Misvaluation of New Trademarks*

Po-Hsuan Hsu[a] Dongmei Li[b] Siew Hong Teoh[c] Kevin Tseng[d]

September 2018

Abstract

We find that firms with more new trademark registrations with the USPTO earn significantly higher abnormal stock returns. This return predictability is stronger in firms that are harder to value, such as larger and more opaque firms; firms with higher analyst earnings forecast dispersion, lower advertising expenses, and higher R&D spending; and firms with trademarks in new product/service categories. Abnormal returns are the greatest in the first year after registration, and may last up to five years. The evidence is consistent with investor limited attention. The stock market undervaluation is greater where the costs of paying attention is higher.

JEL Classification: E22, G11, G12, G14, O34, M31

Keywords: Trademarks, Exploratory trademarks, Stock returns, Limited attention, Uncertainty, Market efficiency

*We thank Allen Berger, Ling Cen, Yen-Cheng Chang, Si Cheng, James Choi, Gjergji Cici, Lauren Cohen, Jason Donaldson, Philip Dybvig, Zhenyu Gao, Armando Gomes, Radha Gopalan, David Hirshleifer, Ted Juhl, Ohad Kadan, Paul Koch, Shing-Yang Hu, Chao Jiang, Wenxi Jiang, Mark Leary, Hong Liu, Yiqing Lu, Felix Meschke, Albert Wang, Yanzhi Wang, Mike Wilkins, Jide Wintoki, Yizhou Xiao, Guofu Zhou, and seminar and conference participants at Chinese University of Hong Kong, National Taiwan University, NYU Shanghai, University of Dayton, University of Kansas, University of South Carolina, and Washington University in St. Louis for helpful discussions. We also thank Robert Stambaugh and Yu Yuan for sharing the mispricing factor returns and Kewei Hou, Chen Xue, and Lu Zhang for sharing the q-factor returns. We thank Yunan Liu and Tong Zhou for their research assistance.

[a] Faculty of Business and Economics, University of Hong Kong.
[b] Darla Moore School of Business, University of South Carolina, Columbia.
[c] Paul Merage School of Business, University of California, Irvine.
[d] School of Business, University of Kansas.

1. Introduction

Intellectual property (IP) is notoriously hard to value. In consequence, the balance sheets of U.S. firms do not include the value of internally generated IP intangibles, and instead, the associated costs of creating them are expensed on the income statement as they are incurred. The treatment of expenditures to generate IP in the same way as other operating expenses in the financial statements makes it hard for investors to value firms, especially in the current knowledge-based economy in which IP intangibles are increasingly more important (Lev 2001; Corrado and Hulton 2010; Peters and Taylor 2017).

There are many types of IPs, such as patents, trademarks, copyrights, and trade secrets. Existing IP studies primarily examine patents, and show that patents increase firm value, and patent-related metrics (such as number of patents, citations received, and patent originality) contain positive information about firm future fundamentals. However, Hirshleifer, Hsu, and Li (2013, 2018) find that the equity market tends to undervalue information contained in patent-related measures about future fundamentals. This may be due to the long road from patents to final products and the associated high uncertainty about the potential future cash flows that can be monetized from patents, and investors' limited information processing capacity.

In this paper, we examine whether investors make systematic mistakes in valuing one form of IP, new trademarks. Survey data suggest that trademarks are equally important assets, if not at times more important than patents, especially in low patent industries.[1] Nevertheless, there are few studies on trademarks in the academic literature. Furthermore, trademarks exist in a broader range

[1] According to the U.S. National Science Foundation's Business R&D and Innovation Survey (NSF BRDIS) in 2008, 15% (11%) of all firms surveyed rate trademarks (patents) as a very important form of IP protection. Among R&D firms, 60% rate trademarks as very important, while 41%, 33%, 50%, and 67% rate utility patents, design patents, copyrights, and trade secrets as very important, respectively. The most recent available NSF BRDIS in 2014 confirms the importance of trademarks, and also shows that both patents and trademarks have grown even more important in 2014 since 2008.

of firms and industries than patents.[2] Hall, Helmers, Rogers, and Sena (2014) report that trademarking is probably the most widely used form of IP protection as it is applicable to essentially any product or service. So investigating trademarks permits testing of the value of IP in a wider range of firms and industries beyond those covered by patents. Legal protection using patents is either infeasible or not meaningful in some industries such as in financial and other services industries.

Additionally, trademarks represent new products/services, which are the outputs at the end of the innovation process. The idea that trademarks reflect a kind of innovation is consistent with the Organization of Economic Cooperation and Development's (OECD) broader definition of innovation. Despite the urging of OECD and other governmental agencies that fund innovation activities to include trademarks as innovation, studies on trademarks remain sparse in the large innovation literature in economics and finance.

In summary, trademarks are an important and separate measure of innovative output from patents, and are especially relevant for the current client-oriented economy. We therefore study whether the equity market can correctly value newly registered trademarks.

According to the U.S. Patent and Trademark Office (USPTO), "a trademark (service mark) is generally a word, phrase, symbol, or design, or a combination thereof, that identifies and distinguishes the source of the goods (services) of one party from those of others." Although trademarks are probably not as hard to value as patents, this does not mean that valuing trademarks is straightforward. By the time a firm registers a new trademark, the associated *technical*

[2] Trademarks registered in service classes increased from 26.7% of all trademarks in 1992 to over 39.0% in 2009 (Graham, Hancock, Marco, and Myers 2013). Faurel, Li, Shanthikumar, and Teoh (2018) suggest that trademarks capture the product development of novel goods or services, and marketing innovations, and provide statistics on the prevalence of trademarks in high and low patent industries. See also Mendonca, Pereira, and Godinho (2004), Millot (2009), and Sandner and Block (2011) for further statistics about the prevalence of trademarks.

uncertainty of whether a product or service is viable would be resolved. However, valuation of a new trademark can still be challenging owing to demand risk (whether consumers like the new product/service or not) and competition risk (whether competitors have a better and cheaper product/service) associated with the new products/services protected by the trademark. Regarding demand risk, forecasting demand for a new product/service based on past records of existing ones may be especially unreliable for disruptive innovations.

An example of the uncertainties involved is the launch by the giant book retailer Barnes & Noble of Nook, the brand name of a new e-reader device in October 2009. This product was a failure, and Barnes & Noble lost a large share of the market to Apple, Samsung, Amazon, and Google.[3] Another example is Daimler Mercedes' Smart, a new brand from a joint venture between Swatch and Daimler Mercedes designed to create a new segment of the car market---a minicar market segment. Although almost 25,000 units were sold in its first appearance in the U.S. market (2008), the sales plummeted to about 15,000 units in the next year and was only 3,000 units in 2017.[4]

On the other hand, the new products associated with new trademarks have also sometimes been major successes. For example, Toyota's Lexus became a famous luxury brand in the automobile market, and gained the world's largest car manufacturer a substantial share of the high-end vehicle market.[5] Apple's iPhone is another famous success story. Since its original model was launched in 2007, its worldwide sales exceeded 6 billion units by the end of 2017.

Our study is the first to examine whether or not the stock market correctly values newly registered trademarks (as a proxy of new products/services). Overvaluation could occur for several

[3] http://www.nytimes.com/2013/02/25/business/media/barnes-noble-weighs-its-nook-losses.html
[4] http://carsalesbase.com/us-car-sales-data/smart
[5] https://www.forbes.com/sites/greatspeculations/2015/06/25/toyotas-lexus-strategy-seems-to-be-paying-off/#3302a1c51fdb

(non-mutually-exclusive) possible reasons. Investors might underestimate the product market risk and competition risk, or might overestimate the improvement in product quality that will be achieved by the new technology. Investors might also be naïve in interpreting marketing hype of new product launches. Furthermore, new products are subject to high uncertainty, and theory in general suggests that this leads to overvaluation when there is disagreement/overconfidence and limits to arbitrage (see, e.g., Miller 1977; Hong, Scheinkman, and Xiong 2006). These arguments imply a negative relation between new trademarks and future abnormal stock returns.

On the other hand, investors may undervalue new trademarks if some investors are inattentive to the potential future cash flows that the new products/services can earn (Hirshleifer and Teoh 2003; Hirshleifer, Lim and Teoh 2011). For example, investors might not fully adjust their beliefs to reflect the fact that a firm introducing a new product/service may indicate that the firm has favorable private information about its prospects. This reasoning implies a positive relation between firms' new trademarks and their future abnormal stock returns.

Our empirical tests use a large sample of 305,422 USPTO trademark registrations of U.S. public firms from 1976 to 2014. We measure a firm's new trademark activities each year as the number of trademarks registered in that year scaled by its total assets (TRAT). Each June, based on TRAT in the past year, we form three portfolios (low, middle, and high) and construct a hedge portfolio that is long the high TRAT portfolio and short the low TRAT portfolio. We then compute their value-weighted excess returns, industry-adjusted returns, and alphas from different factor models over the next year. The hedge portfolio yields an annualized excess return of 5.2% and annualized alphas of 7.8%, 7.0%, and 6.3% from the Fama-French 5-factor model (Fama and French 2015), the q-factor model (Hou, Xue, and Zhang 2015), and the mispricing factor model (Stambaugh and Yuan 2017), respectively. All are significant at the 1% level. The annualized industry-adjusted return of this hedge portfolio is 3.7% and significant at the 5% level. Furthermore, most of these return spreads are from the high TRAT portfolio. Collectively, these findings suggest that investors on average tend to undervalue newly registered trademarks.

We also find that the TRAT-return relation is stronger among larger firms, which suggests that a trading strategy based on our findings can provide substantial profits even after trading costs. Large firms tend to be more complex (see, e.g., Cohen and Lou 2012) and large firms' trademarks are more likely to be contested by competitors (see, e.g., Jones and Weingram 1996; Albuquerque 2009; Kim and Skinner 2012), which increases the difficulty of judging their value implications. The stronger predictability for larger firms is also consistent with anecdotal evidence that larger firms capture more network innovation gains than smaller firms, and investors failing to anticipate such division of the gains.[6]

Previous literature (e.g. Zhang 2006 and Kumar 2009) documents that cognitive biases tend to be stronger among hard-to-value firms. For example, investors with limited attention neglect relevant signals about value. Inattention is a more severe problem for hard-to-value firms because it may be challenging for investors to determine the relevance of different signals, causing neglect of those signals that actually are relevant. Regardless of whether the bias causing neglect of relevant signals derives from limited attention or other sources, we should see a stronger TRAT-return relation among hard-to-value firms. To test this possibility, we conduct independent double sorts on TRAT and each of four uncertainty-related variables: opacity of financial statements, analyst earnings forecast dispersion, R&D spending, and advertising spending. We expect a stronger TRAT-return relation among more opaque firms, and firms with high analyst forecast dispersion, high R&D spending, and low advertising expenditures.

[6] See, e.g., https://www.wsj.com/articles/the-problem-with-innovation-the-biggest-companies-are-hogging-all-the-gains-1531680310.

The evidence using portfolio sorts is supportive. The return predictability of TRAT is strong and significant among firms with greater uncertainty. In contrast, it is weak and often insignificant among firms with lower uncertainty. For example, the annualized Fama-French five-factor alphas of the value-weighted TRAT hedge portfolios is 11.3% and 12.7% among firms with high opacity and high analyst forecast dispersion, respectively, with *t*-statistics all above 4.3. In contrast, the corresponding annualized alphas among firms with low opacity and low analyst dispersion are only 1.2% and 4.2%, respectively, with much smaller *t*-statistics.

To see whether the predictive power of TRAT is incrementally robust to other well-known return predictors (such as size, book-to-market, momentum, asset growth, ROA, net stock issuance, idiosyncratic volatility, R&D/market equity, advertising/assets, skewness, short-term returns, patent/assets), we conduct Fama-MacBeth (1973) regressions including these known predictors as controls. We find that both the rank of TRAT and the logarithm of TRAT still significantly predict next period's return. Furthermore, similar to the findings in the tests using portfolio sorts, we find that the positive return predictability in the Fama-MacBeth regressions is also stronger among larger firms and firms with more uncertainty.

The TRAT effect is distinct from the patent effect on stock returns that has been documented in the prior literature, and holds among a much broader set of firms. We find that the trademark-return relation exists both within the set of firms that does have, and the set of firms that does not have newly granted patents. It is slightly stronger among non-patenting firms. Since most industries have very few patents, the coverage of the trademark effect is much broader. Furthermore, the TRAT effect is stronger among firms with exploratory trademarks, defined as new trademarks registered in classes in which a firm has never registered trademarks over recent years.

We find that the return predictability is strongest in the first year after portfolio formation. The effect is less robust in longer horizons, with alphas from the Fama-French 5-factor model, the q-factor model (Hou, Xue, and Zhang 2015), and the mispricing factor model showing effect for five years, and raw return and industry-adjusted return showing effects only for the first year.[7]

If the TRAT return predictability is driven by some systematic risk not captured by existing factor models, we may use the return on the TRAT hedge portfolio as a factor to capture the risk premium related to new trademarks (see Fama and French 1993). However, when we perform a two-pass characteristics versus covariances regression procedure (Daniel and Titman 1997) to test this, we find that the loading on the TRAT factor is not priced in the cross-section of stock returns. This suggests that the return predictability by TRAT may not be driven by a missing systematic risk factor.

Ours is not the first study to find return predictability using intellectual-property or innovation-related variables. Several studies have provided evidence suggesting that stock prices underreact to the information contained in firms' innovative activities measured by R&D expenditures, patents, and patent-related outputs.[8] Our study goes beyond R&D and patents by studying trademarks as another important form of IP intangibles that investors with limited attention have difficulties valuing appropriately. Even in a domain where technical issues are resolved by having trademarks, investors may still fail to process information about IP adequately because of market-related (product demand, suppliers, and competitors) uncertainty.

Previous studies on R&D and patents miss industry sectors that do not use patents to protect

[7] In untabulated results, the alphas from the Carhart model and the Carhart plus the liquidity factor (Pastor and Stambaugh 2003) model are smaller and no longer significant over years 2-4 for the hedge portfolio.

[8] For patents-related studies, see, e.g., Pakes (1985), Deng, Lev, and Narin (1999), Penman and Zhang (2002), and Hirshleifer, Hsu, and Li (2018). For R&D-related studies, see, e.g., Lev and Sougiannis (1996), Chan, Lakonishok, and Sougiannis (2001), Eberhart, Maxwell, and Siddique (2004), Lev, Sarath, and Sougiannis (2005), Cohen, Diether, and Malloy (2013), and Hirshleifer, Hsu, and Li (2013).

IP, such as service sectors that include financial and information service industries, and consumer sectors such as the food, beverage, and retail industries.[9] By including a much wider representation of industries, our study contributes by providing a fuller picture about the valuation of intellectual property in the innovation literature and the importance of intangibles to the stock market.

This paper is one of a few recent studies that hand collected a large sample of trademarks from the USPTO, and we are the first to examine the stock market return predictability of new trademarks.[10] Existing published studies on trademarks focus on the stock market value relevance of a relatively small sample of trademarks that are from larger firms, in specific industries or registered in foreign countries such as Europe or Australia.[11] These small sample studies are less appropriate for studying stock return predictability which is known to be driven by firm size (Fama and French 1993), industry (Fama and French 1997), and country (Hou, Karolyi, Kho 2011).

2. Trademark basics and value

A trademark is a brand that allows a firm to distinguish and protect its related product/service. According to the USPTO, "Trademarks, copyrights, and patents protect different types of IP. A trademark typically protects brand names and logos used on goods and services. A

[9] Some recent studies examine the effect of brand capital proxied by advertising expenditures on firm value and stock returns (e.g., Vitorino 2013; Belo, Lin, and Vitorino 2014). However, advertising expenditures are only reported in a limited set of industries and do not represent the full effect of trademark values.

[10] Block, De Vries, Schumann, and Sandner (2014) study how trademark applications of start-ups affect valuations by venture capitalists. Faurel et al. (2018) construct a dataset of 123,545 trademark registrations by S&P 1500 firms from 1993 to 2011 to study the relation between trademarks and firm accounting performance (sales and ROA) and how firms motivate trademark creation using incentive structures in CEO compensation.

[11] For example, Bosworth and Rogers (2001) examine a cohort of 60 large Australian firms in 1996. Greenhalgh and Rogers (2006) examine a sample of 673 large UK firms in 1996-2000. More recently, Greenhalgh, Rogers, Schautschick, and Sena (2011) examine 50,000 UK firms in 2000-2008. The only three studies that examine the effect of U.S. trademarks on the stock market are Fosfuri and Giarratana (2009), Sandner and Block (2011), and González-Pedraz and Mayordomo (2012). Fosfuri and Giarratana (2009) is a case study examining only Coca Cola and Pepsi in 1999-2003. Sandner and Block (2011) examine the relation between Tobin's q and trademarks of large public firms (with revenues of at least 400 million Euros) in Europe and the U.S. in 1996-2002. González-Pedraz and Mayordomo (2012) examine the effects of trademarks on Tobin's Q and the trademark announcement abnormal stock returns in only 16 U.S. commercial banks.

copyright protects an original artistic or literary work. A patent protects an invention. For example, if you invent a new kind of vacuum cleaner, you would apply for a patent to protect the invention itself. You would apply to register a trademark to protect the brand name of the vacuum cleaner. And you might register a copyright for the TV commercial that you use to market the product."

Although registration of a trademark with the USPTO is not mandatory, it has several advantages, such as notice to the public of the registrant's ownership of the mark and exclusive right to use the mark on the goods/services listed in the registration. A firm may file a trademark application with the USPTO in some particular product/service classes.[12] Once approved, the trademark is registered and disclosed in the *Official Gazette*, a weekly publication by the USPTO. After a trademark is registered, the firm can use the ® symbol with their trademark and obtain legal trademark protection.[13]

After a firm successfully registers a trademark, it can hold permanent ownership of the trademark if it maintains the mark beyond the sixth year from the registration date and renews the trademark every 10 years from the registration date. The maintenance and renewal process of a trademark requires the firm to submit a specimen or proof to show that a trademark is currently used for each class of goods or services in which the trademark has been registered for.[14] The registration of a trademark therefore carries a signal that the new product/service is a viable one.

Consumers rely on brand names afforded by trademarks to facilitate their search and purchase decisions, especially in circumstances where search costs and information asymmetry

---

[12] There are 45 product/service classes: http://www.wipo.int/classifications/nice/nclpub/en/fr/home.xhtml. A trademark can be filed in one or multiple classes. However, 86.5% of trademark applications are registered in a single class (Graham et al. 2013).

[13] The USPTO's URL (https://www.uspto.gov/sites/default/files/documents/BasicFacts.pdf) contains basic facts about trademarks, and a summary is available in the online appendix to this paper.

[14] Other materials such as the promotion documents or advertisements that demonstrate that the trademark is in use are also acceptable. According to Graham et al. (2013), 47.1% of trademarks registered were maintained after the sixth year. Failure to file the required maintenance and renewal documents in the specified time periods will result in the cancellation of the trademark or invalidation of legal protection.

are high (Graham, Hancock, Marco, and Myers 2013). Registered trademarks thus function as a signaling tool to create awareness of the product/service and its quality and to differentiate from other products/services to achieve a competitive advantage (e.g., Besen and Raskind 1991; Landes and Posner 1987). Persistent promotion of trademarks helps maintain and enhance brand awareness and engender loyalty and trust (Crass, Czarnitzki, and Toole 2016). The consequent market power allow the firm to charge a price premium and earn higher profits. More importantly, the registered trademark confers legal protection such that the firm can sue other individuals and entities to prevent economic loss from competitors' similar marks, images or symbols that can cause customer confusion and erode their market share. Lastly, when a trademark survives the maintenance and renewal process, it becomes even more valuable as it reflects the goodwill embodied in a firm's products and services (Sandner and Block 2011).

3. The data, trademark measure, and summary statistics

3.1. Trademark data and measure of trademark intensity

The initial sample of 4,792,421 trademark registrations is obtained from the USPTO Trademark Case Files Dataset between 1970 and 2015.[15] We restrict our sample to registered trademarks, which are trademarks that are actually in use by the trademark assignees (owners). We also downloaded information about trademark characteristics such as the assignees, product classification, prosecution history, renewal and maintenance history, and prior registration.

Following Hsu, Li, Liu, and Wu (2017), trademark assignees are manually matched to U.S. public firms in the Compustat/CRSP database based on name, location, and industry using the Levenshtein Algorithm (a string matching method) and further manual checking from online

[15] The USPTO Trademark Case Files Dataset (updated in 2015) is downloaded from https://www.uspto.gov/learning-and-resources/electronic-data-products/trademark-case-files-dataset-0.

searches such as Bloomberg Businessweek. We also assign subsidiaries' trademarks to their parent company.

Figure 1 plots annual aggregate number of trademarks registered and the number of trademarks registered per firm by public firms with at least one trademark registered in each year in Panels A and B (red solid line), respectively. We find that the number of trademarks registered by public firms has been growing over time and peaked in 2002 with 13,252 total registered trademarks. The number of trademarks registered per firm also reveals an increasing pattern and peaked in 2008 with 5.4 trademarks per firm.

Our proxy for a firm's new trademark activities in year *t* is defined as the number of trademarks registered by the firm in calendar year *t* scaled by its total assets (in millions) in fiscal year ending in calendar year *t* and is labelled as TRAT. We scale a firm's trademarks by its total assets to control for size effects, following the literature on the effects of R&D expenditures and patents on firm value (Griliches 1981; Hall 1993; Hall, Jaffe, and Trajtenberg 2005). For a firm that does not register any trademark in a year, we set its TRAT to zero for that year. Similar to prior studies that construct R&D- or patent-based return predictor, we find that many firms do not have trademarks registered every year. However, in terms of economic significance, trademark firms account for 76% of the market capitalization of the entire sample.[16] Therefore, firms with non-zero newly registered trademarks are economically important in the economy. In subsequent return predictability analyses, we focus on firms with non-zero newly registered trademarks in the past year since they capture the most recent trademark activities that are more likely to be misvalued by the market.

---

[16] The percentage is even higher in the sample of firms with non-zero R&D or in the sample of firms with non-zero patents.

3.2. Stock returns and accounting data

Our sample consists of firms in the intersection of the Compustat database, the CRSP database (Center for Research in Security Prices), and the trademark database described above. Furthermore, we restrict the sample from 1976 to 2014 because the coverage of R&D expenses is low before 1975 as firms had more discretion in determining what goes into R&D expenses then (The accounting treatment of R&D expense reporting was standardized in 1975 following Financial Accounting Standards Board Statement No. 2.) All domestic common shares trading on NYSE, AMEX, and NASDAQ with accounting and returns data available are included except firms with four-digit standard industrial classification (SIC) codes between 6000 and 6999 (finance, insurance, and real estate sectors) or two-digit SIC codes beginning with 49 (utility). We obtain the stock returns data of sample firms from the CRSP database and their accounting data from the Compustat database. We further exclude closed-end funds, trusts, American Depository Receipts, Real Estate Investment Trusts, units of beneficial interest, and firms with negative book value of equity following Fama and French (1993). To mitigate backfilling bias, we require firms to be included in the Compustat database for two years before including them in our sample. For some of our tests, we also obtain analyst earnings forecast data from the Institutional Brokers Estimate System (IBES) database.

3.3. Summary statistics

In Table 1 (Panel A), we report summary statistics for portfolios formed on TRAT. Specifically, at the end of June of year t, we assign firms with non-zero TRAT into the low (L), middle (M), and high (H) TRAT portfolios based on the 33rd and 67th percentiles of TRAT in year $t-1$. In addition, we assign firms with no trademarks registered in year $t-1$ to the "None" portfolio for comparison. On average, there are 3,217 firms each year from 1976 to 2014, and 1,991 of them are in the "None" group. The three TRAT portfolios are well diversified with the number of firms ranging from 408 to 409.

Panel A reports the time series average of cross-sectional median and mean of TRAT and other firm characteristics that are known return predictors or additional controls. The median (mean) TRAT ranges from 0.16% (0.17%) to 3.14% (4.92%) for the three TRAT portfolios. There is considerable variation across the three TRAT portfolios in size, measured as the market capitalization at the end of June in year *t*. The median (mean) *SIZE* of the low, middle, and high TRAT portfolios is $2,316 million ($9,298 million), $493 million ($1,707 million), and $124 million ($376 million), respectively.

The measures for other known predictors or additional controls used in tests later in the paper include the following. Book-to-market, *BTM*, is the ratio of book equity of fiscal year ending in year $t - 1$ to market equity at the end of year $t - 1$. Momentum *MOM* is the previous eleven-month returns with a one-month gap between the holding period and the current month. Idiosyncratic volatility *IVOL* is measured at the end of June of year *t* as the standard deviation of the residuals from regressing daily stock returns on the Fama-French three-factor returns over the previous 12 months with a minimum of 31 trading days. Skewness *SKEW* is measured at the end of June of year *t* using daily returns over the previous 12 months with a minimum of 31 trading days. For the remaining accounting-based return predictors and additional accounting controls, the accounting items are measured in fiscal year $t - 1$. Return on assets *ROA* is the income before extraordinary items plus interest divided by lagged total assets. Asset growth *AG* is the change in total assets divided by lagged total assets. R&D intensity *RDME* is the R&D expenses divided by market equity at the end of calendar year $t - 1$, and advertising intensity *ADA* is the advertising expense divided by book value of asset.[17] Net stock issuance *NS* is the change in the natural log of the split-adjusted shares outstanding.

The above variables do not exhibit much variation across the TRAT portfolios, except that *ROA* decreases with TRAT and *SKEW* increases with TRAT. However, Panel B shows that the time series averages of the cross-sectional correlations between TRAT and these two variables are not statistically significant. Furthermore, high skewness is known to predict lower returns, whereas our evidence discussed later is that trademark intensity predicts higher returns. Panel B also shows that TRAT generally has low correlations with firm characteristics though the correlation is significantly negative with size, and significantly positive with R&D intensity, advertising intensity and idiosyncratic volatility. The magnitude of the correlation with *IVOL* is the largest at 0.29, so we control for *IVOL* in later tests.

Table 2 reports pooled summary statistics for *TRAT* in Panel A and trademark counts in Panel B for the sample of firms with non-zero trademarks registered by industries using the Fama and French (1997) 48 industry classifications. Recreation (including toys), Textile, Consumer Goods, and Apparel industries have the highest average TRAT; a sample firm in these industries with total assets of $100 million register 2.5 to 4.3 trademarks per year on average. On the other hand, the coal industry has the lowest average TRAT of 0.002. In addition, there are large cross-sectional variations in TRAT and trademark counts across industries and within industry. For example, in Panel B, the 25th percentile of trademark counts is between 1 and 2, and the 75th percentile ranges from 2 to 15. To mitigate the concern that our results may be driven by industry effects, we also report industry-adjusted returns in all the portfolio analyses and control for

[17] We scale R&D expense and advertising expense differently following the strongest form of return predictors related to these variables as identified in the existing literature. This ensures that we test for the incremental robustness of TRAT beyond existing returns predictors already in the literature.

industry effects in the Fama-MacBeth regressions. We also perform portfolio analysis by sorting firms within industry as a robustness check.

4. Return predictive power of trademarks

In this section, we examine whether TRAT predicts stock returns and how systematic risk and information uncertainty may contribute to such predictability. To test these hypotheses, we conduct portfolio sorts first to illustrate the abnormal returns and then Fama-MacBeth regressions to illustrate the robustness of the TRAT effect to other return predictors.

4.1. Portfolio sorts

4.1.1 TRAT effect

The three TRAT portfolios (*L*, *M*, and *H*) and the *None* portfolio are formed as described earlier in Section 3.3. We also form a high-minus-low (H–L) portfolio ("hedge portfolio") that is long the high TRAT portfolio and short the low TRAT portfolio. After forming these portfolios, we hold them for the next twelve months (from July of year t to June of year t+1) and compute their value-weighted monthly returns. Since the USPTO fully discloses trademarks registered in the weekly *Trademark Official Gazette*, the TRAT measure in year t – 1 is publicly observable at the time of portfolio formation. Table 3 Panel A reports the excess returns and industry-adjusted returns for each of the three TRAT portfolios, the *None* portfolio and the hedge portfolio. Excess returns are calculated as the average monthly returns in excess of one-month Treasury bill rate, and the industry-adjusted return is calculated based on the difference between firm's monthly return and the value-weighted average of all firms' monthly returns in the same Fama and French 48 industry group.

Table 3 Panel B examines the relation between TRAT and abnormal portfolio returns. Specifically, we perform time-series regressions of the TRAT portfolios' excess returns on different sets of asset pricing factors: the Fama-French (2015) five factors (the market factor–MKT, the size factor–SMB, the value factor–HML, the profitability factor–RMW, and the investment factor–CMA); the q-factors of Hou, Xue, and Zhang (HXZ 2015), which include the market factor, the size factor, the investment factor, and the profitability factor; and the mispricing factors of Stambaugh and Yuan (SY 2017), which include the market factor, the size factor, and the mispricing factor (management–MGMT and performance–PERF). Controlling for these factors helps ensure that the TRAT effect is not explained by the well-known risk or mispricing factors. Panel C presents the R-squares of all time-series regressions in Panel B.

The excess returns, industry-adjusted returns, and alphas from different factor models increase monotonically with TRAT, implying a positive TRAT-return relation. Furthermore, the TRAT effect is economically and statistically significant. The monthly value-weighted alphas of the hedge portfolio range from 0.53% to 0.65% with *t*-statistics above 3.3. Furthermore, these alpha spreads are mainly driven by the high TRAT portfolios, ranging from 0.48% to 0.62% with *t*-statistics above 3.2. The hedge portfolio's industry-adjusted return is 0.31% and significant at the 5% level. Consistent with the idea that firms with no registered trademark carry lower systematic risk or encounter less mispricing, the industry-adjusted return and alphas of the "None" group are small and insignificant.

Overall, these results suggest that high TRAT firms are undervalued relative to low TRAT firms, and the TRAT effect is incremental to industry effects and recently developed risk and mispricing factors. Furthermore, we construct value-weighted portfolios (which put more weight on larger firms) and rebalance them only once a year. Therefore, these abnormal returns are likely to survive typical transaction costs.

Next, we examine the persistence of the rank of TRAT and the persistence of the return predictability of TRAT. If the rank of TRAT is very persistent, investors should be able to learn from the past and we would not be able to detect mispricing over a long sample period. Panel D of Table 3 reports the probability of staying in the same TRAT group or moving to any of the other three TRAT groups in the next year. Although around half of the firms stay in the same TRAT portfolio, there is considerable movement across TRAT portfolios in the next year so that investor learning from past TRAT may be difficult. For example, for a firm in the high TRAT portfolio in year *t*, the probability of staying in the high TRAT portfolio in year *t*+1 is 51.11%, and the probability of moving to the *None*, low, and middle TRAT portfolios in year *t*+1 is 30.40%, 1.21%, and 17.28%, respectively.

The evidence on the TRAT predictability of returns over a longer horizon is mixed. Panel E of Table 3 presents the hedge portfolio's average monthly excess returns, industry-adjusted returns, and alphas from different factor models over each of the six post-sorting years. We find that the hedge portfolio's returns and alphas are the largest in the first year, and generally decline thereafter to about a third of the first-year magnitude. The excess and industry-adjusted returns are not statistically significant in subsequent years. However, the alphas remain significant though smaller and dissipate only in year 6. The persistence of the alphas are not robust to asset pricing models; for example, the alphas for the Carhart four-factor model and the Carhart four-factor plus the liquidity factor model are not significant beyond the first year (untabulated). Given the mixed result on the persistence of the return predictability, we explore in Section 4.1.3 whether TRAT is systematically priced in the cross-section.

To address the concern that the return predictive ability of TRAT may be driven by the variation in the denominator, total assets, we sort firms with at least one trademark registered over the past year into terciles based on their total assets. We find that total assets do not generate a significant return spread, and that the total assets hedge portfolio's abnormal returns are less than half of those of the TRAT hedge portfolio (untabulated).

We also examine how the returns of the hedge portfolio vary over time. Figure 2 plots the cumulative value-weighted returns of the hedge portfolio from July of 1977 to December of 2015. The hedge portfolio's cumulative returns are upward trending, with a spike in year 2000 (the internet bubble period). However, excluding year 2000 barely changes the time-series average returns of the hedge portfolio.

4.1.2 Interaction of TRAT effect with size and uncertainty

We next test the interaction of the TRAT effect with size and proxies of uncertainty via independent double sorts. We examine the interaction with size to investigate whether the TRAT effect is concentrated among very small firms where trading costs are high. We examine the interaction with uncertainty proxies to investigate whether the TRAT effect is stronger in situations where cognitive biases, such as limited attention, may be more severe.

The uncertainty proxies include opacity of financial statements, analyst earnings forecast dispersion, R&D spending, and advertising spending. Opacity and analyst forecast dispersion are two common proxies for uncertainty (Hirshleifer, Hsu, and Li 2018). Opacity is estimated as the three-year moving sum of the absolute value of discretionary accruals (Hutton, Marcus, and Tehranian 2009), and is an inverse proxy of the transparency of financial statement information. Analyst forecast dispersion is defined as the standard deviation of analysts' EPS forecasts scaled by the absolute value of mean forecasts. R&D expenses are scaled by sales, and advertising expenses are scaled by total assets. R&D activities lead to uncertainty (Hall 1993; Lev and Sougiannis 1996; Aboody and Lev 1998; Chan, Lakonishok, and Sougiannis 2001); when they relate to break-through innovation, they may be disruptive and take longer for the market to understand and adopt. Moreover, R&D activities create information asymmetry and lead to insiders' trading gain (Aboody and Lev 2000). Hence trademarks of R&D-intensive firms are more likely to reflect innovative products with higher complexity and uncertainty. Lastly, firms with lower advertising expenses are less known, and investors tend to have more difficulties judging their new products' market potentials or pay less attention to these firms' new trademarks. For example, Grullon, Kanatas, and Weston (2004) and Lou (2014) show that advertising expenses can attract investors' attention.

To perform these tests, at the end of June of year t, we sort firms into two groups based on each of the characteristics and into three groups based on TRAT separately. The sorting variables are measured in year $t - 1$ except size, which is measured as market capitalization at the end of June of year t. In addition, size groups are based on NYSE median breakpoints, opacity, analyst dispersion, and advertising groups are based on the median of all firms, and R&D groups are based on whether firms have non-missing R&D expenses/sales (active R&D group includes firms that have reported R&D expenses). The intersection results in six portfolios for each firm characteristic. We also form a high-minus-low TRAT portfolio within each characteristic subgroup. We then hold these portfolios over the next twelve months (July of year t to June of year $t + 1$) and rebalance them every year. All portfolios are value-weighted to mitigate the effect of small firms. Similar to Table 3, we calculate the average monthly excess returns, industry-adjusted returns, and alphas estimated from the same set of factor models for these portfolios.

Table 4 presents the results from these independent double sorts. The hedge portfolio's returns and alphas are substantial and significant for larger firms, firms with higher opacity, firms with higher analyst dispersion, firms with lower advertising expenses, and R&D-active firms, but are small and often insignificant in the other subgroups. For example, the monthly average excess returns, industry-adjusted returns, and alphas of the TRAT hedge portfolio are large and significant and range from 0.39% to 0.91% for the large sub-group, whereas they are small and often insignificant, ranging from 0.00% to 0.45% for the small sub-group. The TRAT hedge portfolio's excess return, industry-adjusted return, and alphas are large and significant in the high-opacity subsample, ranging from 0.66% to 0.94%. In contrast, these returns and alphas in the low-opacity subsample are smaller and often insignificant, ranging from 0.09% to 0.24%. Similarly, the hedge portfolio's excess return, industry-adjusted return, and alphas are large and significant among low advertising firms, ranging from 0.43% to 0.89%. In contrast, these returns are much smaller and often insignificant among high advertising firms.

We also verify that these contrasts are not due to the difference in the TRAT spreads. As shown in Table 4, the spread in TRAT does not vary much across the subsamples and is very similar to that in the single sort (Table 2).

A stronger TRAT-return relation among large firms suggests that our finding is not due to market frictions and a trading strategy based on firms' new trademarks likely provides significant returns in excess of trading costs. Furthermore, the results are consistent with a limited attention explanation. Paying attention is more costly for firms that are more opaque and advertise less. Firms with higher analyst dispersion and higher R&D intensity tend also to be more complex and so more challenging for investors with limited attention to understand. Overall, these tests provide fairly strong support for the conjecture that behavioral bias exacerbated by uncertainty contributes to the return predictive power of TRAT.

4.1.3 Is the TRAT effect priced?

In this section, we perform additional analyses to examine the possibility that the TRAT effect is driven by some systematic risk not captured by the factors we have considered so far. If the high-minus-low portfolio we construct in Table 3 creates significantly positive monthly excess returns and alphas, it may be considered as a mimicking portfolio that reflects the risk compensation for bearing one unit of risk exposure to a systematic risk related to new trademark intensity (see Fama and French 1993). For convenience, we refer to the monthly returns on the high-minus-low TRAT portfolios as the "TRAT factor." We employ a two-pass procedure to test if the TRAT factor is priced in the cross-section of stock returns (Daniel and Titman 1997). A significantly priced TRAT factor will support a risk-based explanation for the TRAT effect.

We conduct the test as follows. First, for stock *i* in month *t*, we estimate its exposure to the TRAT factor, $\beta_{i,t}^{TRAT}$, by regressing its monthly excess returns from month $t-59$ to month *t* on the corresponding returns of the TRAT factor and different combinations of the other factors that we have used in Section 4.1.1. Second, for each month *t*, we conduct a cross-sectional regression of stocks' monthly excess returns on their TRAT betas and other betas, such as market betas, estimated from the models used in the first step. The coefficient on $\beta_{i,t}^{TRAT}$ serves as an estimate of the risk premium (known as "lambda") associated with the TRAT factor in month *t*. Lastly, we test the significance of the risk premium by the mean and standard deviation of the time series coefficients on β^{TRAT}. A statistically significant estimate of the risk premium indicates that our TRAT effect is priced in the cross-section.

The results reported in Table 5 indicate that the coefficient on β^{TRAT} (from the second pass) is consistently insignificant across various models used in the first pass: Model 1 includes the market factor (MKT) and the TRAT factor, Model 3 includes the TRAT factor and the Fama and French (2015) five factors, and Model 5 includes the TRAT factor and the factors from the q-factor model (Hou et al. 2015). Models 2, 4, and 6 are the same as Models 1, 3, and 5, respectively, except that we include an intercept in estimating the betas.[18] The fact that the TRAT factor is not priced in various models suggests that there is little support for the existence of an unspecified systematic risk related to new trademarks.

In summary, our results from sorted portfolios and a two-pass procedure cast doubt on the likelihood that the TRAT effect is driven by some unknown systematic risk associated with new trademarks.

4.1.4 TRAT effect and exploratory trademarks

As mentioned earlier, firms sometimes register new trademarks in classes in which they have never registered trademarks over recent years. These are exploratory marks that represent uncharted waters and involve more uncertainty, and hence may be more likely to be mispriced by the market. Therefore, we expect a stronger TRAT effect if the newly registered trademarks are more exploratory.

To test this hypothesis, at the end of June of year t, we split the sample into exploratory and non-exploratory subsamples based on whether the new trademarks registered in year $t-1$ contain at least one exploratory trademark. We define a trademark as an exploratory one if the firm has not registered any marks in this mark's class assigned by the USPTO over the last 10 years (i.e., year $t-11$ to $t-2$).[19] We also independently form three TRAT portfolios as before. We find

[18] The models used in the second pass correspond to those used in the first pass. For example, if we include an intercept in the first pass in estimating individual stock's monthly betas, we also include an intercept in the second pass in estimating the risk premium via monthly cross-sectional regressions.

[19] As mentioned before, there are 45 product/service classes in the USPTO classification system for trademarks. The

that the TRAT return spread is much larger among firms with new exploratory trademarks. Table 6 presents the results.

The monthly value-weighted excess return and industry-adjusted return of the TRAT hedge portfolios within the exploratory subsample are 0.52% and 0.40%, respectively. Both are significant at the 5% level. The alphas (of the hedge portfolio) estimated from the three different factor models range from 0.63% to 0.71% with *t*-statistics above 3. In contrast, the TRAT-return relation is much weaker in the non-exploratory subsample. The excess return and industry-adjusted return of the TRAT hedge portfolio are insignificant and smaller (0.30% and 0.16%). The alphas are also smaller, ranging from 0.34% to 0.41% with lower *t*-statistics. The TRAT spread is similar across these two subsamples. Therefore, this contrast is not driven by the spread in TRAT itself. Furthermore, the average size of the TRAT portfolios are slightly larger among the exploratory subsample.

4.2. Fama-MacBeth regressions

4.2.1 TRAT effect

We next examine the ability of TRAT to predict the cross section of stock returns using monthly Fama-MacBeth regressions to ensure that the positive TRAT-return relation is incrementally robust to other known predictors. This analysis allows us to control more extensively for other characteristics that can predict returns. To correspond this analysis to the analysis using value-weighted portfolio strategy, we use weighted least square in the Fama-MacBeth regressions.

Table 7 shows the time-series average slopes (in percentage) and their *t*-statistics from the monthly cross-sectional regressions. We use the tercile rank of TRAT (*Rank(TRAT)*) and the

average ratio of the number of exploratory trademarks to the number of new trademarks is almost 60% in the exploratory subsample.

natural log transformation of TRAT (*Ln(TRAT)*) to address skewness in TRAT.[20] As in Fama and French (1992), we allow for a minimum six-month lag between the accounting-related control variables and stock returns to ensure that the accounting variables are fully observable to investors. Specifically, for each month from July of year t to June of year $t + 1$, we regress monthly returns of individual stocks on TRAT of year $t - 1$ with or without other control variables. We winsorize all independent variables at the 1% and 99% levels to reduce the outlier effect and standardize all independent variables to zero mean and one standard deviation to facilitate the comparison.

Panel A of Table 7 presents the univariate regression of future returns on TRAT. The slopes on TRAT rank and *Ln(TRAT)* are 0.21% ($t = 2.29$) and 0.15% ($t = 2.41$), respectively. These results are consistent with our finding in single portfolio sort that TRAT significantly and positively predicts stock return. Panel B of Table 7 provides the results from multivariate regressions for different model specifications. In each model, we include the industry fixed effects based on Fama and French 48 industry classifications to mitigate the effect of unobservable industry characteristics on stock returns. We also winsorize all independent variables at the 1% and 99% levels, and standardize all independent variables to zero mean and one standard deviation to facilitate the comparison. We omit the slopes on the industry dummies in the tabulations for brevity.

Models 1 and 2 control for asset growth (*AG*), idiosyncratic volatility (*IVOL*), skewness (*SKEW*), short-term return reversal (*REV*), advertising intensity (*ADA*), book-to-market (*BTM*), R&D intensity (*RDME*), size, momentum (*MOM*), net stock issuance (*NS*), return on assets (*ROA*) and industry dummies. Size, book-to-market, R&D intensity, and advertising intensity are in the natural log form to reduce the skewness associated with these measures. As discussed earlier, all

[20] The logarithmic transformation of innovation-related variables is common in the literature (see Lerner (1994), Aghion, Van Reenen, and Zingales (2013), and Hirshleifer, Hsu, and Li (2018)).

accounting-related control variables are measured in fiscal year ending in year $t - 1$. Size, *IVOL*, *SKEW* are measured at the end of June of year t. *REV* is lagged monthly returns. The slopes on *Rank(TRAT)* and *Ln(TRAT)* are 0.09% ($t = 2.39$) and 0.12% ($t = 3.54$), respectively. The slopes on the other control variables are generally consistent with previous studies (some inconsistencies are due to the weighted-least-square method.). We include firms with missing R&D or missing advertising expenses in the regressions by setting their *RDME* and *ADA* to zero.

Models 3 and 4 present the results with three additional control variables: *RDME* in year $t - 2$, the natural log of total assets (*Ln(Assets)*), and the number of patents granted in year $t - 1$ divided by total assets in fiscal year ending in year $t - 1$. Controlling for further lagged *RDME* ensures that the TRAT effect is not driven by the persistent return predictive power of *RDME*. Controlling for *Ln(Asset)* helps address the concern that the TRAT effect is simply driven by the asset size effect since asset is the denominator in constructing TRAT. Controlling for patent intensity helps address the concern of the correlation between trademark and patent activities since both are popular tools to protect firms' IP. The results are robust to these additional controls. In fact, the slopes on *Rank(TRAT)* and *Ln(TRAT)* remain the same in levels, but with slightly higher *t*-statistics.

We also report the annual averages of monthly slopes on *Rank(TRAT)* and *Ln(TRAT)* from the multivariate regressions (Models 3 and 4) in Figure 1 to examine how the TRAT effect correlates with aggregate trademarks (Panel A) and trademarks per firm (Panel B). We find that the TRAT slopes do not highly correlate with trademark activities. Specifically, the correlation coefficient between aggregate trademarks and the annual average slope of TRAT is only 0.05 for *Rank(TRAT)* and 0.09 for *Ln(TRAT)*. Similarly, the correlation between trademarks per firm and the annual average slope of TRAT is only −0.09 for *Rank(TRAT)* and 0.13 for *Ln(TRAT)*.

Overall, the results presented in Table 7 and Figure 1 indicate that the predictive power of TRAT is distinct from, and robust to the inclusion of other commonly known return predictors, innovation-related variables, and industry effects.[21] And the TRAT effect is not driven by time trends in trademark activities and is more likely driven by market undervaluation of new trademarks.

4.2.2 Interaction of TRAT effect with size and uncertainty

To examine the robustness of the interaction between the TRAT effect and size and uncertainty previously identified through double sorts, we use subsample Fama-MacBeth regressions with the previous controls for the other well-known return predictors. We use *Rank(TRAT)* in the sub-group Fama-MacBeth regressions to reduce noise from the continuous TRAT measure.

Table 8 presents the results from Fama-MacBeth regressions within subsamples split by size and the uncertainty proxies used in Table 4. We use Model 3 in Table 7 Panel B as our main specification, which controls for different sets of well-known return predictors.

Similar to Table 4, we first form subsamples based on firms' size, opacity, analyst dispersion, advertising intensity, or R&D activity. The results in Table 8 show a sharp contrast in the trademark effect across the subsamples even after we control for well-known return predictors and industry effects. For example, the slopes on *Rank(TRAT)* are 0.08% (t = 2.61), 0.31% (t = 2.96), 0.17% (t = 1.65), 0.10% (t = 2.25), and 0.12% (t = 2.40) among large firm, more opaque firms, high dispersion firms, R&D-active firms, and low advertising firms, respectively. In contrast, their counterparts are only 0.06% (t = 1.31), −0.09% (t = −1.56), 0.10% (t = 1.88), −0.02%

[21] In addition, we also control for SG&A/assets and find almost identical results (unreported).

($t = -0.42$), and 0.03% ($t = 0.52$) among small firms, less opaque firms, low dispersion firms, R&D-inactive firms, and high advertising firms.

Table 8 thus confirms the findings from double-sorted portfolios for the cross-sectional return predictive power of TRAT. Taken together, consistent with our hypotheses, both portfolio sorts and Fama-MacBeth regressions provide support for a more pronounced trademark-return relation among firms with higher uncertainty. These findings are consistent with a limited attention explanation for the ability of TRAT to predict abnormal returns.

4.2.3 TRAT effect and exploratory trademarks

Similar to subsection 4.1.4, we examine how the TRAT effect varies with exploratory trademarks controlling for all the well-known return predictors. Table 9 reports the results from monthly Fama-MacBeth cross-sectional regressions within the exploratory and non-exploratory subsamples as formed in subsection 4.1.4. Consistent with the portfolio sorts, we find that the TRAT-return relation is positive and significant in the exploratory subsample, but is smaller and insignificant in the non-exploratory subsample. In untabulated results, we find similar patterns when we define a new trademark as an exploratory mark if the firm has never registered any marks in this new mark's class or over the last five years (instead of ten years used in Table 9). Therefore, the contrast is robust to the horizon used to define exploratory trademarks.

4.2.4 TRAT effect and patent activity

In this subsection, we study the interaction between trademarks and patents. As discussed earlier, since both trademarks and patents are popular tools to protect IP, they may be correlated with each other. Furthermore, patents may culminate in trademarked products/services as outputs at the end of the innovation process, so the return predictability of trademarks may derive in part from the predictability of patents. Therefore, we control for patent intensity in previous regressions. Since some trademark firms have no patents, we divide the sample into a "No Patent" sample (with zero patents granted over the prior year) versus a "With Patent" sample (with patents granted over the prior year) and rerun the Fama-MacBeth regressions for the two subsamples. Trademarks are more widely used than patents in protecting IP, so the No Patent sample is larger than the With Patent sample. Since patents are more often used to protect new technology, while trademarks are more often used to protect new products/services, we expect that the TRAT effect can exist in firms with *and* without patents.

Table 10 shows that the trademark-return relation indeed exists in both subsamples and is slightly stronger among firms with no patents granted over the same year. Specifically, the slopes on *Rank(TRAT)* are 0.11% (t = 2.15) and 0.09% (t = 1.76) among non-patenting and patenting firms, respectively. The finding that the slopes of *Rank(TRAT)* are similar in magnitude in both subsamples confirms that the TRAT effect is more general than and is distinct from the patent effect and is able to explain stock returns in industries in which patents are uncommon.

4.3. Additional robustness check of industry effect

Since trademark activities vary significantly across industries, one potential concern is that the positive TRAT-return relationship results from the variation across industries. To address this concern, we report industry-adjusted returns in portfolio sorts and control for industry effects in the Fama-MacBeth regressions. To further address this concern, we form portfolios based on the rank of TRAT *within* each industry. To ensure sufficient number of firms with nonzero TRAT in each industry, we classify industries based on two-digit SIC codes or the Fama-French 17 industry classifications. Specifically, at the end of June of each year t, we first sort firms with non-zero TRAT into three groups based on the 33rd and 67th percentiles of TRAT in year $t-1$ within each industry. We then assign firms ranked in the top (bottom) tercile within each industry to the high (low) TRAT portfolio. We also construct a TRAT hedge portfolio that is long the high TRAT portfolio and short the low TRAT portfolio. We then hold these portfolios over the next twelve months and rebalance them every year. We compute their value-weighted monthly returns and alphas from different factor models.

Table 11 shows that the excess returns and alphas of these TRAT portfolios are similar (in both magnitude and statistical significance) to those reported in Table 3 where we form the TRAT portfolios based on the full sample tercile breakpoints. These findings further suggest that the positive TRAT-return relationship is robust to the industry effects on returns.

5. Conclusion

Trademarks are an important and widely used form of IP protection, and as the end product of the innovation process, they may be considered a measure of innovation output. We study whether investors understand the value of new trademarks and incorporate information about the registrations of new trademarks efficiently into stock prices. Since technical issues are resolved upon attainment of a new product or service, trademarks may not be associated with as much uncertainty as for patents, which raises the possibility that trademarks might be valued fairly efficiently. However, new trademarks may still be hard to value owing mainly to market and competitor risks associated with the new products/services that are legally protected by new trademarks.

We find that the market does not efficiently price new trademarks. Instead, we find that on average investors undervalue new trademarks, especially among more complex firms, which are larger, more opaque, have higher analyst forecast dispersion, more R&D spending and low advertising spending. We also find that this undervaluation is stronger when new trademarks are exploratory and hence harder to value. These findings are consistent with limited investor attention, and the hypothesis that attention is more severely burdened when uncertainty is high and firms are more complex.

Our evidence suggests that new trademark activities represent intellectual property that contribute substantially to firm value, but are undervalued by investors at the time of their registration. This is reflected in high subsequent abnormal returns. These findings suggest that the S.E.C. and accounting regulators should consider using safe harbor rules to encourage firms to disclose an estimated fair value of new and existing trademarks, either on their balance sheet or as supplementary disclosures. By directing investor attention to the value of trademarks, such changes may potentially improve market efficiency and resource allocation.

References

Aboody, D., and B. Lev. 1998. The value relevance of intangibles: The case of software capitalization. *Journal of Accounting Research* 36, 161-91.

Aboody, D., and B. Lev. 2000. Information asymmetry, R&D, and insider gains. *Journal of Finance* 55, 2747-2766.

Aghion, P., J. Van Reenen, and L. Zingales. 2013. Innovation and Institutional Ownership. *American Economic Review* 103, 277-304.

Albuquerque, A., 2009. Peer firms in relative performance evaluation. *Journal of Accounting and Economics* 48, 69-89.

Belo, F., Lin, X.J., and M. A. Vitorino, 2014, Brand capital and firm value, *Review of Economic Dynamics* 17, 150-169.

Besen, S.M. and Raskind, L.J., 1991. An introduction to the law and economics of intellectual property. *Journal of Economic Perspectives* 5, 3-27.

Block, J.H., De Vries, G., Schumann, J.H., Sandner, P., 2014. Trademarks and venture capital valuation. *Journal of Business Venturing* 29, 525-542.

Bosworth, D. and Rogers, M., 2001. Market value, R&D and intellectual property: an empirical analysis of large Australian firms. *Economic Record* 77, 323-337.

Chan, L. K. C., J. Lakonishok, and T. Sougiannis. 2001. The stock market valuation of research and development expenditures. *Journal of Finance* 56, 2431–56.

Cohen, L., Diether, K. and Malloy, C., 2013. Misvaluing innovation. *Review of Financial Studies* 26, 635-666.

Cohen, L., and D. Lou. 2012. Complicated firms. *Journal of Financial Economics* 104, 383–400.

Corrado, C. and Hulten, C., 2010. How do you measure a technological revolution? American Economic Review 100, 99–104.

Crass, D., Czarnitzki, D., Toole, A.A., 2016. The dynamic relationship between investments in brand equity and firm profitability: Evidence using trademark registrations. Working paper, Centre for European Economic Research (ZEW), KU Leuven, KU Leuven, and US Patent and Trademark Office.

Daniel, K. and Titman, S. (1997), Evidence on the Characteristics of Cross Sectional Variation in Stock Returns. *Journal of Finance* 52, 1-33.

Deng, Z., Lev, B. and Narin, F., 1999. Science and technology as predictors of stock performance. *Financial Analysts Journal* 55, 20-32.

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

Fama, E., and French. K., 1992. The cross-section of expected stock returns. *Journal of Finance* 47, 427–65.

———. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33, 3–56.

———. 1997. Industry costs of equity. *Journal of Financial Economics* 43, 153–93.

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

Fama, E., and J. MacBeth. 1973. Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy* 71, 607–36.

Faurel, L., Li, Q., Shanthikumar D., and Teoh S., 2018. Product Development Innovation: Insights from Trademarks. Working paper.

Fosfuri, A. and Giarratana, M.S., 2009. Masters of war: Rivals' product innovation and new advertising in mature product markets. *Management Science* 55, 181-191.

González-Pedraz, C., & Mayordomo, S. 2012. Trademark activity and the market performance of U.S. commercial banks. *Journal of Business Economics and Management* 13, 931–950.

Graham, S.J., Hancock, G., Marco, A.C., Myers, A.F., 2013. The USPTO trademark case files dataset: Descriptions, lessons, and insights. *Journal of Economics & Management Strategy* 22, 669-705.

Greenhalgh, C., Rogers, M., 2006. The value of innovation: The interaction of competition, R&D and IP. *Research Policy* 35, 562-580.

Greenhalgh, C., Rogers, M., Schautschick, P. and Sena, V., 2011. Trade mark incentives. Working paper.

Griliches, Z. 1981. Market value, R&D, and patents, *Economics Letters* 7, 183-187.

Grullon, G., G. Kanatas, and J. P. Weston, 2004. Advertising, breadth of ownership, and liquidity. *Review of Financial Studies* 17, 439-461.

Hall, B. H. 1993. The stock market's valuation of R&D investment during the 1980's. *American Economic Review* 83, 259-64

Hall, B. H., Christian Helmers, Mark Rogers, and Vania Sena, 2014. The choice between formal and informal intellectual property: a review. *Journal of Economic Literature* 52, 375-423.

Hall, B. H., Adam Jaffe, and Manuel Trajtenberg. 2005. Market value and patent citations, *RAND Journal of Economics* 36, 16-38.

Hirshleifer, D., P. H. Hsu, and D. Li. 2013. Innovative efficiency and stock returns. *Journal of Financial Economics* 107, 632–54.

Hirshleifer, D., P. H. Hsu, and D. Li. 2018. Innovative originality, profitability, and stock returns. *Review of Financial Studies* 31, 2553-2605.

Hirshleifer, D., Lim, S.S. and Teoh, S.H., 2011. Limited investor attention and stock market misreactions to accounting information. *Review of Asset Pricing Studies* 1, 35-73.

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

Hsu, Po-Hsuan, Kai Li, Yunan Liu, and Hong Wu. 2017. New product development and mergers and acquisitions. Working paper.

Hong, H., Scheinkman, J. and Xiong, W., 2006. Asset float and speculative bubbles. *Journal of Finance* 61, 1073-1117.

Hou, K., Karolyi, G.A. and Kho, B.C., 2011. What factors drive global stock returns? *Review of Financial Studies* 24, 2527-2574.

Hou, K., C. Xue, and L. Zhang. 2015. Digesting anomalies: An investment approach. *Review of Financial Studies* 28, 650–705.

Hutton, A.P., Marcus, A.J. and Tehranian, H., 2009. Opaque financial reports, R^2, and crash risk. *Journal of Financial Economics* 94, 67-86.

Jones, C.L. and Weingram, S.E., 1996. The determinants of 10b-5 litigation risk. Working paper.

Kim, I. and Skinner, D.J., 2012. Measuring securities litigation risk. *Journal of Accounting and Economics* 53, 290-310.

Kumar, A., 2009. Hard-to-value stocks, behavioral biases, and informed trading. *Journal of Financial and Quantitative Analysis* 44, 1375-1401.

Landes, W.M. and Posner, R.A., 1987. Trademark law: An economic perspective. *Journal of Law and Economics* 30, 265-309.

Lerner, J. 1994. The importance of patent scope: an empirical analysis. *RAND Journal of Economics* 25, 319-333.

Lev, B. 2001. *Intangibles: Management, Measurement and Reporting*, The Brookings Institution Press.

Lev, B., B. Sarath, and T. Sougiannis. 2005. R&D reporting biases and their consequences. *Contemporary Accounting Research* 22, 977–1026.

Lev, B., and T. Sougiannis. 1996. The capitalization, amortization, and value-relevance of R&D. *Journal of Accounting and Economics* 21, 107–38.

Lou, D. 2014. Attracting investor attention through advertising. *Review of Financial Studies*, 27, 1797–1829.

Mendonça, S., Pereira, T.S. and Godinho, M.M., 2004. Trademarks as an indicator of innovation and industrial change. *Research Policy* 33, 1385-1404.

Miller, E.M., 1977. Risk, uncertainty, and divergence of opinion. *Journal of Finance* 32, 1151-1168.

Millot, V., 2009. Trademarks as an indicator of product and marketing innovations. OECD Science, Technology and Industry Working Papers, 2009/06, OECD Publishing, Paris.

Pakes, A., 1985. On patents, R&D, and the stock market rate of return. *Journal of Political Economy* 93, 390-409.

Pastor, L. and Stambaugh, R.F., 2003. Liquidity risk and expected stock returns *Journal of Political Economy* 111, 642-685

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

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

Sandner, P.G., Block, J., 2011. The market value of R&D, patents, and trademarks. *Research Policy* 40, 969-985.

Stambaugh, R.F. and Yuan, Y., 2017. Mispricing factors. *Review of Financial Studies* 30, 1270-1315.

Vitorino, M.A., 2013. Understanding the effect of advertising on stock returns and firm value: Theory and evidence from a structural model. *Management Science* 60, 227-245.

Zhang, X.F., 2006. Information uncertainty and stock returns. *Journal of Finance* 61, 105-137.

Table 1
Summary statistics and correlations

At the end of June of year t from 1977 to 2015, we sort firms with non-missing trademarks/assets (TRAT) into three groups (Low, Middle, High) based on the 33rd and 67th percentiles of the TRAT measure in year $t-1$. A firm's TRAT is the ratio of the number of trademarks registered in a calendar year to its total assets in the fiscal year ending in the same calendar year. In addition, we assign firms with missing TRAT into the "None" group. Panel A reports the time-series median and mean of cross-sectional average characteristics of firms in each TRAT group. The number of firms in each group is averaged over years. Size is market capitalization (in millions) measured at the end of June of year t. Book-to-market (BTM) is the ratio of book equity of fiscal year ending in year $t-1$ to market capitalization at the end of year $t-1$. Momentum (MOM) is the previous eleven-month returns (with a one-month gap between the holding period and the current month). Return on assets (ROA) is defined as income before extraordinary items plus interest expenses in year $t-1$ divided by lagged total assets. Asset growth (AG) is the change in total assets in year $t-1$ divided by lagged total assets. R&D intensity (RDME) is R&D expenses in fiscal year ending in year $t-1$ divided by market capitalization at the end of year $t-1$. Advertising intensity (ADA) is advertising expense in fiscal year ending in year $t-1$ divided by total asset in fiscal year ending in year $t-1$. Net stock issuance (NS) is the change in the natural log of the split-adjusted shares outstanding in year $t-1$. Skewness (SKEW) is computed at the end of June of year t using daily returns over the previous 12 months (with a minimum of 31 trading days). Idiosyncratic volatility (IVOL) is computed at the end of June of year t as the standard deviation of the residuals from regressing daily stock returns on the Fama-French three factor returns over the previous 12 months (with a minimum of 31 trading days). We winsorize all variables at the 1% and 99% levels except the number of firms. Panel B reports the times-series average of cross-sectional correlations and their p-values between TRAT and the other characteristics.

Panel A: Summary statistics	Time series average of cross-sectional median				Time series average of cross-sectional mean			
	None	Low	Middle	High	None	Low	Middle	High
Number of firms	1991	408	409	409	1991	408	409	409
Trademark/Assets (TRAT)		0.16%	0.78%	3.14%		0.17%	0.84%	4.92%
Size ($mn)	162	2316	493	124	725	9298	1707	376
Book-to-market (BTM)	0.71	0.62	0.59	0.61	1.01	0.79	0.76	0.80
Momentum (MOM)	0.06	0.09	0.08	0.08	0.17	0.13	0.14	0.19
Return on assets (ROA)	0.03	0.05	0.05	0.04	0.00	0.05	0.04	0.01
Asset growth (AG)	0.08	0.08	0.09	0.08	0.23	0.17	0.20	0.18
R&D/Market equity (RDME)	0.00	0.01	0.01	0.01	0.04	0.03	0.03	0.05
Advertising/Assets (ADA)	0.00	0.00	0.00	0.01	0.01	0.01	0.02	0.03
Net stock issuance (NS)	0.01	0.00	0.01	0.01	0.05	0.02	0.03	0.04
Skewness (SKEW)	0.40	0.19	0.28	0.43	0.51	0.19	0.30	0.51
Idiosyncratic volatility (IVOL)	0.03	0.02	0.02	0.03	0.03	0.02	0.03	0.03

Panel B: Correlations	Correlations	p-values
	Trademark/Assets	
Size ($mn)	-0.12	0.00
Book-to-market (BTM)	0.01	0.41
Momentum	0.04	0.22
Return on assets (ROA)	-0.10	0.16
Asset growth (AG)	0.00	0.45
R&D/Market equity (RDME)	0.09	0.08
Advertising/Assets	0.14	0.02
Net stock issuance (NS)	0.04	0.33
Skewness (SKEW)	0.09	0.13
Idiosyncratic volatility (IVOL)	0.29	0.00

Table 2
Trademarks/assets and trademark counts within industries

This table reports the pooled mean, standard deviation (Stdev), minimum (Min), 10th percentile (P10), 25th percentile (P25), median (P50), 75th percentile (P75), 90th percentile (P90), maximum (Max), and skewness (Skew) of the number of newly registered trademarks/assets (TRAT) and trademark counts for firms with non-missing TRAT in industries based on Fama-French 48 industry classifications. The sample for trademark is from 1976 to 2014. A firm's TRAT is the ratio of the number of trademarks registered in a calendar year to its total assets in the fiscal year ending in the same calendar year.

Panel A: Trademark/assets (TRAT)

FF48	Industry	Mean	Stdev	Min	P10	P25	P50	P75	P90	Max	Skew
1	Agriculture	0.018	0.028	0.001	0.002	0.004	0.008	0.019	0.044	0.175	0.359
2	Food Products	0.017	0.037	0.000	0.001	0.002	0.005	0.016	0.042	0.601	0.306
3	Candy and Soda	0.015	0.029	0.000	0.000	0.001	0.005	0.013	0.038	0.228	0.335
4	Beer and Liquor	0.022	0.031	0.000	0.002	0.003	0.011	0.029	0.059	0.310	0.360
5	Tobacco Products	0.006	0.015	0.000	0.000	0.000	0.001	0.005	0.018	0.129	0.346
6	Recreation	0.043	0.083	0.000	0.003	0.007	0.019	0.047	0.091	0.814	0.293
7	Entertainment	0.023	0.056	0.000	0.001	0.002	0.006	0.021	0.062	0.799	0.318
8	Printing and Publishing	0.016	0.027	0.000	0.001	0.002	0.006	0.018	0.039	0.222	0.366
9	Consumer Goods	0.026	0.050	0.000	0.001	0.004	0.010	0.028	0.062	0.881	0.312
10	Apparel	0.025	0.031	0.000	0.003	0.006	0.014	0.032	0.061	0.238	0.348
11	Healthcare	0.016	0.031	0.000	0.001	0.002	0.005	0.019	0.037	0.310	0.341
12	Medical Equipment	0.024	0.031	0.000	0.002	0.005	0.013	0.031	0.055	0.350	0.342
13	Pharmaceutical Products	0.022	0.041	0.000	0.001	0.003	0.009	0.025	0.053	0.883	0.311
14	Chemicals	0.011	0.019	0.000	0.001	0.001	0.004	0.012	0.026	0.179	0.344
15	Rubber and Plastic Products	0.023	0.030	0.000	0.002	0.006	0.014	0.027	0.057	0.274	0.313
16	Textiles	0.030	0.046	0.000	0.002	0.005	0.014	0.033	0.077	0.421	0.332
17	Construction Materials	0.014	0.022	0.000	0.001	0.002	0.006	0.016	0.034	0.236	0.373
18	Construction	0.007	0.013	0.000	0.000	0.001	0.002	0.009	0.019	0.155	0.377
19	Steel Works Etc	0.007	0.015	0.000	0.000	0.001	0.003	0.007	0.016	0.265	0.273
20	Fabricated Products	0.020	0.028	0.000	0.001	0.003	0.009	0.028	0.055	0.173	0.399
21	Machinery	0.013	0.022	0.000	0.001	0.002	0.006	0.015	0.031	0.354	0.313
22	Electrical Equipment	0.020	0.029	0.000	0.002	0.004	0.011	0.025	0.048	0.261	0.333
23	Automobiles and Trucks	0.010	0.018	0.000	0.000	0.001	0.004	0.012	0.025	0.283	0.325
24	Aircraft	0.005	0.010	0.000	0.000	0.000	0.002	0.005	0.014	0.074	0.371
25	Shipbuilding, Railroad Equipment	0.004	0.010	0.000	0.000	0.001	0.001	0.003	0.012	0.061	0.312
26	Defense	0.015	0.021	0.000	0.001	0.001	0.005	0.021	0.043	0.125	0.454
27	Precious Metals	0.007	0.011	0.000	0.000	0.000	0.002	0.013	0.029	0.033	0.516
28	Industrial Metal Mining	0.006	0.009	0.000	0.000	0.001	0.002	0.007	0.017	0.062	0.390
29	Coal	0.002	0.003	0.000	0.000	0.000	0.001	0.002	0.004	0.019	0.354
30	Petroleum and Natural Gas	0.004	0.011	0.000	0.000	0.000	0.001	0.003	0.011	0.160	0.306
32	Communication	0.010	0.035	0.000	0.000	0.001	0.002	0.007	0.022	0.769	0.210
33	Personal Services	0.016	0.024	0.000	0.001	0.002	0.007	0.021	0.040	0.155	0.392
34	Business Services	0.020	0.035	0.000	0.001	0.003	0.009	0.024	0.049	1.056	0.315
35	Computers	0.018	0.029	0.000	0.001	0.002	0.008	0.022	0.046	0.478	0.345
36	Electronic Equipment	0.016	0.030	0.000	0.001	0.002	0.006	0.018	0.038	0.537	0.334
37	Measuring and Control Equipment	0.020	0.030	0.000	0.001	0.004	0.010	0.024	0.046	0.276	0.333
38	Business Supplies	0.012	0.024	0.000	0.001	0.001	0.004	0.012	0.027	0.276	0.321
39	Shipping Containers	0.013	0.026	0.000	0.000	0.002	0.005	0.013	0.032	0.234	0.330
40	Transportation	0.006	0.012	0.000	0.000	0.001	0.002	0.006	0.013	0.181	0.299
41	Wholesale	0.021	0.046	0.000	0.001	0.002	0.007	0.020	0.053	0.687	0.321
42	Retail	0.014	0.026	0.000	0.001	0.002	0.005	0.015	0.034	0.396	0.329
43	Restaurants, Hotels, Motels	0.015	0.025	0.000	0.001	0.003	0.007	0.019	0.035	0.449	0.319

Panel B: Trademark count											
FF48	Industry	Mean	Stdev	Min	P10	P25	P50	P75	P90	Max	Skew
1	Agriculture	3.17	3.10	1.00	1.00	1.00	2.00	4.00	8.00	17.00	0.38
2	Food Products	8.91	11.90	1.00	1.00	2.00	4.00	11.00	24.00	79.00	0.41
3	Candy and Soda	15.06	23.55	1.00	1.00	2.00	6.00	15.00	41.00	132.00	0.38
4	Beer and Liquor	10.06	13.48	1.00	1.00	2.00	4.00	12.00	31.00	77.00	0.45
5	Tobacco Products	9.31	16.01	1.00	1.00	2.00	4.00	10.00	18.00	90.00	0.33
6	Recreation	20.97	67.87	1.00	1.00	2.00	4.00	12.00	35.00	760.00	0.25
7	Entertainment	12.04	32.49	1.00	1.00	2.00	4.00	9.00	23.00	364.00	0.25
8	Printing and Publishing	10.67	18.97	1.00	1.00	2.00	5.00	12.00	25.00	222.00	0.30
9	Consumer Goods	10.81	19.97	1.00	1.00	2.00	4.00	12.00	26.00	239.00	0.34
10	Apparel	7.03	9.55	1.00	1.00	2.00	4.00	9.00	16.00	113.00	0.32
11	Healthcare	3.65	5.01	1.00	1.00	1.00	2.00	4.00	8.00	56.00	0.33
12	Medical Equipment	6.70	12.20	1.00	1.00	1.00	3.00	7.00	15.00	201.00	0.30
13	Pharmaceutical Products	7.78	16.30	1.00	1.00	1.00	3.00	7.00	18.00	261.00	0.29
14	Chemicals	7.72	10.62	1.00	1.00	2.00	3.00	9.00	21.00	80.00	0.44
15	Rubber and Plastic Products	6.55	13.31	1.00	1.00	1.00	2.00	5.00	14.00	96.00	0.34
16	Textiles	5.19	8.22	1.00	1.00	1.00	3.00	5.00	11.00	67.00	0.27
17	Construction Materials	5.44	8.19	1.00	1.00	1.00	3.00	6.00	13.00	78.00	0.30
18	Construction	3.27	4.68	1.00	1.00	1.00	2.00	3.00	7.00	42.00	0.27
19	Steel Works Etc.	3.98	5.59	1.00	1.00	1.00	2.00	4.00	10.00	51.00	0.35
20	Fabricated Products	4.19	5.19	1.00	1.00	1.00	2.00	5.00	12.50	28.00	0.42
21	Machinery	5.14	8.64	1.00	1.00	1.00	3.00	5.00	11.00	110.00	0.25
22	Electrical Equipment	4.48	8.27	1.00	1.00	1.00	2.00	4.00	9.00	109.00	0.30
23	Automobiles and Trucks	6.78	15.15	1.00	1.00	1.00	3.00	6.00	14.00	189.00	0.25
24	Aircraft	8.18	11.86	1.00	1.00	1.00	3.00	9.00	22.00	81.00	0.44
25	Shipbuilding, Railroad Equipment	5.41	6.08	1.00	1.00	1.00	3.00	9.00	13.00	29.00	0.40
26	Defense	9.40	12.97	1.00	1.00	1.00	5.00	11.00	24.00	65.00	0.34
27	Precious Metals	1.44	1.04	1.00	1.00	1.00	1.00	2.00	2.00	6.00	0.42
28	Industrial Metal Mining	3.74	4.64	1.00	1.00	1.00	2.00	4.00	11.00	26.00	0.37
29	Coal	1.79	1.13	1.00	1.00	1.00	1.00	3.00	4.00	5.00	0.70
30	Petroleum and Natural Gas	6.56	10.17	1.00	1.00	1.00	2.00	7.00	19.00	82.00	0.45
32	Communication	10.20	19.57	1.00	1.00	2.00	4.00	11.00	25.00	327.00	0.32
33	Personal Services	3.19	3.63	1.00	1.00	1.00	2.00	4.00	6.00	39.00	0.33
34	Business Services	4.27	6.75	1.00	1.00	1.00	2.00	5.00	9.00	132.00	0.34
35	Computers	5.43	9.90	1.00	1.00	1.00	2.00	5.00	11.00	91.00	0.35
36	Electronic Equipment	4.91	15.05	1.00	1.00	1.00	2.00	4.00	8.00	299.00	0.19
37	Measuring and Control Equipment	4.24	5.35	1.00	1.00	1.00	2.00	5.00	10.00	51.00	0.42
38	Business Supplies	7.30	10.07	1.00	1.00	2.00	4.00	8.00	19.00	90.00	0.33
39	Shipping Containers	6.66	12.08	1.00	1.00	1.00	2.00	5.00	18.00	82.00	0.39
40	Transportation	3.59	4.37	1.00	1.00	1.00	2.00	4.00	8.00	32.00	0.36
41	Wholesale	4.81	6.27	1.00	1.00	1.00	2.00	6.00	12.00	70.00	0.45
42	Retail	5.91	9.30	1.00	1.00	1.00	3.00	6.00	14.00	134.00	0.31
43	Restaurants, Hotels, Motels	5.18	8.39	1.00	1.00	1.00	3.00	5.00	11.00	96.00	0.26

Table 3
Return predictive power of trademarks/assets – Single-sorted portfolio analysis

At the end of June of year *t* from 1977 to 2015, we form portfolios based on trademark/assets (TRAT) in year *t* – 1 as in Table 2. We also construct a high-minus-low (High–Low) portfolio by holding a long (short) position in the high (low) TRAT portfolio. We then hold these portfolios over the next twelve months (July of year *t* to June of year *t* + 1). In Panel A, we report their average monthly returns in excess of one-month Treasury bill rate (Exret) as well as their average monthly industry-adjusted returns. The portfolio industry-adjusted returns (Ind-adjret) are based on the difference between individual firms' returns and the returns of firms in the same industry (based on Fama-French 48 industry classifications). In Panels B and C, we report the alphas and R^2 from the regression of the time-series of portfolio excess returns on various factor models: the Fama-French five factors (the market factor–MKT, the size factor–SMB, the value factor–HML, the robust-minus-weak factor—RMW, and the conservative-minus-aggressive factor—CMA) as in Fama and French (2015), alphas from the investment-based factor model (q-factor model) of Hou, Xue, and Zhang (HXZ 2015) and from the mispricing factor model of Stambaugh and Yuan (2017). All returns and alphas are value-weighted and expressed in percentage. The *t*-statistics are reported in parentheses. R-square is adjusted. Panel D presents the probability of transition for the TRAT portfolios. Panel E presents the high-minus-low portfolio's average monthly excess returns, average monthly industry-adjusted returns, alphas from the Fama-French five-factor model, alphas from the q-factor model, and alphas from the mispricing factor model from July of year *t* to June of year *t*+1 (1st post sorting year), July of year *t*+1 to June of year *t* + 2 (2nd post sorting year), July of year *t*+2 to June of year *t*+3 (3rd post-sorting year), July of year *t*+3 to June of year *t*+4 (4th post- sorting year), July of year *t*+4 to June of year *t*+5 (5th post-sorting year), and July of year *t*+5 to June of year *t* + 6 (6th post-sorting year).

A. Excess and adjusted returns			B. Alpha from different factor models			C. R^2 of different factor models		
Trademark Rank	Exret	Ind-adjret	FF 5f	HXZ (q-factor)	Mispricing	FF 5f	HXZ (q-factor)	Mispricing
None	0.59%	-0.03%	0.04%	0.10%	0.09%	0.94	0.94	0.94
	(2.24)	(-0.38)	(0.61)	(1.42)	(1.24)			
Low	0.59%	-0.03%	-0.03%	0.02%	-0.04%	0.97	0.97	0.97
	(2.86)	(-1.02)	(-0.76)	(0.51)	(-1.13)			
Middle	0.78%	0.07%	0.27%	0.28%	0.21%	0.91	0.90	0.91
	(3.28)	(1.42)	(3.20)	(2.90)	(2.49)			
High	1.02%	0.28%	0.62%	0.60%	0.48%	0.88	0.84	0.83
	(3.24)	(2.34)	(4.73)	(3.83)	(3.23)			
High-Low	0.43%	0.31%	0.65%	0.58%	0.53%	0.63	0.54	0.50
	(2.20)	(2.16)	(4.63)	(3.65)	(3.31)			

D. Transition matrix of TRAT portfolios

	TRAT Rank in Year t+1			
TRAT Rank in Year t	None	Low	Middle	High
None	77.87%	5.84%	7.29%	8.99%
Low	23.14%	62.15%	13.73%	0.98%
Middle	28.40%	15.42%	42.11%	14.08%
High	30.40%	1.21%	17.28%	51.11%

E. Returns and alphas of the high-minus-low TRAT portfolio over longer horizons

			Alphas from different factor models			R^2 of different factor models		
Post-sorting Year	Exret	Ind-adjret	FF 5f	HXZ (q-factor)	Mispricing	FF 5f	HXZ (q-factor)	Mispricing
1	0.43%	0.31%	0.65%	0.58%	0.53%	0.63	0.54	0.50
	(2.20)	(2.16)	(4.63)	(3.65)	(3.31)			
2	0.07%	0.09%	0.22%	0.25%	0.30%	0.63	0.57	0.56
	(0.37)	(0.68)	(1.91)	(1.99)	(2.30)			
3	0.19%	0.15%	0.40%	0.48%	0.49%	0.64	0.60	0.58
	(1.04)	(1.06)	(3.43)	(3.82)	(3.74)			
4	0.16%	0.20%	0.33%	0.35%	0.36%	0.64	0.59	0.55
	(0.94)	(1.57)	(2.97)	(2.95)	(2.79)			
5	0.25%	0.24%	0.38%	0.40%	0.49%	0.59	0.52	0.55
	(1.44)	(1.83)	(3.25)	(3.07)	(3.80)			
6	0.06%	0.06%	0.17%	0.16%	0.28%	0.50	0.43	0.48
	(0.38)	(0.46)	(1.41)	(1.22)	(2.19)			

Table 4
Return predictive power of trademarks/assets – Double-sorted portfolio analysis

At the end of June of each year *t*, we independently sort firms into three trademark/assets (TRAT) portfolios and two groups by each of the following characteristics: firm size, opacity, analyst earnings forecast dispersion, R&D spending/sales, and advertising spending/assets from top to bottom. The sorting variables are measured in year *t* – 1 except size, which is market capitalization at the end of June of year *t*. Opacity is defined as the three-year moving sum of the absolute value of discretionary accruals (Hutton, Marcus, and Tehranian 2009), and is an inverse proxy of the transparency of financial reports. Analyst dispersion is defined as the standard deviation of analysts' EPS forecasts scaled by the absolute value of mean forecasts. R&D expenses and advertising expenses are scaled by total assets. The size groups are formed based on NYSE median breakpoints. Opacity, analyst dispersion, and advertising groups are based on the median of all firms. The R&D-active (R&D-inactive) subsample includes firms with non-missing (missing) R&D/Sales. We also construct a high-minus-low TRAT portfolio in each group sorted by one of the firm characteristics and hold these portfolios for the next 12 months. For each portfolio, we report the time series average of cross-sectional mean and median size and TRAT, and average monthly value-weighted excess return (Exret), industry-adjusted returns (Ind-adjret), and alphas and R^2 from different factor models. The alphas are estimated from the regression of the time-series of portfolio excess returns on various factor models including the Fama-French five factors (the market factor–MKT, the size factor–SMB, the value factor–HML, the robust-minus-weak–RMW factor, and the conservative-minus-aggressive factor– CMA), the investment-based factor model of Hou, Xue, and Zhang (HXZ 2015), and the mispricing factor model of Stambaugh and Yuan (2017). All returns and alphas are in percentage. The *t*-statistics are reported in parentheses. The sample period for returns is from July 1977 to December 2015. R-square is adjusted.

A. Size subsamples

Small firms

		Mean		Median		Returns		Alphas			R^2		
Trademark Rank	Firm No.	TRAT	Size ($mn)	TRAT	Size ($mn)	Exret	Ind-adjret	FF 5f	HXZ (q-factor)	Mispricing	FF 5f	HXZ (q-factor)	Mispricing
L	117	0.002	506	0.002	491	0.90%	0.20%	-0.19%	-0.03%	-0.17%	0.92	0.90	0.89
						(3.08)	(1.63)	(-2.25)	(-0.30)	(-1.51)			
M	281	0.009	343	0.009	279	0.88%	0.17%	-0.03%	0.04%	-0.18%	0.96	0.95	0.93
						(3.04)	(1.46)	(-0.54)	(0.61)	(-2.02)			
H	374	0.051	187	0.032	108	0.95%	0.20%	0.25%	0.32%	0.10%	0.96	0.94	0.93
						(3.09)	(1.51)	(3.74)	(3.79)	(1.13)			
H-L						0.05%	0.00%	0.45%	0.35%	0.27%	0.48	0.23	0.22
						(0.35)	(0.00)	(4.12)	(2.60)	(1.91)			

Large firms

		Mean		Median		Returns		Alphas			R^2		
Trademark Rank	Firm No.	TRAT	Size ($mn)	TRAT	Size ($mn)	Exret	Ind-adjret	FF 5f	HXZ (q-factor)	Mispricing	FF 5f	HXZ (q-factor)	Mispricing
L	292	0.001	12943	0.001	4182	0.58%	-0.03%	-0.02%	0.02%	-0.04%	0.97	0.97	0.97
						(2.86)	(-1.06)	(-0.63)	(0.57)	(-1.04)			
M	128	0.007	4609	0.007	2203	0.78%	0.06%	0.33%	0.32%	0.27%	0.89	0.87	0.88
						(3.31)	(1.16)	(3.49)	(3.08)	(2.90)			
H	34	0.034	2500	0.025	1766	1.10%	0.36%	0.89%	0.83%	0.75%	0.77	0.71	0.71
						(3.30)	(2.40)	(4.59)	(3.73)	(3.61)			
H-L						0.51%	0.39%	0.91%	0.80%	0.79%	0.44	0.33	0.30
						(2.28)	(2.34)	(4.52)	(3.58)	(3.66)			

B. Opacity subsamples														
Low opacity														
		Mean		Median		Returns		Alphas				R^2		
Trademark Rank	Firm No.	TRAT	Size ($mn)	TRAT	Size ($mn)	Exret	Ind-adjret	FF 5f	HXZ (q-factor)	Mispricing	FF 5f	HXZ (q-factor)	Mispricing
L	263	0.001	17052	0.001	4295	0.64%	-0.01%	-0.03%	-0.01%	-0.03%	0.95	0.94	0.94
						(2.85)	(-0.49)	(-0.60)	(-0.12)	(-0.53)			
M	205	0.006	3716	0.006	1063	0.79%	0.06%	0.03%	0.05%	0.02%	0.87	0.86	0.86
						(3.20)	(0.82)	(0.27)	(0.48)	(0.20)			
H	135	0.034	786	0.024	250	0.88%	0.14%	0.06%	0.13%	0.17%	0.79	0.79	0.79
						(3.11)	(1.23)	(0.45)	(0.93)	(1.20)			
H-L						0.24%	0.15%	0.09%	0.14%	0.20%	0.44	0.47	0.49
						(1.35)	(1.19)	(0.66)	(0.99)	(1.45)			
High opacity													
		Mean		Median		Returns		Alphas				R^2	
Trademark Rank	Firm No.	TRAT	Size ($mn)	TRAT	Size ($mn)	Exret	Ind-adjret	FF 5f	HXZ (q-factor)	Mispricing	FF 5f	HXZ (q-factor)	Mispricing
L	145	0.001	12191	0.001	2710	0.57%	-0.13%	-0.04%	0.19%	0.04%	0.85	0.86	0.84
						(1.73)	(-2.85)	(-0.29)	(1.44)	(0.28)			
M	172	0.007	1896	0.006	595	1.04%	0.41%	0.47%	0.61%	0.38%	0.81	0.80	0.79
						(2.68)	(2.93)	(2.63)	(3.30)	(1.95)			
H	206	0.044	503	0.028	147	1.39%	0.65%	0.90%	0.88%	0.70%	0.71	0.66	0.66
						(3.09)	(2.87)	(3.51)	(3.13)	(2.45)			
H-L						0.82%	0.79%	0.94%	0.69%	0.66%	0.20	0.15	0.12
						(2.62)	(3.03)	(3.16)	(2.22)	(2.06)			

C. Analyst forecast dispersion subsamples

Low dispersion

		Mean		Median		Returns		Alphas			R^2		
Trademark Rank	Firm No.	TRAT	Size ($mn)	TRAT	Size ($mn)	Exret	Ind-adjret	FF 5f	HXZ (q-factor)	Mispricing	FF 5f	HXZ (q-factor)	Mispricing
L	192	0.001	19681	0.001	6241	0.65%	-0.05%	-0.02%	0.04%	-0.02%	0.96	0.95	0.95
						(2.92)	(-2.54)	(-0.48)	(0.70)	(-0.39)			
M	127	0.006	5863	0.005	2387	1.06%	0.25%	0.39%	0.39%	0.22%	0.83	0.82	0.85
						(4.33)	(3.25)	(3.74)	(3.54)	(2.09)			
H	59	0.026	2066	0.019	1106	0.92%	0.15%	0.33%	0.34%	0.39%	0.80	0.79	0.79
						(3.02)	(1.12)	(2.27)	(2.24)	(2.54)			
H-L						0.28%	0.20%	0.35%	0.30%	0.41%	0.34	0.34	0.33
						(1.48)	(1.36)	(2.18)	(1.84)	(2.43)			

High dispersion

		Mean		Median		Returns		Alphas			R^2		
Trademark Rank	Firm No.	TRAT	Size ($mn)	TRAT	Size ($mn)	Exret	Ind-adjret	FF 5f	HXZ (q-factor)	Mispricing	FF 5f	HXZ (q-factor)	Mispricing
L	99	0.001	5826	0.001	2218	0.58%	-0.04%	-0.08%	0.04%	-0.03%	0.85	0.86	0.84
						(1.87)	(-0.88)	(-0.59)	(0.30)	(-0.23)			
M	102	0.006	1821	0.005	718	0.80%	0.17%	0.26%	0.35%	0.25%	0.85	0.83	0.83
						(2.10)	(1.98)	(1.64)	(2.05)	(1.43)			
H	98	0.032	829	0.021	367	1.31%	0.51%	0.98%	1.04%	0.68%	0.77	0.69	0.68
						(2.75)	(2.56)	(4.06)	(3.65)	(2.28)			
H-L						0.73%	0.55%	1.06%	1.00%	0.71%	0.39	0.27	0.26
						(2.18)	(2.37)	(3.82)	(3.27)	(2.25)			

D. R&D subsamples

R&D-inactive

		Mean		Median		Returns		Alphas			R^2		
Trademark Rank	Firm No.	TRAT	Size ($mn)	TRAT	Size ($mn)	Exret	Ind-adjret	FF 5f	HXZ (q-factor)	Mispricing	FF 5f	HXZ (q-factor)	Mispricing
L	150	0.002	5126	0.002	1704	0.60%	-0.04%	-0.24%	-0.17%	-0.17%	0.88	0.86	0.86
						(2.80)	(-0.70)	(-2.95)	(-1.97)	(-2.05)			
M	131	0.008	1262	0.008	382	0.76%	-0.02%	-0.17%	-0.15%	-0.21%	0.86	0.82	0.83
						(3.29)	(-0.33)	(-1.75)	(-1.34)	(-1.90)			
H	116	0.048	292	0.031	103	0.94%	0.19%	0.05%	0.04%	0.05%	0.83	0.80	0.81
						(3.44)	(1.73)	(0.41)	(0.30)	(0.42)			
H-L						0.33%	0.23%	0.29%	0.22%	0.23%	0.40	0.34	0.35
						(2.19)	(1.81)	(2.28)	(1.57)	(1.70)			

R&D-active

		Mean		Median		Returns		Alphas			R^2		
Trademark Rank	Firm No.	TRAT	Size ($mn)	TRAT	Size ($mn)	Exret	Ind-adjret	FF 5f	HXZ (q-factor)	Mispricing	FF 5f	HXZ (q-factor)	Mispricing
L	256	0.002	11753	0.002	2781	0.59%	-0.03%	0.04%	0.08%	0.00%	0.95	0.95	0.95
						(2.86)	(-0.79)	(0.79)	(1.61)	(-0.08)			
M	275	0.008	1919	0.008	553	0.81%	0.11%	0.39%	0.38%	0.33%	0.88	0.87	0.87
						(3.23)	(1.77)	(3.81)	(3.41)	(3.18)			
H	283	0.048	413	0.031	136	1.03%	0.31%	0.73%	0.72%	0.57%	0.86	0.80	0.79
						(3.12)	(2.22)	(4.81)	(3.83)	(3.30)			
H-L						0.44%	0.33%	0.69%	0.63%	0.58%	0.61	0.50	0.46
						(2.05)	(2.05)	(4.39)	(3.50)	(3.22)			

E. Advertising/assets subsample

Low advertising

		Mean		Median		Returns		Alphas			R^2		
Trademark Rank	Firm No.	TRAT	Size ($mn)	TRAT	Size ($mn)	Exret	Ind-adjret	FF 5f	HXZ (q-factor)	Mispricing	FF 5f	HXZ (q-factor)	Mispricing
L	244	0.002	7141	0.001	1998	0.51%	-0.06%	-0.10%	-0.06%	-0.08%	0.92	0.93	0.92
						(2.42)	(-1.54)	(-1.50)	(-1.00)	(-1.29)			
M	226	0.008	1265	0.008	435	0.68%	0.04%	0.12%	0.14%	0.12%	0.90	0.90	0.90
						(2.62)	(0.58)	(1.28)	(1.45)	(1.38)			
H	195	0.043	295	0.029	113	1.14%	0.38%	0.79%	0.74%	0.59%	0.84	0.78	0.78
						(3.36)	(2.41)	(4.64)	(3.78)	(3.15)			
H-L						0.63%	0.43%	0.89%	0.80%	0.67%	0.58	0.48	0.43
						(2.69)	(2.46)	(4.89)	(4.11)	(3.31)			

High advertising

		Mean		Median		Returns		Alphas			R^2		
Trademark Rank	Firm No.	TRAT	Size ($mn)	TRAT	Size ($mn)	Exret	Ind-adjret	FF 5f	HXZ (q-factor)	Mispricing	FF 5f	HXZ (q-factor)	Mispricing
L	164	0.002	12903	0.002	3006	0.64%	-0.01%	0.02%	0.10%	-0.01%	0.90	0.88	0.89
						(3.07)	(-0.14)	(0.29)	(1.15)	(-0.10)			
M	183	0.008	2092	0.008	563	0.81%	0.05%	0.26%	0.27%	0.11%	0.82	0.81	0.82
						(3.41)	(0.80)	(2.15)	(1.99)	(0.98)			
H	197	0.049	463	0.031	141	0.84%	0.15%	0.33%	0.34%	0.30%	0.85	0.82	0.83
						(2.87)	(1.37)	(2.69)	(2.41)	(2.14)			
H-L						0.19%	0.16%	0.31%	0.24%	0.31%	0.48	0.41	0.43
						(1.11)	(1.15)	(2.35)	(1.53)	(2.05)			

Table 5
Tests for the price of risk associated with trademarks/assets

This table presents the estimated risk premium associated with exposure to the TRAT factor and other factors using a two-pass procedure (Daniel and Titman 1997). First, for stock i in month t, we estimate its exposure to the TRAT factor, $\beta_{i,t}^{TRAT}$, by regressing its monthly excess returns from month $t-59$ to month t on the corresponding returns of the TRAT factor and different combinations of the other factors. Then, for each month t, we conduct a cross-sectional regression of stocks' monthly excess returns on their TRAT betas and other betas estimated from the models used in the first pass. The coefficient on $\beta_{i,t}^{TRAT}$ serves as an estimate of the risk premium (known as "lambda") associated with the TRAT factor in month t. Lastly, we test the significance of the risk premium by the mean and standard deviation of the time series coefficients on β^{TRAT}. The time-series average coefficients on β^{TRAT} and other betas estimated from different models and their t-statistics (in parentheses) are reported. Model 1 includes the market factor (MKT) and the TRAT factor in estimating the betas. Model 2 is the same as Model 1 except that it includes an intercept term. Model 3 includes the TRAT factor and the Fama and French (2015) five factors; Model 5 includes the TRAT factor and the factors from the q-factor model (Hou, Xue, and Zhang 2015). Models 4 and 6 are the same as Models 3 and 5, respectively, except that they include an intercept term in both passes.

	Intercept	β_{TRAT}	β_{Mkt}	β_{SML}	β_{HML}	β_{RMW}	β_{CMA}	β_{qmkt}	β_{qme}	β_{qia}	β_{qroe}
Model 1		0.0021	0.0080								
		(1.3145)	(3.8139)								
Model 2	0.0083	0.0010	0.0021								
	(4.5687)	(0.6419)	(1.2336)								
Model 3		0.0021	0.0077	0.0018	-0.0001	-0.0008	-0.0005				
		(1.5103)	(3.7280)	(1.8724)	(-0.0665)	(-0.9763)	(-0.7118)				
Model 4	0.0074	0.0009	0.0024	0.0008	0.0006	-0.0006	-0.0001				
	(4.2440)	(0.7127)	(1.4804)	(0.9235)	(0.6324)	(-0.7350)	(-0.1526)				
Model 5		0.0019						0.0077	0.0019	-0.0001	-0.0007
		(1.3094)						(3.7331)	(1.9478)	(-0.2164)	(-0.9627)
Model 6	0.0078	0.0009						0.0020	0.0007	0.0001	-0.0009
	(4.4111)	(0.6319)						(1.2607)	(0.7770)	(0.1545)	(-1.2098)

Table 6
Return predictive power of trademarks/assets and exploratory trademarks

This table reports the return predictive power of trademark/assets (TRAT) within exploratory and non-exploratory trademark subsamples. At the end of June of year *t* from 1977 to 2015, we split the sample into exploratory and non-exploratory subsamples based on whether any of the trademarks registered in year $t - 1$ are exploratory. We define a trademark as an exploratory trademark if the firm has not registered any trademarks in this trademark's class (assigned by the USPTO) over the last 10 years (i.e., year $t - 11$ to $t - 2$). In addition, at the end of June of each year *t* from 1977 to 2015, we independently sort firms into three trademark/assets (TRAT) portfolios as in Table 3. We also construct a high-minus-low TRAT portfolio within the two subsamples and hold these portfolios for the next 12 months. For each portfolio, we report average monthly value-weighted excess return (Exret), industry-adjusted returns (Ind-adjret), and alphas and R^2 from different factor models as described in Table 3. The *t*-statistics are reported in parentheses. The sample period for returns is from July 1977 to December 2015. R-square is adjusted.

Exploratory subsample														
		A. Mean		B. Median		C. Returns		D. Alphas			E. R^2		
Trademark Rank	Firm No.	Trademark/ Assets (TRAT)	Size ($mn)	Trademark/ Assets (TRAT)	Size ($mn)	Exret	Ind-adjret	FF 5f	HXZ (q-factor)	Mispricing	FF 5f	HXZ (q-factor)	Mispricing
L	139	0.002	11569	0.002	2912	0.59%	-0.03%	-0.01%	0.04%	-0.05%	0.94	0.93	0.94
						(2.87)	(-1.82)	(-0.10)	(0.75)	(-0.89)			
M	152	0.008	2325	0.008	637	0.76%	0.09%	0.19%	0.19%	0.18%	0.87	0.85	0.86
						(3.24)	(1.47)	(2.06)	(1.94)	(1.85)			
H	158	0.051	512	0.033	163	1.10%	0.37%	0.71%	0.71%	0.58%	0.81	0.75	0.75
						(3.23)	(2.18)	(4.41)	(3.86)	(3.01)			
H-L						0.52%	0.40%	0.71%	0.67%	0.63%	0.51	0.40	0.38
						(2.24)	(2.19)	(4.16)	(3.45)	(3.10)			

Non-exploratory subsample													
		A. Mean		B. Median		C. Returns		D. Alphas			E. R^2		
Trademark Rank	Firm No.	Trademark/ Assets (TRAT)	Size ($mn)	Trademark/ Assets (TRAT)	Size ($mn)	Exret	Ind-adjret	FF 5f	HXZ (q-factor)	Mispricing	FF 5f	HXZ (q-factor)	Mispricing
L	257	0.002	8720	0.002	2194	0.57%	-0.02%	-0.05%	-0.01%	-0.06%	0.95	0.94	0.94
						(2.73)	(-1.23)	(-0.92)	(-0.26)	(-1.01)			
M	242	0.008	1533	0.008	457	0.83%	0.10%	0.32%	0.38%	0.26%	0.88	0.87	0.87
						(3.22)	(1.36)	(3.48)	(3.76)	(2.49)			
H	229	0.047	352	0.030	118	0.87%	0.14%	0.30%	0.40%	0.30%	0.89	0.86	0.87
						(2.93)	(1.18)	(2.78)	(3.31)	(2.43)			
H-L						0.30%	0.16%	0.34%	0.41%	0.35%	0.61	0.59	0.54
						(1.59)	(1.21)	(2.77)	(3.15)	(2.51)			

Table 7
Return predictive power of trademarks/assets – Fama-MacBeth regressions (full sample)

This table reports the average slopes (in %) and their *t*-statistics in parentheses from monthly Fama and MacBeth (1973) cross-sectional using weighted least square regressions. For each month from July of year *t* to June of year *t* + 1, we regress monthly returns of individual stocks on the tercile rank of TRAT as defined in Table 3 (Rank(TRAT)) or the natural log of TRAT (Ln(TRAT)) of year *t* – 1. Panel A reports the results of univariate regressions. Panel B reports results of multivariate regression on two different sets of control variables and industry dummies based on Fama and French 48 industry classifications. All accounting-based control variables are measured in year *t* – 1 except Lagged Ln(1+R&D/Market equity), which is measured in year *t* – 2. We omit the intercept and the slopes on the 48 industry dummies for brevity. Ln(1+Patents/Assets) is the natural log of one plus the number of patents granted in year *t* – 1 divided by total asset in fiscal year ending in year *t* – 1. All the other variables are defined as in Table 1. All independent variables are normalized to zero mean and one standard deviation after winsorization at the 1% and 99% levels. The return data are from July of 1977 to December of 2015. R-square (number of firms) is the time-series average of the R-squares (number of firms) from the monthly cross-sectional regressions.

Panel A: Univariate regression	Model 1		Model 2	
	Slope	*t*-stat	Slope	*t*-stat
Rank(TRAT)	0.21	(2.29)		
Ln(TRAT)			0.15	(2.41)
R^2	0.01		0.02	
Number of firms	1213		1213	

Panel B: Multivariate regression	Model 1		Model 2		Model 3		Model 4	
	Slope	*t*-stat	Slope	*t*-stat	Slope	*t*-stat	Slope	*t*-stat
Rank(TRAT)	0.09	(2.39)			0.09	(2.44)		
Ln(TRAT)			0.12	(3.54)			0.12	(3.66)
Asset growth (AG)	0.02	(0.43)	0.02	(0.52)	0.02	(0.52)	0.02	(0.60)
Idiosyncratic volatility (IVOL)	0.06	(0.48)	0.06	(0.48)	0.07	(0.61)	0.07	(0.61)
Skewness (SKEW)	-0.06	(-1.64)	-0.06	(-1.54)	-0.06	(-1.66)	-0.06	(-1.56)
Short-term return reversal (REV)	-0.49	(-8.10)	-0.49	(-8.10)	-0.50	(-8.37)	-0.50	(-8.32)
Ln(1+Advertising/Assets)	0.04	(1.14)	0.03	(1.09)	0.04	(1.24)	0.04	(1.19)
Ln(Book-to-market)	0.12	(2.17)	0.14	(2.68)	0.12	(1.78)	0.13	(1.97)
Ln(1+R&D/Market equity)	0.08	(1.28)	0.07	(1.09)	0.07	(0.79)	0.07	(0.75)
Ln(Size)	-0.08	(-1.24)	-0.04	(-0.53)	-0.02	(-0.13)	-0.01	(-0.06)
Momentum	0.21	(2.52)	0.20	(2.48)	0.19	(2.41)	0.19	(2.38)
Net stock issuance (NS)	-0.12	(-3.35)	-0.12	(-3.44)	-0.14	(-3.81)	-0.14	(-3.90)
Return on assets (ROA)	0.06	(1.11)	0.04	(0.74)	0.05	(0.82)	0.03	(0.58)
Ln(Assets)					-0.04	(-0.29)	-0.01	(-0.07)
Lagged Ln(1+R&D/Market equity)					0.00	(0.01)	0.00	(0.01)
Ln (1+Patents/Assets)					0.02	(0.46)	0.01	(0.27)
Industry dummy	Y		Y		Y		Y	
R^2	0.36		0.36		0.37		0.37	
Number of firms	1112		1112		1100		1100	

Table 8
Return predictive power of trademarks/assets – subsample Fama-MacBeth regressions

This table reports the average slopes (in %) and their *t*-statistics in parentheses from monthly Fama and MacBeth (1973) cross-sectional regressions within subsamples split by different variables. All models follow the specification as in Model 3 of Table 7 Panel B. The subsamples of size, opacity, analyst forecast dispersion, R&D spending, and advertising spending are formed as in Table 4. All variables are defined as in Tables 1 and 7. The method is the same as in Table 7.

	Small		Large		Low opacity		High opacity		Low dispersion		High dispersion	
	Slope	*t*- stat	Slope	*t*- stat	Slope	*t*- stat	Slope	*t*- stat	Slope	*t*- stat	Slope	*t*- stat
Rank(TRAT)	0.06	(1.31)	0.08	(2.61)	-0.09	(-1.56)	0.31	(2.96)	0.10	(1.88)	0.17	(1.65)
Asset growth (AG)	0.03	(0.72)	0.01	(0.28)	0.01	(0.10)	0.04	(0.40)	0.01	(0.21)	-0.02	(-0.23)
Idiosyncratic volatility (IVOL)	0.02	(0.16)	0.02	(0.24)	0.16	(1.07)	0.10	(0.49)	0.05	(0.48)	0.22	(1.45)
Skewness (SKEW)	-0.06	(-1.85)	-0.05	(-1.56)	-0.04	(-0.68)	-0.07	(-0.77)	-0.04	(-0.90)	-0.08	(-1.08)
Short-term return reversal (REV)	-0.57	(-9.24)	-0.41	(-8.03)	-0.48	(-5.93)	-0.29	(-2.27)	-0.42	(-6.05)	-0.40	(-3.98)
Ln(1+Advertising/asset)	0.05	(1.22)	0.03	(0.94)	0.03	(0.59)	0.07	(0.68)	0.03	(0.66)	0.21	(2.51)
Ln(Book-to-market)	-0.02	(-0.28)	0.11	(1.61)	0.15	(1.81)	-0.06	(-0.43)	0.19	(2.31)	-0.04	(-0.28)
Ln(1+R&D/Market equity)	0.25	(2.59)	0.00	(-0.06)	0.27	(1.69)	0.19	(1.07)	0.12	(0.91)	0.19	(1.18)
Ln(Size)	-0.32	(-2.78)	0.01	(0.07)	0.37	(1.46)	-0.30	(-0.90)	0.42	(2.25)	-0.22	(-0.95)
Momentum	0.26	(3.77)	0.15	(2.05)	0.05	(0.42)	0.16	(1.13)	0.15	(1.68)	0.28	(2.36)
Net stock issuance (NS)	-0.13	(-3.15)	-0.13	(-3.52)	-0.14	(-3.10)	-0.18	(-2.02)	-0.09	(-1.99)	-0.08	(-1.00)
Return on assets (ROA)	0.16	(2.82)	0.02	(0.44)	-0.03	(-0.35)	0.01	(0.09)	-0.04	(-0.68)	0.13	(1.17)
Ln(Assets)	0.29	(2.92)	-0.04	(-0.35)	-0.43	(-1.84)	0.22	(0.75)	-0.44	(-2.34)	0.29	(1.11)
Lagged Ln(1+R&D/Market equity)	-0.05	(-0.63)	0.03	(0.42)	-0.06	(-0.42)	-0.03	(-0.22)	-0.02	(-0.20)	-0.16	(-1.08)
Ln (1+Patents/Assets)	0.03	(0.71)	0.02	(0.64)	0.00	(0.01)	0.06	(0.55)	0.03	(0.46)	0.19	(1.98)
Industry dummy	Y		Y		Y		Y		Y		Y	
R^2	0.21		0.42		0.45		0.45		0.51		0.50	
Number of firms	667		433		609		519		375		282	

	R&D-inactive		R&D-active		Low ADA		High ADA	
	Slope	*t*- stat	Slope	*t*- stat	Slope	*t*- stat	Slope	*t*- stat
Rank(TRAT)	-0.02	(-0.42)	0.10	(2.25)	0.12	(2.40)	0.03	(0.52)
Asset growth (AG)	0.02	(0.39)	0.06	(1.31)	0.07	(1.40)	0.02	(0.34)
Idiosyncratic volatility (IVOL)	-0.08	(-0.63)	0.10	(0.79)	0.00	(-0.02)	0.13	(0.86)
Skewness (SKEW)	0.02	(0.41)	-0.07	(-1.49)	-0.08	(-1.65)	-0.07	(-1.34)
Short-term return reversal (REV)	-0.57	(-7.67)	-0.47	(-7.16)	-0.62	(-8.70)	-0.45	(-6.01)
Ln(1+Advertising/asset)	0.09	(1.72)	0.02	(0.53)	0.01	(1.12)	0.02	(0.41)
Ln(Book-to-market)	0.04	(0.49)	0.15	(1.88)	0.19	(2.29)	0.03	(0.39)
Ln(1+R&D/Market equity)	-0.17	(-1.45)	0.07	(0.64)	0.03	(0.29)	0.14	(0.98)
Ln(Size)	-0.42	(-1.92)	0.16	(0.78)	-0.14	(-0.72)	-0.11	(-0.46)
Momentum	0.08	(0.79)	0.18	(2.22)	0.17	(1.91)	0.27	(3.09)
Net stock issuance (NS)	-0.13	(-2.49)	-0.17	(-4.06)	-0.17	(-3.83)	-0.11	(-1.79)
Return on assets (ROA)	0.08	(0.90)	0.01	(0.09)	0.08	(1.07)	0.07	(0.77)
Ln(Assets)	0.19	(1.03)	-0.15	(-0.83)	0.00	(0.03)	0.02	(0.09)
Lagged Ln(1+R&D/Market equity	0.03	(0.37)	-0.02	(-0.22)	0.06	(0.53)	0.00	(0.01)
Ln (1+Patents/Assets)	0.00	(-0.07)	0.02	(0.32)	0.00	(-0.06)	0.02	(0.46)
Industry dummy	Y		Y		Y		Y	
R^2	0.44		0.41		0.44		0.46	
Number of firms	331		701		607		494	

Table 9
Return predictive power of trademarks/assets and exploratory trademarks – subsample Fama-MacBeth regressions

This table reports the time-series average slopes (in %) and their *t*-statistics in parentheses from monthly Fama and MacBeth (1973) cross-sectional regressions within the exploratory and non-exploratory trademark subsamples (as formed in Table 6). All firms have nonzero trademark/assets (TRAT). All variables are defined as in Table 7. The method is the same as in Table 7.

	Exploratory		Non-exploratory	
	Slope	*t*-stat	Slope	*t*-stat
Rank(TRAT)	0.11	(2.04)	0.07	(1.40)
Asset growth (AG)	0.02	(0.30)	-0.02	(-0.34)
Idiosyncratic volatility (IVOL)	0.14	(1.06)	0.00	(-0.02)
Skewness (SKEW)	-0.06	(-1.24)	-0.07	(-1.56)
Short-term return reversal (REV)	-0.50	(-6.53)	-0.52	(-8.04)
Ln(1+Advertising/asset)	0.03	(0.72)	0.02	(0.50)
Ln(Book-to-market)	-0.01	(-0.11)	0.18	(2.29)
Ln(1+R&D/Market equity)	0.02	(0.12)	0.14	(1.27)
Ln(Size)	-0.22	(-0.92)	-0.11	(-0.56)
Momentum	0.24	(2.59)	0.14	(1.65)
Net stock issuance (NS)	-0.16	(-2.90)	-0.11	(-2.64)
Return on assets (ROA)	0.03	(0.37)	0.10	(1.53)
Ln(Assets)	0.06	(0.31)	0.03	(0.19)
Lagged Ln(1+R&D/Market equity)	0.16	(1.18)	-0.16	(-1.60)
Ln (1+Patents/Assets)	0.01	(0.09)	0.07	(1.35)
Industry dummy	Y		Y	
R^2	0.51		0.42	
Number of firms	412		688	

Table 10
Return predictive power of trademarks/assets and patent activities

This table reports the time-series average slopes (in %) and their *t*-statistics in parentheses from monthly Fama and MacBeth (1973) cross-sectional regressions within subsamples split by patent activity. All firms have nonzero trademarks/assets (TRAT) over the past year. If a firm has no patents granted over the past year, it is included in the "No Patent" group. If a firm has nonzero patents granted over the past year, it is included in the "With Patent" group. All variables are defined as in Table 7. The method is the same as in Table 7.

	No Patent		With Patent	
	Slope	*t*-stat	Slope	*t*-stat
Rank(TRAT)	0.11	(2.15)	0.09	(1.76)
Asset growth (AG)	-0.02	(-0.45)	0.05	(1.03)
Idiosyncratic volatility (IVOL)	0.05	(0.37)	0.05	(0.38)
Skewness (SKEW)	0.00	(-0.10)	-0.06	(-1.18)
Short-term return reversal (REV)	-0.52	(-7.91)	-0.53	(-7.37)
Ln(1+Advertising/Assets)	0.04	(1.00)	0.03	(0.69)
Ln(Book-to-market)	-0.05	(-0.59)	0.21	(2.41)
Ln(1+R&D/Market equity)	0.33	(2.58)	-0.01	(-0.10)
Ln(Size)	-0.27	(-1.56)	0.17	(0.76)
Momentum	0.24	(2.79)	0.11	(1.15)
Net stock issuance (NS)	-0.15	(-3.12)	-0.15	(-3.30)
Return on assets (ROA)	0.06	(0.74)	0.06	(0.84)
Ln(Assets)	0.20	(1.37)	-0.23	(-1.12)
Lagged Ln(1+R&D/Market equity)	-0.15	(-1.23)	0.03	(0.33)
Ln (1+Patents/Assets)	0.00	(0.18)	0.05	(0.80)
Industry dummy	Y		Y	
R^2	0.36		0.46	
Number of firms	653		492	

Table 11
Return predictive power of trademarks/assets – portfolio analysis based on within-industry sorts

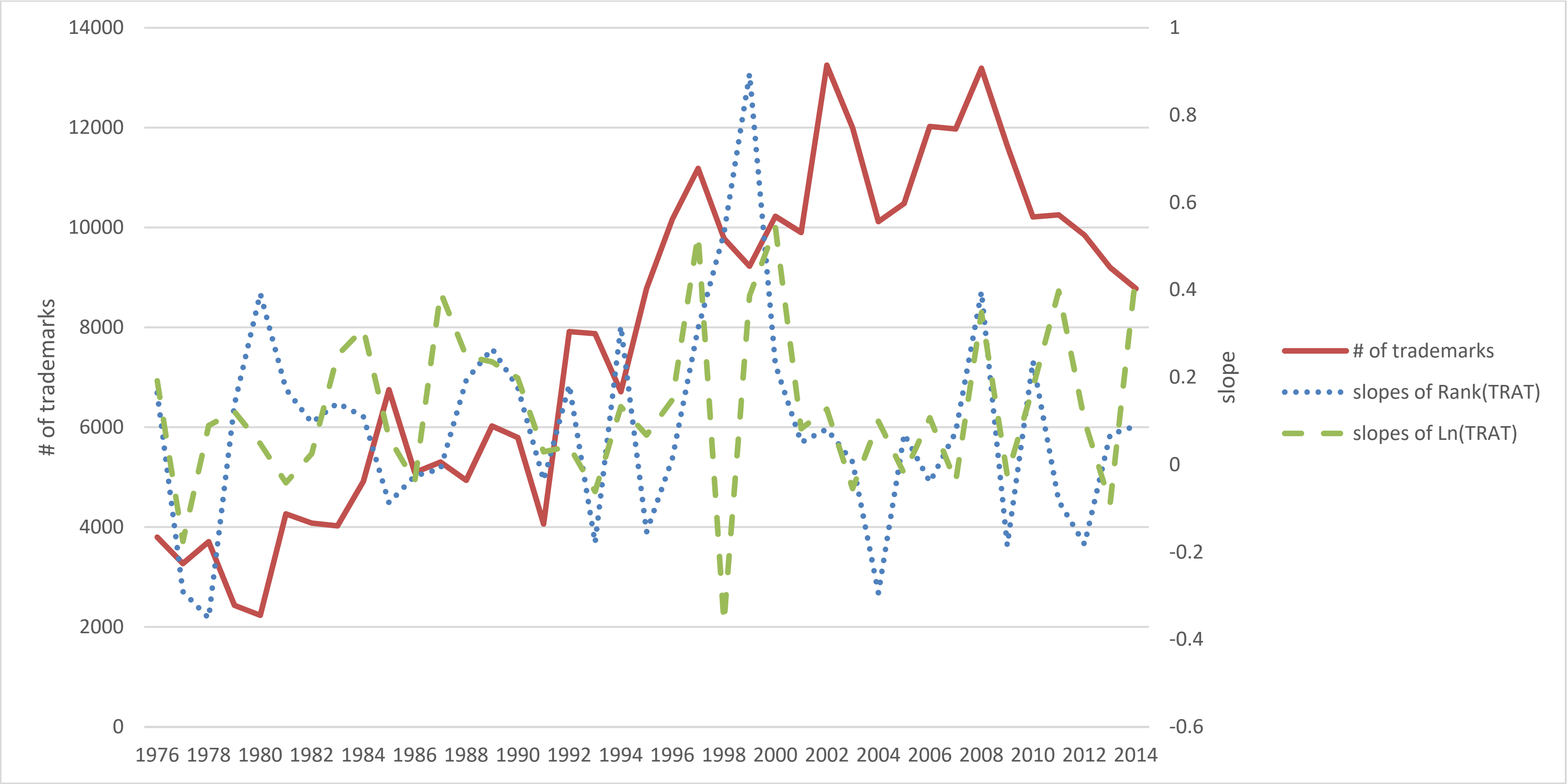
At the end of June of each year *t* from 1977 to 2015, we form portfolios based on trademarks/assets (TRAT) in year *t* – 1 using tercile breakpoints within each industry. We then assign all the firms ranked in the top (bottom) tercile within each industry into the high (low) TRAT portfolio, and so on. We hold these portfolios over the next 12 months. Panel A reports the average monthly excess returns and alphas when industries are defined based on 2-digit SIC codes. Panel B reports the average monthly excess returns and alphas when industry is defined based on Fama-French 17 industries (FF17). Factor models are defined as in Table 3. All returns and alphas are value-weighted and expressed in percentage. The *t*-statistics are reported in parentheses. R-square is adjusted.

A. Sorting within industries based on 2-digit SIC codes							
		Alphas			R^2		
TRAT	Exret	FF 5F	HXZ (q-factor)	Mispricing	FF 5f	HXZ (q-factor)	Mispricing
Low	0.60%	0.01%	0.05%	-0.03%	0.97	0.96	0.97
	(2.90)	(0.37)	(1.27)	(-0.66)			
Middle	0.69%	0.06%	0.07%	0.08%	0.94	0.93	0.93
	(3.15)	(0.98)	(1.14)	(1.35)			
High	0.91%	0.32%	0.39%	0.34%	0.90	0.88	0.89
	(3.19)	(3.26)	(3.68)	(3.16)			
High-Low	0.31%	0.30%	0.34%	0.36%	0.55	0.51	0.51
	(2.07)	(2.83)	(2.95)	(3.11)			

B. Sorting within industry (FF17)							
		Alphas			R^2		
TRAT	Exret	FF 5F	HXZ (q-factor)	Mispricing	FF 5f	HXZ (q-factor)	Mispricing
Low	0.60%	0.01%	0.05%	-0.02%	0.97	0.96	0.97
	(2.92)	(0.26)	(1.24)	(-0.63)			
Middle	0.74%	0.14%	0.15%	0.14%	0.94	0.93	0.94
	(3.23)	(2.24)	(2.26)	(2.17)			
High	0.92%	0.38%	0.44%	0.37%	0.90	0.88	0.88
	(3.01)	(3.79)	(3.78)	(3.08)			
High-Low	0.32%	0.37%	0.39%	0.39%	0.64	0.57	0.56
	(1.81)	(3.28)	(3.08)	(3.00)			

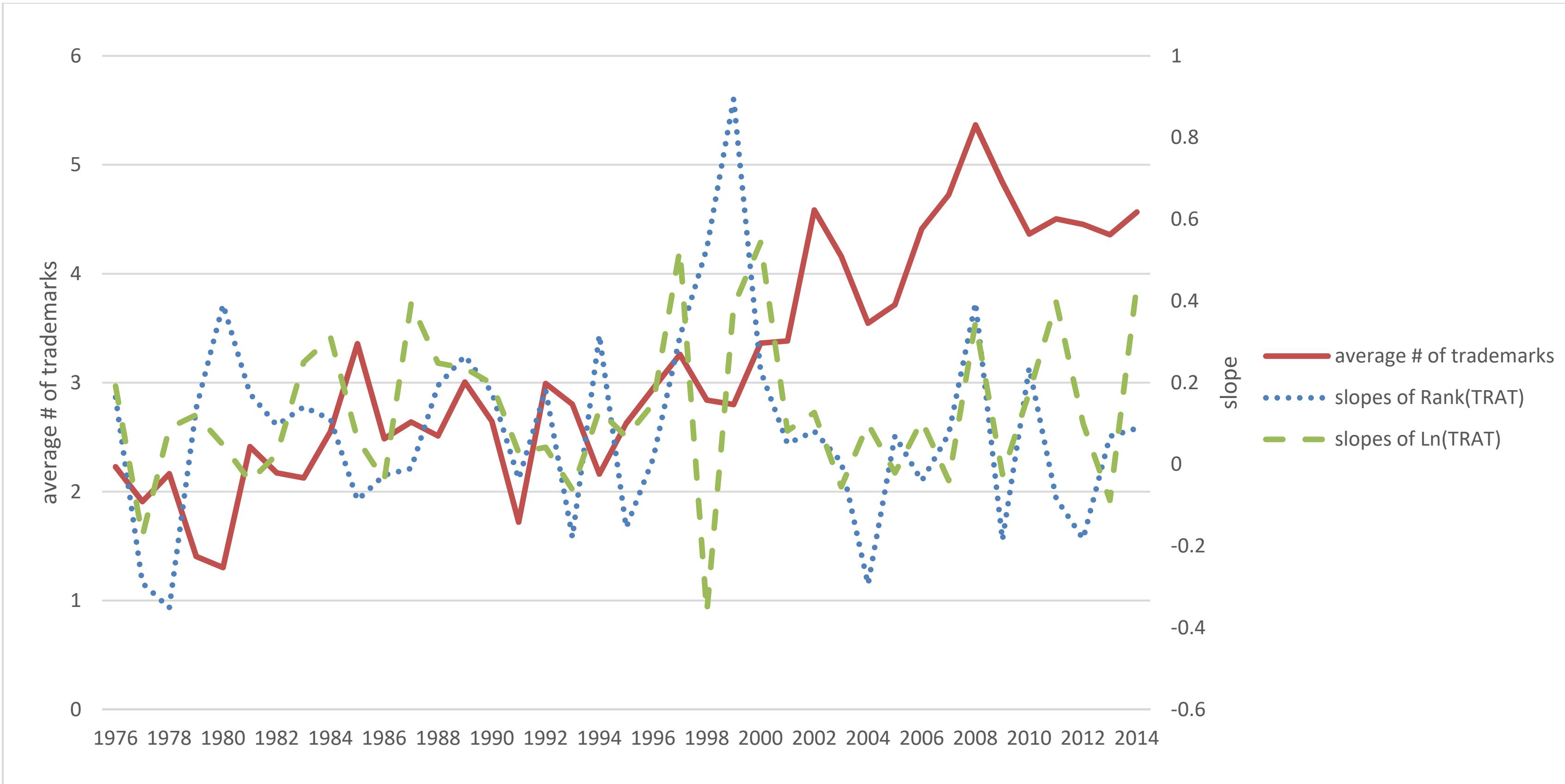
Figure 1
Trademarks and Fama-MacBeth slopes by year

Panel A: Aggregate trademark numbers and Fama-MacBeth slopes on trademarks/assets by year



This figure plots the aggregate number of trademarks registered from 1976 to 2014 by all public firms included in our sample (left vertical axis). It also plots annual average Fama-MacBeth slopes of tercile rank of trademark/assets (Rank(TRAT)) and the natural log of trademark/assets (Ln(TRAT)) in the right vertical axis. The monthly Fama-MacBeth slopes are estimated from Models (3)-(4) of Table 6 Panel B and averaged in each year corresponding to the year of the TRAT measure.

Panel B: Average trademark numbers and Fama-MacBeth slopes on trademarks/assets by year



This figure plots the average number of trademarks registered per public firm from 1976 to 2014. The sample only includes public firms with at least one trademark registered in each year (left vertical axis). It also plots annual average Fama-MacBeth slopes of tercile rank of trademark/assets (Rank(TRAT)) and the natural log of trademark/assets (Ln(TRAT)) in the right vertical axis. The monthly Fama-MacBeth slopes are estimated from Models (3)-(4) of Table 6 Panel B and averaged in each year corresponding to the year of the TRAT measure.

Figure 2
Cumulative returns on the high-minus-low trademark intensity portfolio

This figure plots the cumulative value-weighted return on the high-minus-low trademark/assets portfolio (as formed in Table 3) from July of 1977 to December 2015.