Pricing Technological Innovators: Patent Intensity and Life-Cycle Dynamics

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ABSTRACT

Technological innovators are priced differently from other firms, earning higher stock returns controlling for standard factors, with less punishment for aggressive capital investment and weak profitability. We create the new variable patent intensity (PI), patents received divided by market capitalization, available from 1926. On average, high-PI firms comprise ten percent of aggregate market capitalization but over half of five-year-forward public-company patenting. Aged portfolios and standard factors show significant alphas a decade post-formation. Adding an expected growth factor, alphas disappear and loadings display life-cycle dynamics: high, declining growth; aggressive, increasing investment; and weak, improving profitability.

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

JEL Classification: G12, E20.

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Abstract

Technological innovators are priced differently from other firms, earning higher stock returns controlling for standard factors, with less punishment for aggressive capital investment and weak profitability. We create the new variable patent intensity (PI), patents received divided by market capitalization, available from 1926. On average, high-PI firms comprise ten percent of aggregate market capitalization but over half of five-year-forward public-company patenting. Aged portfolios and standard factors show significant alphas a decade post-formation. Adding an expected growth factor, alphas disappear and loadings display life-cycle dynamics: high, declining growth; aggressive, increasing investment; and weak, improving profitability.

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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] As famously hypothesized by Nelson (1959) and Arrow (1962), private required returns to innovation may be inefficiently high after accounting for large societal benefits. Importantly, Arrow also pointed to sizeable absolute risks, stating "*By the very definition of information, invention must be a risky process...*" (p. 616). Subsequent research documents specific channels that might cause high costs of capital for innovators, including extremely uncertain outcomes (Scherer, 1998), embedded real options that leverage risk (Berk, Green, and Naik, 2004), and financing frictions such as information asymmetry (Hall, 2002, Hall and Lerner, 2010).

Do innovators in fact have higher returns than non-innovators, and do standard asset pricing models capture these differences? Our study answers these questions. Of particular note, 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).[2] 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 returns and risk of innovative firms, emphasizing dynamics and sources of mispricing. 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

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

[2]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).

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 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, 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). Our study thus provides a coherent empirical framework that connects technological innovation, expected growth, and expected returns as they evolve through the life-cycle of innovative firms. We 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 investment dollar. High-PI portfolios give the cheapest way to purchase equity interest in the recently produced public-market patent stock and its stream of future rents. Given persistent firm-level patenting, high-PI portfolios also approximate the cheapest way to purchase public equity claims to future patent grants.

We relate patent intensity 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.[3] In contrast, firms without valuable existing assets should invest proportionally more in riskier directions, such as new product markets, 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 are older, larger, with valuable and profitable assets in place, and lower-risk innovation. By contrast, we hypothesize that high-PI firms are younger, smaller, with less valuable and profitable assets in place, and riskier innovation. Frictions in innovation financing (Hall and Lerner, 2010) also yield predictions for the returns of low- and high-intensity innovators. Low-PI firms are likely to have valuable and profitable assets-in-place, enabling internal cash-flow funding. High-PI firms lack such internal funding, increasing financing frictions. Patent intensity therefore captures key elements of theories of innovation heterogeneity and financing frictions.

Patent-intensity sorted portfolios produce a significant spread in returns of approximately seven percent annually. A positive and statistically significant return spread remains for ten years following portfolio formation, consistent with high costs of capital for innovators. 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 innovators 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.[4] This factor could address technologi-

[3] 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. Bustamente and Zucchi (2022) study explorative versus exploitative innovation in a model of industry equilibrium.

[4] See their equation 1.

cally innovative firms and their life-cycle dynamics. We find that the HMXZ expected growth factor eliminates abnormal returns of patent-intensity sorted portfolios, not only immediately after formation, but at nearly all horizons up to ten years. Our study therefore 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.[5] The importance of their factor should spur further research on modeling expected growth and its relation to cost-of-capital.

Risk dynamics 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 somewhat aggressive, and become much more so within two to three years following formation. Investment loadings remain more aggressive than non-innovators for a full decade. Finally, innovators show weak profitability loadings immediately after formation, but these strengthen substantially over the following decade. Thus, risk dynamics reveal a technological-innovator life cycle of sequential growth, investment, and profitability.

The explosion in variety of empirical asset pricing models has generated the critique of "too many" models (Cochrane, 2011). An important branch of research uses statistical techniques to select and combine predictors (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 and 4), and the connection of their factors to economically intuitive firm fundamentals explains their enduring popularity. We add to this tradition by showing that technolog-

[5] 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.

ical innovators are mispriced by static versions of the HXZ and FF models for a decade following portfolio formation, but that accounting for dynamics with the HMXZ expected growth factor resolves mispricing. Further, factor loadings capture economically important aspects of innovator life-cycle dynamics.

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 stock-price impacts in short windows following patent-grant 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,[6] 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 high costs of capital for innovators, in both raw returns and relative to standard benchmarks. We further show that account-

[6]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). Innovation and innovation capacity also relate most generally to intangible capital (Crouzet, Eberly, Eisfeldt, and Papanikolaou, 2022).

ing for expected growth is necessary to accurately estimate expected returns. Finally, 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 over shorter samples 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 interpreation of missing R&D data. Patent counts do not have missing data, and we categorize every firm with no patents as a "non-innovator". 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, with the primary difference being a larger loading on expected growth for patent intensity. 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 trend. Innovators are therefore critical to our understanding of asset pricing, and their valuations ultimately affect economy-wide capital allocation and growth.

2. Technological Innovators and Patent Intensity

This section first shows strong connections between publicly listed firms and total patenting activity in the United States from 1926. We define our main variable, patent intensity (PI), and characterize differences between more and less patent-intensive firms.

The patent data we use in our study, and procedures for merging with CRSP and Compustat data, are standard. The United States Patent & Trademark Office (USPTO) provides complete patent data, with downloadable text starting in 1976.[7] For patents filed between 1926-1975, Kelly, Papanikolaou, Seru, and Taddy (2021) provide cleaned and tabulated data from USPTO image files.[8] Combining these two sources covers all U.S. patents issued from 1926-2021. We link patents to public companies using CRSP permno-patent links from Kogan, Papanikolaou, Seru, and Stoffman (2017).[9]

2.1. Public company innovators

Patenting by publicly traded companies allows investors to easily purchase equity claims on technological progress. Observable prices reflect the market's valuation of innovation. Our paper further argues that technological innovation plays a key role in asset pricing, specifically for firm returns and risk. We therefore first show that public companies are important to total patenting activity. Second, and conversely, technologically innovative firms comprise a substantial portion of the public company universe throughout our sample.

Figure 1, Panel A, shows annual patent counts beginning in 1926 for i) the entire patent sample, ii) the subsample of patents in which the assignee matches at the time of granting a CRSP firm that trades on the NYSE, AMEX, or Nasdaq exchanges, and iii) a smaller subsample restricted to US-based CRSP assignees (shrcd is 10 or 11). Panel B shows for the two subsamples their annual shares of all patents awarded. For most

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

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

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

of the past century, US-based CRSP assignees comprise from twenty to forty percent of U.S. patenting.[10] Thus, the public companies commonly used in empirical asset pricing studies are important to technological progress.

Conversely, technologically innovative firms are important to the standard CRSP sample of US-based firms traded on the three major exchanges. Each year on June 30 we classify firms as "innovators" or "non-innovators" based on whether they received a patent in the prior 12-month period.[11] Patent-based classification of technological innovators is natural since patents are standardized and tangible legal claims with uniform and immediate reporting by the USPTO. Figure 1, Panels C-F show the importance of technological innovators to the CRSP universe of publicly traded firms over the past century. The innovator share by firm count (Panels C-D) ranges from twenty to fifty percent with sharp fluctuations. The innovators share by market capitalization (Panels E-F) ranges from fifty to seventy-five percent, and appears slow-moving and mean-reverting. Our main results use value-weighted portfolios, so the large and stable market-capitalization weighted shares of innovators are most relevant.

The sectoral composition of innovative and non-innovative firms changes over time. Figure 2, Panels A and B respectively decompose the value-weighted portfolios of innovative and non-innovative firms into ten Fama-French industries. In the innovator portfolio, the allocations to manufacturing and consumer durables decrease over time, while business equipment and healthcare increase. Technological innovation therefore concentrates in different sectors of the economy throughout the sample, as expected.

[10]Toward the end of the sample, the difference between all CRSP assignees and U.S.-based CRSP assignees is due to growing importance of cross-listed foreign firms that receive U.S. patents.

[11]The USPTO publishes its Official Gazette every Tuesday with information on patents granted that day, so patent information is immediately observable. See `https://www.uspto.gov/learning-and-resources/official-gazette`. Links from patent assignees to CRSP firms are reliable, but linking assignees to pre-IPO firms is more challenging. We therefore drop firms from our analysis that have less than a twelve-month CRSP history. Throughout the paper, we use a twelve-month lookback period for patent counts to prevent mechanical persistance from overlapping windows. Our results are however robust to alternatives such as two- or three-year windows for patent counts.

2.2. Patent intensity

On June 30 of every year, for each CRSP firm we define patent intensity (PI) as the ratio of patents received in the prior twelve months divided by current CRSP market capitalization. Using a one-year window for patents prevents mechanical persistence, and our results are robust to using longer windows. (See Section 5.) Scaling by market capitalization reflects the logic of theories of investment heterogeneity where firms innovate differently depending whether or not they have valuable assets in place (Klepper, 1996, Akcigit and Kerr, 2018). Purchasing equity in high-PI firms gives, per dollar invested, concentrated exposure to recent patenting activity. Scaling by market capitalization also mirrors prior measures such as the book-to-market ratio, which can be thought of as a measure of asset intensity.

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

It would be a tremendous mistake to conclude that the high-PI group is inconsequential because of its small market capitalization. The high-PI group owns on average 62.5% of the universe of patents created by public firms in the prior year, and has legal claim to the technological progress and stream of rents thereby created. Moreover, their patenting activity is persistent. The high-PI group contributes 60% of patents granted to the sample in the following year, 58% in the next three years, and 56.5% in the next five years. With a relatively small allocation of equity capital (11.3% of total market capitalization), one can purchase concentrated equity interest in the majority of not only recent but also future public-market patenting activity.

Characteristics of the three groups are also shown in Table 1. These include age and B/M (Panel A, available from 1926) and profitability and investment (Panel B, available from 1963). Non-innovators are younger on average and by median than innovators. This seems to contradict 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 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 consider PI to be a measure of "technological-innovation value", or the most cost-efficient way to purchase patenting activity. We return later to further comparisons of PI with B/M. Considering investment and profitability, low-intensity innovators have the highest investment rates in physical assets, and the highest profitability. High-intensity innovators on average have the lowest investment in physical assets and the lowest profitability.

Panel B also shows differences in composition of total assets across the three groups. High-intensity innovators have less physical capital (PPE = 23.4% vs approximiately 30% for non-innovators and low-intensity innovators), but considerably more current assets and cash. Thus, high-intensity innovators have less assets-in-place, but their high levels of working capital and cash can help to fund risky innovation and exercise of growth opportunities. Low-intensity innovators have the highest level of intangibles, consistent with prior acquisitions that have created goodwill.

We conclude that patent intensity captures important differences across firms. The non-innovator archetype is a modestly sized, shorter-lived value firm with moderate investment and profitability. Low patent-intensity firms are large and long-lived, with significant investments in physical assets, high profitability, and high M/B ratios. High-intensity innovators are young and small, appear as "value" by the B/M measure, invest less in physical assets and have low profitability, but produce the lion's share of technological innovation among listed public firms. Because of these important differences, we anticipate the pricing of PI-portfolios to be a meaningful challenge for traditional asset-pricing factors such as size, value, investment, and profitability.

2.3. The life-cycle of innovative firms

One measurable aspect of life-cycle is transition, across patent intensity groups and exiting from the sample. Table 2, Panel A, shows average transition and exit probabilities across the three PI-groups, at horizons of one, three, and five years. For comparison, Panel B shows similar probabilities for the B/M ratio, with break points set on a year-by-year basis identical to the percentiles of the PI-sorts. The break points in Panel B are calculated conditional on not having a negative or missing book value. Missing or negative book values are not trivial, 12% of the sample on average, a general difficulty for accounting-based characteristics that does not apply to patent intensity.

One key finding from Table 2 is that non-innovators exit at a much higher rate than innovators. At all horizons, non-innovators exit at about twice the rate of low-intensity innnovators, and 30-50% more frequently than high-intensity innovators. The exit rates of non-innovators are large even in comparison with the value firms in Panel B (6.1 vs. 2.7%, 16.1 vs. 11.9%, and 24.1 vs. 19.6% at one, three, and five years), despite the strong link between value and distress (e.g. Garlappi and Yan, 2011). The high delisting rate of non-innovators helps to explain their low average age shown previously. Many delistings are negative events, which affects stock performance (Shumway, 1997).

Table 2 also shows that PI sorts are highly persistent. At every horizon, high-intensity innovators have a greater probability of remaining within their category than do growth firms, low-intensity innovators have higher staying probabilities than neutral firms, and non-innovators have higher staying probabilities than value firms. Patent intensity is a fundamental and persistent characteristic, even in comparison with the B/M ratio (or alternatively q).

Another way to document innovator life cycle is to track changes in portfolio characteristics following formation. Figure 3 shows the evolution of PI-sorted portfolio characteristics for ten years post-formation, value weighting the characteristics in each year. The panels also show a neutral benchmark that combines all firms into one group. The characteristics of the aged portfolios are driven by survivorship as in the selection model of Jovanovic (1982), and also by changes in the survivors. The neutral benchmark reflects changes expected from earlier investigations of broad cross-sections of firms.[12] In particular, as the neutral benchmark ages, 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 PI-sorted portfolios show important differences. In Panels A and B, for two different measures investment becomes more aggressive in the high-PI portfolios as they age. In Panels C and D, for two standard measures profitability improves more rapidly for high-PI than other firms. Panel E shows that sales growth behaves much like investment, increasing following formation. Finally, In Panel F market betas show remarkably persistent differences, consistent with the idea that PI captures fundamental and long-lasting differences between firms. These results reflect only univariate portfolio characteristics, but suggest important and durable differences in PI-sorted portfolios that could be important for asset pricing.

3. Patent Intensity and Stock Returns

We show that innovators have higher returns than non-innovators, both in raw returns and after controlling for standard risk factors. Further, expected growth is crucial to capture the average returns of innovative firms.

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

3.1. Portfolio performance

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

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 smaller numbers of firms, so we sort innovators into 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 of increasing PI. Portfolio HL is a zero-cost portfolio, short the non-patenting portfolio "0" and long the highest PI portfolio. Table 3 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 3, Panel A, the annualized average excess returns (monthly returns multiplied by twelve) increase monotonically across portfolios in the full sample from 7.76% for the non-patenting portfolio 0 to 11.91% for the high-PI stocks. The sample starting in 1963 confirms the increasing average excess returns. The HL portfolio earns economically and statistically significant returns of about 4.2% over the full sample and 7.1% over the post-1963 sample. CAPM regressions (Panel B) show market betas slightly increasing with PI, but not sufficiently to explain returns. The CAPM HL alphas decrease relative to raw returns (by 2.4% and 5.3% in full-sample and post-1963), but remain significantly positive. Controlling for FF3 factors (Panel C) does not substantially change inference about portfolio performance. Among innovators, higher PI is associated with larger size loadings and somewhat more value than growth.

The HML factor is commonly described as value *versus* growth, but in the remainder of this paper we make the case that high patent intensity portfolios capture key aspects of value *and* growth. The construction of patent intensity already suggests a tension in the traditional value versus growth dichotomy: The patent count numerator appears to be a natural driver of growth while market capitalization in the denominator suggests value. Consistent with these countervailing effects, the HML loadings across PI-sorted portfolios are modest.[13] The HML factor cannot explain the returns of technological innovators.

The FF5 model (Panel D), which adds investment and profitability factors, does not resolve technological-innovator mispricing. If anything, the difficulties deepen. The profitability loadings align negatively with PI, opposite the direction needed to explain PI-sorted returns since the profitability factor earns a positive premium. Investment loadings increase with PI, but the magnitudes are modest and not statistically significant. The net effect is a stronger alpha sort than the CAPM or three-factor models, with a highly significant HL alpha of 6.9%.[14]

Two additional observations from Table 3 merit attention. First, the empirical finance literature commonly finds that the short sides of long-short anomaly portfolios earn the majority of long-short alphas, consistent with the hypothesis of Miller (1977) on the importance of short-sale constraints.[15] In other words, overvaluation is generally thought to be more of a problem in financial markets than undervaluation, due to the key role of short-sales constraints in limits to arbitrage. In contrast, the long side of the patent intensity anomaly delivers well over half of the abnormal returns in both sample periods and under all benchmarks. This finding is consistent with the long-standing idea that innovation is risky and hard to value (Hall, 1993, Hall and Hall, 1993). Our second observation is that the short side of the anomaly still matters, and this portfolio is based on a remarkably simple and robust characteristic. Portfolio 0

[13] Fama and French (2015) discuss that B/M is most useful in a low-dimensional model, where it summarizes different sources of variation. In a higher-dimensional model with explicit investment and profitability factors B/M becomes redundant. See also Hou, Xue, and Zhang (2015).

[14] The Internet Appendix shows that including a momentum factor as in Fama and French (2018) has little effect on our results since momentum loadings on the PI-sorted portfolios are small.

[15] See for example Stambaugh, Yu, and Yuan (2012)

consists of the single indicator variable that a firm has not received a patent in the last year. Though the magnitude of the alpha is economically modest, -1.67% per year for the five-factor model, it is nonetheless highly statistically significant. Benchmarking to standard pricing models, non-innovators earn negative abnormal returns and high-PI firms earn large positive abnormal returns.

3.2. The roles of investment and profitability

We show that variations in investment and profitability do not earn the same premia for innovative firms as for non-innovative firms. Our approach is to sort *within* the groups of all innovators ($PI > 0$ and three or more patents in last three years) and all non-innovators (all other firms) on the profitability and investment characteristics. We create long-short portfolios 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.[16]

Table 4 shows results. For the investment anomaly (Panel A), the return spread for non-innovators has the familiar negative sign and is statistically significant. The return spread for innovators is also negative, but lower magnitude and not statistically significant. The difference in spreads cannot be statistically distinguishedfrom zero. Controlling for FF5 factors, the alpha difference becomes significantly positive, at 4.7% p.a. ($t = 2.55$) driven by a negative loading on investment. Specifically, innovators have a wider spread in investment loadings than non-innovators, but earn a lower return spread, resulting in the positive alpha difference. Profitability sorts (Panel B) display equally interesting differences. Non-innovators show the familiar positive return spread, 4.33% p.a. ($t = 1.91$). To the contrary, among non-innovators the return spread is *negative* (-2.5% p.a.) but not significant. The return spread difference is consequently

[16] The Internet Appendix shows similar comparisons for market beta, size, and B/M characteristics.

large, -6.83% p.a. ($t = -3.07$). Controlling for the FF5 factors, the HL portfolio for non-innovators shows no abnormal performance. In contrast, for innovators the HL alpha is -5.03% p.a. ($t = -2.81$), reflecting that the portfolio strongly covaries with the profitability factor (HL loading equals 1.62, $t = 11.49$) even though profitability does not earn a return spread among innovators.

These findings help to explain the mispricing of innovators under the FF5 model. In the aggregate data, the return spreads earned for investment and profitability are driven more by non-innovators than non-innovators. Innovators have strong variation in these characteristics, but the return spreads are weaker or even opposite to the overall population.

3.3. Pricing with q-factors

Motivated by the first-order conditions of an optimizing firm, Hou, Xue, and Zhang (2015) develop their $q4$ model with market, size, investment, and profitability factors.[17] Their $q4$ model and Fama and French (2015) are sometimes viewed as competitors, but for our purposes the similarities are more relevant. Fama and French (2015) also have market, size, investment, and profitability factors, and acknowledge that their value factor is largely redundant after accounting for the other four.[18] While the $q4$ and FF5 models may differ in specific cases, the economic motivation and content of the models are similar.

More distinctly, the $q5$ model of Hou, Mo, Xue, and Zhang (2021) adds an expected growth factor, which is new to the literature. This factor captures the idea that a firm's current growth may not be a sufficient summary statistic for its future expected growth

[17]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)).

[18]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.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 on all three characteristics.

(see HMXZ equation 1).[19] Technological innovation may naturally predict an increase in growth due to the creation of growth options, either by creating new products or reducing costs. Empirical evidence for innovation raising growth is provided by Kogan, Papanikolaou, Seru, and Stoffman (2017), and we should therefore expect technological innovators to load on the HMXZ expected growth factor.

Table 5, Panel A, shows performance of the PI-sorted portfolios using $q4$ factors. The alphas are similar to or stronger than for FF5, increasing monotonically from -1.94% in portfolio zero to 6.79% in portfolio 4, or 8.73% for the HL portfolio ($t = 3.83$).[20] The $q4$ loadings are also similar to FF5. For example, investment and particularly profitability loadings decrease with PI. Thus, $q4$ presents a very similar picture to FF5, with strong, positive abnormal performance for technological innovators.

Adding the expected growth factor (EG) of the $q5$ model in Panel B, the picture changes. All alphas become statistically insignificant, and the source of the change is the expected growth factor. Non-patenting firms have a negative loading on EG (-0.16), and coefficient estimates increase with patent intensity, reaching 0.59 for the highest PI firms. The expected growth loading of the HL portfolio is 0.75 ($t = 5.66$), implying $q5$-benchmark returns that dramatically increase with PI, exactly as is needed to explain the portfolio returns. While the remaining $q5$ alphas still increase with PI, and the HL alpha is 2.62% p.a., all are statistically indistinguishable from zero. Thus, expected growth is the key to accurately pricing technological innovators.

3.4. Build-up or resolution?

We have previously argued that technological innovators possess important aspects of both growth *and* value, explaining why the traditional B/M ratio, or value versus growth, does not help to explain technological innovator returns. The most colloquial meaning of "value" is undervaluation relative to some benchmark. Prior literature notes

[19]One can also see that expected growth matters in the accounting identity of Fama and French (2015), allowing for variation in future quantities (see their equation 3).

[20]In untabulated results, we confirm that the larger alphas relative to FF5 are not driven by the slightly later start of 1967 that we use in this table to accommodate $q5$-factors.

that earning an alpha relative to a benchmark cannot establish relative valuation, since high returns can either "build-up" or "resolve" valuation discrepancies. Binsbergen, Boons, Opp, and Tamoni (2021) propose a methodology to distinguish between these two cases. We apply their methodology, and find that technological innovators are undervalued relative to the CAPM benchmark, nearly as strongly as traditional "value" firms. This finding, combined with our prior results, supports that technological innovators reflect important aspects of both growth and value.

The methodology of Binsbergen, Boons, Opp, and Tamoni (2021) assumes 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 market portfolio in year fifteen. This creates an empirical pricing kernel that can be used to value other portfolios. Starting in 1963, we estimate the fair market value of anomaly portfolios, including PI-portfolios, using their dividend discount model and CAPM-SDF. For 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 portfolio price and the fair market value imputed 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. We track the same group of stocks throughout the 15 years and keep the endpoint constant, which forces the price wedge to equal zero in year 15. We carry out this methodology for PI as well as size, value, investment, and profitability portfolios.

Figure 4 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: The market itself is "misvalued" in the years after portfolio formation as it ages.[21] The long-short portfolios in the top left corner should not be as strongly affected by this benchmark issue, since it affects both

[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 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 are "resolution," or reduction of existing mispricing. The top right panel of Figure 4 shows separate price wedges for the long and short sides of each traditional anomaly. To avoid the benchmark issue shown by the market portfolio, we display price-wedge differences, subtracting from each anomaly price wedge the market-portfolio price wedge. We observe potentially important differences in the direction of mispricing and speed of resolution: for example, small stocks have a small undervaluation wedge that dissipates quickly.

Price wedge dynamics for patent intensity portfolios are shown in the bottom two panels of Figure 4. The HL portfolio appears in the left-hand panel and the long and short sides separately (relative to the market) are on the right-hand side. According to the benchmark model, the long-short portfolio is initially undervalued by a little less than twenty percent, all deriving from undervaluation of patent-intensive firms. These results help to interpret the CAPM alphas previously reported in Table 3, Panel A. These showed no CAPM mispricing for non-innovators, consistent with the negligible price wedge for the short side of the patent-intensity long-short portfolio. On the other hand, Table 3, Panel A, showed large positive CAPM alphas for high-PI firms. The bottom right-hand panel of Figure 4 reveals that these abnormal returns should be interpreted as undervaluation that takes several years to resolve. The price-wedge results thus match early discussion of undervaluation of technological innovation by investors, perhaps because of short-sightedness or misunderstanding the value of innovation (Hall, 1993, Hall and Hall, 1993). Quantitatively, the near 20% undervaluation of the high-PI portfolio is nearly as large as the long side of the traditional "value" portfolio, and also larger than the undervaluation of any of the other traditional anomaly portfolios. The results therefore support that patent-intensity portfolios are not only growth portfolios as shown in the prior section, but also possess the defining characteristic of "value", undervaluation.

The price wedge dynamics in Figure 4 also show considerable persistence of technological-innovator undervaluation. Section 4 further investigates the persistence of innovator mispricing using aged portfolios.

4. Life-Cycle Dynamics

We show risk and alpha dynamics of patent-intensity sorted portfolios for a decade following the initial sort date. To form 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 $K = 0, 1, ..., 9$. 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 K-aged portfolio returns are identical to the returns one would receive if forming the portfolios at year $t - K$, rebalancing at the end of each month to current value weights based on the stocks remaining from the original portfolio sort. In other words, we study portfolios of firms that were classified K years ago by PI.[22] The analysis reveals the evolution of risk and performance of the initially sorted portfolios over time.

Table 6 shows raw returns of the aged portfolios and alpha dynamics for the CAPM, FF3, and FF5 models for the full sample (Panel A) and subsample beginning in 1963 (Panel B). The results are striking. In both samples, the raw return differences of the HL portfolio begin at about 7% annually, and slowly decline over the following decade. In the full sample the HL return difference remains statistically significant at the 5% level for the full decade, and exceeds 3% annually every year but one. Under CAPM and FF3 risk adjustment, positive abnormal returns remain statistically significant for two to three years after portfolio formation.

The addition of the investment and profitability factors in the FF5 portfolios (Panel B) not only makes abnormal performance larger, but also more persistent. For the long-short portfolio, the FF5 alpha remains significant at the 5% level for a full decade following portfolio formation, exceeding 4% in every year but one. Non-patenters have

[22] Baba Yara, Boons, and Tamoni (2023) study differences between aged and newly sorted portfolios for a range of anomalies.

significantly negative FF5 alphas in all years. As discussed by Binsbergen and Opp (2019), persistence in abnormal performance, or significant inaccuracy in costs of capital over long time periods, can imply highly inefficient real investment. The FF5 model produces inaccurate benchmarks for PI-sorted portfolio returns for a decade following formation.[23]

Table 7 shows that the expected growth factor of the $q5$ model resolves these difficulties for nearly all portfolios and horizons. Panel A shows alphas, which are nearly all statistically indistinguishable from zero. Panels B-F show the dynamics of factor loadings and provide statistical tests for changes. The factor loading dynamics are also depicted in Figure 5.

Table 7 and Figure 5 reveal a compelling economic story of innovative-firm dynamics. First, consider expected growth itself (Panel F of Table 7). The initial spread is strong and monotonic, with the high-PI loading equal to 0.59, the non-innovator loading -0.16, and the net HL loading equal to 0.75. We typically anticipate loadings with a strong initial sort to mean-revert. The expected growth loadings do so, but with a twist. The four innovator expected-growth loadings cluster in a range from 0.07 to 0.17 by the end of the decade, all significantly different from their initially highly dispersed values. In contrast, the non-innovator loading stays negative and statistically significant throughout the decade, and its change over the full decade is indistinguishable from zero. As a consequence, even after ten years the HL expected growth loading is 0.3, significant at the 5% level. Innovator and non-innovator expected growth loadings revert very slowly to apparently different means, and non-innovator expected growth is persistently low.

The loadings on investment (Table 7, Panel D) also persistently distinguish innovators from non-innovators. The non-innovator loading begins at 0.23 ($t = 4.45$), and is the only positive estimate (conservative) in year one following formation. The non-innovator loading slowly increases over the decade, becoming more conservative. The

[23] The Internet Appendix shows that the FF6 model, which adds momentum, produces similar, if anything stronger, mispricing of the aged portfolios.

high-intensity innovators move in the other direction. Their initial loading of -0.14 is statistically indistinguishable from zero, but rapidly becomes more negative (aggressive) before flattening out. By year ten, the high-PI portfolio shows an investment loading of -0.38 (aggressive, $t = -4.33$). Thus, the initially strong difference in investment loadings in year one (HL equals -0.36, $t = -2.3$), becomes even more pronounced by year ten (HL equals -0.67, $t = -5.94$).[24] Investment loading dynamics contradict the anticipated convergence of portfolio risk in the decade following portfolio formation. Rather than converge, the initially more aggressive investment loadings of high-PI firms relative to non-innovators in year one following formation become even more pronounced by the end of the decade.

The final piece of the economic story is profitability. Once again the initial sort on loadings is strong and monotonic, with non-innovators loading slightly positively on profitability (0.09, $t = 2.33$) and high-intensity innovators loading negatively (-0.66, $t = -6.82$). Over time mean-reversion occurs, but slowly, and in the 10th year high-intensity innovators still load negatively (-0.27, $t = -2.8$). Over the ten-year period, non-innovator profitability changes insignificantly (year ten minus year one loading difference equals -0.02, $t = -1.05$). Meanwhile, the most intense innovators move strongly towards robust profitability (year ten minus year one loading diference equals 0.41, $t = 4.82$).

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.[25]

[24] Figure 5 Panel F further shows that this divergence of investment loadings is predictable, as shown by the strong overlap between expected growth loadings and two-year-forward investment loadings.

[25] The dynamics of size loadings are also consistent with the effects of innovation. Naturally, we expect *ex ante* that size loadings should decrease over time as firms age and survivors become larger. Most of the portfolios show gradually decreasing size loadings, but the most innovation-intensive portfolio shows the most rapid decline, consistent with these firms growing fastest.

5. Alternative Measures of Technological Innovation

We compare patent intensity (PI) with three additional measures of technological innovation. First, PI3 is defined similarly to PI, but the numerator is the average number of patents per year over the prior three years. Second, KPSS is the measure of Kogan, Papanikolaou, Seru, and Stoffman (2017), scaled by market capitalization for comparability with PI. The KPSS measure captures the dollar value of patents embedded in short-window announcement effects around the patent-grant announcement.

Our third measure of innovative activity is R&D intensity (RDI), the ratio of research and developlment expenditures to market capitalization. Conceptually, R&D expenditures are an input to technological innovation, while patents are an output. The success of research and development is uncertain, but prior literature (e.g., Bound, Cummins, Griliches, Hall, and Jaffe, 1982) shows that R&D expenses predict patenting. 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 1976 (fiscal year 1975 for the R&D data). Chan, Lakonishok, and Sougiannis (2001) first show a positive relationship between R&D expenses and returns, and also scale R&D by market capitalization. Although R&D data is available prior to fiscal-year 1975, in 1974 the FASB issued SFAS No. 2, which standardized and required accounting for R&D costs, for fiscal years beginning in 1975 or later.[26] Hou, Mo, Xue, and Zhang (2021) confirm a positive relationship between RDI and abnormal returns with standard factors in a sample extended to 2016.

Relative to prior literature, we make an important change 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, sorting into quintiles and deciles respectively. Stocks with missing or zero R&D are excluded.[27] We treat stocks

[26]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).

[27]See Chan, Lakonishok, and Sougiannis (2001) Table VI, p. 2449, and Hou, Xue, and Zhang (2020) Appendix A.5.4, p. 2104. See also Cohen, Diether, and Malloy (2013).

with missing R&D in Compustat as having no R&D. Following our sorting methodology for patents, R&D portfolio zero comprises all stocks with zero or missing R&D ("non-innovators"), and we sort the remaining firms ("innovators") into four equal bins by firm count.

Our approach to missing or zero R&D data is different but informative. First, as Peters and Taylor (2017) explain, SFAS No. 2 gives 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 sensible. 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 6. Including these firms therefore broadens our analysis.

Table 8 compares the PI measure with the three alternatives. Panel A shows correlations, Panel B shows full sample results, Panel C begins in 1963 to accommodate profitability and investment factors, and Panel D begins in 1976 when the RDI measure becomes available.

The correlations of the three measures are all positive, with the strongest correlations between PI and PI3 (0.95 in full sample), fairly strong correlation between PI and RDI (0.74 beginning in 1976), and moderate correlation between PI and KPSS (0.42 in full sample). Intuitively, PI and PI3 capture the same idea and their difference amounts to a robustness check. PI and RDI are closely related, and reflect different stages in the innovation process. The KPSS measure and PI reflect heterogeneity in innovation (e.g., Klepper, 1996, Akcigit and Kerr, 2018) in different ways. KPSS captures the dollar value of immediate announcement effects, and will be larger for firms whose innovations can be more easily and immediately valued by the market.

We see these similarities and differences reflected in Panels B-D of Table 8. The returns, alphas, and loadings of the PI and PI3 portfolios are similar throughout the table, and the comparison in Panel C ("Differences", PI-PI3) shows no statistical distinction between the two long-short portfolios.

The differences between PI and KPSS are more meaningful. Throughout the table, the long-short return spreads and alphas are larger for PI than for KPSS. For example, in Panel C the HL return spread for PI is 7.1% annually and highly statistically significant, whereas the HL return spread for KPSS is less than 1% and statistically indistinguishable from zero. The FF5 alphas of the long-short portfolios are closer (6.9% vs. 3.2%), but still differ by 3.7% annually, significant at the 5% level. These differences in returns and alphas are intutitive, since the original purpose of the KPSS measure is to capture short-run valuation changes. The PI measure in contrast is largest for firms without valuable assets in place, with innovations that are riskier and harder to value according to theories of innovation heterogeneity. Remarkably, $q5$ risk adjustment in Panel D reconciles the differences between PI and KPSS. The comparison in the second to last row shows that the alphas are statistically indistinguishable under the $q5$ model, with the realignment attributable to large and statistically significant differences in four of the five factor loadings. Relative to KPSS, the PI portfolio loads more negatively on profitability, and more positively on market beta, size, and expected growth. These differences are consistent with the idea that PI captures innovation by small, risky, unprofitable firms without valuable assets in place, but with high expected growth.

Due to the shorter availability of R&D data, we can only compare PI and RDI in Panel D. The return spreads, alphas, and loadings are broadly comparable. The final row in the panel shows that the main statistical difference is that PI has a larger expected growth loading (0.93 for PI, $t = 6.8$ vs. 0.52 for RDI, $t = 4.2$, difference is 0.42, $t = 3.7$). This difference is economically sensible, since patenting occurs at a later stage in the innovation process than R&D, presumably when expected growth is more immediate. The other similarities between PI and RDI results suggest that missing and zero R&D firms, often discarded in prior studies, can reasonably be allocated to portfolio 0 as in our study. An important benefit of patent intensity relative to RDI is the length of the sample, which begins in 1926 rather than 1976, an extra fifty years of data. Patent intensity is a useful new measure of technological innovation.

6. Conclusion

Over the past century, approximately a quarter of publicly listed US 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, and risky, technological innovation plays no explicit role in leading factor models of expected returns. Our paper proposes a simple patent-based measure that shows the importance of technological innovation for average returns and risk.

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. Further, a portfolio of firms with high patenting intensity earns significant abnormal returns for a full decade after portfolio formation, according to standard factor 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 improve their profitability. The expected growth factor of HMXZ 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.

Appendix: Variable Definitions

We use the following variable definitions:

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

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

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

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

PPE: property, plant and equipment.

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

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

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

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

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

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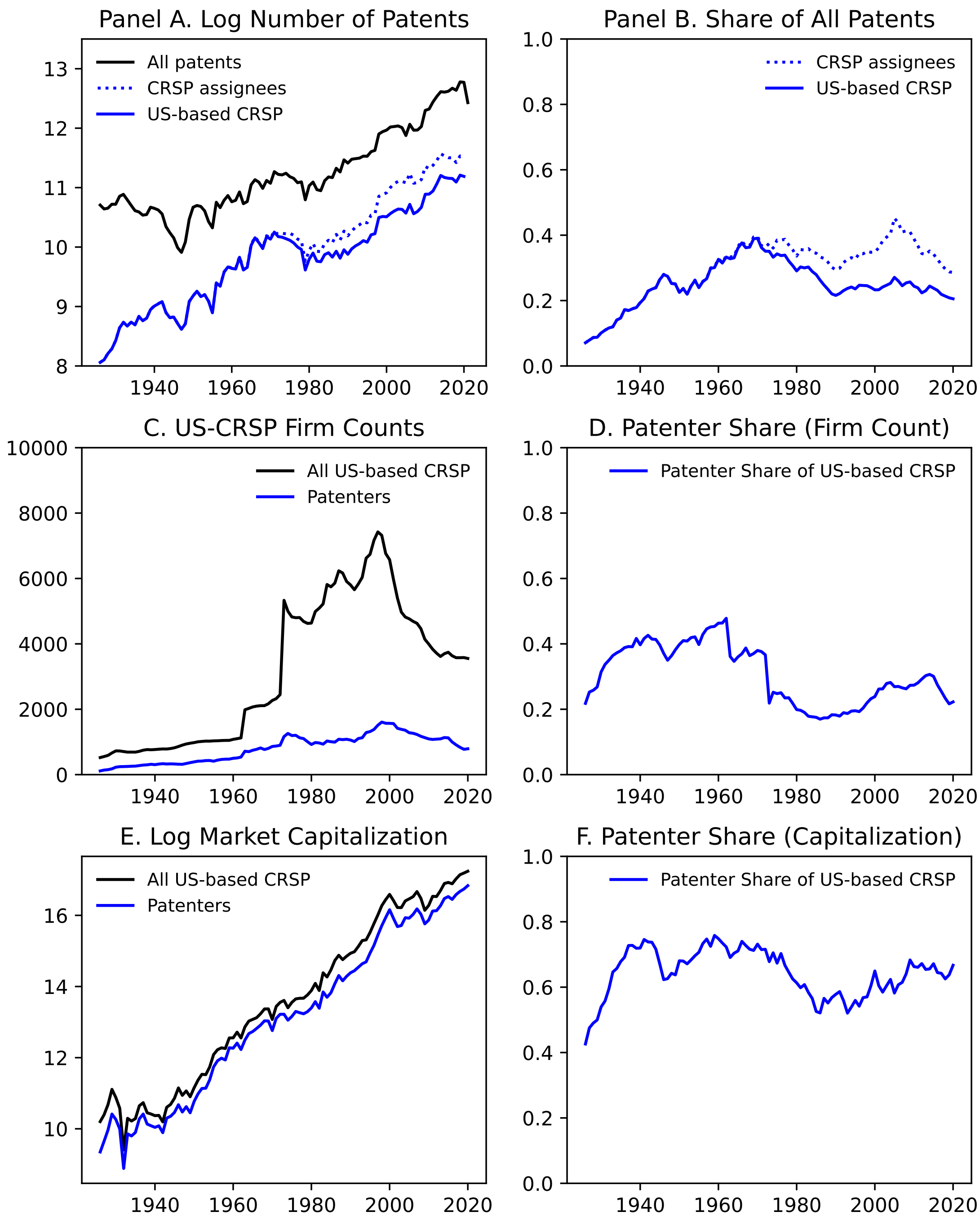

Figure 1: Patenting and Public Firms. Panel A shows the log number of patents per calendar year of patent assignees (all, CRSP, and US-based CRSP). CRSP assignee is any CRSP firm assigned a patent in current year, and US-based CRSP assignees are US-incorporated firms with common stock (shrcd 10 or 11).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

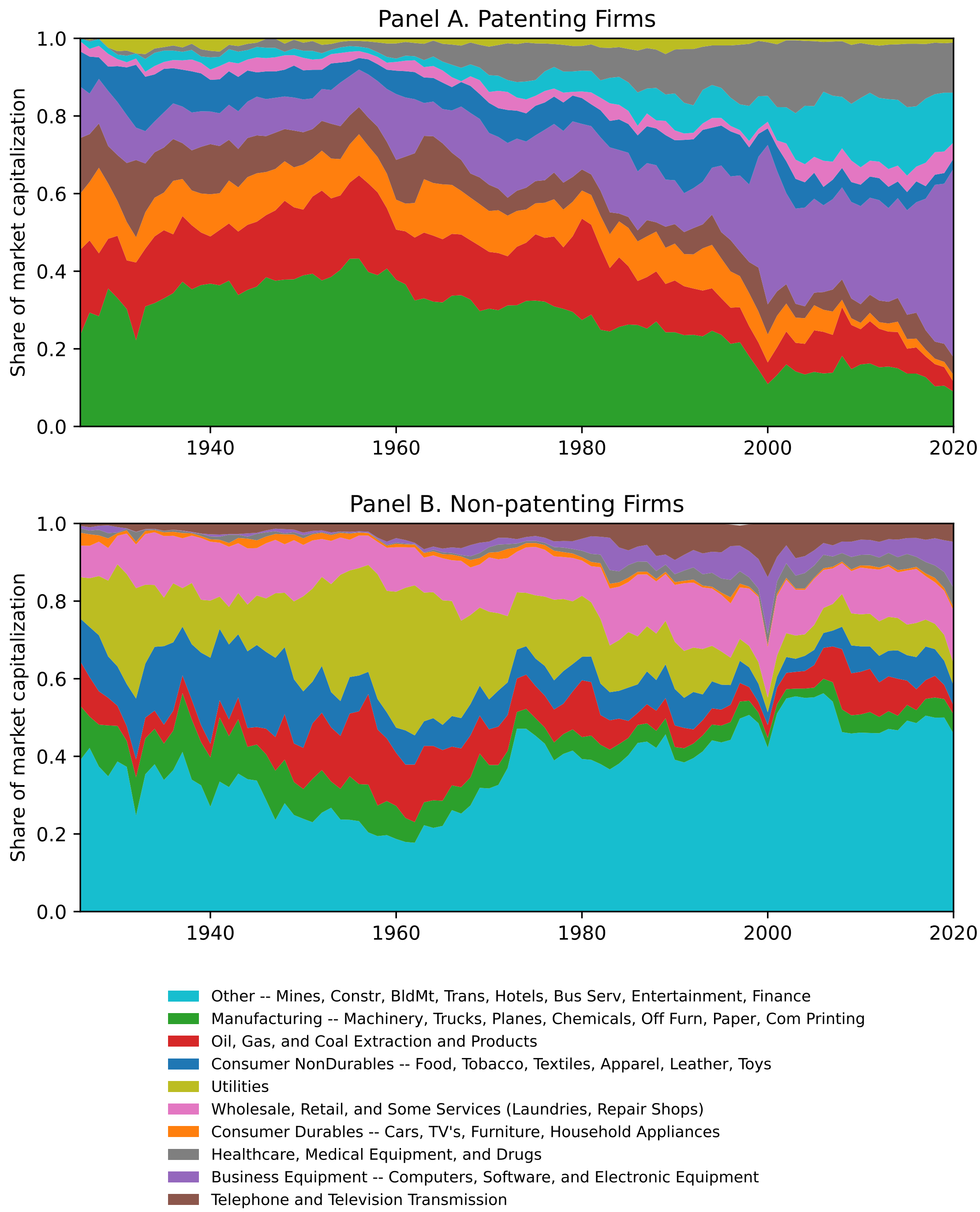

Figure 2: Sector Composition of Patenting and Non-patenting Firms. Panel A shows sectors' market capitalization shares of total market capitalization of patenting firms. For each sector, we calculate the market capitalization of patenting firms in the sector and divide by the total market capitalization 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.

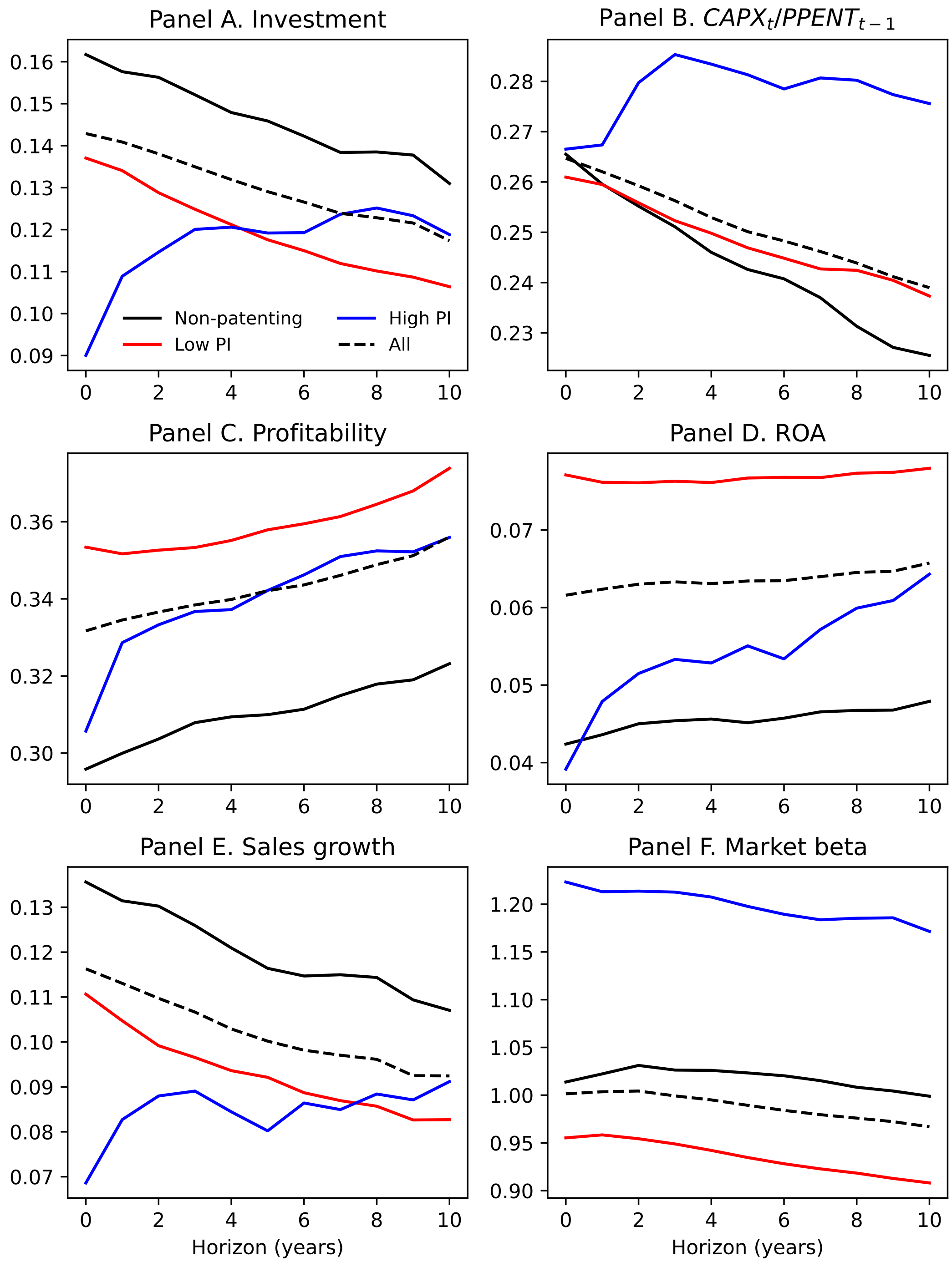

Figure 3: Dynamics of Patent-Intensity Portfolio Characteristics. This figure shows dynamics of variables indicated in the panel headings for aged PI-sorted portfolios. Characteristic and market-beta definitions are given in the Appendix. Characteristics are measured by the calendar year of their fiscal year-end, allocated to portfolios formed the following June, and market betas are measured at the end of June. Firms are initially sorted every year at the end of June into three portfolios. The first consists of non-patenting firms (PI=0). Remaining firms are split equally into two portfolios, low- and high-PI. The stocks are held in the portfolios over horizon of 10 years. Portfolio formation begins in 1963 and ends ten years before the end of our sample. For all portfolios, we first calculate the annual value-weighted average at the specified horizon and then average across years. The dotted line shows value-weighted statistics for all firms.

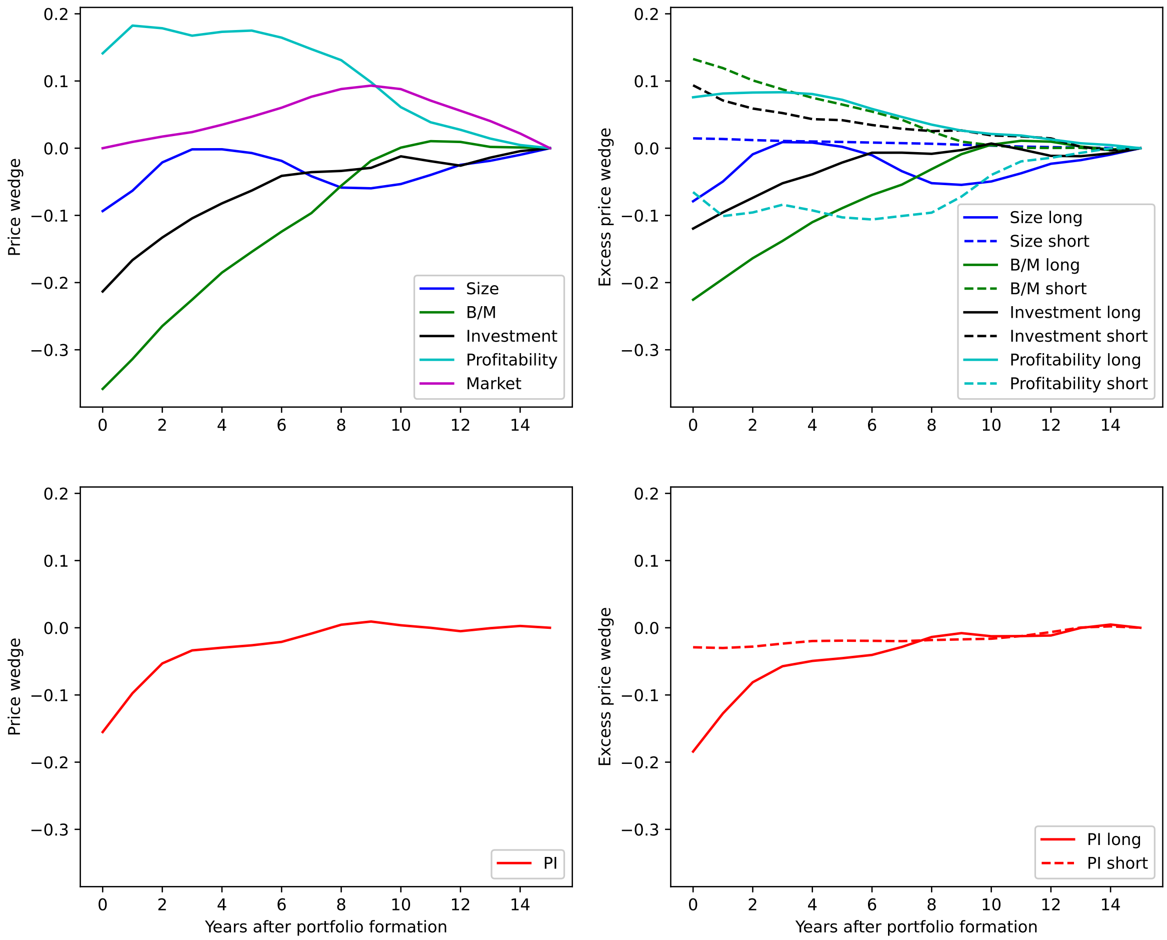

Figure 4: Price Wedge Dynamics. The figure shows price wedge dynamics for portfolios sorted on size, book-to-market, investment, and profitability in the top row and portfolios sorted on PI in the bottom row. Price wedges are calculated as the difference between observed and fair market value from the 15-year dividend discount model and CAPM SDF of 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 portfolio with the highest (lowest) value of b/m or profitability (size or investment) and the short side is the 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.

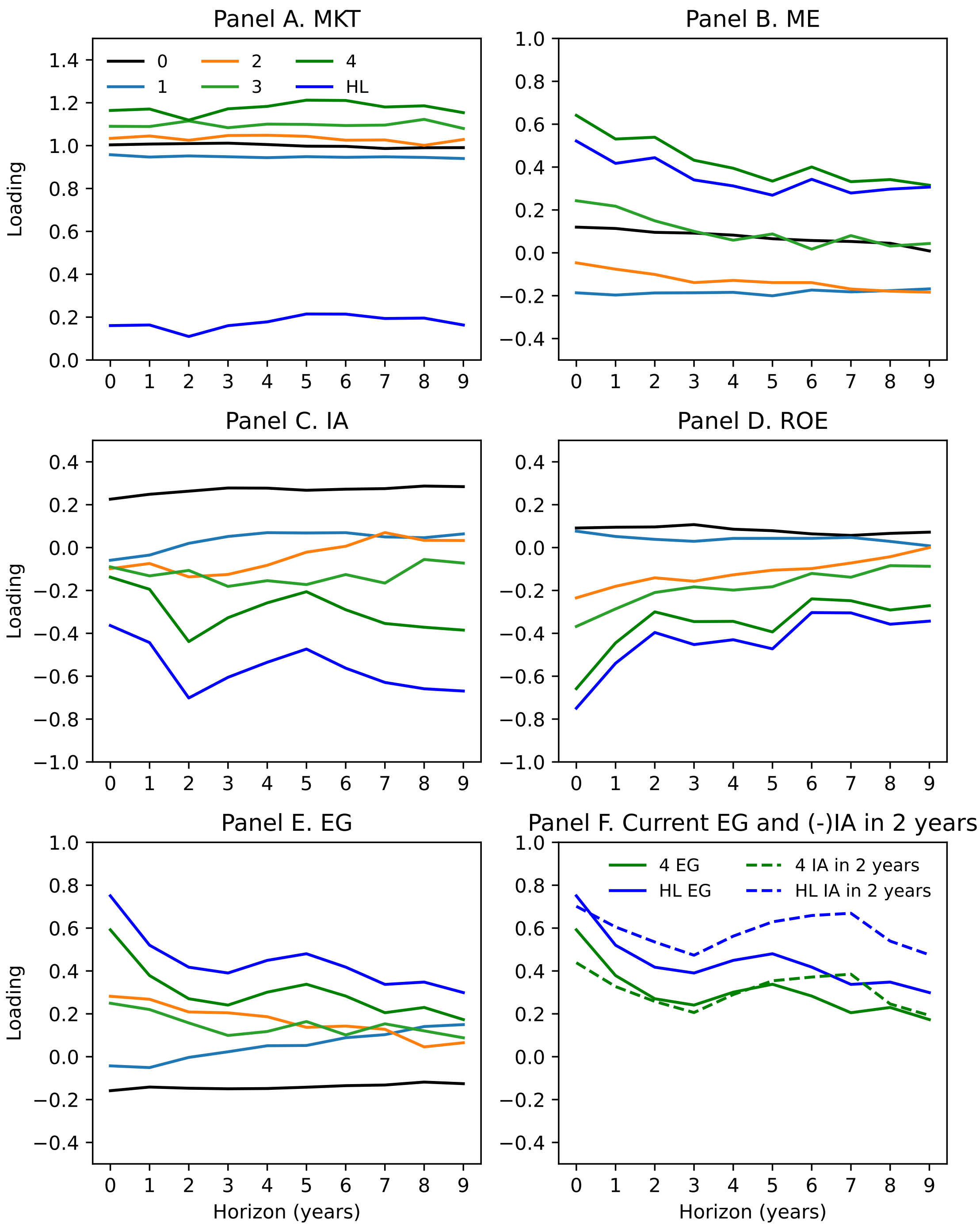

Figure 5: Aged Patent-Intensity Portfolios, $q5$ Loading Dynamics. The figure shows dynamics of $q5$ loadings for aged PI-sorted portfolios, as indicated in headings of panels A-E. Panel F shows HL and high-PI expected growth (EG) loadings overlaid with (negative) investment (IA) loadings two years ahead. The investment loadings are plotted negatively to facilitate comparison. Portfolio construction follows the description in Section 3 and the aged portfolios are value-weighted, rebalanced monthly, following the description in Section 4. The sample begins in 1967 to accommodate availability of the $q5$ factors.

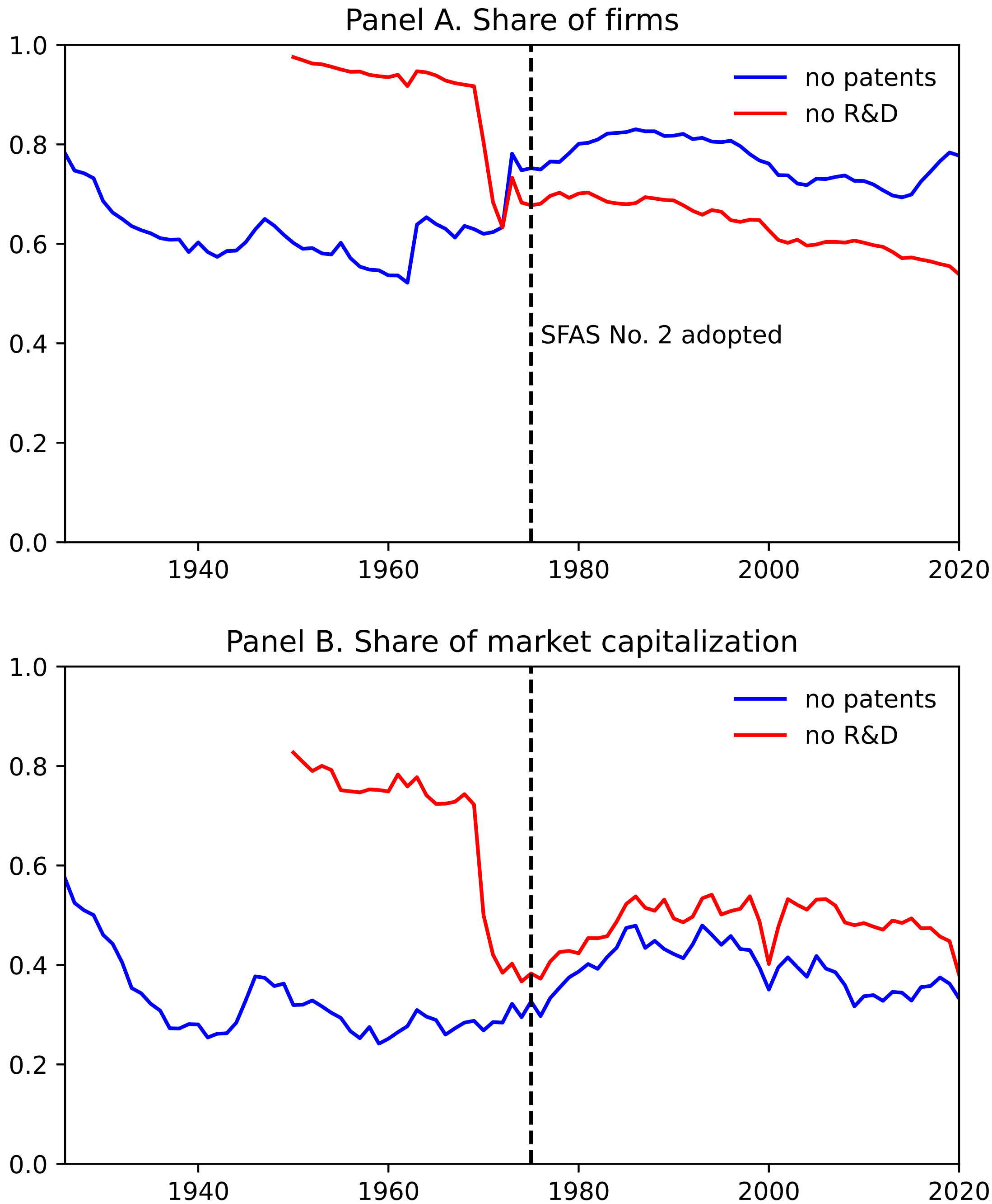

Figure 6: Non-innovators According to R&D and Patenting. Panel A shows the fraction of CRSP firms with no patenting activity (blue line) and fraction of firms with zero or missing R&D activity (red line). Panel B shows the fraction of the total CRSP market capitalization that belongs to these firms. The sample is identical to Figure 1.

Table 1: Patent Intensity (PI) and Firm Characteristics. This table shows characteristics of firms sorted on patent intensity PI, defined as patents received in the prior year divided by market capitalization. We sort every year at the end of June into three groups. Non-patenting firms have PI=0. The remaining firms are split into two equal groups by firm count, low- and high-PI. Panel A begins in 1926. Share of firms is the percentage of all companies in each category. Share of cap is the share of total market capitalization in each category. Share of patents is the share of all patents granted to US-based CRSP assignees at the time of sorting or as indicated, granted to firms in each category. Panel B begins in 1963. Characteristics and asset types are based on information at the time of sorting and are defined in the Appendix. Mean and median indicate whether the value is from cross-sectional mean or median, before averaging across years. 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. Summary statistics beginning 1926			
Portfolio shares (columns sum to 1)			
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	0.581
Share of patents (next 5 years)	0.017	0.418	0.565
Characteristics			
CRSP age mean	13.313	20.289	15.420
CRSP age median	11.710	17.693	13.000
BM mean	1.592	0.807	1.150
BM median	1.010	0.666	0.924
Panel B. Summary statistics beginning 1963			
Characteristics			
Investment mean	0.137	0.164	0.090
Investment median	0.075	0.091	0.043
Profitability mean	0.164	0.257	0.095
Profitability median	0.210	0.264	0.165
Asset composition (share of total assets)			
PPE	0.301	0.294	0.234
Intangibles	0.070	0.100	0.070
Current assets	0.513	0.519	0.625
Cash	0.128	0.157	0.203

Table 2: Transition Probabilities of PI- vs. B/M-sorted Portfolios. Panel A shows the transition probabilities over one, three, and five years between portfolios of stocks sorted by PI as described in the notes of Table 1. Rows specify the initial portfolio and columns the ending portfolio, with "out" designating a stock that leaves the sample. Entries indicate the conditional probability of moving from the initial portfolio (rows) to the destination portfolio (columns), and sum to one across columns. Panel B shows equivalent transition probabilities for book-to-market (B/M) sorts, where "Missing" denotes firms with negative or missing book-to-market ratios. To improve comparison, the B/M sorts are based on the same percentiles as the PI sorts: Each year, we calculate the percentages of firms in each of the three PI-sorted portfolios and use these percentages to categorize stocks by B/M. The unconditional probabilities (shares) of non-patenting, low-PI, and high-PI portfolios are 68.2%, 15.9% and 15.9%, respectively (see table 1). These probabilities apply also to the B/M-sorted portfolios for stocks with non-missing B/M (89.7% of stocks have non-missing B/M). Accordingly, the unconditional probabilities of the three B/M-sorted portfolios are: 68.2%*89.7%=61.2% (high B/M or value), 15.9%*89.7%=14.3% (medium B/M or neutral), and 15.9%*89.7%=14.3% (low B/M or growth). Transition probabilities are calculated annually from 1926 to 2020. The presented transition probabilities are time-series averages.

Panel A. PI-sorted portfolios					Panel B. B/M-sorted portfolios					
	Non-pat.	Low PI	High PI	Out		Value	Neutral	Growth	Missing	Out
Transition probabilities over 1 year										
Non-patenting	86.8	4.6	2.6	6.0	Value	85.8	6.5	1.6	1.6	4.5
Low PI	17.8	67.0	12.7	2.6	Neutral	34.8	43.8	16.1	1.7	3.6
High PI	12.7	12.0	71.2	4.1	Growth	9.7	19.8	63.0	3.8	3.6
					Missing	11.8	2.8	7.1	63.2	15.1
Transition probabilities over 3 years										
Non-patenting	76.0	5.2	2.8	16.0	Value	73.7	7.7	3.1	2.2	13.4
Low PI	17.4	58.7	16.0	7.9	Neutral	43.5	28.2	15.3	2.3	10.7
High PI	13.3	15.1	60.0	11.7	Growth	21.0	20.3	43.8	4.0	10.9
					Missing	17.6	4.9	7.2	42.2	28.1
Transition probabilities over 5 years										
Non-patenting	67.7	5.5	2.9	24.0	Value	65.8	7.8	3.5	2.3	20.7
Low PI	17.1	53.7	16.8	12.4	Neutral	45.1	22.2	13.5	2.3	16.9
High PI	12.9	16.5	52.4	18.2	Growth	25.7	18.5	35.2	3.6	17.1
					Missing	20.3	5.7	6.4	30.3	37.3

Table 3: Patent-Intensity Sorts and Performance, Fama-French Factors. The table shows the average excess returns of PI-sorted portfolios in panel A and regressions of excess portfolio returns (in excess of the risk-free rate) on a constant and market excess returns (Panel B), the Fama-French three factors (Panel C), and the Fama-French five factors (Panel D). Portfolio 0 consists of non-patenting firms and the remaining portfolios are sorted by PI annually into equal groups by firm count. HL is a zero-cost portfolio, long portfolio 4 and short portfolio 0. Stocks are sorted at the end of June. The time period of each panel is indicated in the headings. In this and remanining tables (unless stated differently), the portfolios are value-weighted, rebalanced monthly. The underlying portfolio returns are at monthly frequency, and the estimates of the average excess returns and constants (alphas) are annualized by multiplying by twelve. t-statistics based on Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses. */**/*** 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										
Ex. ret.	7.76***	8.46***	11.91***	4.15***	6.75***	6.26***	8.76***	9.7***	13.81***	7.06***
	(3.82)	(4.41)	(4.77)	(3.85)	(2.98)	(3.15)	(3.96)	(3.82)	(4.12)	(3.42)
Panel B. CAPM										
Constant	-0.5	0.52*	1.91**	2.41**	-0.32	-0.24	1.68**	1.68	4.93**	5.25***
	(-1.04)	(1.66)	(2.35)	(2.42)	(-0.48)	(-0.45)	(2.46)	(1.59)	(2.57)	(2.63)
Mkt-RF	1.0***	0.96***	1.21***	0.21***	1.01***	0.93***	1.01***	1.15***	1.27***	0.26***
	(69.36)	(91.24)	(42.98)	(7.64)	(57.79)	(71.22)	(60.69)	(43.28)	(27.14)	(5.34)
R^2	0.95	0.97	0.89	0.14	0.93	0.94	0.9	0.82	0.67	0.07
Panel C. Fama-French 1993										
Constant	-0.94**	0.81***	1.54*	2.47**	-1.33***	0.44	1.93***	1.31	3.79**	5.12***
	(-2.28)	(3.05)	(1.92)	(2.45)	(-2.76)	(1.04)	(2.77)	(1.23)	(2.2)	(2.62)
Mkt-RF	0.96***	0.99***	1.15***	0.19***	1.02***	0.95***	1.01***	1.08***	1.13***	0.11*
	(84.19)	(123.49)	(42.05)	(5.83)	(68.83)	(99.1)	(52.89)	(31.28)	(21.04)	(1.75)
SMB	0.08**	-0.12***	0.26***	0.18*	0.09**	-0.19***	-0.01	0.31***	0.72***	0.63***
	(2.47)	(-9.17)	(3.58)	(1.81)	(2.14)	(-15.23)	(-0.23)	(3.63)	(5.78)	(3.85)
HML	0.14***	-0.07***	0.05	-0.09	0.22***	-0.11***	-0.06*	0.0	0.08	-0.14*
	(5.65)	(-4.69)	(1.01)	(-1.39)	(7.31)	(-5.54)	(-1.84)	(0.09)	(1.24)	(-1.68)
R^2	0.96	0.98	0.9	0.18	0.95	0.96	0.9	0.85	0.76	0.25
Panel D. Fama-French 2015										
Constant					-1.67***	0.24	2.19***	2.19**	5.22***	6.89***
					(-3.48)	(0.55)	(3.12)	(2.09)	(3.07)	(3.55)
Mkt-RF					1.02***	0.96***	1.01***	1.09***	1.13***	0.11**
					(77.74)	(95.13)	(64.79)	(34.01)	(24.3)	(2.13)
SMB					0.13***	-0.18***	-0.05*	0.23***	0.59***	0.46***
					(5.39)	(-13.73)	(-1.65)	(3.9)	(7.61)	(4.83)
HML					0.22***	-0.08***	-0.08**	-0.09	-0.1	-0.32***
					(6.6)	(-3.68)	(-2.03)	(-1.28)	(-1.11)	(-2.84)
CMA					-0.04	0.0	0.08	0.14	0.22	0.26
					(-1.14)	(0.13)	(1.37)	(1.53)	(1.52)	(1.6)
RMW					0.12***	0.04*	-0.12***	-0.3***	-0.47***	-0.58***
					(2.98)	(1.86)	(-3.18)	(-3.79)	(-3.16)	(-3.4)
R^2					0.96	0.96	0.9	0.86	0.78	0.32

Table 4: Characteristics Sorts for Innovative vs. Non-innovative Firms. The table shows average excess long-short returns sorted on investment (Panel A) and profitability (Panel B) for subsamples of innovative and non-innovative firms, as well as FF5 alphas and loadings. Stocks are labeled as innovators and non-innovators at the end of June in each year t and then sorted into five portfolios within the two groups. Innovative firms are firms that have at least one patent in the last year and three patents over the last three years. The remaining firms are treated as non-innovative. The table shows the returns of the bottom portfolio 0, top portfolio 4, and the long-short (HL) 4-0. Investment and profitability are defined in the notes to the Table 1. Following Hou, Xue, and Zhang (2020), we discard stocks with negative book equity. The sample period is 1963-2021. t-statistics from Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses. */**/*** indicate significance level at 10, 5, and 1%.

Portfolio	Ex. ret.	Alpha	Mkt-RF	SMB	HML	CMA	RMW
Panel A. Investment							
Non-innovative							
0	9.26***	-1.66*	1.09***	0.42***	0.08	0.5***	0.07
	(3.83)	(-1.88)	(53.71)	(11.88)	(1.53)	(6.84)	(1.09)
4	5.29*	-2.73***	1.14***	0.31***	0.03	-0.41***	0.11*
	(1.95)	(-3.28)	(59.9)	(8.34)	(0.59)	(-7.79)	(1.82)
HL	-3.97***	-1.07	0.05**	-0.11***	-0.05	-0.91***	0.04
	(-3.02)	(-0.93)	(2.22)	(-2.71)	(-1.27)	(-10.11)	(0.59)
Innovative							
0	9.05***	-0.26	1.08***	0.05	-0.2***	0.78***	-0.08
	(3.99)	(-0.24)	(51.19)	(1.37)	(-3.63)	(10.06)	(-1.28)
4	7.4***	3.41***	1.04***	-0.1***	-0.2***	-0.63***	-0.12***
	(2.84)	(3.63)	(46.69)	(-3.67)	(-4.58)	(-8.35)	(-3.14)
HL	-1.65	3.66***	-0.04	-0.15***	-0.0	-1.4***	-0.04
	(-0.98)	(2.99)	(-1.46)	(-3.42)	(-0.05)	(-17.85)	(-0.54)
Difference (Innovative - Non-innovative)							
HL	2.33	4.73**	-0.09**	-0.05	0.05	-0.49***	-0.08
	(1.37)	(2.55)	(-2.31)	(-0.7)	(0.56)	(-3.64)	(-0.72)
Panel B. Profitability							
Non-innovative							
0	3.78	-0.32	1.14***	0.4***	-0.15**	-0.35***	-1.14***
	(1.12)	(-0.2)	(34.21)	(5.77)	(-2.3)	(-3.08)	(-11.18)
4	8.11***	-1.6***	1.08***	0.24***	0.12***	-0.11**	0.46***
	(3.46)	(-2.58)	(59.91)	(7.47)	(3.16)	(-2.21)	(10.76)
HL	4.33*	-1.28	-0.06	-0.16**	0.27***	0.24*	1.6***
	(1.91)	(-0.75)	(-1.43)	(-2.36)	(4.04)	(1.84)	(17.53)
Innovative							
0	10.89***	6.66***	1.07***	0.48***	-0.52***	0.32*	-1.32***
	(3.05)	(3.59)	(24.93)	(5.83)	(-5.41)	(1.82)	(-8.05)
4	8.39***	1.63***	0.95***	-0.13***	-0.16***	0.02	0.3***
	(4.27)	(3.02)	(82.74)	(-6.2)	(-5.83)	(0.52)	(8.46)
HL	-2.5	-5.03***	-0.12***	-0.61***	0.36***	-0.29*	1.62***
	(-0.91)	(-2.81)	(-2.77)	(-7.92)	(3.9)	(-1.77)	(11.49)
Difference (Innovative - Non-innovative)							
HL	-6.83***	-3.75	-0.06	-0.45***	0.09	-0.53**	0.02
	(-3.07)	(-1.43)	(-1.12)	(-4.21)	(0.75)	(-2.38)	(0.09)

Table 5: Patent Intensity and q-Factors. The table shows the results of regressing the PI-portfolio returns on a constant and the q4-factors (Hou, Xue, and Zhang, 2015), market (MKT), size (ME), investment (IA), and profitability (ROE) in Panel A, or q5-factors (Hou, Mo, Xue, and Zhang, 2021), adding expected growth (EG) in panel B. Portfolio 0 consists of non-patenting firms and the remaining portfolios are sorted by PI annually into equal groups by firm count. HL is a zero-cost portfolio, long portfolio 4 and short portfolio 0. Stocks are sorted at the end of June. The time period is 1967-2021. t-statistics from Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses. */**/*** indicate significance level at 10, 5, and 1%.

	0	1	2	3	4	HL
Panel A. q4-factors						
Constant	-1.94***	0.06	2.89***	3.46***	6.79***	8.73***
	(-3.09)	(0.13)	(3.72)	(2.75)	(3.62)	(3.83)
MKT	1.02***	0.96***	1.0***	1.06***	1.09***	0.07
	(50.66)	(89.75)	(53.05)	(27.76)	(20.15)	(1.0)
ME	0.14***	-0.18***	-0.08**	0.22***	0.58***	0.44**
	(2.66)	(-10.88)	(-1.98)	(2.58)	(4.54)	(2.53)
IA	0.2***	-0.07**	-0.06	-0.05	-0.05	-0.26*
	(4.26)	(-2.23)	(-1.35)	(-0.72)	(-0.44)	(-1.7)
ROE	0.04	0.06***	-0.14***	-0.29***	-0.47***	-0.51***
	(1.2)	(2.8)	(-3.26)	(-4.56)	(-5.2)	(-4.68)
R^2	0.95	0.96	0.9	0.86	0.78	0.28
Panel B. q5-factors						
Constant	-0.65	0.41	0.59	1.43	1.97	2.62
	(-1.16)	(0.83)	(0.82)	(1.18)	(1.25)	(1.43)
MKT	1.0***	0.96***	1.03***	1.09***	1.16***	0.16***
	(55.9)	(89.61)	(60.53)	(28.98)	(24.3)	(2.71)
ME	0.12**	-0.19***	-0.05	0.24***	0.64***	0.52***
	(2.3)	(-11.34)	(-1.25)	(2.95)	(5.18)	(3.06)
IA	0.23***	-0.06**	-0.1**	-0.09	-0.14	-0.36**
	(4.45)	(-2.06)	(-2.48)	(-1.15)	(-1.11)	(-2.3)
ROE	0.09**	0.08***	-0.23***	-0.37***	-0.66***	-0.75***
	(2.33)	(3.41)	(-5.22)	(-4.92)	(-6.82)	(-6.12)
EG	-0.16***	-0.04	0.28***	0.25***	0.59***	0.75***
	(-3.96)	(-1.39)	(6.1)	(3.03)	(5.4)	(5.66)
R^2	0.95	0.96	0.91	0.86	0.8	0.34

Table 6: Aged Patent-Intensity Portfolios, Returns and Alphas. The table shows average excess and abnormal returns (alphas) of aged PI-sorted portfolios. At the end of June of year t, stocks are sorted into K-aged portfolios based on the patent-intensity sort from the end of June of year $t-K$. All portfolios are rebalanced monthly based on market capitalization at the end of the prior month. The sample period begins in 1926 in Panel A and in 1963 in Panel B and ends in 2021 for both panels. Portfolio 0 consists of non-patenting firms and the remaining portfolios are sorted by PI. HL is a zero-cost portfolio with a long position in portfolio 4 and a short position in portfolio 0. The left-most column indicates the portfolio and, if applicable, the benchmark model for alphas. t-statistics from Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses. */**/*** indicate significance level at 10, 5, and 1%.

Portfolio/	Horizon ($K+1$, years)									
Model	1	2	3	4	5	6	7	8	9	10
Panel A. 1926-	Excess returns									
0	7.76***	7.78***	7.75***	7.27***	7.72***	7.83***	9.14***	8.05***	8.07***	7.98***
	(3.82)	(3.79)	(3.75)	(3.52)	(3.75)	(3.81)	(4.49)	(4.41)	(4.44)	(4.39)
4	15.02***	14.84***	12.52***	10.41***	10.54***	11.78***	14.1***	11.38***	11.65***	11.2***
	(4.85)	(4.89)	(4.28)	(3.49)	(3.68)	(4.0)	(4.82)	(4.37)	(4.44)	(4.39)
HL	7.26***	7.06***	4.77***	3.14**	2.82**	3.96***	4.96***	3.32**	3.59**	3.22**
	(4.42)	(4.36)	(3.09)	(2.03)	(1.96)	(2.72)	(3.3)	(2.3)	(2.39)	(2.16)
	Alphas									
CAPM/HL	4.04***	3.98***	2.13	0.48	0.24	0.94	1.6	0.39	0.65	0.64
	(2.9)	(2.68)	(1.46)	(0.34)	(0.18)	(0.73)	(1.16)	(0.27)	(0.45)	(0.42)
FF3/HL	3.51**	3.74***	2.28*	0.58	0.31	0.94	2.04	1.24	1.79	2.07
	(2.57)	(2.69)	(1.68)	(0.44)	(0.24)	(0.75)	(1.56)	(0.94)	(1.33)	(1.49)
Panel B. 1963-	Excess returns									
0	6.75***	6.83***	6.91***	6.63***	6.65***	6.45***	6.45***	6.65***	6.44***	6.31***
	(2.98)	(3.04)	(3.08)	(2.98)	(3.01)	(2.93)	(2.93)	(3.05)	(2.99)	(2.94)
4	13.81***	14.11***	11.72***	9.46***	9.37***	9.82***	10.86***	10.02***	9.65***	9.97***
	(4.12)	(4.28)	(3.75)	(2.99)	(3.04)	(3.15)	(3.38)	(3.17)	(3.05)	(3.16)
HL	7.06***	7.28***	4.81**	2.82	2.72	3.36*	4.41**	3.38*	3.2	3.66*
	(3.42)	(3.5)	(2.41)	(1.46)	(1.49)	(1.89)	(2.32)	(1.75)	(1.61)	(1.8)
	Alphas									
CAPM/HL	5.25***	5.37**	2.95	0.76	0.75	1.26	2.17	1.18	0.92	1.51
	(2.63)	(2.55)	(1.41)	(0.38)	(0.4)	(0.72)	(1.17)	(0.61)	(0.46)	(0.74)
FF3/HL	5.12***	5.93***	4.12**	1.79	1.65	2.3	3.39**	2.64	2.38	3.04*
	(2.62)	(3.2)	(2.34)	(1.01)	(1.0)	(1.38)	(1.97)	(1.54)	(1.38)	(1.73)
FF5/0	-1.67***	-1.68***	-1.66***	-1.91***	-1.79***	-1.77***	-1.73***	-1.47***	-1.58***	-1.64***
	(-3.48)	(-3.62)	(-3.43)	(-3.99)	(-3.73)	(-3.75)	(-3.65)	(-3.21)	(-3.43)	(-3.5)
1	0.24	-0.05	0.11	-0.04	-0.03	0.27	0.32	0.19	0.03	0.35
	(0.55)	(-0.11)	(0.26)	(-0.09)	(-0.06)	(0.55)	(0.71)	(0.45)	(0.07)	(0.79)
2	2.19***	2.68***	1.64***	1.64**	1.14*	0.56	0.76	0.42	1.06*	0.46
	(3.12)	(3.92)	(2.65)	(2.5)	(1.84)	(0.92)	(1.34)	(0.72)	(1.76)	(0.79)
3	2.19**	1.61*	1.19	1.54*	1.84**	1.83**	0.98	1.73**	0.54	0.84
	(2.09)	(1.68)	(1.42)	(1.78)	(2.06)	(2.03)	(1.05)	(2.0)	(0.55)	(0.94)
4	5.22***	6.46***	5.01***	2.5*	1.98	2.19*	3.39**	3.0**	2.7*	3.49**
	(3.07)	(4.05)	(3.24)	(1.82)	(1.51)	(1.66)	(2.37)	(2.08)	(1.9)	(2.42)
HL	6.89***	8.14***	6.67***	4.42***	3.77**	3.96***	5.12***	4.47***	4.28***	5.12***
	(3.55)	(4.57)	(3.8)	(2.8)	(2.44)	(2.6)	(3.11)	(2.72)	(2.62)	(3.06)

Table 7: Aged Patent-Intensity Portfolios, $q5$ Alpha and Loading Dynamics. The table shows the abnormal returns (alphas in Panel A) relative to $q5$-factor model Hou, Mo, Xue, and Zhang (2021) and the loadings on the model's factors (Panels B-F) of PI-sorted portfolios (indicated in rows) for holding period of one-year at different investment horizons (indicated in columns). Details of the portfolio construction and investment horizons are described in the Table 6 notes. The sample period begins in 1967, to accommodate the q-factors, and ends in 2021. t-statistics from Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses. */**/*** indicate significance level at 10, 5, and 1%.

	Horizon ($K+1$, years)										
	1	2	3	4	5	6	7	8	9	10	10-1
Panel A. Alpha											
0	-0.65	-0.79	-0.69	-1.07*	-0.87	-0.95*	-0.91	-0.62	-1.08*	-1.04*	-0.39
	(-1.16)	(-1.38)	(-1.2)	(-1.91)	(-1.56)	(-1.7)	(-1.61)	(-1.12)	(-1.94)	(-1.79)	(-1.08)
1	0.41	0.52	0.29	0.02	-0.31	-0.01	-0.14	-0.55	-0.77	-0.4	-0.81
	(0.83)	(0.98)	(0.56)	(0.03)	(-0.59)	(-0.01)	(-0.23)	(-0.98)	(-1.28)	(-0.71)	(-1.32)
2	0.59	0.68	0.26	0.62	0.23	0.02	0.13	-0.05	1.25	0.25	-0.34
	(0.82)	(0.87)	(0.33)	(0.75)	(0.32)	(0.03)	(0.18)	(-0.07)	(1.57)	(0.33)	(-0.37)
3	1.43	0.6	0.44	1.22	1.59	1.14	0.63	0.89	-0.41	0.14	-1.29
	(1.18)	(0.51)	(0.39)	(1.04)	(1.42)	(1.01)	(0.58)	(0.9)	(-0.39)	(0.14)	(-1.25)
4	1.97	3.69	2.9	0.6	-0.39	-0.26	0.66	1.3	0.98	2.17	0.2
	(1.25)	(1.59)	(1.33)	(0.37)	(-0.25)	(-0.17)	(0.4)	(0.76)	(0.57)	(1.24)	(0.11)
HL	2.62	4.48*	3.59	1.67	0.48	0.69	1.58	1.93	2.06	3.21	0.59
	(1.43)	(1.68)	(1.45)	(0.89)	(0.26)	(0.4)	(0.81)	(0.99)	(1.03)	(1.57)	(0.31)
Panel B. Market beta											
0	1.0***	1.01***	1.01***	1.01***	1.01***	1.0***	1.0***	0.99***	0.99***	0.99***	-0.01
	(55.9)	(56.19)	(57.09)	(58.21)	(62.2)	(59.64)	(53.56)	(60.21)	(58.95)	(57.06)	(-1.62)
1	0.96***	0.95***	0.95***	0.95***	0.94***	0.95***	0.95***	0.95***	0.95***	0.94***	-0.02
	(89.61)	(82.59)	(72.39)	(77.13)	(85.72)	(77.45)	(78.98)	(92.59)	(93.32)	(90.25)	(-1.55)
2	1.03***	1.05***	1.03***	1.05***	1.05***	1.04***	1.03***	1.03***	1.0***	1.03***	-0.01
	(60.53)	(59.47)	(53.08)	(52.68)	(66.57)	(61.72)	(66.27)	(63.58)	(62.74)	(65.38)	(-0.25)
3	1.09***	1.09***	1.12***	1.08***	1.1***	1.1***	1.09***	1.1***	1.12***	1.08***	-0.01
	(28.98)	(36.95)	(47.55)	(47.67)	(44.61)	(46.29)	(48.04)	(50.71)	(52.96)	(44.75)	(-0.34)
4	1.16***	1.17***	1.12***	1.17***	1.18***	1.21***	1.21***	1.18***	1.19***	1.15***	-0.01
	(24.3)	(32.79)	(24.25)	(29.33)	(30.53)	(27.28)	(28.53)	(27.78)	(26.68)	(22.77)	(-0.24)
HL	0.16***	0.16***	0.11*	0.16***	0.18***	0.21***	0.21***	0.19***	0.2***	0.16***	0.0
	(2.71)	(3.69)	(1.91)	(3.23)	(3.63)	(3.98)	(4.09)	(3.66)	(3.52)	(2.68)	(0.06)
Panel C. Size											
0	0.12**	0.11**	0.1*	0.09*	0.08*	0.07	0.06	0.05	0.04	0.01	-0.11***
	(2.3)	(2.31)	(1.88)	(1.88)	(1.84)	(1.56)	(1.17)	(1.18)	(1.09)	(0.19)	(-8.09)
1	-0.19***	-0.2***	-0.19***	-0.19***	-0.18***	-0.2***	-0.17***	-0.18***	-0.18***	-0.17***	0.02
	(-11.34)	(-14.32)	(-12.47)	(-13.46)	(-11.56)	(-8.03)	(-8.52)	(-9.82)	(-8.54)	(-8.15)	(0.64)
2	-0.05	-0.08*	-0.1***	-0.14***	-0.13***	-0.14***	-0.14***	-0.17***	-0.18***	-0.18***	-0.14***
	(-1.25)	(-1.94)	(-3.44)	(-6.24)	(-5.47)	(-5.63)	(-6.26)	(-6.66)	(-7.5)	(-6.99)	(-3.39)
3	0.24***	0.22***	0.15***	0.1**	0.06	0.09**	0.02	0.08*	0.03	0.04	-0.2***
	(2.95)	(3.61)	(3.17)	(2.44)	(1.35)	(2.0)	(0.46)	(1.68)	(0.75)	(0.95)	(-3.42)
4	0.64***	0.53***	0.54***	0.43***	0.39***	0.33***	0.4***	0.33***	0.34***	0.32***	-0.33***
	(5.18)	(6.34)	(4.54)	(4.94)	(5.32)	(3.9)	(4.23)	(3.14)	(3.4)	(3.01)	(-4.73)
HL	0.52***	0.42***	0.44***	0.34***	0.31***	0.27**	0.34**	0.28*	0.3**	0.31**	-0.21***
	(3.06)	(3.36)	(2.72)	(2.66)	(2.91)	(2.23)	(2.51)	(1.94)	(2.21)	(2.14)	(-2.93)

Table 7, Aged Portfolios, $q5$ Dynamics – continued.

	Horizon ($K+1$, years)										
	1	2	3	4	5	6	7	8	9	10	10-1
Panel D. Investment loading (IA)											
0	0.23***	0.25***	0.26***	0.28***	0.28***	0.27***	0.27***	0.28***	0.29***	0.28***	0.06**
	(4.45)	(4.7)	(5.12)	(5.13)	(5.73)	(6.29)	(5.89)	(5.94)	(6.92)	(6.6)	(2.35)
1	-0.06**	-0.03	0.02	0.05**	0.07***	0.07*	0.07*	0.05	0.05	0.06**	0.12***
	(-2.06)	(-1.28)	(0.79)	(2.12)	(2.68)	(1.91)	(1.87)	(1.46)	(1.4)	(2.06)	(3.07)
2	-0.1**	-0.07	-0.14**	-0.13**	-0.08*	-0.02	0.01	0.07*	0.03	0.03	0.13***
	(-2.48)	(-1.62)	(-2.42)	(-2.3)	(-1.93)	(-0.52)	(0.15)	(1.83)	(0.86)	(0.89)	(2.74)
3	-0.09	-0.13	-0.11	-0.18**	-0.15***	-0.17***	-0.13**	-0.17***	-0.06	-0.07	0.02
	(-1.15)	(-1.6)	(-1.53)	(-2.42)	(-2.67)	(-2.9)	(-2.0)	(-2.78)	(-0.95)	(-1.35)	(0.28)
4	-0.14	-0.19	-0.44***	-0.33***	-0.26***	-0.21**	-0.29***	-0.35***	-0.37***	-0.38***	-0.25**
	(-1.11)	(-1.3)	(-3.03)	(-3.83)	(-3.24)	(-2.33)	(-3.25)	(-3.95)	(-4.14)	(-4.33)	(-2.09)
HL	-0.36**	-0.44**	-0.7***	-0.61***	-0.54***	-0.47***	-0.56***	-0.63***	-0.66***	-0.67***	-0.31**
	(-2.3)	(-2.31)	(-3.8)	(-5.07)	(-4.96)	(-4.41)	(-4.75)	(-5.28)	(-5.78)	(-5.94)	(-2.47)
Panel E. Profitability loading (ROE)											
0	0.09**	0.09**	0.1**	0.11***	0.09**	0.08**	0.06	0.06	0.07*	0.07*	-0.02
	(2.33)	(2.38)	(2.33)	(2.62)	(2.18)	(2.03)	(1.46)	(1.34)	(1.72)	(1.81)	(-1.05)
1	0.08***	0.05**	0.04	0.03	0.04*	0.04	0.04	0.05*	0.03	0.01	-0.07**
	(3.41)	(2.21)	(1.6)	(1.27)	(1.92)	(1.61)	(1.48)	(1.87)	(1.17)	(0.3)	(-2.12)
2	-0.23***	-0.18***	-0.14***	-0.16***	-0.13***	-0.11**	-0.1***	-0.07**	-0.04	0.0	0.23***
	(-5.22)	(-4.78)	(-3.31)	(-2.97)	(-2.69)	(-2.55)	(-2.59)	(-2.1)	(-1.26)	(0.0)	(4.91)
3	-0.37***	-0.29***	-0.21***	-0.18***	-0.2***	-0.18***	-0.12**	-0.14***	-0.08*	-0.09*	0.28***
	(-4.92)	(-5.17)	(-4.56)	(-3.24)	(-3.71)	(-3.5)	(-2.39)	(-2.71)	(-1.69)	(-1.79)	(4.09)
4	-0.66***	-0.44***	-0.3***	-0.35***	-0.34***	-0.39***	-0.24***	-0.25***	-0.29***	-0.27***	0.39***
	(-6.82)	(-4.65)	(-2.77)	(-4.68)	(-4.1)	(-4.0)	(-3.03)	(-3.05)	(-2.89)	(-2.8)	(4.92)
HL	-0.75***	-0.54***	-0.4***	-0.45***	-0.43***	-0.47***	-0.3***	-0.3***	-0.36***	-0.34***	0.41***
	(-6.12)	(-4.48)	(-2.96)	(-5.01)	(-4.19)	(-3.96)	(-2.87)	(-2.81)	(-2.84)	(-2.87)	(4.82)
Panel F. Expected-growth loading (EG)											
0	-0.16***	-0.14***	-0.15***	-0.15***	-0.15***	-0.14***	-0.14***	-0.13***	-0.12***	-0.13***	0.03
	(-3.96)	(-3.34)	(-3.59)	(-3.41)	(-3.48)	(-3.56)	(-3.21)	(-3.34)	(-2.98)	(-3.01)	(1.43)
1	-0.04	-0.05	-0.0	0.02	0.05	0.05	0.09**	0.1***	0.14***	0.15***	0.19***
	(-1.39)	(-1.49)	(-0.09)	(0.68)	(1.38)	(1.16)	(2.07)	(2.63)	(3.3)	(3.92)	(4.62)
2	0.28***	0.27***	0.21***	0.2***	0.19***	0.14***	0.14***	0.13***	0.05	0.07	-0.22***
	(6.1)	(5.62)	(4.52)	(4.21)	(3.75)	(2.83)	(3.3)	(3.3)	(1.12)	(1.53)	(-4.0)
3	0.25***	0.22**	0.16**	0.1	0.12*	0.16**	0.1*	0.15**	0.12**	0.09	-0.16**
	(3.03)	(2.53)	(2.09)	(1.27)	(1.73)	(2.53)	(1.73)	(2.5)	(2.02)	(1.51)	(-2.2)
4	0.59***	0.38***	0.27**	0.24**	0.3***	0.34***	0.28***	0.21*	0.23**	0.17	-0.42***
	(5.4)	(2.88)	(2.3)	(2.19)	(2.83)	(3.45)	(2.72)	(1.77)	(1.97)	(1.52)	(-3.09)
HL	0.75***	0.52***	0.42***	0.39***	0.45***	0.48***	0.42***	0.34**	0.35**	0.3**	-0.45***
	(5.66)	(3.26)	(2.86)	(2.86)	(3.36)	(3.88)	(3.22)	(2.41)	(2.45)	(2.15)	(-3.14)

Table 8: Alternative Innovation Measures. We compare patent intensity with alternative measures. PI3 is average patent count over the last 36 months divided by market capitalization. KPSS is the sum of nominal values of patents granted to the firm over the last twelve months divided by market capitalization. RDI is R&D expense (prior fiscal year) divided by market capitalization. Portfolio 0 consists of non-innovative stocks (zero or missing value of the relevant measure). Remaining stocks are sorted into four portfolios based on the relevant measure. The long-short portfolio is long portfolio 4 and short portfolio 0. Panel A shows correlations between long-short portfolio returns. Panels B-D show average excess returns, alphas, and factor loadings of portfolio 0, portfolio 4, and long-short portfolios. Estimates in Panel B are from the full time period 1926-2021. Panel C starts in 1963 to accommodate investment and profitability factors, and Panel D in 1976 due to availability of reliable R&D data. Panels C and D show differences between portfolios formed on PI and alternatives as indicated. *t*-statistics from Newey-West heteroscedasticity and autocorrelation consistent standard errors with five lags are reported in parentheses. */**/*** indicate significance level at 10, 5, and 1%.

A. Correlations				1926-			1963-			1976-	
			PI	PI3	KPSS	PI	PI3	KPSS	PI	PI3	KPSS
PI3			0.95			0.94			0.94		
KPSS			0.42	0.44		0.34	0.36		0.38	0.4	
RDI			-	-	-	-	-	-	0.74	0.74	0.34
B. 1926-		Excess returns			Alphas				FF3 Loadings		
	0	4	HL	FF3	FF5	Q5	Mkt-RF	SMB	-	-	HML
PI	7.76***	15.02***	7.26***	3.51**	-	-	0.29***	0.47***	-	-	0.04
	(3.82)	(4.85)	(4.42)	(2.57)	-	-	(6.88)	(3.67)	-	-	(0.49)
PI3	7.8***	14.96***	7.16***	3.47***	-	-	0.29***	0.47***	-	-	0.03
	(3.8)	(4.9)	(4.5)	(2.67)	-	-	(6.7)	(4.5)	-	-	(0.4)
KPSS	7.76***	10.28***	2.52**	2.3***	-	-	0.14***	-0.23***	-	-	-0.08
	(3.82)	(4.64)	(2.5)	(2.67)	-	-	(2.93)	(-4.41)	-	-	(-1.04)
C. 1963-		Excess returns			Alphas				FF5 Loadings		
	0	4	HL	FF3	FF5	Q5	Mkt-RF	SMB	CMA	RMW	HML
PI	6.75***	13.81***	7.06***	5.12***	6.89***	-	0.11**	0.46***	0.26	-0.58***	-0.32***
	(2.98)	(4.12)	(3.42)	(2.62)	(3.55)	-	(2.13)	(4.83)	(1.6)	(-3.4)	(-2.84)
PI3	6.76***	14.22***	7.46***	5.49***	7.47***	-	0.11**	0.44***	0.19	-0.59***	-0.28***
	(2.97)	(4.34)	(3.78)	(3.01)	(4.39)	-	(2.16)	(4.89)	(1.1)	(-4.64)	(-2.86)
KPSS	6.75***	7.69***	0.94	2.87***	3.18***	-	-0.02	-0.31***	0.09	-0.15***	-0.32***
	(2.98)	(3.72)	(0.83)	(3.21)	(3.59)	-	(-0.96)	(-7.97)	(1.23)	(-2.61)	(-6.2)
<u>Differences</u>											
PI-PI3	-0.02	-0.41	-0.39	-0.37	-0.58	-	0.0	0.05	0.02	0.02	0.06
	(-0.17)	(-0.55)	(-0.52)	(-0.49)	(-0.63)	-	(0.2)	(1.06)	(0.31)	(0.62)	(0.93)
PI-KPSS	-	6.13***	6.13***	2.26	3.71**	-	0.15***	0.81***	-0.06	-0.57***	0.42***
	-	(2.89)	(2.89)	(1.4)	(2.3)	-	(3.39)	(7.71)	(-0.51)	(-6.91)	(4.34)
PI3-KPSS	0.02	6.53***	6.52***	2.62*	4.29***	-	0.15***	0.76***	-0.08	-0.59***	0.37***
	(0.17)	(3.3)	(3.27)	(1.82)	(3.22)	-	(3.37)	(9.83)	(-0.82)	(-7.32)	(4.32)
D. 1976-		Excess returns			Alphas				*q*5 Loadings		
	0	4	HL	FF3	FF5	Q5	MKT	ME	IA	ROE	EG
PI	8.39***	14.31***	5.92**	3.48	5.8***	1.21	0.18***	0.58***	-0.42**	-0.91***	0.93***
	(3.43)	(3.71)	(2.38)	(1.55)	(2.59)	(0.58)	(2.61)	(2.94)	(-2.56)	(-6.84)	(6.8)
PI3	8.53***	14.83***	6.3***	3.88*	6.46***	2.78	0.17**	0.52***	-0.45***	-0.94***	0.86***
	(3.47)	(3.95)	(2.68)	(1.84)	(3.36)	(1.32)	(2.55)	(3.33)	(-2.88)	(-7.13)	(6.75)
KPSS	8.39***	9.01***	0.62	2.28**	2.64***	0.44	0.02	-0.27***	-0.36***	-0.28***	0.42***
	(3.43)	(3.91)	(0.48)	(2.26)	(2.69)	(0.39)	(0.58)	(-3.24)	(-4.51)	(-4.1)	(5.74)
RDI	8.18***	13.41***	5.23**	2.54	5.84***	4.28**	0.15**	0.49***	-0.41***	-0.86***	0.52***
	(3.48)	(3.61)	(2.17)	(1.22)	(2.93)	(2.15)	(2.54)	(2.79)	(-3.03)	(-6.93)	(4.21)
<u>Difference</u>											
PI-KPSS	-	5.3**	5.3**	1.2	3.16	0.77	0.16***	0.86***	-0.06	-0.63***	0.51***
	-	(2.1)	(2.1)	(0.63)	(1.61)	(0.44)	(3.11)	(6.9)	(-0.48)	(-6.83)	(4.94)
PI-RDI	0.2	0.9	0.7	0.94	-0.03	-3.07*	0.03	0.1	-0.02	-0.05	0.42***
	(0.68)	(0.58)	(0.44)	(0.58)	(-0.02)	(-1.81)	(0.61)	(1.5)	(-0.15)	(-0.57)	(3.68)