile and short the lowest quintile. More details can be found in the caption of table 11.

		Ex. Ret.	q4					
		Constant	Constant	MKT	ME	IA	ROE	R^2
Beta	Non-Inno	-1.941	-3.038	0.718***	-0.075	-0.454***	-0.163**	0.41
		(-0.73)	(-1.35)	(16.39)	(-1.22)	(-4.52)	(-2.19)	
	Inno	-0.706	-2.139	0.657***	-0.404***	-0.480***	-0.277***	0.31
		(-0.23)	(-0.82)	(12.92)	(-5.64)	(-4.12)	(-3.21)	
	Diff	1.235	0.899	-0.061	-0.329***	-0.027	-0.114*	0.06
		-0.52	(0.43)	(-1.51)	(-5.77)	(-0.29)	(-1.66)	
Size	Non-Inno	-4.236	-7.777***	0.237***	-0.876***	0.104	0.680***	0.41
		(-1.61)	(-3.67)	(5.82)	(-15.01)	(1.11)	(9.89)	
	Inno	-7.544**	-9.875***	0.169***	-1.188***	0.061	1.073***	0.51
		(-2.46)	(-3.96)	(3.52)	(-17.29)	(0.55)	(13.26)	
	Diff	-3.308*	-2.098	-0.068**	-0.312***	-0.043	0.393***	0.19
		(-1.68)	(-1.18)	(-2.00)	(-6.38)	(-0.55)	(6.82)	
B/M	Non-Inno	4.283**	1.768	-0.021	0.111**	1.192***	-0.471***	0.34
		-2.33	(0.98)	(-0.61)	(2.22)	(14.86)	(-8.02)	
	Inno	5.290**	0.365	0.115***	0.261***	1.150***	-0.818***	0.35
		-2.28	(0.16)	(2.69)	(4.25)	(11.62)	(-11.29)	
	Diff	1.006	-1.403	0.137***	0.151**	-0.042	-0.347***	0.08
		-0.49	(-0.58)	(2.92)	(2.24)	(-0.39)	(-4.39)	
Invest	Non-Inno	-4.556***	-1.975*	0.083***	-0.192***	-0.806***	0.202***	0.37
		(-3.74)	(-1.68)	(3.65)	(-5.92)	(-15.44)	(5.27)	
	Inno	-2.679	2.200	0.025	-0.214***	-1.360***	0.152***	0.43
		(-1.30)	(1.41)	(0.84)	(-5.00)	(-19.73)	(3.01)	
	Diff	1.877	4.175**	-0.058	-0.022	-0.554***	-0.049	0.06
		-0.96	(2.11)	(-1.51)	(-0.41)	(-6.30)	(-0.77)	
Profit	Non-Inno	6.225**	-0.774	-0.101**	-0.261***	0.271***	1.099***	0.37
		-2.35	(-0.34)	(-2.31)	(-4.15)	(2.68)	(14.85)	
	Inno	-3.65	-4.586*	-0.108**	-0.816***	0.192*	0.904***	0.43
		(-1.20)	(-1.87)	(-2.31)	(-12.09)	(1.77)	(11.38)	
	Diff	-9.876***	-3.812	-0.007	-0.555***	-0.079	-0.195**	0.07
		(-3.44)	(-1.26)	(-0.12)	(-6.65)	(-0.59)	(-1.99)	

Table A10: Aged Patent-Intensity Portfolios, Q-Factor Loadings Dynamics, 1967-2021. The table shows the loadings on the q factors (indicated in panel headings) of PI-sorted portfolios for holding period of one-year at different investment horizons (indicated in rows). The last row shows the difference in loadings between horizon 10 and 0. The construction of the underlying portfolios is described in detail in notes to table 8. t-statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses. The time period of the sample is given by availability of the q factors, i.e., 1967-2021. */**/*** indicate significance level at 10, 5, and 1%, respectively.

	Panel A. MKT					
Horizon (years)	0	1	2	3	4	HL
0	0.98***	0.95***	1.02***	1.08***	1.15***	0.17***
	(55.85)	(86.26)	(60.46)	(29.18)	(23.18)	(2.85)
1	0.99***	0.94***	1.03***	1.08***	1.16***	0.17***
	(55.89)	(79.07)	(59.05)	(36.91)	(31.16)	(3.78)
2	0.99***	0.95***	1.02***	1.11***	1.1***	0.11**
	(57.22)	(69.85)	(52.34)	(47.16)	(23.82)	(1.97)
3	0.99***	0.94***	1.04***	1.08***	1.15***	0.16***
	(57.88)	(73.03)	(51.96)	(47.28)	(28.67)	(3.24)
4	0.99***	0.94***	1.04***	1.09***	1.17***	0.18***
	(61.68)	(83.78)	(65.76)	(44.25)	(30.03)	(3.69)
5	0.98***	0.94***	1.03***	1.09***	1.19***	0.22***
	(59.66)	(75.58)	(60.55)	(45.74)	(26.81)	(4.01)
6	0.98***	0.94***	1.02***	1.08***	1.2***	0.22***
	(54.97)	(77.33)	(66.78)	(47.67)	(28.35)	(4.24)
7	0.97***	0.94***	1.02***	1.09***	1.17***	0.2***
	(61.09)	(91.42)	(63.97)	(53.25)	(27.45)	(3.78)
8	0.97***	0.94***	1.0***	1.11***	1.17***	0.2***
	(59.86)	(91.77)	(62.31)	(52.43)	(26.28)	(3.65)
9	0.97***	0.94***	1.02***	1.08***	1.14***	0.17***
	(57.63)	(88.71)	(64.0)	(44.41)	(22.36)	(2.81)
10	0.96***	0.95***	1.0***	1.05***	1.18***	0.21***
	(53.19)	(79.31)	(51.9)	(39.24)	(21.49)	(3.21)
10-0	-0.02**	0.0	-0.02	-0.04	0.02	0.04
	(-2.26)	(-0.25)	(-0.89)	(-1.13)	(0.57)	(0.95)

Table A10-continued.

Horizon (years)	Panel B. ME					
	0	1	2	3	4	HL
0	0.12**	-0.19***	-0.05	0.23***	0.61***	0.49***
	(2.36)	(-12.25)	(-1.44)	(2.99)	(5.12)	(2.98)
1	0.11**	-0.19***	-0.08**	0.2***	0.51***	0.39***
	(2.28)	(-14.31)	(-2.15)	(3.65)	(6.25)	(3.25)
2	0.1*	-0.19***	-0.1***	0.13***	0.52***	0.42***
	(1.95)	(-12.25)	(-3.58)	(3.01)	(4.41)	(2.62)
3	0.09*	-0.18***	-0.14***	0.08**	0.42***	0.33**
	(1.88)	(-13.09)	(-6.42)	(2.0)	(4.76)	(2.55)
4	0.09*	-0.18***	-0.14***	0.04	0.38***	0.3***
	(1.9)	(-11.5)	(-6.36)	(1.03)	(5.21)	(2.79)
5	0.07*	-0.2***	-0.15***	0.09**	0.33***	0.26**
	(1.68)	(-8.21)	(-5.57)	(2.04)	(3.76)	(2.11)
6	0.06	-0.17***	-0.15***	0.01	0.39***	0.33**
	(1.29)	(-8.4)	(-6.55)	(0.18)	(4.17)	(2.44)
7	0.06	-0.18***	-0.17***	0.05	0.33***	0.27*
	(1.36)	(-9.79)	(-6.84)	(1.29)	(3.1)	(1.88)
8	0.05	-0.18***	-0.19***	0.03	0.33***	0.28**
	(1.26)	(-8.51)	(-7.64)	(0.66)	(3.28)	(2.09)
9	0.02	-0.17***	-0.19***	0.04	0.3***	0.29**
	(0.37)	(-7.88)	(-7.26)	(0.87)	(2.95)	(2.05)
10	0.02	-0.17***	-0.2***	0.04	0.26**	0.25
	(0.36)	(-7.98)	(-8.31)	(0.94)	(2.33)	(1.61)
10-0	-0.1***	0.02	-0.15***	-0.18***	-0.35***	-0.25***
	(-8.05)	(0.64)	(-3.56)	(-2.93)	(-5.15)	(-3.35)

Table A10-continued.

Horizon (years)	Panel C. IA					
	0	1	2	3	4	HL
0	0.25***	-0.06**	-0.11***	-0.12*	-0.17	-0.42***
	(5.13)	(-2.15)	(-2.59)	(-1.7)	(-1.39)	(-2.8)
1	0.28***	-0.04	-0.08	-0.15**	-0.21	-0.49***
	(5.39)	(-1.5)	(-1.57)	(-2.23)	(-1.43)	(-2.6)
2	0.29***	0.01	-0.14**	-0.12*	-0.47***	-0.76***
	(5.74)	(0.47)	(-2.27)	(-1.84)	(-3.3)	(-4.21)
3	0.3***	0.04*	-0.12**	-0.21***	-0.35***	-0.65***
	(5.71)	(1.82)	(-2.09)	(-2.94)	(-3.93)	(-5.48)
4	0.3***	0.06**	-0.08*	-0.17***	-0.28***	-0.58***
	(6.15)	(2.41)	(-1.71)	(-3.21)	(-3.44)	(-5.4)
5	0.28***	0.06	-0.01	-0.17***	-0.22**	-0.5***
	(7.03)	(1.58)	(-0.23)	(-3.13)	(-2.32)	(-4.54)
6	0.28***	0.06	0.03	-0.15**	-0.29***	-0.57***
	(6.36)	(1.57)	(0.57)	(-2.31)	(-3.04)	(-4.68)
7	0.29***	0.04	0.07*	-0.16***	-0.35***	-0.64***
	(6.29)	(1.13)	(1.88)	(-3.05)	(-3.77)	(-5.25)
8	0.29***	0.05	0.03	-0.07	-0.37***	-0.67***
	(7.34)	(1.31)	(0.58)	(-1.14)	(-3.99)	(-5.71)
9	0.29***	0.07**	0.02	-0.08	-0.39***	-0.68***
	(6.97)	(1.99)	(0.43)	(-1.56)	(-4.03)	(-5.79)
10	0.3***	0.08***	0.04	-0.1	-0.23**	-0.53***
	(6.28)	(2.82)	(0.88)	(-1.58)	(-2.05)	(-4.07)
10-0	0.05**	0.14***	0.14**	0.01	-0.06	-0.11
	(2.11)	(3.8)	(2.42)	(0.16)	(-0.49)	(-0.8)

Table A10-continued.

Horizon (years)	Panel D. ROE					
	0	1	2	3	4	HL
0	0.1***	0.08***	-0.25***	-0.38***	-0.69***	-0.79***
	(2.7)	(3.31)	(-5.57)	(-5.35)	(-6.84)	(-6.37)
1	0.11***	0.05**	-0.19***	-0.3***	-0.45***	-0.56***
	(2.73)	(2.04)	(-4.98)	(-5.87)	(-4.59)	(-4.57)
2	0.11***	0.04	-0.15***	-0.21***	-0.32***	-0.43***
	(2.71)	(1.4)	(-3.51)	(-4.56)	(-2.95)	(-3.24)
3	0.12***	0.02	-0.17***	-0.19***	-0.35***	-0.47***
	(2.96)	(0.95)	(-3.07)	(-3.31)	(-4.66)	(-5.15)
4	0.09**	0.04*	-0.13***	-0.2***	-0.36***	-0.45***
	(2.41)	(1.67)	(-2.75)	(-3.88)	(-4.12)	(-4.36)
5	0.09**	0.04	-0.11**	-0.19***	-0.4***	-0.49***
	(2.24)	(1.34)	(-2.53)	(-3.69)	(-3.99)	(-4.05)
6	0.07	0.04	-0.09**	-0.13***	-0.24***	-0.31***
	(1.64)	(1.25)	(-2.4)	(-2.67)	(-3.03)	(-2.96)
7	0.06	0.04	-0.08**	-0.13***	-0.25***	-0.32***
	(1.48)	(1.58)	(-2.3)	(-2.68)	(-3.06)	(-2.89)
8	0.07*	0.03	-0.05	-0.09*	-0.29***	-0.36***
	(1.86)	(1.04)	(-1.29)	(-1.76)	(-2.82)	(-2.85)
9	0.08*	0.01	-0.01	-0.1**	-0.26***	-0.34***
	(1.92)	(0.31)	(-0.27)	(-1.98)	(-2.7)	(-2.86)
10	0.07	0.01	0.01	-0.07	-0.28**	-0.35**
	(1.59)	(0.38)	(0.18)	(-1.23)	(-2.44)	(-2.57)
10-0	-0.04**	-0.07**	0.25***	0.32***	0.4***	0.44***
	(-2.36)	(-2.24)	(4.91)	(4.4)	(4.92)	(5.09)

Table A10-continued.

	Panel E. EG					
Horizon (years)	0	1	2	3	4	HL
0	-0.18***	-0.03	0.28***	0.29***	0.64***	0.82***
	(-4.88)	(-0.9)	(5.54)	(3.8)	(5.92)	(6.52)
1	-0.16***	-0.03	0.26***	0.27***	0.4***	0.56***
	(-4.2)	(-0.82)	(4.92)	(3.71)	(3.06)	(3.63)
2	-0.17***	0.02	0.21***	0.19***	0.29***	0.46***
	(-4.29)	(0.6)	(4.08)	(2.87)	(2.59)	(3.3)
3	-0.17***	0.05	0.2***	0.14**	0.25**	0.42***
	(-4.19)	(1.39)	(3.74)	(2.04)	(2.18)	(3.0)
4	-0.16***	0.07*	0.17***	0.15**	0.32***	0.48***
	(-3.95)	(1.85)	(3.28)	(2.35)	(2.85)	(3.49)
5	-0.15***	0.08*	0.11**	0.19***	0.35***	0.5***
	(-4.11)	(1.76)	(2.2)	(3.18)	(3.25)	(3.81)
6	-0.14***	0.11***	0.12***	0.12**	0.29***	0.44***
	(-3.65)	(2.65)	(2.63)	(2.02)	(2.66)	(3.22)
7	-0.14***	0.12***	0.11***	0.15***	0.23*	0.37***
	(-3.68)	(3.41)	(2.91)	(2.64)	(1.95)	(2.6)
8	-0.13***	0.15***	0.06	0.13**	0.23*	0.36**
	(-3.35)	(3.28)	(1.46)	(2.3)	(1.85)	(2.39)
9	-0.13***	0.15***	0.08**	0.11*	0.18	0.31**
	(-3.21)	(3.72)	(2.03)	(1.81)	(1.44)	(2.09)
10	-0.12***	0.19***	0.04	0.08	0.17	0.29**
	(-2.84)	(4.56)	(0.8)	(1.35)	(1.57)	(2.18)
10-0	0.06***	0.21***	-0.25***	-0.21***	-0.46***	-0.53***
	(2.9)	(5.37)	(-4.01)	(-2.84)	(-3.74)	(-4.07)