New Market Entry, Trademarks, and Stock Returns*

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

Abstract

As a proxy for firms' entry into new markets, new trademarks reflect growth options but also involve significant uncertainty, such as market acceptance, contestability, and renewal. We propose that firms' future stock returns increase with their new trademarks because of undervaluation owing to limited attention or increased systematic risk. We show that new trademark strongly predicts higher abnormal stock returns. Furthermore, this relation is significantly stronger among large, opaque, high analyst dispersion, high analyst coverage, low advertising, and R&D-active firms, and is stronger among firms with new exploratory trademarks. Such return predictability does not last in longer horizons of multiple years and is not priced in the cross-section of stock returns. These results suggest that the stock market tends to undervalue new trademarks due to behavioral biases.

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

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

* 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

Firms generate revenue by offering products and services to the market, and have to innovate to strengthen their market positions or to expand their customer bases. With the occurrence of technological changes and industry restructuring, it is necessary for firms to provide novel products or services to respond to or generate new needs from existing customers or to attract new customers. Thus, creating new product lines and monetizing their market potential are critical for firms' survival and prosperity, which are value-relevant for shareholders.

It is difficult to estimate future outcome of a firm's attempt in bringing a new product line to the market. Forecasting based on past records of existing products is often unreliable since the firm enters into unchartered water, and the probability distribution of a brand new product/service is largely unknown. For example, the giant book retailer Barnes & Noble launched Nook, an e-reader device based on the Android platform, in October 2009. This new brand has been a failure, and Barnes & Noble lost a large share of the market to Apple, Samsung, Amazon, and Google.[1] Another example is Daimler Mercedes' Smart, which is a new brand from cooperation between Swatch and Daimler Mercedes. It targeted the mini car market that was not covered by its manufacturers in the past. Although it sold almost 25,000 units 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.[2]

On the other hand, there were also big-time successes. For example, Toyota's Lexus became a famous, luxurious brand in the automobile market, and gained the world's largest car manufacturer a substantial share of the high-end vehicle market.[3] Apple's iPhone is another prominent story:

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

since its original model was launched in 2007, its worldwide sales has exceeded 6 billion units by the end of 2017.[4]

Firms' attempts in launching new product lines may have asset pricing implication as follows. On the one hand, investors are often constrained in information processing ability and attention, and cannot capture and digest all product news. The difficulty and uncertainty in evaluating the potential of new product lines exacerbate the constraints on investors' cognitive processing power, which leads them to overdiscount future benefits from the success of new product lines.[5] On the other hand, new product lines create new growth options to firms and thus increase their systematic risk exposure as well as expected stock returns.[6] These discussions collectively point to a positive relation between new product lines and future stock returns due to overdiscounted growth opportunities, and underreaction to news, or increased systematic risk.

When a firm plans to launch a new product line that aims at different customers and creates new market image, it needs to create a new brand name and register with the US Patent and Trademark Office (USPTO) in the form of trademark (Millot, 2009).[7] The registration of the new trademark ensures the firm's efforts in creating a new product line will be legally protected by the federal trademark laws and will not be diluted or pirated by others. Later, the firm markets new products or services under this trademark, which will attract customers' attention and build market

[4] https://www.statista.com/statistics/263401/global-apple-iphone-sales-since-3rd-quarter-2007

[5] Although firms expect new products/services to bring significant cash flows in the future, valuing trademark activities can be hard for general investors due to complexity and uncertainty. Prior studies suggest that investors tend to overdiscount the cash flow prospects of R&D-intensive or patenting firms owing to high uncertainty and complexity associated with innovations or fail to take into account the benefits of innovation due to limited attention, which results in underpricing of innovation (see, e.g., Hall 1993; Lev and Sougiannis 1996; Aboody and Lev 1998, 2000; Chan, Lakonishok, and Sougiannis 2001; Lev, Sarath, and Sougiannis 2005; Hirshleifer, Hsu, and Li 2013, 2017).

[6] The literature has argued that firms' innovative activities create growth options or increase systematic risk exposure (e.g., Kothari, Laguerre, and Leone 2002; Chambers, Jennings, and Thompson 2002; Berk, Green, and Naik 2004; Lin 2012; Kogan and Papanikolaou 2014). The relation between aggregate innovative activities and market premium has been discussed in Greenwood and Jovanovic (1999), Hobijn and Jovanovic (2001), Laitner and Stolyarov (2003), and Hsu (2009).

[7] As defined by the US Patent and Trademark Office (USPTO), a trademark is a brand name (see https://www.uspto.gov/trademarks-getting-started/trademark-basics)

image.[8] We thus propose that firms with more newly registered trademarks may provide significantly higher abnormal stock returns, and furthermore, this predictive power should be stronger among hard-to-value firms. We test these propositions using the newly available trademark database of the USPTO.[9]

We first collect the USPTO Trademark Case Files Dataset which contains detailed information of 7,857,955 trademark applications filed with and 4,792,421 trademarks registered with the USPTO between 1970 and 2015. It includes data on trademark characteristics, assignees (owners), classification, prosecution history, renewal and maintenance history, prior registration, etc. We follow Hsu, Li, Liu, and Wu (2017) to identify trademark assignees and then manually match these assignees to U.S. public firms based on their name, location, and industry. As a result, we have a sample of 305,422 registered trademark records assigned to U.S. public firms from 1976 to 2014 in our sample.

We measure a firm's trademark activities as the number of new trademarks registered in a year scaled by its total assets in that year (TRAT). Based on TRAT in the past year, we form three portfolios (low, middle, and high) and track their value-weighted returns in excess of the T-bill rate. The high TRAT portfolio yields an annualized value-weighted excess return of 12.24%, and also has large and significant alphas 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). Specifically, the annualized value-weighted alpha of the high TRAT

[8] Due to search costs and information asymmetry, consumers rely on trademarks to facilitate their decisions (Graham, Hancock, Macro, and Myers 2013). Registered trademark thus functions as a signaling tool for good merits (such as quality) and differentiates itself from other products/services to achieve a competitive advantage (e.g., Besen and Raskind, 1991; Landes and Posner, 1987). The literature has shown that the number of trademarks is positively associated with market shares and profit margins (Greenhalgh and Rogers 2006; Crass, Czarnitzki and Toole 2016).

[9] Due to the lack of US-based trademark database in the past, prior studies on the value-relevance of trademarks are mainly based on European trademark data (Graham et al. 2013). A recent study exploiting this database is Block, De Vries, Schumann, and Sandner (2014), which finds that start-up firms' trademark number is positively related to their evaluation from venture capitalists based on a sample of 2,341 start-ups.

portfolio is 7.4%, 7.2%, and 5.8% from these factor models, respectively. All are significant at the 1% level. In addition, annualized industry-adjusted returns of this high TRAT portfolio is 3.4% and significant at the 5% level.

We also construct a hedge portfolio based on longing the high TRAT portfolio and shorting the low TRAT portfolio, which yields an annualized value-weighted excess return of 5.2%. The TRAT hedge portfolio provides annualized value-weighted alphas of 7.8%, 7.0%, and 6.3% from the Fama-French 5-factor model, the q-factor model, and the mispricing factor model, respectively (all are significant at the 1% level). Moreover, annualized industry-adjusted returns of this hedge portfolio is 3.7% and significant at the 5% level. Furthermore, excluding the year 2000 barely change the results, which suggests that this TRAT effect is not driven by market exuberance.

To further examine whether the return predictive power of TRAT only exists in small firms or is subject to liquidity concerns, we conduct independent double sorts on TRAT and firm size. We find that the TRAT-return relation is in fact stronger among large firms, which suggests that our finding is not due to market frictions and a trading strategy based on firms' new trademarks indeed provides significant returns in excess of trading costs. Such a seemingly profitable strategy may reflect behavioral biases or risk premiums.

To examine the driving forces for the return predictive power of TRAT, we conduct independent double sorts on TRAT and one of the following five variables: opacity, analyst dispersion, analyst coverage, advertising spending, and R&D spending.[10] We find that the return

---

[10] Opacity and analyst dispersion are two common proxies for value uncertainty (Hirshleifer, Hsu, and Li 2017). 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. 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 more likely 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. Barber and Odean

predictability of TRAT is strong and significant among large firms, opaque firms, firms with high analyst dispersion, high analyst coverage, low advertising spending, and firms active in R&D. On the other hand, the return predictability of TRAT is weak and often insignificant among small firms, transparent firms, firms with low analyst dispersion, low analyst coverage, high advertising spending, and firms inactive in R&D. Specifically, 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 dispersion, respectively, with *t*-statistics all above 4.3. In contrast, annualized alphas among firms with low opacity and low analyst dispersion are only 1.2% and 4.2%, respectively, with much smaller *t*-statistics. This sharp contrast suggests that behavioral biases contribute to the return predictability of new trademarks because opacity and analyst dispersion reflect value uncertainty (Hirshleifer, Hsu, and Li 2017), advertising spending is positively associated with investor attention (Barber and Odean 2008; Grullon, Kanatas, and Weston 2004), and size and R&D activities are positively related to complexity (Cohen and Lou 2012).[11]

We then conduct Fama-MacBeth (FM 1973) regressions to ensure that this predictive power is 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 return reversal, assets size, patent/assets, and industry effects. The results are robust and consistent with the portfolio sorts. In the full sample, the TRAT-return relation is strong and significantly positive at the 1% level even after we control for all the return predictors mentioned above. Furthermore, this relation is significantly stronger among larger firms, higher R&D firms, and lower advertising firms based on either full-sample regressions with interaction

(2008) show that investors focus on stocks that grab their attention, and Grullon, Kanatas, and Weston (2004) show that firms with higher advertising expenses attract more investors.

[11] In addition, large firms' trademarks are more likely to be contested by competitors (see, e.g., Jones and Weingram, 1996; Albuquerque, 2009; Kim and Skinner, 2012).

terms or regressions within subsamples.

The trademark effect is more general than and distinct from the effect of patents on stock returns documented in the literature. Specifically, we find that the trademark-return relation exists in firms with *and* without newly granted patents, and is slightly stronger among non-patenting firms. Furthermore, this relation is stronger among firms with exploratory trademarks, defined as new trademarks registered in new classes in which a firm has never registered trademarks over recent years. This additional test further suggests that the TRAT effect is due to behavioral biases since exploratory trademarks represent uncharted waters, which involve more value uncertainty and can lead to investors paying less attention.

Further analyses suggest that the TRAT-return relation cannot be attributed to (unknown) systematic risk. We first examine the long-term return predictability and find that the TRAT effect does not last longer than one year. This result is inconsistent with a risk explanation because systematic risk-based return predictability should persist longer than mispricing-based return predictability (Chambers, Jennings, and Thompson 2002) and risk embedded in new product lines should not resolve within one year. Moreover, if the TRAT effect is driven by some systematic risk that is not covered by conventional factors, we may use the return on the hedge portfolio as a factor that reflects the risk premium related to trademarks (see Fama and French 1993) and test if it is priced across all stocks using a two-pass procedure (see Cochrane 2001). We do not find that the loading on the TRAT factor is priced in the cross-section of stock returns.

This study relates to the literature on valuation of intellectual property (IP). Previous studies in this area focus on R&D and patents, which mainly apply to industries that focus on technological innovation, but miss those sectors that do not use patents to protect IP, such as service industries.[12]

[12] For example, Chan, Lakonishok, and Sougiannis (2001), Lev, Sarath, and Sougiannis (2005), Penman and Zhang (2002), and Eberhart, Maxwell, and Siddique (2004) show that firms' R&D expenditures predict stock returns. Pakes

Hall, Helmers, Rogers, and Sena (2014) report that trademark is probably the most widely used form of IP protection as it is applicable to essentially any product or service. Based on 2008's Business R&D and Innovation Survey, 15% of surveyed firms indicate trademarks as an important form of IP protection, while 5%, 6%, 12%, and 14% firms indicate utility patents, design patents, copyrights, and trade secrets as important forms of IP protection, respectively. Even among firms reporting R&D expenditures, 60% indicate trademarks as an important IP protection, while 41%, 33%, 50%, and 67% indicate utility patents, design patents, copyrights, and trade secrets as important IP protection, respectively. Furthermore, trademarks capture almost all types of innovation (such as service and marketing innovation) and exist in a broader range of firms and industries (Millot 2009; Graham et al. 2013).[13] Therefore, it is important to study market valuation of trademark, which has a much wider and general implication.[14]

This study is also related to the literature on the role of limited attention in asset pricing, especially from the perspective of intangible assets. Prior studies have documented that investors underreact to the benefits from firms' innovative activities including R&D investments and patent output (Lev and Sougiannis 1996; Chan, Lakonishok, and Sougiannis 2001; Hirshleifer, Hsu, and Li 2013, 2017). This study extends this stream of literature by showing that investors also underreact to the value of new product market opportunities, which supports the findings in prior studies and highlights the importance of further investigation on intangible asset pricing.

(1985), Deng, Lev, and Narin (1999), Cohen, Diether, and Malloy (2013), Hirshleifer, Hsu, and Li (2013, 2017) present evidence that firms' R&D and patent activities predict significantly higher abnormal stock returns.

[13] Mendonca, Pereira, and Godinho (2004) show that trademarks better capture the innovation activities of firms in the service industries, which is particularly important given those industries' increased prominence in the U.S. economy. In addition, Faurel, Li, Shanthikumar, and Teoh (2017) suggest that trademarks capture the product development of novel goods or services, and also marketing innovations. This is supported by the evidence: trademark registered in service classes increased from 26.7% of all trademarks in 1992 to over 39.0% in 2009 (Graham et al., 2013). As discussed in Graham, et al. (2013) and Graham, Marco, and Myers (2015), trademarks are prevalent in both high- and low-patent industries and are thus a valuable supplementary proxy for innovative output.

[14] Some recent studies examine the effect of advertising expenditures on firm value and stock returns (e.g., Belo, Lin, and Vitorino, 2014; Vitorino, 2013). In contrast, our focus is on the asset pricing implication of firms' entry into new markets, which cannot be captured by advertising expenditures that (mainly) focus on existing products/brands.

2. Trademark Basics

The first legal system of trademarks was created in France in 1857, with the "Legislation Relating to Commercial Marks and Product Marks" that justifies the laws and enforcements of trademarks and infringements (Millot, 2009). In Britain, the trademark system was established in 1862, with the "Merchandise Marks Act" that made it a criminal offense to imitate another's trademarks. In the U.S., the trademark system was first attempted to establish a federal trademark regime in 1870. The Agreement on Trade-Related Aspects of Intellectual Property Rights in 1994 is the latest attempt to standardize the trademark procedures across countries. Overall, the procedure and protection of trademarks are largely similar in most developed countries (Millot, 2009).

The modern U.S. federal trademark registration system was established with the Lanham Act in 1946.[17] The USPTO defines a trademark as "any word, name, symbol, device, or any combination, used or intended to be used to identify and distinguish the goods/services of one seller or provider from those of others, and to indicate the source of the goods/services".[18] The article 15 of the Agreement on Trade-Related Aspects of Intellectual Property Rights defines trademarks as "any sign, or any combination of signs, capable of distinguishing the goods or services of one undertaking from those of other undertakings, shall be capable of constituting a trademark".[19]

A firm may file a trademark application to the USPTO for a new trademark that will be used in some particular product/service classes.[20] In the application file, the applicant also needs to provide

[17] Although the Act has been amended several times since, it remains the primary federal trademark statute in providing nationwide regulation and protection for trademark registration (Graham et al. 2013).
[18] See https://www.uspto.gov/trademarks-getting-started/trademark-basics
[19] See http://www.wipo.int/wipolex/en/other_treaties/details.jsp?group_id=22&treaty_id=231
[20] 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. 86.5% of trademark applications are registered in single classes

a proof of the actual use of the trademark in commerce, such as a specimen, or can file an Intent-to-Use statement to agree to provide a proof in the next six months (Statement of Use) by filing (Graham et al., 2013).[21] When the application has met the minimum filing requirements, an application serial number is assigned and the application is forwarded to an examining attorney in the USPTO. The attorney will review the trademark application, which includes a search for conflicting marks and an examination of the written application, the drawing, and any specimen. The attorney's job is to ensure the novelty of the filed trademark that is reasonably distinct from existing trademarks and can be easily identified by the public. The attorney may reject the application if the proposed trademark has been commonly used by the public (e.g., "Police"), if it is only descriptive of the product or of its quality (e.g., "Cheese" and "Delicious"), if it has no distinctive characters, if it has a scandalous connotation, or else if it refers to specific official emblems (e.g., "California") (see, e.g., Millot, 2009; Graham et al., 2013).[22]

If the examining attorney raises no correction requests or objections, or if the applicant has addressed all concerns and overcome all objections raised by the attorney, the examining attorney will approve the trademark to be published in the *Official Gazette*, a weekly publication of the USPTO published on Tuesday. After the mark is published in the *Official Gazette*, a third party may file a notice of opposition to the trademark's registration during this 30-day period after

(Graham et al., 2013). The application fees can be found via https://www.uspto.gov/trademarks-application-process/filing-online/trademark-application-fee-structure.

[21] It is noteworthy that 45.9% of intent-to-use applications are abandoned without being registered.

[22] 8.3% of trademark applications were rejected by examining attorneys (Graham et al. 2013). If the applicant decides that minor corrections are required, he/she will issue a letter (Office Action) to request corrections. If the attorney decides that the proposed trademark should not be registered, he/she will issue a letter (Office Action) explaining any substantive reasons for refusal, and any technical or procedural deficiencies in the application. The applicant needs to respond to the Office Action within six (6) months of the mailing date of the Office action, or the application will be declared abandoned.

publication.[23] If no opposition is filed or if the opposition is unsuccessful, the application enters the next stage of the registration process.

Before the official registration of the trademark, the applicant will need to file statement of use to prove the actual use of the trademark in commerce if such a proof has not been provided in initial application. After all these necessary conditions are met, the trademark can be officially registered.[24]

After a trademark is registered, the firm can use the ® symbol associated with their trademark and is able to market its products and services under trademark protection. New products and services as well as the new trademarks they bear attract customers' attention and accumulates market image. Persistent promotions of trademarks helps maintain and enhance brand awareness. Due to search costs and information asymmetry, consumers rely on trademarks to facilitate their decisions (Graham et al. 2013). Registered trademark thus functions as a signaling tool for good merits (such as quality) and differentiates itself from other products/services to achieve a competitive advantage (e.g., Besen and Raskind 1991; Landes and Posner 1987).

After a firm successfully registers a trademark, it can claim for incontestability by filing the Declaration of Incontestability in the completion of the fifth year from the registration date. Such a claim shields the firm from challenges based on descriptiveness such as (1) the trademark merely describes the goods or services, (2) the mark is descriptive because it is primarily merely a surname, and (3) the mark is descriptive because it is a geographic place name. Firms have strong

[23] When a notice of opposition is filed, the owner of the opposed application has 30 days to file an answer with the Trademark Trial and Appeal Board (TTAB), which is a body within the USPTO responsible for hearing and deciding certain kinds of trademark-related cases. 98.1% of published applications were registered (Graham et al. 2013).

[24] As shown in Graham et al. (2013), 78.8% of all applications were eventually granted. The median time from application to registration is 1.2 years for all registrations filed with actual use and is 1.9 years for all those filed based on intent-to-use.

incentives to file the incontestability claim so that they can use incontestability as a defense against an action for trademark infringement in federal courts (Sloane and Winston 2009).

Firms can hold permanent ownership of their trademarks if they can maintain the trademarks in the sixth year from registration dates and to renew the trademarks every 10 years from registration dates.[25] 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. Between the fifth and sixth year after registration, the owner must file the Declaration of Use of Mark in Commerce to show the continued use of the trademark and pay fees to maintain the registration.[26] In particular, the owner needs to present a specimen that is currently used for each class of goods or services in which the trademark has been registered for.[27] Further, on the date between the ninth and tenth years after the registration (and each successive ten-year period thereafter), the owner needs to renew the trademark registration by filing the Application for Renewal of Registration of a Mark, together with the Declaration of Use, by proving the continued use of the trademark and pay fees.[28]

When a trademark survives, it is valuable to its owners as it reflects the goodwill a firm and its products and services have. Based on continued use and marketing of the trademark, customers associate it with specific impressions and attributes that help them make decisions and may even

[25] The relevant procedures for maintaining and renewing trademarks can be found on the USPTO website: https://www.uspto.gov/trademarks-maintaining-trademark-registration/keeping-your-registration-alive and https://www.uspto.gov/trademarks-application-process/filing-online/registration-maintenancerenewalcorrection-forms. The renewal frequency was 20 years before November 1989 and reduced to 10 years after the enactment of Trademark Law Revision Act of 1988 [Title 1 of Pub. L. 100-667, 102 Stat. 3935 (15 U.S.C. 1051)]. Registrations can be renewed within one year before the end of every 10-year period after the registration date or within the 6-month grace period thereafter.

[26] The owner can still file extension for six months after the sixth year from registration.

[27] 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.

[28] The owner can still file extension for six months after each successive ten-year period after registration. Among patents that were maintained in the sixth year, 68.9% were renewed in the tenth year (Graham et al. 2013)).

present loyalty and trust to it. All these effects lead to market power and uniqueness of that trademark, which allow the firm to charge market premium in associated products and/or services. More importantly, the firm is able to sue other individuals and entities for using similar marks, images, or symbols that may confuse customers and result in economic loss.

3. The data, trademark measure, and summary statistics

3.1. Trademark data and measure of trademark intensity

We download the USPTO Trademark Case Files Dataset we download contains detailed information of 7,857,955 trademark applications filed with and 4,792,421 trademarks registered with the USPTO between 1970 and 2015.[29] It includes data on trademark characteristics, assignees (owners), classification, prosecution history, renewal and maintenance history, prior registration, etc. Because 45.9% of applications are abandoned without being registered (Graham et al. 2013), we restrict our sample trademarks to those that were successfully registered in the USPTO to ensure that all trademarks we consider are in actual use by trademark assignees.

After downloading the data and filtering out unregistered applications, we follow Hsu et al. (2017) to identify trademark assignees and then manually match these assignees to U.S. public firms based on name, location, and industry. Specifically, we first harmonize all assignee names by grouping all names of the same assignee together. We then match these unique assignee names to a list of public company names and their identifier (permno) in the Compustat/CRSP database using the Levenshtein Algorithm and manual checking (based on locations and available information from online searches such as Bloomberg BusinessWeek). As a result, we complete a

[29] 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.

sample of 305,422 registered trademark records assigned to U.S. public firms from 1976 to 2014 after the usual filters (discussed later). 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 (13,252 trademarks registered in total). In addition, the number of trademarks registered per firm also reveals an increasing pattern and peaked in 2008 (5.4 trademarks per firm).

Our main proxy for a firm's new trademark activities in year *t* is defined as the number of trademarks registered by the firm with the USPTO 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, 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. 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. Thus, in subsequent analyses, we focus on firms with newly registered trademarks in the past year since they capture the most recent trademark activities which are more likely to carry systematic risk or are more likely misvalued by the market. In term of economic significance for firms with non-zero trademarks, their total market capitalization accounts for 76% of the entire sample.[30] Therefore, it is economically significant to focus on firms with non-zero trademarks registered in one year.

[30] This ratio is higher than the ratio of sample firms with non-zero, no-missing R&D or sample 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 2015 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. 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 coverage and 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 four portfolios formed on TRAT. Specifically, at the end of June of year *t*, we assign all firms with non-zero TRAT into three portfolios (low, middle, and high) based on their TRAT in year t – 1. The low, middle, and high TRAT portfolios are formed 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 "No" portfolio as a comparison. On average, there are 3,217 firms each year from 1976 to 2014, and 1,991 of them are in the "No" group. The three TRAT portfolios are well diversified with the number of firms ranging from 408 to 409.

We then report their time series average of cross-sectional median and mean of TRAT and other firm characteristics that are known to have predictive power for stock returns in the literature. There is large variation in TRAT across the portfolios. The median (mean) TRAT ranges from 0.16% (0.17%) to 3.14% (4.92%) for the three TRAT portfolios. The average size, defined as the market capitalization at the end of June in year *t*, 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 median and mean of book-to-market (BTM, 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, the previous eleven-month returns with a one-month gap between the holding period and the current month), asset growth (AG, change in total assets in year t – 1 divided by lagged total assets), R&D intensity (RDME, R&D expenses in fiscal year ending in year t – 1 divided by market equity at the end of year t – 1), advertising intensity (ADA, advertising expense in fiscal year ending in year t – 1 divided by book value of asset at the end of year t – 1), net stock issues (NS, change in the natural log of the split-adjusted shares outstanding in year t – 1), and idiosyncratic volatility (IVOL, 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) do not vary much across the TRAT portfolios. Firms with higher TRAT do have higher skewness (SKEW, measured at the end of June of year *t* using daily returns over the previous 12 months with a minimum of 31 trading days), but the correlation between SKEW and TRAT is low as we present in Panel B. Furthermore, high skewness is known to predict lower returns. Similarly, return on assets (ROA, income before extraordinary items plus interest expenses in year $t-1$ divided by lagged total assets) on average decreases with TRAT.

We also report the time series averages of cross-sectional correlations and their p-values between TRAT and other firm characteristics in Panel B of Table 1. Consistent with Panel A, TRAT is not highly correlated with most of these characteristics. Although some of the correlations are statistically significant, the levels are generally low (except IVOL). In particular, the correlations between TRAT and book-to-market, momentum, asset growth, and R&D intensity are only 0.01, 0.04, 0.00, and 0.09, respectively. We find that the correlation between TRAT and SKEW is only 0.09 (with a p-value of 0.13). Although IVOL significantly correlates with TRAT (0.29 with a p-value of 0.00), we control for IVOL in the Fama-MacBeth regressions.

In sum, these summary statistics suggest that our TRAT measure is a firm characteristic that is distinct from other established stock return predictors.

Panel A of Table 2 reports pooled summary statistics of our TRAT measure and trademark counts for firms in our sample (with non-zero trademarks registered) across industries based on the Fama and French (1997) 48 industry classifications. Recreation (including toys), Textile, Consumer Goods, and Apparel industries have the highest TRAT, ranging from 0.025 to 0.043. These numbers suggest that a sample firm in these industries with total assets of 100 million dollars register 2.5 to 4.3 trademarks per year on average. On the other hand, Coal has the lowest TRAT of 0.002. In addition, there are large cross-sectional variations in TRAT and trademark counts across industries. For TRAT, the 25th percentile varies from 0.000 to 0.007, and the 75th percentile varies from 0.002 to 0.047. In terms of trademark counts reported in Panel B, the 25th percentile is between 1 and 2, and the 75th percentile ranges from 2 to 15. This shows that firms' engagement in trademark activity varies widely, and some firms engage significantly in trademark activities.

To mitigate the concern that our results are driven by the variation across industries, we report industry-adjusted returns in all the portfolio analyses and control for 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 valuation 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

At the end of June of year *t* from 1977 to 2015, we sort firms with non-zero TRAT into three TRAT portfolios based on the 33rd and 67th percentiles of TRAT in year $t - 1$. Firms with TRAT above the 67th percentile are assigned to the High (H) portfolio, firms with TRAT between the 33rd and 67th percentiles are assigned to the middle (M) portfolio, and firms with TRAT below the 33rd percentile are assigned to the Low (L) portfolio. We assign firms with no trademark registered into the "No" portfolio. To examine the TRAT-return relation, at the end of each June, we form a high-minus-low (H–L) portfolio ("hedge portfolio") that takes a long position in the high TRAT portfolio and a short position in the low TRAT portfolio, and rebalance them in the next June. 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.

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. In Panel A of Table 3, we report average monthly returns in excess of one-month Treasury bill rate (excess returns) as well as industry-adjusted returns for these portfolios to make sure that the TRAT effect is not driven by industry effects. For each stock in a month, we calculate its industry-adjusted return as the difference between its simple monthly return and the average of all firms' monthly returns in the same industry (based on Fama and French 48 industry classifications).

Panel B of Table 3 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 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.

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. The hedge portfolio's industry-adjusted return is 0.31% and significant at the 5% level. Consistent with the idea that firms with no trademark registered carry lower systematic risk or encounter less mispricing, the industry-adjusted return and alphas of the "No" group are small and insignificant. Panel C presents the R-squares of all time-series regressions in Panel B.

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 and are more tradable.

We examine how the probability of transitioning from one portfolio into another. We find that although around half of the firms stay in the same portfolio from previous year, there are a fair amount of probability that a firms move to another portfolio. For example, when a firm was in the M portfolio in year $t - 1$, it has a chance of 28.40% to move to the No portfolio, 15.42% to move to the L portfolio, 42.11% to stay in the M portfolio, and 14.08% to the H portfolio in year t.

We also examine how the returns of the hedge portfolio vary over time. Figure 2 plots the cumulative value-weighted return of the hedge portfolio from July of 1977 to December of 2015. The hedge portfolio's cumulative returns are upward trending. Furthermore, excluding year 2000 (the internet bubble period) barely changes the time-series average returns of the hedge portfolio. This suggests that the TRAT effect is unlikely to be driven by market exuberance.

Moreover, to address the concern that the return predictive ability of TRAT may be driven by the variation in 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.

We also examine if the TRAT effect lasts in a longer horizon. In Panel D of Table 3 we present the returns and alphas of the hedge portfolio in years after portfolio formation. Specifically, it presents the hedge portfolio's average monthly excess returns, average monthly industry-adjusted returns, alphas from Fama-French five factors, alphas from the q-factor model, and alphas from the mispricing factor model in the following six horizons: the July of year t to June of year t + 1, July of year t +1 to June of year t + 2, July of year t +2 to June of year t + 3, July of year t +3 to June of year t + 4, July of year t + 4 to June of year t + 5, and July of year t + 5 to June of year t + 6. We find that the hedge portfolio's returns and alphas are no longer significant after the first year horizon, which supports an undervaluation explanation rather than a risk explanation. As argued in Chambers, Jennings, and Thompson (2002), mispricing-based return predictability should be corrected in a short period while risk-based return predictability should persist for a long period. If new product lines proxied by new trademarks increase higher systematic risk, such risk is less likely to resolve within a one-year period because it takes time to convert new product lines into revenue and profits.

4.1.2 The interaction between the TRAT effect and other effects

We next test the interaction of the TRAT effect with other six effects via independent double sorts. The other three effects we consider are size, opacity, analyst dispersion, analyst coverage, R&D spending, and advertising spending. Firm size is an important characteristic that explains stock returns and reflects systematic risk (Fama and French 1992, 1993). Opacity and analyst dispersion, on the other hand, are two common proxies for value uncertainty (Hirshleifer, Hsu, and Li 2017). 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. Analyst coverage denotes the number of stock analysts following a stock, and R&D expenses and advertising expenses are scaled by total assets.

To perform these tests via independent double sorts, at the end of June of year *t*, we sort firms into two groups based on each of the six characteristics and into three groups based on TRAT. 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, analyst coverage, 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 (active R&D group include firms that have reported R&D expenses). The intersection results in six portfolios. We also form a high-minus-low (H–L) TRAT portfolio (hedge portfolio) in each group for one of the six characteristics. 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.

Tables 4 presents the results from independent double sorts. The hedge portfolio's returns and alphas are substantial and significant among larger firms, firms with higher opacity, firms with higher analyst dispersion, firms with higher analyst coverage, firms with lower advertising expenses, and R&D-active firms, but are small and often insignificant in the other firms. For example, the monthly average excess returns and industry-adjusted returns of the TRAT hedge portfolio are 0.51% and 0.39%, respectively, in larger firms. The monthly alphas range from 0.79% from the mispricing model to 0.91% from the Fama-French five-factor model. In contrast, in smaller firms, these returns and alphas are small and often insignificant, ranging from 0.00% (industry-adjusted returns) to 0.45% (Fama-French five-factor model). 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 indeed provides significant returns in excess of trading costs.

We also find similar sharp contrasts in other five firm characteristics. Specifically, the TRAT hedge portfolio's excess return, industry-adjusted return, and alphas from different factor models are large and significant in the high-opacity subsample, ranging from 0.66% (industry-adjusted return) to 0.94% (Fama-French five factor model). 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 from factor models 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).

The results based on size-sorted portfolios suggest that the predictive ability of TRAT is more tradable and less subject to liquidity concerns. Different from other return anomalies that are stronger among small firms Fama and French, 2008; Stambaugh, Yu, and Yuan, 2015; Stambaugh and Yuan, 2017), the TRAT effect we present is stronger among larger firms. Thus, it is less likely the TRAT effect overlaps with existing anomalies.

The results reported in Table 4 also suggest that the return predictive power of TRAT increases with value uncertainty and/or limited attention. As discussed earlier, valuing new trademark activity can be difficult due to market uncertainty (whether consumer will like the new product/service or not), contestability (whether the uniqueness of a trademark will be challenged by others five years after its registration), and renewal requirement (whether a trademark will still be in use six years after its registration). Intuitively, it is harder to value the impact of TRAT on larger firms, more opaque firms, firms with higher analyst dispersion, firms with lower analyst coverage, R&D-active firms, or firms with lower advertising expenses for the reasons discussed in the introduction.[31] Overall, independent double sorts provide fairly strong support for the conjecture that limited attention and value uncertainty contributes to the return predictive power of TRAT.

We also argue that a stronger TRAT effect among large firms and firms with lower advertising expenses does not support a risk-based explanation for our results. If the TRAT effect is related to increased systematic risk, it is expected to be stronger among small firms, which is not what we find.[32] Also, systematic risk does not predict a stronger TRAT effect among firms receiving lower attention, measured by analyst coverage and advertising expenses.

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 that is not covered by the factors we 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 trademark intensity (see Fama and French 1993). For convenience in terminology, we refer to the monthly

---

[31] For the relation between size and complexity, see Cohen and Lou (2012), Jones and Weingram (1996), Albuquerque (2009), and Kim and Skinner (2012). Large firms are more complex to investors and any information is more slowly incorporated into stock prices (Cohen and Lou 2012). The impact of new trademarks on large firms is thus even more difficult for evaluate to investors, which has two implications: first, investors with limited attention are more likely to underreact to trademark news; and second, investors are expected to over-discount the value associated with new trademarks due to complexity and value uncertainty. Both suggest a stronger return predictive ability of the TRAT among large firms.

[32] Fama and French (1992) find that small firms outperform large firms in subsequent stock returns on average, and attributed such a pattern to systematic risk related to financial constraints, default risk, or cash flow uncertainty (Chan, Chen, and Hsieh, 1985; Chan and Chen, 1991). Systematic risk associated with new trademarks include increased growth options and possible financial constraints due to possible failure. Li (2012) shows that the positive R&D-return relation only occurs to financially constrained firms.

returns on the high-minus-low 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 (see Cochrane 2001). A finding of a significantly priced TRAT factor will support a risk-based explanation for the TRAT effect.

We process the test as follows.[33] First, we conduct a 60-month rolling window estimation to estimate the beta associated with the TRAT factor, $\beta_{i,t}^{TRAT}$, for stock *i* using its stock returns in the most recent 60 months. Then, we conduct a cross-sectional regression in each month to estimate the coefficient on $\beta_{i,t}^{TRAT}$, which serves as an estimate of the risk premium (known as “lambda”) associated with the TRAT factor in a month. Lastly, we test the significance of the risk premium by the time series mean and standard deviation of the coefficients on β^{TRAT} across all months and report the results in Table 5. A statistically significant estimate of the risk premium indicates that our TRAT effect is priced in stock returns.

The results reported in Table 5 indicate that β^{TRAT} is consistently insignificant across various models: Model 1 includes both the market factor (MKT) and the TRAT factor, Model 3 includes the TRAT factor and the Fama French five-factors, and Model 5 includes the TRAT factor and the q-factor factors. Models 2, 4, and 6 are the same as Models 1, 3, and 5 except that we do not include the intercept term in the cross-sectional regression in estimating the risk premium. The fact the TRAT factor is not priced in the various models casts does not support the existence of unspecified systematic risk related to the launch of new trademarks.

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

---

[33] For stock *i* in month *t*, we estimate its $\beta_{i,t}^{TRAT}$ by regressing its monthly excess returns on the TRAT factor and other factors that we have used in Section 4.1.1 from month *t*-59 to month *t*. For each month in our sample period, we regress the monthly excess returns of stocks on the TRAT betas (and other betas such as market betas) to calculate the coefficient on the betas in the month.

4.1.4 TRAT effect and exploratory trademarks

Since exploratory marks represent uncharted waters, they involve more value uncertainty and hence may be more undervalued 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 $t - 2$).[34] We also independently form three TRAT portfolios as before. We find 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 and industry-adjusted return of the TRAT hedge portfolio is 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.

[34] As mentioned before, there are 45 product/service classes in the USPTO classification system for trademarks. The average ratio of the number of exploratory trademarks to the number of new trademarks is almost 60% in 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 robust at the firm level. This analysis allows us to control more extensively for other characteristics that can predict returns and to verify whether the positive TRAT-return relation as identified in portfolio sorts is driven by other known return predictors. To match the value-weighted portfolio strategy, we use weighted least square in the 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 natural log transformation of TRAT (Ln(TRAT)) to address skewness in TRAT.[35] 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

[35] 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 (2017).

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 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. We include firms with missing R&D or missing patents by setting their RDME and patent/assets to zero. 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.[36] 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 TRAT effect and other effects

To examine the robustness of the interaction between the TRAT effect and other effect identified through double sorts, we use subsample Fama-MacBeth regressions, which allow us to control for many well-known return predictors. To avoid the high correlation between the interaction term and its component variables, we focus on Rank(TRAT) in the following tests.

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

Table 8 presents the results from Fama-MacBeth regressions within subsamples split by each of those six proxies as in Table 4. We use Models 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, analyst coverage, 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 TRAT are 0.08% (t = 2.61), 0.31% (t = 2.96), 0.17% (t = 1.65), 0.11% (t = 2.43), 0.10% (t = 2.25), and 0.12% (t = 2.40) among large firm, opaque firms, high dispersion firms, high analyst coverage 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), 0.06% (t = 1.07), −0.02% (t = −0.42), and 0.03% (t = 0.52) among small firms, transparent firms, low dispersion firms, low analyst coverage firms, R&D-inactive firms, and high advertising firms.

Table 8 thus confirms the findings from double-sorted portfolios and supports our argument that behavioral biases lead to the 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 value uncertainty or lower attention. These findings are consistent with our argument based on behavioral biases. However, we would not interpret our results as that new trademarks do not involve uncertainty among firms with low analyst dispersion and firms with low opacity. Instead, new trademarks may be easier to evaluate among these firms since investors' cognitive biases (namely, limited attention) is less severe among these firms.

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 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 new class.

4.2.4 TRAT effect and patent intensity

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. Therefore, we control for patent intensity in previous regressions and find that the TRAT effect is robust to the patent intensity effect documented in the literature. In fact, trademarks are more widely used than patents in protecting IP. Therefore, the sample of firms with newly registered trademarks are larger than the sample of firms with newly granted patents. 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 exists in firms with *and* without patents.

To test this hypothesis, we form two subsamples based on firms' patent activity among firms with nonzero TRAT. If a firm has no patents granted over the past year, it is included in the "No Patent" subsample. If a firm has nonzero patents granted over the past year, it is included in the "With Patent" subsample. We then conduct monthly Fama-MacBeth regressions within these subsamples. Table 10 shows that the trademark-return relation indeed exists in both subsamples and is slightly stronger among firms with nonzero patents granted over the same year. Specifically, the slopes on 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 TRAT are similar 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 the 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 2-digit SIC codes or the Fama-French 17 industry classifications. Specifically, at the end of June of each year t, we sort firms with non-zero TRAT into three portfolios based on the 33rd and 67th percentiles of TRAT in year t – 1 within each industry. Firms ranked in the top (bottom) tercile within each industry are assigned to the high (low) TRAT portfolio, and so on. We also construct a TRAT hedge portfolio as the high-minus-low portfolio as in Table 3. 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

We study whether firms' launch of new trademarks offer any asset pricing implications. Since there are lots of uncertainty associated with entering into new markets, it is hard to evaluate the impact of new trademarks. For example, it is uncertain whether the market is willing to accept new product/service under the new mark, whether a new trademark will be contested by other firms, and whether a firm is willing to renew a trademark down the road. Owing to limited attention, we hypothesize that the market may temporarily undervalue firms with more newly registered trademarks. Furthermore, this mispricing should be stronger among firms with more valuation uncertainty, such as larger firms and firms with higher R&D spending or lower advertising expenses. Furthermore, undervaluation of new trademarks is more severe when they are exploratory, which involve more uncertainty. On the other hand, we do not find that trademark intensity carries long-term return predictive power and is insignificantly priced in a two-pass procedure. Our empirical analyses are more supportive to a behavioral explanation for a novel trademark-return relation.

This return predictive power of new trademarks is also more general than and distinct from the effect of patents on stock returns as it exists in both patenting and non-patenting firms, and is slightly stronger in the latter. Although we do not rule out risk-based explanations, the most plausible interpretation of the evidence is that the market underweights the information contained in new trademark registration. Our evidence also suggests that trademark activities create important intellectual property and can be a useful input for firm valuation.

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 (1), 277-304.

Albuquerque, A., 2009. Peer firms in relative performance evaluation. *Journal of Accounting and Economics*, 48(1), pp.69-89.

Alter, A. L., and D. M. Oppenheimer. 2006. Predicting short-term stock fluctuations by using processing fluency. *Proceedings of the National Academy of Science* 103:9369-72

Anderson, E. W., E. Ghysels, and J. L. Juergens, 2009. The impact of risk and uncertainty on expected returns, *Journal of Financial Economics* 94, 233-263.

Barber, B., and T. Odean, 2008. All that glitters: the effect of attention and news on the buying behavior of individual and institutional investors, *Review of Financial Studies*, 21(2), 785-818.

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(1), pp.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.

Bossaerts, P., P. Ghirardato, S. Guarnaschelli, and W. R. Zame. 2010. Ambiguity in asset markets: Theory and experiment. *Review of Financial Studies* 23, 1325–59

Cao, H. H., T. Wang, and H. H. Zhang. 2005. Model uncertainty, limited market participation, and asset prices. *Review of Financial Studies* 18:1219–51.

Chan, K. C., and N.-F. Chen. 1991. Structural and return characteristics of small and large firms. *Journal of Finance* 46(4), 1467-1484.

Chan, K. C., N.-F. Chen, and D. A. Hsieh. 1985. An exploratory investigation of the firm size effect. *Journal of Financial Economics* 14(3), 451-471.

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.

Chen, Z., and L. Epstein. 2002. Ambiguity, risk and asset returns in continuous time. *Econometrica* 70:1403–43

Cohen, L., Diether, K. and Malloy, C., 2013. Misvaluing innovation. *Review of Financial Studies*, 26(3), pp.635-666.

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

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.

Deng, Z., Lev, B. and Narin, F., 1999. Science and technology as predictors of stock performance. *Financial Analysts Journal*, 55(3), pp.20-32.

Dow, J., and S. R. da Costa Werlang. 1992. Uncertainty aversion, risk aversion, and the optimal choice of portfolio. *Econometrica* 60:197–204.

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(2), pp.623-650.

Fama, E., and F. Kenneth. 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.

———. 2000. Forecasting profitability and earnings. *Journal of Business* 73:161–75.

———. 2006. Profitability, investment and average returns. *Journal of Financial Economics* 82:491–518.

———. 2008. Dissecting anomalies. *Journal of Finance* 63:1653–78.

———. 2015. A five-factor asset pricing model. *Journal of Financial Economics*.

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

Faurel, Lucile and Li, Qin and Shanthikumar, Devin M. and Teoh, Siew Hong, CEO Incentives and New Product Development: Insights from Trademarks (September 22, 2017). Working paper

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.

Graham, S.J., Marco, A.C., Myers, A.F., 2015. Monetizing marks: Insights from the USPTO trademark assignment dataset. Working paper, Georgia Institute of Technology and United States Patent and Trademark Office.

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

Greenwood, J., and B. Jovanovic, 1999. The information-technology revolution and the stock market. *American Economic Review Papers and Proceedings* 89, 116-22.

Griliches, Z. 1981. Market value, R&D, and patents, *Economics Letters* 7(2), 183-187.

Grullon, G., G. Kanatas, and J. P. Weston, 2004. Advertising, breadth of ownership, and liquidity. *Review of Financial Studies* 17(2), 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.

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

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

Hsu, P. H. 2009. Technological innovations and aggregate risk premiums. *Journal of Financial Economics* 94, 264-279.

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. 2017. Innovative originality, profitability, and stock returns. *Review of Financial Studies*, Forthcoming.

Hsu, Po-Hsuan, Kai Li, Yunan Liu, and Hong Wu. 2017. New Product Development and Mergers and Acquisitions. Working paper.

Izhakian, Y., and D. Yermack, 2017. Risk, ambiguity, and the exercise of employee stock options, *Journal of Financial Economics*, 124, 65-85.

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(1), pp.290-310.

Laitner, J., and D. Stolyarov. 2003. Technological change and the stock market. *American Economic Review* 93, 1240-1267.

Landes, W.M. and Posner, R.A., 1987. Trademark law: An economic perspective. *Journal of Law and Economics*, 30(2), pp.265-309.

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

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.

Mendonça, S., Pereira, T.S. and Godinho, M.M., 2004. Trademarks as an indicator of innovation and industrial change. *Research Policy*, 33(9), pp.1385-1404.

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(2), pp.390-409.

Penman, S.H. and Zhang, X.J., 2002. Accounting conservatism, the quality of earnings, and stock returns. *The Accounting Review*, 77(2), pp.237-264.

Rogers, Edward S. 1910. Some Historical Matter concerning Trade-Marks. *Michigan Law Review*, Vol. 9, No. 1 (Nov., 1910), pp. 29-43.

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

Stambaugh, R.F., Y. Jianfeng, and Y. Yuan. 2015. Arbitrage asymmetry and the idiosyncratic volatility puzzle. *Journal of Finance* 70(5), 1903-1948.

Stambaugh, R.F. and Yuan, Y., 2017. Mispricing factors. *Review of Financial Studies*, 30(4), pp.1270-1315.

Sloane P.S. and Winston L.J., 2009. Incontestability: Does Anybody Really Understand It? *INTA Bulletin* 64 (14), August 1, 2009.

Song, H., and N. Schwarz. 2008. If it's hard to read, it's hard to do: Processing fluency affects effort prediction and motivation. *Psychological Science* 19:986–88.

———. 2009. If it's difficult to pronounce, it must be risky: Fluency, familiarity, and risk perception. *Psychological Science* 20:135–38.

———. 2010. If it's easy to read, it's easy to do, pretty, good, and true: Fluency effects on judgment, choice, and processing style. *The Psychologist* 23:108–11.

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.

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 "No" 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 issues (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			
	No	Low	Middle	High	No	Low	Middle	High
Number of firms	1991	408	409	409	1991	408	409	409
Trademark/Assets		0.00	0.01	0.03		0.00	0.01	0.05
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	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 with 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: Trademarks/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	Restaraunts, 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 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 high-minus-low portfolio's average monthly excess returns, average monthly industry-adjusted returns, alphas from Fama-French five factors, alphas from the q-factor model, and alphas from the mispricing factor model in the July of year *t* to June of year *t* + 1 (1 year post sorting), July of year *t* +1 to June of year *t* + 2 (2 year post sorting), July of year *t* +2 to June of year *t* + 3 (3 year post sorting), July of year *t* +3 to June of year *t* + 4 (4 year post sorting), July of year *t* +4 to June of year *t* + 5 (5 year post sorting), and July of year *t* +5 to June of year *t* + 6 (6 year post sorting).

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
No	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. Returns and alphas of the high-minus-low portfolio in longer horizons

Years post sorting	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	0.08%	0.09%	0.24%	0.29%	0.32%	0.63	0.57	0.57
	(0.44)	(0.66)	(2.08)	(2.22)	(2.39)			
3	0.17%	0.15%	0.39%	0.43%	0.47%	0.67	0.61	0.60
	(0.91)	(1.06)	(3.39)	(3.45)	(3.57)			
4	0.16%	0.14%	0.33%	0.35%	0.36%	0.64	0.59	0.55
	(0.94)	(1.00)	(2.97)	(2.95)	(2.79)			
5	0.26%	0.24%	0.35%	0.40%	0.48%	0.61	0.54	0.57
	(1.39)	(1.68)	(2.84)	(2.91)	(3.55)			
6	0.10%	0.09%	0.20%	0.20%	0.30%	0.51	0.44	0.49
	(0.57)	(0.62)	(1.46)	(1.40)	(2.12)			

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 six characteristics: firm size, opacity, analyst dispersion, analyst coverage, 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. Analyst coverage denotes the number of stock analysts following a stock, and R&D expenses and advertising expenses are scaled by total assets. The size groups are formed based on NYSE median breakpoints. Opacity, analyst dispersion, analyst coverage, 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 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.

Size subsample													
Small firms													
		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	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													
		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	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)			

Opacity subsample													
Low opacity													
		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	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													
		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	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)			

Dispersion subsample

Low dispersion

Trademark Rank	Firm No.	A. Mean Trademark/ Assets (TRAT)	A. Mean Size ($mn)	B. Median Trademark/ Assets (TRAT)	B. Median Size ($mn)	C. Returns Exret	C. Returns Ind-adjret	D. Alphas FF 5f	D. Alphas HXZ (q-factor)	D. Alphas Mispricing	E. R^2 FF 5f	E. R^2 HXZ (q-factor)	E. R^2 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

Trademark Rank	Firm No.	A. Mean Trademark/ Assets (TRAT)	A. Mean Size ($mn)	B. Median Trademark/ Assets (TRAT)	B. Median Size ($mn)	C. Returns Exret	C. Returns Ind-adjret	D. Alphas FF 5f	D. Alphas HXZ (q-factor)	D. Alphas Mispricing	E. R^2 FF 5f	E. R^2 HXZ (q-factor)	E. R^2 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)			

Analyst coverage subsample													
Low coverage													
		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	75	0.001	1910	0.001	1019	0.56%	0.07%	-0.34%	-0.32%	-0.26%	0.86	0.84	0.84
						(1.91)	(1.02)	(-2.96)	(-2.51)	(-2.05)			
M	151	0.006	719	0.006	397	0.67%	-0.03%	-0.13%	-0.04%	-0.08%	0.91	0.91	0.91
						(2.31)	(-0.43)	(-1.43)	(-0.46)	(-0.83)			
H	235	0.041	319	0.025	161	0.77%	0.11%	0.17%	0.20%	0.16%	0.93	0.90	0.91
						(2.21)	(1.45)	(1.68)	(1.70)	(1.36)			
H-L						0.21%	0.04%	0.51%	0.51%	0.42%	0.49	0.32	0.31
						(1.00)	(0.32)	(3.24)	(2.79)	(2.22)			
High coverage													
		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	283	0.001	15846	0.001	4696	0.63%	-0.03%	-0.04%	0.03%	-0.03%	0.97	0.96	0.97
						(2.78)	(-1.19)	(-0.92)	(0.68)	(-0.71)			
M	208	0.006	4468	0.005	1577	0.92%	0.18%	0.36%	0.40%	0.26%	0.91	0.88	0.89
						(3.36)	(2.43)	(4.08)	(3.89)	(2.57)			
H	123	0.030	1448	0.020	641	1.10%	0.38%	0.63%	0.65%	0.52%	0.85	0.80	0.80
						(3.06)	(2.30)	(4.29)	(3.76)	(2.97)			
H-L						0.46%	0.42%	0.67%	0.62%	0.55%	0.54	0.44	0.42
						(2.02)	(2.20)	(4.11)	(3.36)	(2.88)			

Advertising/assets subsample														
Low advertising														
		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	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													
		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	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)			

R&D subsample														
R&D-inactive														
		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	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													
		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	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)			

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

This table presents the loadings of TRAT betas in the cross-section of stock returns. The monthly returns on the high-minus-low portfolios in Table 3 is the "TRAT factor." For stock *i* in month *t*, we estimate its $\beta_{i,t}^{TRAT}$ by regressing its monthly excess returns on the TRAT factor and other factors that we have used in Table 3 from month *t*-59 to month *t*. Then, we conduct a cross-sectional regression in each month to estimate the coefficient on $\beta_{i,t}^{TRAT}$, which serves as an estimate of the risk premium (known as "lambda") associated with the TRAT factor in a month. For each month in our sample period, we regress the monthly excess returns of stocks on the TRAT betas (and other betas such as market betas) to calculate the coefficient on the betas in the month. Lastly, we test the significance of the risk premium by the time series mean and standard deviation of the coefficients on β^{TRAT} across all months. The coefficients on β^{TRAT} and other betas are reported. Numbers in parentheses report the t-statistics. Model 1 includes both the market factor (MKT) and the TRAT factor; Model 2 is the same as Model 1 but does not include intercept term in cross-sectional regressions; Model 3 includes the TRAT factor and the Fama French five-factors; Model 4 is the same as Model 3 but does not include intercept term in cross-sectional regressions. Model 5 includes the TRAT factor and the q-factor factors; Model 6 is the same as Model 5 but does not include intercept term in cross-sectional regressions.

	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 number of patent 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, dispersion, analyst coverage, R&D spending, and advertising spending and are formed as in Table 4. All variables are defined as in Tables 1 and 6. The method is the same as in Table 6.

	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	

	Low analyst		High analyst		R&D-inactive		R&D-active		Low ADA		High ADA	
	Slope	*t*- stat	Slope	*t*- stat	Slope	*t*- stat	Slope	*t*- stat	Slope	*t*- stat	Slope	*t*- stat
Rank(TRAT)	0.06	(1.07)	0.11	(2.43)	-0.02	(-0.42)	0.10	(2.25)	0.12	(2.40)	0.03	(0.52)
Asset growth (AG)	-0.07	(-1.07)	0.02	(0.38)	0.02	(0.39)	0.06	(1.31)	0.07	(1.40)	0.02	(0.34)
Idiosyncratic volatility (IVOL)	-0.02	(-0.15)	0.13	(1.09)	-0.08	(-0.63)	0.10	(0.79)	0.00	(-0.02)	0.13	(0.86)
Skewness (SKEW)	-0.07	(-1.28)	-0.06	(-1.45)	0.02	(0.41)	-0.07	(-1.49)	-0.08	(-1.65)	-0.07	(-1.34)
Short-term return reversal (REV)	-0.51	(-5.69)	-0.37	(-5.41)	-0.57	(-7.67)	-0.47	(-7.16)	-0.62	(-8.70)	-0.45	(-6.01)
Ln(1+Advertising/asset)	-0.08	(-1.46)	0.05	(1.43)	0.09	(1.72)	0.02	(0.53)	0.01	(1.12)	0.02	(0.41)
Ln(Book-to-market)	-0.09	(-1.03)	0.14	(1.99)	0.04	(0.49)	0.15	(1.88)	0.19	(2.29)	0.03	(0.39)
Ln(1+R&D/Market equity)	0.41	(2.93)	0.08	(0.82)	-0.17	(-1.45)	0.07	(0.64)	0.03	(0.29)	0.14	(0.98)
Ln(Size)	-0.28	(-1.66)	0.26	(1.53)	-0.42	(-1.92)	0.16	(0.78)	-0.14	(-0.72)	-0.11	(-0.46)
Momentum	0.14	(1.41)	0.20	(2.15)	0.08	(0.79)	0.18	(2.22)	0.17	(1.91)	0.27	(3.09)
Net stock issuance (NS)	-0.10	(-1.53)	-0.13	(-2.92)	-0.13	(-2.49)	-0.17	(-4.06)	-0.17	(-3.83)	-0.11	(-1.79)
Return on assets (ROA)	0.09	(1.11)	0.01	(0.13)	0.08	(0.90)	0.01	(0.09)	0.08	(1.07)	0.07	(0.77)
Ln(Assets)	0.20	(1.26)	-0.24	(-1.47)	0.19	(1.03)	-0.15	(-0.83)	0.00	(0.03)	0.02	(0.09)
Lagged Ln(1+R&D/Market equity	-0.10	(-0.82)	-0.03	(-0.41)	0.03	(0.37)	-0.02	(-0.22)	0.06	(0.53)	0.00	(0.01)
Ln (1+Patents/Assets)	0.00	(-0.04)	0.00	(0.10)	0.00	(-0.07)	0.02	(0.32)	0.00	(-0.06)	0.02	(0.46)
Industry dummy	Y		Y		Y		Y		Y		Y	
R^2	0.34		0.41		0.44		0.41		0.44		0.46	
Number of firms	404		617		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 5). All firms have nonzero trademark/assets (TRAT). All variables are defined as in Table 6. The method is the same as in Table 6.

	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 6. The method is the same as in Table 6.

	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

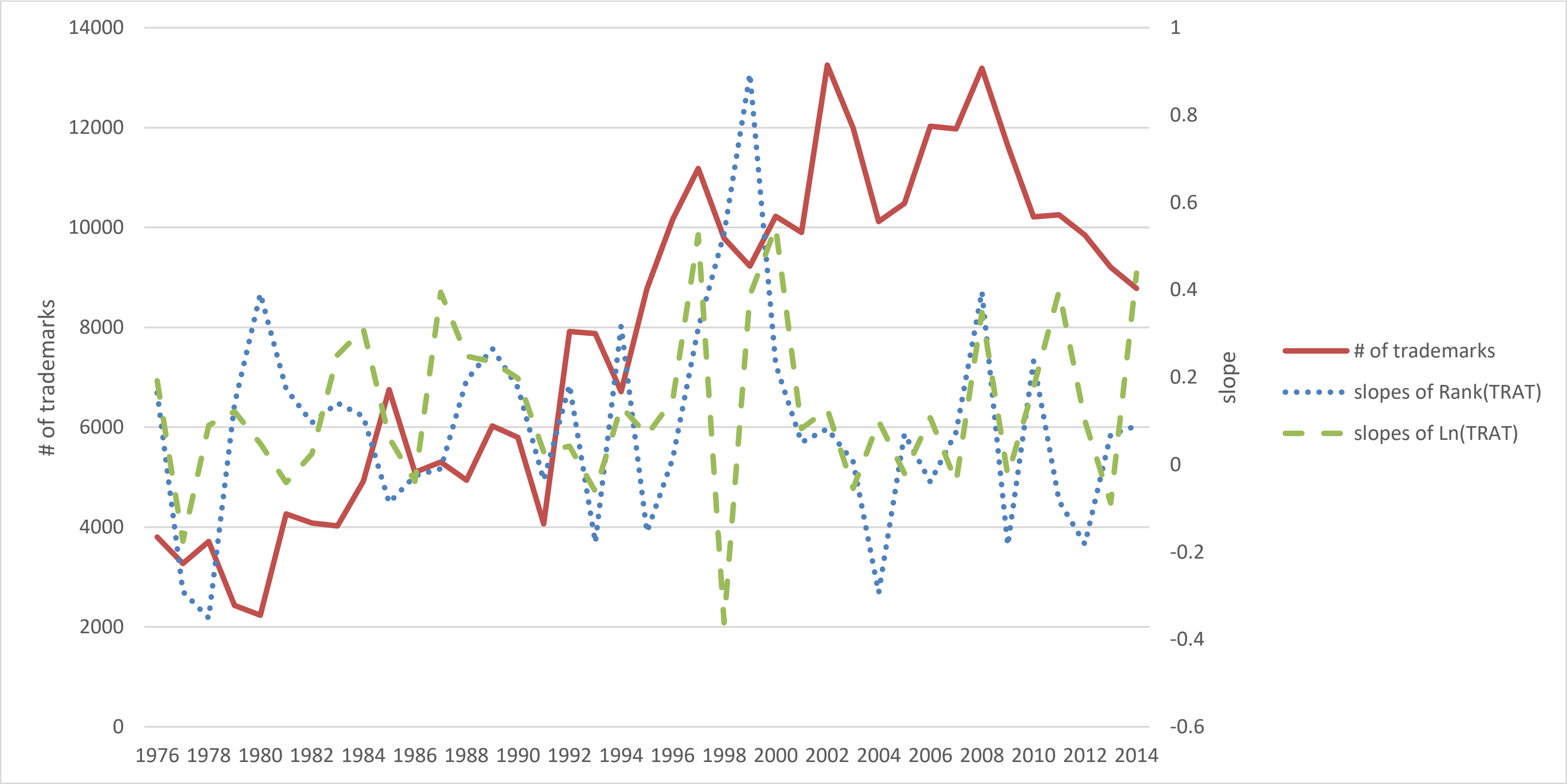
At the end of June of each year *t* from 1977 to 2015, we form portfolios based on trademarks/assets (TRAT) in year *t* – 1 using tercile breakpoints within each industry. We then assign all the firms ranked in the top (bottom) tercile within each industry into the high (low) TRAT portfolio, and so on. 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)			

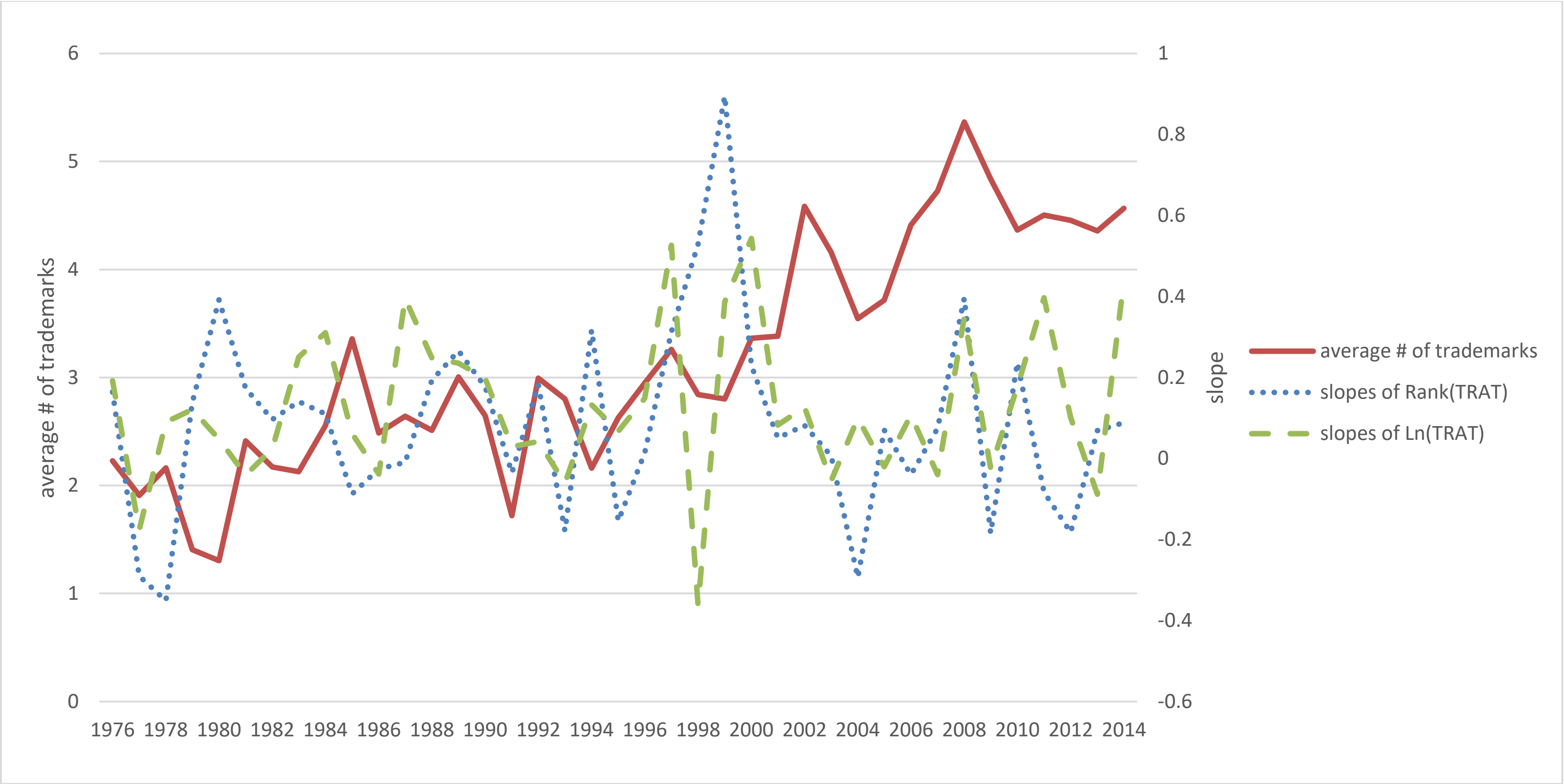
Figure 1
Trademarks and Fama-MacBeth slopes by year

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.