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Valuation of New Trademarks

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Abstract. Firms often register trademarks as they launch new products or services. We find that the number of new trademark registrations positively predicts firm profitability, stock returns, and underreaction by analysts in their earnings forecasts. Using the Federal Trademark Dilution Act (FTDA) as an exogenous shock to trademark protection, we find that greater trademark protection strengthens the predictability of new trademark registrations. Together, our evidence suggests that investors undervalue new trademark registrations.

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Keywords: innovation • trademarks • exploratory trademarks • stock returns • limited attention • uncertainty • market efficiency • analyst forecast • anomalies • trading strategies

1. Introduction

Intangible assets are notoriously hard to value. In particular, the balance sheets of U.S. firms do not include the value of internally generated intellectual property (IP) intangibles, such as patents, trademarks, copyrights, and trade secrets, and instead, the associated costs of creating them (e.g., research and development costs) are expensed on the income statement as they are incurred. Treating expenditures that generate IP internally in the same way as other operating expenses makes it hard for investors to value firms in the current knowledge-based economy, where IP intangibles are important main assets (Chan et al. 2001, Lev 2001, Corrado and Hulten 2010, Peters and Taylor 2017).

Existing research on IP valuation primarily examines patents, but few study trademarks, which are distinct from patents and are often viewed as an even more important form of IP protection.[1] Unlike patents that typically occur in the earlier stages of the innovation process, trademarks are registered when new products/services are ready for commercialization and represent outputs at the end of the innovation process awaiting the final market test of success.[2] Therefore, by the time a firm registers a trademark, the associated technical uncertainty of whether a product/service is viable would have been resolved. However, valuation of a new trademark can still be challenging owing to demand uncertainty (whether consumers like the new product/service or not) and competition uncertainty (whether competitors have a better and cheaper product/service) associated with the new products/services protected by the trademark.[3] For example, forecasting demand for a new product/service based on past records of existing ones may be especially unreliable for new products/services resulting from disruptive innovations.

In this paper, we examine how the stock market values newly registered trademarks, which is a type of innovation output that has not garnered much attention in the finance and innovation literatures despite its importance (detailed in Section 2). Trademark registration with the U.S. Patent and Trademark Office (USPTO) reflects firms' ambition to penetrate a new market segment and commitment to building and protecting the associated brand equity. However, investors are often attention constrained and may fail to adequately incorporate the benefits of trademark registration and the additional future cash flows generated by the new products/services protected by trademarks.[4] The complexity and uncertainty associated with valuing new trademarks imposes extra burden on cognitive processing power, which leads inattentive investors to underestimate future benefits from the success of new trademarks launched by firms and hence undervalue these firms.[5] These discussions collectively predict a positive relation between new trademarks and future stock returns because of investor underreaction to future benefits conferred by new trademarks.

Our empirical tests use a large sample of 305,422 USPTO trademark registrations of U.S. public firms from 1976 to 2014. We measure a firm's new trademark intensity each year as the number of trademarks registered in that year scaled by its total assets (TRAT). We scale a firm's trademarks by its total assets, following the literature on the effects of R&D expenditures and patents on firm value (Griliches 1981, Hall 1993, Hall et al. 2005). We then examine whether a firm's new trademark intensity predicts its stock returns. At the end of each June, based on TRAT in the past year, we form three portfolios (low, middle, and high) and construct a hedge portfolio that is long the high TRAT portfolio and short the low TRAT portfolio.[6] We then compute their value-weighted excess returns, industry-adjusted returns, and alphas from different factor models over the next year.

The hedge portfolio yields an annualized excess return of 5.2% and annualized alphas of 7.8%, 7.0%, and 6.3% from the Fama-French five-factor model (Fama and French 2015), the q-factor model (Hou et al. 2015), and the mispricing factor model (Stambaugh and Yuan 2017), respectively. All are significant at the 1% level. The annualized industry-adjusted return of this hedge portfolio is 3.7% and significant at the 5% level. Furthermore, most of these return spreads are from the high TRAT portfolio. These results are not driven by the denominator in TRAT because sorting sample firms on total assets yields a much weaker return predictability.[7]

To see whether the predictive power of TRAT is incrementally robust to other well-known return predictors (such as size, book-to-market, momentum, asset growth, profitability, net stock issuance, idiosyncratic volatility, research and development (R&D)/market equity, advertising/assets, skewness, short-term returns, and patent/assets), we conduct Fama-MacBeth (Fama and MacBeth 1973) regressions including these known predictors as controls and total assets to ensure that the TRAT effect is not driven by the denominator. We find that TRAT significantly predicts next year's return, regardless whether we use the rank of TRAT or a continuous form of TRAT. Our results are also robust to using the raw or industry-adjusted number of newly registered trademarks. In addition, excluding the Internet bubble period does not reduce the TRAT effect significantly (see Section 4.3).

A common concern on studies of abnormal return predictability is that the return predictability may be driven by some systematic risk not captured by existing well-known factor models. Firms with more new trademarks may be subject to higher systematic risk in two ways. New trademarks reflect new market opportunities, and these growth options carry higher systematic risk from implicit leverage (Berk et al. 2004). The launch of new trademarks requires firms to adjust their production lines and marketing activities, and the reallocation of resources and operations incurs adjustment costs that could be risky in bad times (Zhang 2005).

Following Fama and French (1992), we use the return on the TRAT hedge portfolio as a factor to capture the risk premium related to new trademarks. Then we perform a two-pass characteristics versus covariances regression procedure (Daniel and Titman 1997) to test whether the abnormal return predictability is driven by risk. However, we find that the loading on the TRAT factor is not priced in the cross-section of stock returns, which suggests that the return predictability of TRAT is less likely to be driven by a missing systematic risk factor.

In addition, we examine the predictive ability of TRAT over longer horizons and find that this predictability is the strongest in the first year after portfolio formation. The predictability over longer horizons declines and is not robust to industry adjustment. Raw returns and industry-adjusted returns are statistically significant only for the first year. The weak long-term predictability is more supportive of an underreaction explanation (Chambers et al. 2002, Hirshleifer et al. 2018, Fitzgerald et al. 2020). Nevertheless, as is typical for anomaly studies, we acknowledge that these tests do not necessarily fully rule out potential risk explanations.[8]

To study the economic channel that may lead to underreaction to new trademarks, we first examine the value relevance of new trademarks by testing whether they are associated with better future profitability such as return on assets (ROA) and return on equity (ROE). We find that, in our sample, TRAT predicts significantly higher ROA and ROE, consistent with the findings in Faurel et al. (2019) that trademarks are associated with increases in future sales. When a firm's TRAT increases from the lowest tercile to the highest tercile, its next year's ROA and ROE increase by 1.88 and 5.08 percentage points, respectively, all else equal. This increase is economically substantial compared with the sample mean (median) ROA of 1.57 (4.88) percentage points and the sample mean (median) ROE of 1.99 (10.80) percentage points.

Before we turn to return prediction, we examine how equity analysts, who are sophisticated infomediaries, value the information in new trademarks. As in Teoh and Wong (2002), analysts' underestimation of future cash flows from new trademarks may persuade inattentive investors who rely on them to also undervalue new trademarks. Additionally, analysts' reactions may represent the reaction of sophisticated equity investors, so if sophisticated investors underreact, it is likely that the general population of investors would also underreact. Therefore, we examine whether new trademarks predict analyst earnings forecast errors (AFEs). We find that AFE increases significantly with TRAT. AFE in the highest TRAT tercile is on average 0.2 percentage points higher than that in the lowest TRAT tercile, all else equal, which is economically significant compared with the sample mean (median) AFE of 0.31 (0.21) percentage points. These results suggest that new trademark intensity contains value-relevant information that even experts such as financial analysts fail to incorporate fully. Investors who rely on financial analysts' recommendations, consequently, may not adequately recognize the value of new trademarks either.

A behavioral explanation for the return predictability of TRAT would predict greater predictability in complex firms with hard-to-value businesses. The additional cognitive burden would increase behavioral biases, such as inattention, and, therefore, increase undervaluation (Zhang 2006, Kumar 2009). For example, complexity increases sources of attention failures, signal neglect, and analytical failure, as identified in Hirshleifer and Teoh (2003). Complex firms and firms with high operational uncertainty tend to have a larger number of value-relevant signals, so it is easier for an inattentive investor to neglect some. Also, the structure of a more complex firm (e.g., product market structure and production function) is more complicated, so an inattentive investor is more likely to have analytical failures about the structure of such a firm. Therefore, we expect a stronger return predictability of TRAT among firms with more complexity and valuation uncertainty.

To test these predictions,we conduct portfolio sorts and Fama-MacBeth regressions within subsamples formed by firm characteristics related to complexity and value uncertainty, such as size, opacity of financial statements, analyst earnings forecast dispersion, R&D spending, and advertising spending. Both methods show a stronger TRAT-return relation among larger firms,more opaque firms, and firmswith high analyst forecast dispersion, high R&D spending, and low advertising expenditures. For example, the annualized Fama-French five-factor alphas of the value-weighted TRAT hedge portfolios are 11.3% and 12.7% among firms with high opacity and high analyst forecast dispersion, respectively, with *t* statistics all above 4.3.

The stronger return predictability of TRAT among larger firms suggests that a trading strategy based on our findings can provide substantial profits even after trading costs. Furthermore, large firms tend to be more complex (Cohen and Lou 2012), and their trademarks are more likely to be contested by competitors (American Intellectual Property Law Association 2013, Ertekin et al. 2018), which increases the difficulty of judging their value implications.[9]

In addition, we expect a stronger TRAT effect when new trademarks reflect firms' exploration of new unfamiliar areas, which tend to be highly uncertain. This is confirmed in the data as we find a stronger TRAT effect among firms with exploratory new trademarks, defined as trademarks registered in classes in which a firm has never registered trademarks over recent years.

Although TRAT is based on the number of newly registered trademarks, which does not reflect the heterogenous value of new trademarks, this *noise* in fact makes it even harder for us to identify any predictability. If the predictability of TRAT identified above is driven by undervaluation of new trademarks, it should be stronger for more valuable trademarks. We use the industry-level rate of oppositions to trademark registrations as a proxy of trademark value. Firms can file oppositions to new trademark applications before the USPTO officially registers those trademarks. Presumably, a trademark is more valuable if it is challenged by others before its registration.[10] We find a stronger TRAT-return relation in industries with higher opposition rates.

To strengthen the causal interpretation of the documented new trademark effects, we implement two tests. First, we examine how the TRAT effects vary after an exogenous shock to trademark protection because of a law change, the enactment of Federal Trademark Dilution Act (FTDA) in January 1996. We find that the effects of TRAT on future stock returns, profitability, and analyst earnings forecast errors are significantly strengthened during the seven years after the FTDA was enacted (1996–2002).[11] Because this Act is specifically designed to protect trademarks and therefore increases trademark value exogenously, such a time-series variation in the TRAT effects helps rule out alternative explanations for the TRAT effects, such as other omitted firm characteristics.

Second, using an event study, we find significantly positive cumulative abnormal returns (CARs) around new trademark registrations. The abnormal event returns are a proxy for a local average treatment effect and reflect the positive information about future fundamentals contained in new trademark registrations because other firm characteristics are unlikely to change coincidentally around the event dates. Although investors react positively to new trademark registration events, our postevent return predictability (return anomaly) implies that investors underreact to new trademark registrations at the event date.

The TRAT effect is distinct from the patent effect on stock returns that has been documented in the prior literature. Conceptually, trademarks are designed to distinguish a firm's products/services from others and protect the brand equity, whereas patents are designed to protect technological innovation. Because many innovations cannot be protected by patents, trademarks are much more ubiquitous than patents: the industry coverage for trademarks is much larger than for patents. To differentiate the two effects empirically, we examine how the trademark effect varies across patenting and nonpatenting firms. We find that the trademark-return relation exists both in firms with and without newly granted patents and is slightly stronger among nonpatenting firms.

This paper is one of a few recent studies that hand-collected a large sample of trademarks from the USPTO, and, to our knowledge, we are the first to examine the stock market return predictability of new trademarks, an important and prevailing class of IP. The existing innovation literature has focused primarily on patents, missing studying innovation in a broad swath of the economy, especially for service-oriented industries that include financial and information service industries, and consumer sectors such as the food, beverage, and retail industries. In addition, existing studies on trademarks often use a much smaller sample of firms, such as large firms, and firms in specific industries or foreign countries. By including a much wider representation of industries, our study contributes by providing a fuller picture about the valuation of IP in the finance literature and the importance of intangibles to the stock market.

Ours is not the first study to find return predictability using IP or innovation-related variables. Nevertheless, our study highlights trademarks as another important form of IP that investors may have difficulties valuing appropriately owing to cognitive biases such as limited attention. Even in a domain where technical issues are resolved by the time of having trademarks registered, investors may still fail to process the information about IP adequately because of market-related (product demand, suppliers, and competitors) complexity and uncertainty.

2. Trademark Basics and Literature Review

2.1. Trademark as IP

A trademark is a brand that allows a firm to distinguish and protect its related product/service. According to the USPTO, "Trademarks, copyrights, and patents protect different types of IP. A trademark typically protects brand names and logos used on goods and services. A copyright protects an original artistic or literary work. A patent protects an invention. For example, if you invent a new kind of vacuum cleaner, you would apply for a patent to protect the invention itself. You would apply to register a trademark to protect the brand name of the vacuum cleaner. And you might register a copyright for the TV commercial that you use to market the product."

Although the registration of a trademark with the USPTO is not mandatory, it has several advantages, such as notice to the public of the registrant's ownership of the mark and exclusive right to use the mark on the goods/services listed in the registration. A firm may file a trademark application with the USPTO in some particular product/service classes.[12] The firm also needs to submit a specimen or proof to show that a trademark is currently used for each class of goods or services in which the application covers.[13] Once approved, the trademark is registered and disclosed in the *Official Gazette*, published weekly on every Tuesday by the USPTO. After a trademark is registered, the firm can use the ® symbol with their trademark and obtain legal trademark protection.[14] The registration of a trademark therefore carries a signal that the new product/service is already commercially viable.

Consumers rely on brand names afforded by trademarks to facilitate their search and purchase decisions, especially in circumstances where search costs and information asymmetry are high (Gao and Hitt 2012, Graham et al. 2013). Registered trademarks thus function as a signaling tool to create awareness of the product/service, to reduce information asymmetry about quality, and to differentiate from other products/services to achieve a competitive advantage (Landes and Posner 1987, Besen and Raskind 1991). The consequent market power allows the firm to charge a price premium and earn higher profits. More importantly, registered trademarks confer legal protection such that the firm can sue other individuals and entities to prevent economic loss from competitors' similar marks, images, or symbols that can cause customer confusion and erode their market share.

Survey data suggest that trademarks are equally important assets, if not at times more important than patents, especially in low-patent industries.[15] Nevertheless, there are few studies on trademarks in the finance literature. Furthermore, trademarks exist in a broader range of firms and industries than patents.[16] For example, legal protection using patents is either infeasible or not meaningful in some industries such as in financial and other service industries. Hall et al. (2014) report that trademarking is probably the most widely used form of IP protection as it is applicable to essentially any product or service. Therefore, investigating trademarks permits testing of the value of IP in a wider range of firms and industries beyond those covered by patents.

Although patents are obtained in the earlier stages of the innovation process, trademarks represent new products/services, which are the outputs at the end of the innovation process. The Organization of Economic Cooperation and Development (OECD) defines innovation as "the implementation of a new or significantly improved product (goods or service), or process, a new marketing method, or a new organizational method in business practices, workplace organization or external relations." The focus of the definition on the end product or service, and even its marketing method clearly encompasses the new products and services that are represented by the new trademarks in the broader definition of innovation. Thus, we are interested in how investors value the trademark form of innovation. Despite the urging of OECD and other governmental agencies that fund innovation activities to include trademarks as innovation, studies on trademarks remain sparse in the large innovation literature in economics and finance. In summary, trademarks are an important and separate measure of innovative outputs from patents and are especially relevant for the current client-oriented economy.

2.2. Literature Review

As discussed previously, trademark is a comprehensive measure of valuable brand capital. Although some recent studies have examined the effect of brand capital on firm value and stock returns, they measure brand capital by advertising expenditures (Vitorino 2013, Belo et al. 2014) or surveys (Barth et al. 1998, Dou et al. 2020). Both types of measures and data sources are limited compared with trademarks. Only a limited set of industries report advertising expenditures, which do not reflect the full coverage and effect of brand capital. Similarly, those surveys cover a relatively limited subset of U.S. public firms. Our study thus offers a comprehensive and large-scale analysis of the value created by new brands.

Because of data availability, prior studies on trademarks often use a much smaller sample of firms, such as large firms, and firms in specific industries or foreign countries.[17] For example, Bosworth and Rogers (2001) examine a cohort of 60 large Australian firms in 1996. Greenhalgh and Rogers (2006) examine a sample of 673 large UK firms in 1996–2000. Greenhalgh et al. (2011) examine 50,000 UK firms in 2000–2008. There are only three studies that examine the effect of U.S. trademarks on the stock market to the best of our knowledge. Fosfuri and Giarratana (2009) is a case study examining only Coca-Cola and Pepsi in 1999–2003. Sandner and Block (2011) examine the relation between Tobin's Q and trademarks of large public firms (with revenues of at least 400 million Euros) in Europe and the United States in 1996–2002. González-Pedraz and Mayordomo (2012) examine the effects of trademarks on Tobin's Q and the trademark announcement abnormal stock returns in only 16 U.S. commercial banks. Our study not only confirms the findings of prior studies based on small-scale trademark data but also performs a thorough investigation of two explanations for the return predictability of trademarks: underreaction and risk.

This paper is also related to prior studies on return predictability associated with intangible investments and assets. The literature has documented return predictability for firms' innovative activities measured by R&D intensity (Lev and Sougiannis 1996, Chan et al. 2001, Eberhart et al. 2004, Lev et al. 2005), R&D abilities (Cohen et al. 2013, Hirshleifer et al. 2013), and patents (Pakes 1985, Deng et al. 1999, Penman and Zhang 2002, Hirshleifer et al. 2018, Fitzgerald et al. 2020). The main interpretation of these patterns is that stock prices underreact to the information contained in these activities. Because most firms do not report R&D and patenting activities, our paper adds to this literature by showing that trademark, as a comprehensive measure of innovation, also contains useful information of a firm's fundamentals and is often undervalued by investors, especially when it is newly registered. Even in a domain where technical issues are resolved by the time of having trademarks registered, investors may still fail to process the information about IP adequately because of market-related (product demand, suppliers, and competitors) complexity and uncertainty.

3. Data, Trademark Measure, and Summary Statistics

3.1. Trademark Data and Measure of New Trademark Intensity

The initial sample of 4,792,421 trademark registrations is obtained from the USPTO Trademark Case Files Data set between 1970 and 2015.[18] We restrict our sample to registered trademarks, which are trademarks that are actually in use by the trademark assignees (owners). We also downloaded information about trademark characteristics such as the assignees, product classification, prosecution history, renewal and maintenance history, and prior registration.

Trademark assignees are manually matched to U.S. public firms in the Compustat/Center for Research in Security Prices (CRSP) database based on name, location, and industry using the Levenshtein Algorithm (a string matching method) and further manual checking from online searches such as Bloomberg Businessweek.[19] We also assign subsidiaries' trademarks to their parent companies based on the subsidiary-parent links from Capital IQ.[20]

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 (a) and (b) (solid line), respectively. The number of trademarks registered by public firms has been growing over time and peaked in 2002 with 13,252 total registered trademarks. The number of trademarks registered per firm also reveals an increasing pattern and peaked in 2008 with 5.4 trademarks per firm.

Our proxy for a firm's new trademark activities in year t is defined as the number of trademarks registered by the firm in calendar year t scaled by its total assets (in millions) in fiscal year ending in calendar year t and is labelled as TRAT. We scale a firm's trademarks by its total assets to control for size effects, following the literature on the effects of R&D expenditures and patents on firm value (Griliches 1981, Hall 1993, Hall et al. 2005). For a firm that does not register any trademark in a year, we set its TRAT to zero for that year. Similar to prior studies that construct R&D- or patent-based return predictors, we find that many firms do not have new trademarks registered every year. However, in terms of economic significance, firms with new trademarks account for 76% of the market capitalization of the entire sample.[21] Therefore, firms with nonzero newly registered trademarks are economically important in the economy. In subsequent return predictability analyses, we focus on firms with nonzero newly registered trademarks in the past year because they capture the most recent trademark activities that are more likely to be misvalued by the market.

3.2. Stock Returns and Accounting Data

Our sample consists of firms in the intersection of the Compustat database, the CRSP database, and the trademark database described previously. Furthermore, we restrict the sample period to 1976–2014 because the coverage of R&D expenses is low before 1975 as firms had more discretion in determining what goes into R&D expenses then (the accounting treatment of R&D expense reporting was standardized in 1975 following Financial Accounting Standards Board Statement No. 2). All domestic common shares trading on New York Stock Exchange (NYSE), American Stock Exchange (AMEX), National Association of Securities Dealers Automated Quotations (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 (1992). To mitigate backfilling bias, we require firms to be included in the Compustat database for two years before including them in our sample. For some of our tests, we also obtain analyst earnings forecast data from the Institutional Brokers Estimate System (IBES) database.

3.3. Summary Statistics

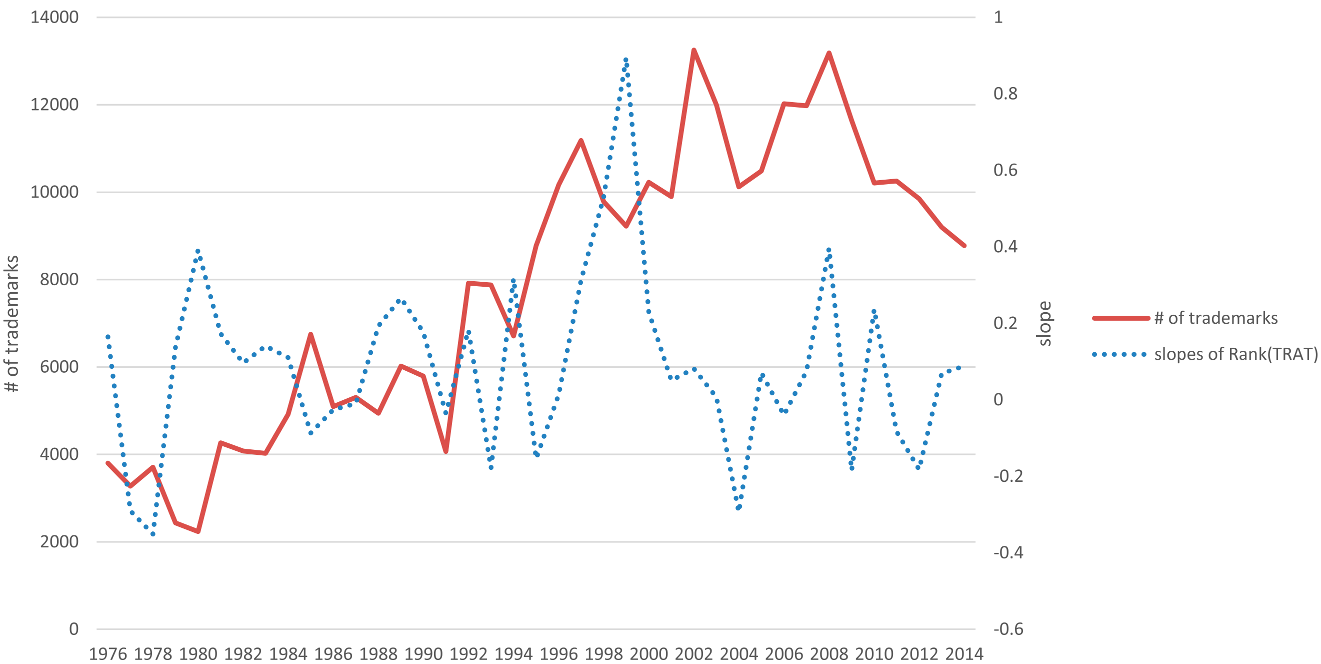
In Table 1, we report summary statistics for portfolios formed on TRAT. Specifically, at the end of June of year t, we assign firms with nonzero TRAT into the low (L), middle (M), and high (H) TRAT portfolios based on the 33rd and 67th percentiles of TRAT in year $t-1$. In addition, we assign firms with no trademarks registered in year $t-1$ to the "None" portfolio for comparison.[22] On average, there are 3,217 firms each year from 1976 to 2014, and 1,991 of them are in the "None" group. The three TRAT portfolios are well diversified with the number of firms ranging from 408 to 409.

Table 1 reports the time-series average of cross-sectional median and mean of TRAT and other firm characteristics that are known return predictors or additional controls. The median (mean) TRAT are 0.16% (0.17%), 0.78% (0.84%), and 3.14% (4.92%) for the three TRAT portfolios. There is considerable variation across the three TRAT portfolios in size, measured as the market capitalization at the end of June in year t. The median (mean) *SIZE* of the low, middle, and high TRAT portfolios is \$2,316 million (\$9,298 million), \$493 million (\$1,707 million), and \$124 million (\$376 million), respectively.

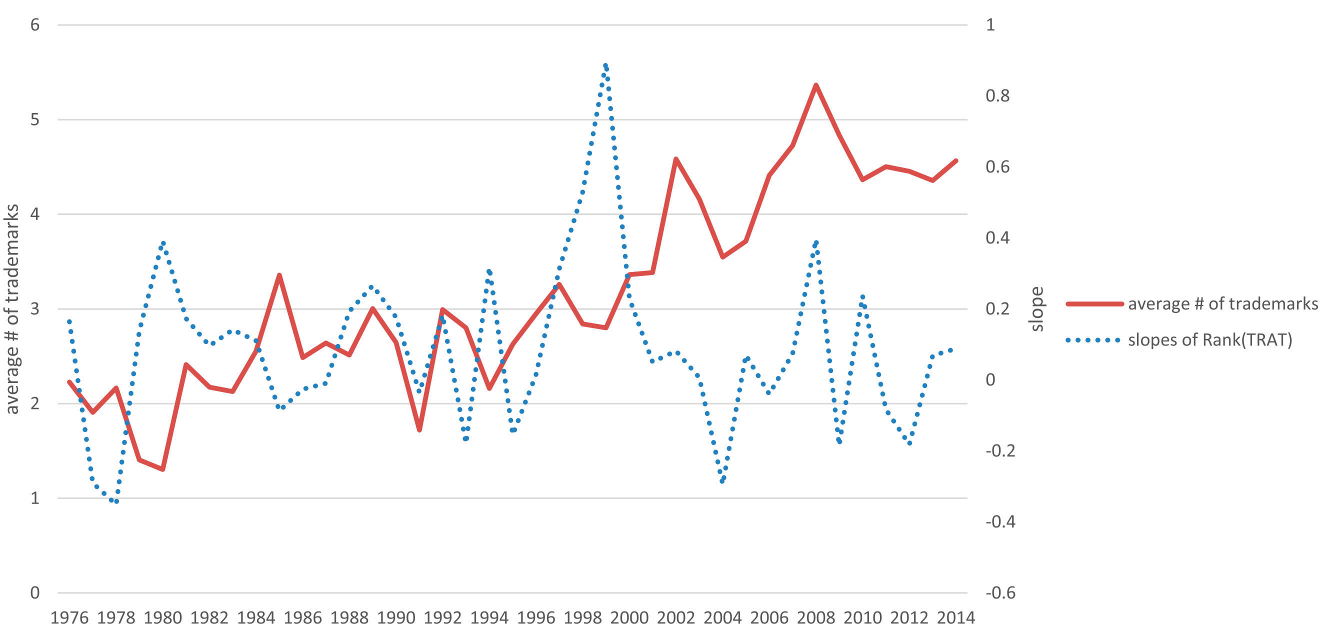
The measures for other known predictors or additional controls used in tests later in the paper include the following. Book-to-market ratio, *BTM*, is the ratio of book equity of fiscal year ending in year $t-1$ to market equity at the end of year $t-1$. Momentum, *MOM*, is the previous eleven-month returns with a one-month gap between the holding period and the current month. Idiosyncratic volatility, *IVOL*, is measured at the end of June of year t as the standard deviation of the residuals from regressing daily stock returns on the Fama-French three-factor returns over the previous 12 months with a minimum of 31 trading days. Skewness, *SKEW*, is measured at the end of June of year t using daily returns over the previous 12 months with a minimum of 31 trading days. For the remaining accounting-based return predictors and

Figure 1. (Color online) Trademarks and Fama-MacBeth Slopes by Year

(a)



(b)



Notes. (a) Aggregate trademark numbers and Fama-MacBeth slopes on new 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 new trademarks/assets (*Rank(TRAT)*). The monthly Fama-MacBeth slopes are estimated from model 3 of Table 4 and averaged in each year corresponding to the year of the TRAT measure. (b) Average trademark numbers and Fama-MacBeth slopes on new 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 new trademarks/assets (*Rank(TRAT)*). The monthly Fama-MacBeth slopes are estimated from model 3 of Table 4 and averaged in each year corresponding to the year of the TRAT measure.

additional accounting controls, the accounting items are measured in fiscal year $t - 1$. Return on assets, *ROA*, is the income before extraordinary items plus interest divided by lagged total assets. Asset growth, *AG*, is the change in total assets divided by lagged total assets. R&D intensity, *RDME*, is the R&D expenses

Table 1. Summary Statistics

	Time-series average of cross-sectional median				Time-series average of cross-sectional mean			
	None	Low	Middle	High	None	Low	Middle	High
Number of firms	1991	408	409	409	1991	408	409	409
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
Idisosyncratic volatility (IVOL)	0.03	0.02	0.02	0.03	0.03	0.02	0.03	0.03

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

divided by market equity at the end of calendar year $t-1$, and advertising intensity, *ADA*, is the advertising expense divided by book value of asset.[23] Net stock issuance, *NS*, is the change in the natural log of the split-adjusted shares outstanding.

These variables do not exhibit much variation across the TRAT portfolios, except that *ROA* decreases with TRAT and *SKEW* increases with TRAT. However, online appendix Table IA1 shows that the time-series averages of the cross-sectional correlations between TRAT and these two variables are not statistically significant. Furthermore, high skewness is known to predict lower stock returns, whereas our evidence discussed later is that TRAT predicts higher stock returns. Online appendix Table IA1 also shows that TRAT generally has low correlations with firm characteristics, although the correlation is significantly negative with size and significantly positive with R&D intensity, advertising intensity, and idiosyncratic volatility. The magnitude of the correlation with *IVOL* is the largest at 0.29, so we control for *IVOL* in later tests.

Online appendix Table IA2 reports pooled summary statistics for *TRAT* in panel A and trademark counts in panel B for the sample of firms with nonzero trademarks registered by industries using the Fama and French (1997) 48 industry classifications. Recreation (including toys), textile, consumer goods, and apparel industries have the highest average TRAT; a sample firm in these industries with total assets of $100 million registers 2.5 to 4.3 trademarks per year on average. On the other hand, the coal industry has the lowest average TRAT of 0.002. In addition, there are large cross-sectional variations in TRAT and trademark counts across industries and within industry. For example, in panel B, the 25th percentile of trademark counts is between 1 and 2, and the 75th percentile ranges from 2 to 15. To mitigate the concern that our results may be driven by industry effects, we also report industry-adjusted returns in all the portfolio analyses and control for 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 New Trademark Intensity

In this section, we examine whether TRAT predicts stock returns and how systematic risk 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

The three TRAT portfolios (L, M, and H) and the *None* portfolio are formed as described earlier in Section 3.3.[24] We also form a high-minus-low (H–L) hedge portfolio that is long in the high TRAT portfolio and short in the low TRAT portfolio. After forming these portfolios, we hold them for the next 12 months (from July of year t to June of year $t+1$) and compute their value-weighted monthly returns. Because the USPTO fully discloses trademarks registered in the weekly *Trademark Official Gazette* (published every Tuesday), the TRAT measure in year $t-1$ is publicly observable at the time of portfolio formation. Table 2, panel A, reports the excess returns and industry-adjusted returns for each of the three TRAT portfolios, the None portfolio, and the hedge portfolio. Excess returns are calculated as the average monthly returns in excess of one-month Treasury bill rate, and the industry-adjusted return is calculated based on the difference between a firm's monthly return and the value-weighted average of all firms' monthly returns in the same Fama-French 48 industry group.

Table 2, panel B, examines the relation between TRAT and abnormal portfolio returns. Specifically, we perform time-series regressions of the TRAT portfolios' excess returns on different sets of asset pricing factors: the Fama-French (2015) five factors (the market factor–MKT, the size factor–SMB, the value factor–HML, the profitability factor–RMW, and the investment factor–CMA); the q-factors of Hou et al. (2015) (HXZ), which include the market factor, the size factor, the investment factor, and the profitability factor; and the mispricing factors of Stambaugh and Yuan (2017) (SY), which include the market factor, the size factor, and the mispricing factors (management–MGMT and performance–PERF). Controlling for these factors helps ensure that the TRAT effect is not explained by the well-known risk or mispricing factors. Panel C presents the R^2s of all time-series regressions in panel B.

Table 2. Return Predictive Power of New Trademarks/Assets: Single-Sorted Portfolio Analysis

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

Notes. At the end of June of year t from 1977 to 2015, we form portfolios based on new trademarks/assets (TRAT) in year $t-1$ as in Table 1. 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 12 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) and their average monthly industry-adjusted returns. The portfolio industry-adjusted returns (Ind-adjret) are based on the difference between individual firms' returns and the returns of firms in the same industry (based on Fama-French 48 industry classifications). In panels B and C, we report the alphas and R^2 from the regression of the time-series of portfolio excess returns on various factor models: the Fama-French five factors (the market factor–MKT, the size factor–SMB, the value factor–HML, the robust-minus-weak factor—RMW, and the conservative-minus-aggressive factor—CMA) as in Fama and French (2015), alphas from the investment-based factor model (q-factor model) of Hou et al. (2015) (HXZ), 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^2 is adjusted.

The excess returns, industry-adjusted returns, and alphas from different factor models increase monotonically with TRAT, implying a positive TRAT-return relation. Furthermore, the TRAT effect is economically and statistically significant. The monthly value-weighted alphas of the hedge portfolio range from 0.53% to 0.65% with t statistics above 3.3. These alpha spreads are mainly driven by the high TRAT portfolio, ranging from 0.48% to 0.62% with t statistics above 3.2. For brevity, we report the factor loadings of the hedge portfolio in panel A of online appendix Table IA4. The hedge portfolio's industry-adjusted return is 0.31% and significant at the 5% level. Consistent with the idea that firms with no registered trademark carry lower systematic risk or encounter less mispricing, the industry-adjusted returns and alphas of the None group are small and insignificant.

In addition to the return measures reported in Table 2, we also consider the characteristic-adjusted returns of Daniel et al. (1997) (DGTW) and the four-factor model of Carhart (1997).[25] The monthly DGTW adjusted return spread of 0.86% (t = 6.17) and the Carhart alpha of 0.29% (t = 2.22) show that the TRAT anomaly result is robust to the DGTW specification and the Carhart four-factor model.

The magnitude of these abnormal return spreads is comparable to the literature on innovation-related anomalies. For example, Chan et al. (2001, table 7) show that top R&D (scaled by market equity) quintile portfolio outperforms the bottom quintile by 0.6% per month relative to the Fama-French (1993) three-factor model. In addition, Hirshleifer et al. (2013, 2018) show that innovative efficiency and innovative originality, different aspects of innovation activities proxied by R&D and patents, generate monthly abnormal return of 0.46% and 0.35%, respectively, relative to the Carhart four-factor model. As discussed earlier, most firms do not report R&D and patent activities. Thus, although trademark registration is often the final fruition of innovation, there is little public information for investors to detect ongoing innovation before the registration. As a result, the TRAT effect we document may impound news over the entire innovation process and thus can be large. Although technical uncertainty about the viability of the new products/services is resolved by the trademark registration date, market uncertainty about the adoption of the new products/services remains.

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 or mispricing factors. Furthermore, we construct value-weighted portfolios (which put more weight on larger firms) and rebalance them only once a year. Therefore, these abnormal returns are likely to survive typical transaction costs.

Next, we examine the persistence of the rank of TRAT and the persistence of the return predictability of TRAT. If the rank of TRAT is very persistent, investors should be able to learn from the past and we would not be able to detect mispricing over a long sample period. Panel B of online appendix Table IA4

Table 3. Returns and Alphas of the High-Minus-Low TRAT Portfolio over Longer Horizons

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

Notes. High-minus-low portfolio's average monthly excess returns, average monthly industry-adjusted returns, alphas from the Fama-French five-factor model, alphas from the q-factor model, and alphas from the mispricing factor model from July of year t to June of year $t+1$ (first postsorting year), July of year $t+1$ to June of year $t+2$ (second postsorting year), July of year $t+2$ to June of year $t+3$ (third postsorting year), July of year $t+3$ to June of year $t+4$ (fourth postsorting year), July of year $t+4$ to June of year $t+5$ (fifth postsorting year), and July of year $t+5$ to June of year $t+6$ (sixth postsorting year).

reports the probability of staying in the same TRAT group or moving to any of the other three TRAT groups in the next year. Although around half of the firms stay in the same TRAT portfolio, there is a considerable amount of movements across TRAT portfolios in the next year so that investor learning from past TRAT may be difficult. For example, for a firm in the high TRAT portfolio in year t, the probability of staying in the high TRAT portfolio in year $t+1$ is 51.11%, and the probability of moving to the low, middle, and none TRAT portfolios in year $t+1$ is 1.21%, 17.28%, and 30.40%, respectively.

To address the concern that the return predictive ability of TRAT may be driven by the variation in the denominator, total assets, we sort firms with positive TRAT over the past year into terciles based on their total assets alone. We find that total assets do not generate a significant return spread, and that the total assets hedge portfolio's abnormal returns are insignificant and much smaller in magnitude than those of the TRAT hedge portfolio. The results are reported in online appendix Table IA5.

Our portfolio analyses suggest that the return predictive ability of TRAT cannot be attributed to common systematic risk. To further understand whether such predictability is driven by systematic risk that we do not capture, we examine the long-term predictability of TRAT. Specifically, we present the hedge portfolio's average monthly excess returns, industry-adjusted returns, and alphas from different factor models over each of the six postsorting years in Table 3. The evidence on the TRAT predictability of returns over a longer horizon is mixed. We find that the hedge portfolio's returns and alphas are the largest in the first year, and generally decline thereafter to about a third of the first-year magnitude. The excess and industry-adjusted returns are not statistically significant in subsequent years. However, the alphas remain significant though smaller and dissipate only in year 6. The weak long-term predictability is more supportive of an underreaction explanation than a systematic risk explanation because firms' exposures to systematic risk are often persistent (Chambers et al. 2002, Hirshleifer et al. 2018, Fitzgerald et al. 2020). To further examine a systematic risk explanation, we explore in the next section whether TRAT is systematically priced in the cross-section.

4.2. Is the TRAT Effect Priced?

In this section, we perform additional analyses to examine the possibility that the TRAT effect is driven by some systematic risk not captured by the factors we have considered thus far. If the high-minus-low TRAT portfolio (i.e., the hedge portfolio) we construct in Table 2 creates significantly positive monthly excess returns and alphas, it may be considered as a mimicking portfolio that reflects the risk compensation for bearing one unit of risk exposure to a systematic risk related to new trademark intensity (Fama and French 1993). For convenience, we refer to the monthly returns on the hedge portfolio as the *TRAT factor*. We use a two-pass procedure to test whether the TRAT factor is priced in the cross-section of stock returns (Daniel and Titman 1997). A significantly priced TRAT factor will support a risk-based explanation for the TRAT effect.

We conduct the test as follows. First, for stock i in month t, we estimate its exposure to the TRAT factor, $\beta_{i,t}^{TRAT}$, by regressing its monthly excess returns from month $t-59$ to month t on the corresponding returns of the TRAT factor and different combinations of the other factors that we have used in Section 4.1. Second, for each month t, we conduct a cross-sectional regression of stocks' monthly excess returns on their TRAT betas and other betas, such as market betas, estimated from the models used in the first step. The coefficient on $\beta_{i,t}^{TRAT}$ serves as an estimate of the risk premium (known as lambda) associated with the TRAT factor in month t. Last, we test the significance of the risk premium by the mean and standard deviation of the time-series coefficients on β^{TRAT}. A statistically significant estimate of the risk premium indicates that our TRAT effect is priced in the cross-section.

The results reported in online appendix Table IA6 indicate that the coefficient on β^{TRAT} (from the second pass) is consistently insignificant across various models used in the first pass: model 1 includes the market factor (MKT) and the TRAT factor, model 3 includes the TRAT factor and the Fama and French (2015) five factors, and model 5 includes the TRAT factor and the factors from the q-factor model (Hou et al. 2015). Models 2, 4, and 6 are the same as models 1, 3, and 5, respectively, except that we include an intercept in estimating the betas.[26] Although the coefficient on β^{TRAT} in model 3 is positive, 0.0021, it is statistically insignificant (t = 1.51) and much smaller compared with the market premium (0.0077, t = 3.73). The fact that the TRAT factor is not priced in various models suggests that there is little support for the existence of an unspecified systematic risk related to new trademarks.

The full set of our results, taken as a whole, points to a consistent behavioral explanation for the TRAT anomaly rather than a risk explanation. However, the TRAT anomaly shows some long-term predictability and our two-pass procedure to rule out risk explanations is unable to price some factors and so they may be of low power or unreliable. We therefore mention the usual caveat that we have not definitively ruled out risk explanations.

Table 4. Return Predictive Power of New Trademarks/Assets: Fama-MacBeth Regressions (Full Sample)

	Model 1		Model 2		Model 3	
	Slope	*t* statistic	Slope	*t* statistic	Slope	*t* statistic
Rank(TRAT)	0.21	(2.29)	0.09	(2.39)	0.09	(2.44)
Asset growth (AG)			0.02	(0.43)	0.02	(0.52)
Idiosyncratic volatility (IVOL)			0.06	(0.48)	0.07	(0.61)
Skewness (SKEW)			–0.06	(–1.64)	–0.06	(–1.66)
Short-term return reversal (REV)			–0.49	(–8.10)	–0.50	(–8.37)
Ln(1+Advertising/Assets)			0.04	(1.14)	0.04	(1.24)
Ln(Book-to-market)			0.12	(2.17)	0.12	(1.78)
Ln(1+R&D/Market equity)			0.08	(1.28)	0.07	(0.79)
Ln(Size)			–0.08	(–1.24)	–0.02	(–0.13)
Momentum			0.21	(2.52)	0.19	(2.41)
Net stock issuance (NS)			–0.12	(–3.35)	–0.14	(–3.81)
Return on assets (ROA)			0.06	(1.11)	0.05	(0.82)
Ln(Assets)					–0.04	(–0.29)
Lagged Ln(1+R&D/Market equity)					0.00	(0.01)
Ln (1+Patents/Assets)					0.02	(0.46)
Industry dummy			Y		Y	
R^2	0.01		0.36		0.37	
Number of firms	1213		1112		1100	

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

4.3. Fama-MacBeth Regressions

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

Table 4 shows the time-series average slopes (in percentage) and their t-statistics from the monthly cross-sectional regressions. Following the portfolio sorts, we use the tercile rank of TRAT, *Rank(TRAT)*.[27] 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.

Model 1 of Table 4 presents the univariate regression of future returns on TRAT. The slope on *Rank(TRAT)* is 0.21% (t = 2.29), which is consistent with our finding from single portfolio sort that TRAT significantly and positively predicts stock return. Models 2 and 3 of Table 4 provide the results from multivariate regressions with different sets of control variables. In each model, we include the industry fixed effects based on Fama-French 48 industry classifications to mitigate the effect of unobservable industry characteristics on stock returns. We omit the slopes on the industry dummies in the tabulations for brevity.

Model 2 controls 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.[28] As discussed earlier, all accounting-related control variables are measured in fiscal year ending in year $t-1$. Size, *IVOL*, and *SKEW* are measured at the end of June of year t. *REV* is lagged monthly returns. The slope on *Rank(TRAT)* is 0.09% (t = 2.39). The slopes on the other control variables are generally consistent with previous studies (some inconsistencies are because of 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.

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

We also report the annual averages of monthly slopes on *Rank(TRAT)* from the multivariate regressions (model 3) in Figure 1 to examine how the TRAT effect correlates with aggregate trademarks (a) and trademarks per firm (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 rank is only 0.05. Similarly, the correlation between trademarks per firm and the annual average slope of TRAT rank is only −0.09.

In addition, as a robustness check, we exclude the 24 months from July 1998 to June 2000 or the 36 months from January 1998 to December 2000 in these cross-sectional regressions. The TRAT anomaly remains robust. The slope on *Rank(TRAT)* is 0.07% (t = 2.00) and 0.07% (t = 1.90) when we exclude the 24 and 36 months, respectively, in model 3. We also conduct additional robustness tests by using the logarithm of the number of new trademarks (model 1 of online appendix Table IA7) or the logarithm of the number of new trademarks scaled by industry median (model 2 of online appendix Table IA7) and find results consistent with model 3.

Overall, the results presented in Table 4 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. Figure 1, on the other hand, indicates that the TRAT effect is not driven by time trends in trademark activities.[29]

5. Value Relevance of New Trademark Intensity and Analyst Earnings Forecast Errors

An important presumption for an explanation based on undervaluation of new trademarks is the value relevance of new trademarks. In this section, we first examine whether new trademark intensity (TRAT) contains useful information about firms' future profitability. We then examine whether experts, such as financial analysts, can fully understand the value relevance of TRAT. If these professionals undervalue new trademarks, it will be more likely for investors who rely on financial analysts to suffer from the same bias.

5.1. TRAT and Future Profitability

We conduct panel regressions of profitability in year $t+1$ on year t's TRAT tercile rank (*Rank(TRAT)*), controlling for other well-known determinants of future profitability. We measure profitability by return on assets—ROA (or return on equity—ROE), defined as net income before extraordinary items scaled by lagged assets (or book equity). Following the literature, we control for firm size (*Ln(ME)*), the market-to-book equity ratio (*MTB*), firm age (*Ln(Age)*), ROA (or ROE), change in ROA (or ROE), advertising expenses scaled by lagged assets, R&D expenses scaled by lagged assets, capital expenditures scaled by lagged assets, industry fixed effects based on the Fama-French 48 industry classifications, and year fixed effects. All control variables are measured in year t.[30] Standard errors are clustered by firm to adjust for the times-series correlations. We use the sample period of 1976–2014 in this test. To reduce the effect of outliers, we winsorize all variables (except *Rank(TRAT)*) at the 1% and 99% level each year.

Table 5, panel A, reports the regression results on future profitability. The effect of *Rank(TRAT)* on future ROA (or ROE) is statistically significant and economically substantial. For example, in model 1, the coefficient of 0.939% (t = 3.16) for the TRAT tercile rank implies an average increase of 1.88 percentage points in next year's ROA between the lowest and the highest TRAT groups, all else equal. This is economically substantial compared with the sample mean (median) ROA of 1.57 (4.88) percentage points. Similarly, the slope on the TRAT rank is 2.54% (t = 1.97) in model 2, which implies an economically substantial impact of TRAT on next year's ROE

Table 5. New Trademarks/Assets (TRAT), Future Profitability, and Analyst Earnings Forecast Errors

	Panel A		Panel B
	(1)	(2)	(1)
	ROA_{t+1}	ROE_{t+1}	AFE_{t+1}
Rank(TRAT)	0.939	2.54	0.101
	(3.16)	(1.97)	(3.26)
Ln(ME)	0.862	2.37	0.0528
	(6.57)	(4.91)	(2.44)
MTB	0.0156	1.33	–0.000286
	(0.23)	(3.00)	(–0.04)
Ln(Age)	–0.134	1.73	–0.144
	(-0.75)	(1.72)	(–3.31)
ROA	60.4		1.35
	(17.59)		(2.91)
ΔROA	–11.0		0.400
	(-2.29)		(0.74)
ROE		39.8	
		(4.72)	
ΔROE		–5.50	
		(–1.43)	
Earn_Vol			0.304
			(1.15)
Coverage			–0.00494
			(–1.82)
AFE_Past			17.2
			(4.33)
Advertising/assets	8.86	–4.71	1.33
	(2.36)	(–0.21)	(1.60)
R&D/assets	–0.932	–48.7	1.65
	(-0.21)	(-3.30)	(3.08)
Capex/assets	–4.68	–38.7	0.293
	(–1.58)	(–2.69)	(0.33)
Industry fixed effects	Y	Y	Y
Year fixed effects	Y	Y	Y
R^2	0.433	0.304	0.203
Observations	48,482	48,482	13,977

Notes. This table reports the panel regression results. Panel A shows results on future profitability including ROA and ROE. We regress ROA (or ROE) in year $t + 1$ on year t's TRAT tercile rank (*Rank(TRAT)*), firm size (*Ln(ME)*), the market-to-book equity ratio (*MTB*), firm age (*Ln(Age)*), ROA (or ROE), change in ROA (or ROE), advertising expenses scaled by lagged assets, R&D expenses scaled by lagged assets, capital expenditures scaled by lagged assets, industry fixed effects, and year fixed effects. ROA (or ROE) is defined as net income before extraordinary items scaled by lagged assets (or book equity). The sample period of the future profitability test is 1976–2014. Panel B shows results on analyst forecast errors. We regress analyst earnings forecast errors (AFE) in year $t + 1$ on year t's TRAT tercile rank (*Rank(TRAT)*), firm size (*Ln(ME)*), the market-to-book equity ratio (*MTB*), firm age (*Ln(Age)*), ROA, change in ROA, volatility of ROA over the past five years (*Earn_Vol*), analyst coverage (*Coverage*), analyst forecast errors in year $t - 1$ (*AFE_Past*), advertising expenses scaled by lagged assets, R&D expenses scaled by lagged assets, capital expenditures scaled by lagged assets, industry fixed effects, and year fixed effects. *AFE* is defined as the difference between actual annual earnings per share (EPS) multiplied by the number of shares outstanding at the fiscal year end and the latest annual consensus EPS forecast before the earnings announcement multiplied by its corresponding number of shares outstanding, scaled by lagged assets. The sample period of the analyst forecast error test is 1993–2014. In both tests, we weight the observations by market equity at the end of year t in the regressions and cluster standard errors by firm. All coefficients are multiplied by 100. For brevity, we omit the intercepts and the slopes on fixed effects. The t statistics are in parentheses. All variables (except *Rank(TRAT)*) are winsorized at the 1% and 99% levels by year.

because the sample mean (median) ROE is 1.99 (10.80) percentage points.

5.2. TRAT and Analyst Earnings Forecast Errors

Given that TRAT is significantly positively associated with firms' future profitability, we next examine if financial experts, such as financial analysts, understand and fully incorporate this value-relevant information into their earnings forecasts. We conduct panel regression of year t+1's analyst earnings forecast errors (*AFE*) on year t's TRAT tercile rank (*Rank(TRAT)*), controlling for other well-known determinants of AFE. Following So (2013), we measure *AFE* as the difference between actual annual earnings per share (EPS) multiplied by the number of shares outstanding at the fiscal year end and the latest annual consensus EPS forecast before the earnings announcement multiplied by its corresponding number of shares outstanding, scaled by lagged assets. Following the literature (Abarbanell and Bernard 1992, Teoh and Wong 2002, Dichev and Tang 2009), we control for firm size (*Ln(ME)*), the market-to-book equity ratio (*MTB*), firm age (*Ln(Age)*), ROA, change in ROA, volatility of ROA over the past five years (*Earn_Vol*), analyst coverage (*Coverage*), year t's analyst forecast error (*AFE_Past*), advertising expenses scaled by lagged assets, R&D expenses scaled by lagged assets, and capital expenditures scaled by lagged assets, as well as industry fixed effects and year fixed effects. Standard errors are clustered by firm to adjust for the times-series correlations. We start the sample period in 1993 to avoid measurement error issues in IBES during earlier periods.[31] To reduce the effect of outliers, we winsorize all variables (except *Rank(TRAT)*) at the 1% and 99% levels each year.

The results reported in Table 5, panel B, show that analysts significantly underreact to TRAT; their future forecast errors significantly increase with TRAT. The effect is also economically meaningful. The 0.101% (t = 3.26) coefficient of *Rank(TRAT)* indicates that next year's *AFE* in the highest TRAT group is on average 0.2 percentage points higher than that in the lowest TRAT group, all else equal. This is economically significant compared with the sample mean (median) forecast error of 0.31 (0.21) percentage points.

These results suggest that even financial analysts are inefficient processors of the information about future profitability that is contained in TRAT. Because many investors rely on analyst earnings forecasts, we expect that investors will similarly misvalue TRAT, which is consistent with an undervaluation explanation for the return predictive power of TRAT.[32]

6. Identification Tests

Because new trademark activities may correlate with other unobservable firm characteristics, we need clean identification to draw a causal inference of the evidence documented previously. In this section, we provide two types of tests to mitigate endogeneity concerns and improve identification for making causal inferences.

First, we examine an exogenous shock from changes in the laws regarding legal protection against trademark dilution.[33] Several past studies suggest that the FTDA of 1995 introduced a major exogenous shock that enhanced trademark protection and therefore increased the value of trademarks (Peterson et al. 1999, Roe 2008, Brauneis and Heald 2011, Heath and Mace 2020).[34] The FTDA became effective in January 1996 until it was challenged by the U.S. Supreme Court's decision in the Moseley v. V Secret Catalogue case in 2002 (Roe 2008).[35] Therefore, we refer to the period from 1996 to 2002 as the FTDA subperiod.

We examine whether TRAT increases future ROA and ROE by more, and whether analysts and investors underreact by more during the FTDA period relative to the other periods. Because the FTDA is an exogenous shock that increased trademark value, any difference in the TRAT effects over the FTDA period (1996–2002) would be attributable to trademark value. If instead some missing firm characteristic that is a correlate of TRAT is responsible for our previous findings of the TRAT predictability, then this missing firm characteristic would also need to change to coincide with the FTDA period to explain any change in the TRAT effects over the FTDA period. Essentially, this is a cross-sectional event study test to show whether the reaction from stock returns, ROA, ROE, or analyst forecast error (AFE) to the FTDA shock event varies with the number of new trademarks.

Second, we examine the event study of the announcement of the new trademark registrations. Firm fundamentals that may affect long-run returns are unlikely to change in the very short announcement window, which reduces omitted variable problems and the consequent need to control for potential changes in firm fundamentals. The drawback of this event study method is that a sufficient fraction of investors needs to be attentive to the events to yield statistically significant abnormal returns in the event window.

6.1. Exogenous Shocks to Trademark Value from Changes in Trademark Laws

We investigate how the TRAT effects documented earlier vary with the FTDA. Because this Act is designed to enhance trademark protection, if investors do not fully incorporate the benefits of new trademarks, we should observe stronger TRAT effects on future profitability, analyst earnings forecast errors, and stock returns after the passage of the FTDA. We implement this identification test as follows: first, we use the Fama-MacBeth regressions to estimate the time-varying TRAT effects on stock returns, profitability, and analyst

Table 6. Exogenous Shock: FTDA

	Slope			
	(1) Return	(2) ROA	(3) ROE	(4) AFE
I_{FTDA}	0.29	0.67	2.04	0.09
	(2.95)	(2.07)	(2.47)	(2.69)
Constant	0.04	0.30	0.36	0.03
	(1.16)	(2.16)	(1.03)	(1.73)
R^2	0.02	0.10	0.14	0.27
Observations	462	39	39	22

Notes. This table reports the coefficients and their *t* statistics in parentheses from ordinary least squares (OLS) regressions of monthly or annual slopes on TRAT on I_{FTDA}, an indicator variable that equals one for 1996 to 2002 and zero otherwise. The slopes on TRAT are estimated from the monthly or annual Fama-MacBeth regressions for stock returns (model 3 of Table 4), profitability, and analyst earnings forecast errors. Coefficients in columns (2), (3), and (4) are multiplied by 100. The sample period is from 1976 to 2014 in Columns (1)–(3) and from 1993 to 2014 in Column (4).

earnings forecast errors. (We use the same set of controls for returns, profitability and AFE regressions as in model 3 of Tables 4 and 5, respectively). We then regress these time-series slopes of TRAT on an indicator variable I_{FTDA} that equals one for the 1996–2002 period and 0 otherwise. Significantly positive coefficients on I_{FTDA} in these regressions would enhance a causal interpretation of the TRAT effects documented previously.

Table 6 reports significantly positive coefficients on I_{FTDA} in all regressions. The coefficients on I_{FTDA} are significantly positive when the dependent variable reflects the TRAT effect on stock returns, ROA, ROE, and AFE, respectively. Because the FTDA is an exogenous shock to trademark protection and hence trademark value, these findings provide cleaner support of a causal inference of the TRAT effects documented earlier.[36]

We also implement a supplementary identification test using the Supreme Court case of Moseley v. V Secret Catalogue as another exogenous shock because Roe (2008) suggests that the value gains in the FTDA subperiod were reversed with this case decision. To directly compare with the TRAT effects in the FTDA subperiod, we regress the time-series slopes on TRAT over 1996–2006 on an indicator variable $I_{Moseley}$ that equals one for the subperiod 2003 to 2006.[37] Online appendix Table IA9 shows a negative coefficient on $I_{Moseley}$ in all the regressions, and the coefficients are statistically significant when the dependent variables reflect the TRAT effect on stock returns and AFE. Thus, there is weak evidence consistent with Roe (2008) that the Moseley v. V Secret Catalogue case reduced the trademark protection of the FTDA. These results serve as additional evidence for the causal interpretation of the TRAT effects documented earlier.

6.2. Event Study of New Trademark Registration

In this section, we conduct an event study to examine the information content of the new trademark registration events. The advantage of an event study is that the return response in the narrow window around trademark registration is unlikely to be driven by a change in total assets (i.e., the denominator of TRAT) or a change in other omitted firm characteristics that may drive the TRAT predictability. Instead, the abnormal event returns more likely reflect information about future fundamentals contained in new trademark registrations. In addition, the event study compares the valuation effect of trademark registration with the counterfactual valuation effect without trademark registration and therefore provides a cleaner identification test.

We measure CAR using market-adjusted returns. The results are robust to other measures of CAR, such as industry-adjusted returns. Multiple registrations on a given day are treated as a single event. Online appendix Table IA10 shows that CARs are significantly positive around trademark registration dates.[38] Although investors react positively to new trademark registrations, our postevent return predictability (return anomaly) findings imply that investors do not fully incorporate the value implications around the event dates and underreact to new trademark registrations.

7. Conditional TRAT Effects

If limited attention drives the undervaluation of trademarks, we expect that the return predictability of TRAT would be stronger for firms with more complexity or hard-to-value businesses and firms facing higher uncertainty. Complexity and uncertainty associated with valuing new trademarks impose extra burdens on cognitive processing power, which increase inattention. To test these predictions, we conduct portfolio sorts and Fama-MacBeth regressions within subsamples formed by firm-level characteristics related to complexity and uncertainty.

7.1. TRAT Effect with Size and Uncertainty

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

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

To perform these tests, at the end of June of year t, we sort firms into two groups based on each of the characteristics and into three groups based on TRAT separately. The sorting variables are measured in year $t-1$ except size, which is measured as market capitalization at the end of June of year t. In addition, size groups are based on NYSE median breakpoints, opacity, analyst dispersion, and advertising groups are based on the median of all firms, and R&D groups are based on whether firms have nonmissing R&D expenses (active R&D group includes firms that have reported R&D expenses). The intersection results in six portfolios for each firm characteristic. We also form a high-minus-low TRAT portfolio within each characteristic subgroup. We then hold these portfolios over the next 12 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 2, we calculate the average monthly excess returns, industry-adjusted returns, and alphas estimated from the same set of factor models for these portfolios.

Online appendix Table IA11 presents the results from these independent double sorts. The hedge portfolio's returns and alphas are substantial and significant for larger firms, firms with higher opacity, firms with higher analyst dispersion, firms with lower advertising expenses, and R&D-active firms but are small and often insignificant in the other subgroups. For example, the monthly average excess returns, industry-adjusted returns, and alphas of the TRAT hedge portfolio are large and significant and range from 0.39% to 0.91% for the large subgroup, whereas they are small and often insignificant, ranging from 0.00% to 0.45% for the small subgroup. The TRAT hedge portfolio's excess return, industry-adjusted return, and alphas are large and significant in the high-opacity subsample, ranging from 0.66% to 0.94%. In contrast, these returns and alphas in the low-opacity subsample are smaller and often insignificant, ranging from 0.09% to 0.24%. Similarly, the hedge portfolio's excess return, industry-adjusted return, and alphas are large and significant among low advertising firms, ranging from 0.43% to 0.89%. In contrast, these returns are much smaller and often insignificant among high advertising firms.

We also verify that these contrasts are not due to the difference in the TRAT spreads. As shown in online appendix Table IA11, the spread in TRAT does not vary much across the subsamples and is very similar to that in the single sort (Table 2).

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

7.1.2. Fama-MacBeth Regressions. We rerun the Fama MacBeth regressions following the model 3 specification in Table 4 that controls for the different sets of well-known return predictors but now splitting the sample by size and the uncertainty proxies of online appendix Table IA11. Online appendix Table IA12 reports the results for the subsamples based on firm size, opacity, analyst dispersion, advertising intensity, or R&D activity.

Online appendix Table IA12 shows sharp differences in the TRAT effect across the subsamples, noting that these differences are after controlling for well-known return predictors and industry effects. For example, the slopes on *Rank(TRAT)* are 0.08% ($t=$ 2.61), 0.31% ($t=2.96$), 0.17% ($t=1.65$), 0.10% ($t=2.25$), and 0.12% ($t=2.40$) among large firms, more opaque firms, high dispersion firms, R&D-active firms, and low advertising firms, respectively. In contrast, their counterparts are only 0.06% (t = 1.31), −0.09% (t = −1.56), 0.10% (t = 1.88), −0.02% (t = −0.42), and 0.03% (t = 0.52) among small firms, less opaque firms, low dispersion firms, R&D-inactive firms, and high advertising firms, respectively.

Online appendix Table IA12 thus confirms the findings from double-sorted portfolios for the cross-sectional return predictive power of TRAT. Taken together, consistent with our hypotheses, both portfolio sorts and Fama-MacBeth regressions provide support for a more pronounced trademark-return relation among firms with higher uncertainty. These findings are consistent with an underreaction explanation due to behavioral bias for the ability of TRAT to predict abnormal returns.

7.2. TRAT Effect and Exploratory Trademarks

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

To test this hypothesis, at the end of June of year t, we split the sample into exploratory and nonexploratory subsamples based on whether the new trademarks registered by the sample firm 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 $t-2$).[39] We also independently form three TRAT portfolios as before. We find that the TRAT return spread is much larger among firms with exploratory new trademarks (i.e., in the exploratory subsample). Online appendix Table IA13 presents the results.

The monthly value-weighted excess return and industry-adjusted return of the TRAT hedge portfolio 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 nonexploratory subsample. The excess return and industry-adjusted return of the TRAT hedge portfolio are insignificant and smaller (0.30% and 0.16%, respectively). 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 is slightly larger among the exploratory subsample.

7.2.2. Fama-MacBeth Regressions. Online appendix Table IA14 reports the results from monthly Fama-MacBeth cross-sectional regressions within the exploratory and nonexploratory subsamples as formed in the preceding subsection. Consistent with the portfolio sorts, we find that the TRAT-return relation is positive and significant in the exploratory subsample but is smaller and insignificant in the nonexploratory 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 5 years (instead of 10 years used in online appendix Table IA14). Therefore, the contrast is robust to the horizon used to define exploratory trademarks.

7.3. TRAT Effect and Trademark Opposition

7.3.1. Portfolio Sorts. Our main predictor based on the number of newly registered trademarks does not distinguish the quality of trademarks, which likely affects their predictive ability. We use the industry-level rate of oppositions to trademark registrations to proxy for trademark quality, with higher opposition rates reflecting higher quality (Sandner and Block 2011, Nasirov 2020), to examine whether *TRAT* predictability increases with quality.[40] We expect a stronger TRAT effect if the newly registered trademarks are in industries with higher opposition rates.

To test this hypothesis, at the end of June of year t, we assign firms into high and low trademark opposition subsamples based on the industry trademark opposition rate in year $t-1$. We use the Fama-French 48 groups for industry classification. We also independently sort firms into three TRAT portfolios as before.

Online appendix Table IA15 shows that the TRAT return spread between the highest and lowest portfolios is larger in industries with higher opposition rates. The monthly value-weighted excess return and industry-adjusted return of the TRAT hedge portfolio within the high opposition subsample are 0.45% and 0.42%, respectively, with both significant at the 5% level. In contrast, the TRAT-return relation is much weaker in the low opposition subsample. The TRAT spread is similar, but the excess return and industry-adjusted return of the TRAT hedge portfolio are insignificant and much smaller (0.18% and 0.14%, respectively).

7.3.2. Fama-MacBeth Regressions. Online appendix Table IA16 reports the results from monthly Fama-MacBeth cross-sectional regressions within the high and low opposition subsamples as formed above. Consistent with the portfolio sorts, we find that the TRAT-return relation is positive and significant in the high opposition subsample but is smaller and insignificant in the low opposition subsample.

8. Robustness Tests

8.1. TRAT Effect and Patent Activity

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

Online appendix Table IA17 shows that the TRAT-return relation indeed exists in both subsamples and is slightly stronger among firms with no patents granted over the same year. Specifically, the slopes on *Rank(TRAT)* are 0.11% ($t = 2.15$) and 0.09% ($t = 1.76$) among nonpatenting and patenting firms, respectively. The finding that the slopes of *Rank(TRAT)* are similar in magnitude in both subsamples confirms that the TRAT effect is more general than and is distinct from the patent effect and is able to explain stock returns in industries in which patents are uncommon.

8.2. TRAT Effect Within Industry

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

Online appendix Table IA18 shows that the excess returns and alphas of these TRAT portfolios are similar (in both magnitude and statistical significance) to those reported in Table 2 where we form the TRAT portfolios based on the full sample tercile breakpoints. These findings further suggest that the positive TRAT-return relation is robust to the industry effects on returns.

9. Conclusion

Trademarks are an important and widely used form of IP protection, and as the end product of the innovation process, they may be considered a measure of innovation outputs that have asset pricing implications. Because technical issues are resolved on attainment of a new product or service, trademarks may not be associated with as much uncertainty as for patents, which raises the possibility that trademarks might be valued fairly efficiently. However, new trademarks may still be hard to value because of market and competitor uncertainties associated with the new products/services and investors' difficulties in assessing new complex information about potential new markets and customer groups for the new products.

We find that the market does not efficiently price new trademarks. On average, investors undervalue new trademarks, especially among more complex/hard-to-value firms, which are larger and more opaque and have higher analyst forecast dispersion, more R&D spending, and lower advertising spending. Furthermore, the undervaluation is stronger when new trademarks are exploratory and hence harder to value and among industries with more valuable trademarks proxied by the opposition rate. We also show that new trademark intensity contains important information about firms' future profitability and that even financial experts such as analysts do not appear to fully understand the value relevance of this signal in their forecasts. These findings are consistent with the limited investor attention theory, and the hypothesis that attention is more severely burdened when uncertainty is high, and firms are more complex.

To enhance the causal interpretation of our results, we conduct two additional tests. Using an exogenous shock to trademark protection, we show that the TRAT effects are stronger when trademark protection is enhanced by the FTDA. We also find that new trademark registration contains positive value effect based on significantly positive announcement returns via an event study. These findings confirm that our baseline results are more likely to be driven by the value of trademarks rather than other omitted variables.

Our evidence suggests that new trademark activities represent intellectual property that contributes substantially to firm value but are undervalued by investors at the time of their registrations. This is reflected in high subsequent profitability, analyst forecast errors, and abnormal stock returns. These findings suggest that the Securities and Exchange Commission (SEC) and accounting regulators should consider using safe harbor rules to encourage firms to disclose an estimated fair value of new and existing trademarks, either on their balance sheets or as supplementary disclosures. By directing investor attention to the value of trademarks, such changes may potentially improve market efficiency and resource allocation.

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Endnotes

[1] Trademarks are an important and separate measure of innovative outputs from patents and are especially relevant for the current client-oriented economy. However, studies on trademarks remain sparse in the large innovation literature in economics and finance.

[2] The Organization of Economic Cooperation and Development (OECD) defines innovation as "the implementation of a new or significantly improved product (goods or service), or process, a new marketing method, or a new organizational method in business practices, workplace organization or external relations." The focus of this definition on the end product or service, and even its marketing method clearly encompasses new products/services that are represented by new trademarks in the broad definition of innovation.

[3] An example of the uncertainties involved is the launch of Nook by Barnes & Noble, a new e-reader device in October 2009. Another example is Daimler Mercedes' Smart, a new brand for minicar from a joint venture between Swatch and Daimler Mercedes designed to create a new segment of the car market. Both failed the market tests miserably: http://www.nytimes.com/2013/02/25/business/media/barnes-noble-weighs-its-nook-losses.html and http://carsalesbase.com/us-car-sales-data/smart, respectively.

[4] The literature has documented that investors are often attention-constrained and may fail to adequately incorporate corporate news in stock pricing (Hirshleifer and Teoh 2003; Peng and Xiong 2003, 2006; Peng 2005; Cohen and Frazzini 2008; Hirshleifer et al. 2011; Cohen et al. 2019; Fitzgerald et al. 2020).

[5] Although firms expect new products/services to bring significant cash flows in the future, valuing trademark activities can be hard for general investors because of complexity and uncertainty. Prior studies suggest that investors tend to underreact to new information (Bernard and Thomas 1990), especially when the new information is complex (You and Zhang 2009). Furthermore, the evidence documented in past studies on innovation suggests that investors tend to underestimate the cash flow prospects of R&D-intensive or patenting firms owing to the high complexity associated with innovation or fail to take into account the benefits of innovation because of limited attention, which results in underpricing of innovation (Hall 1993; Lev and Sougiannis 1996; Aboody and Lev 1998, 2000; Chan et al. 2001; Lev et al. 2005; Hirshleifer et al. 2013, 2018).

[6] We also form decile TRAT portfolios and find consistent results.

[7] This method of addressing the denominator concern is in a similar vein to Lou and Shu (2017).

[8] In addition, we also acknowledge that alphas from the Fama-French five-factor model, the q-factor model, and the mispricing factor model are significant over some long horizons.

[9] The stronger predictability for larger firms is also consistent with anecdotal evidence that larger firms capture more network innovation gains than smaller firms, and investors failing to anticipate such division of the gains. See, for example, https://www.wsj.com/articles/the-problem-with-innovation-the-biggest-companies-are-hogging-all-the-gains-1531680310.

[10] Sandner and Block (2011) show that filing oppositions against competitors' trademark applications increases firms' value, and Nasirov (2020) shows that trademarks that conquered oppositions are more valuable.

[11] We examine how the TRAT effect varies over 1996–2002 because the FTDA was challenged by the U.S. Supreme Court's decision in the Moseley v. V Secret Catalogue case in 2002 (Roe 2008).

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

[13] Other materials such as the promotion documents or advertisements that demonstrate that the trademark is in use are also acceptable.

[14] The USPTO's URL (https://www.uspto.gov/sites/default/files/documents/BasicFacts.pdf) contains basic facts about trademarks.

[15] According to the U.S. National Science Foundation's Business R&D and Innovation Survey (NSF BRDIS) in 2008, 15% (11%) of all surveyed firms rate trademarks (patents) as a very important form of IP protection. Among R&D firms, 60% rate trademarks as very

important, whereas 41%, 33%, 50%, and 67% rate utility patents, design patents, copyrights, and trade secrets as very important, respectively. The most recent available NSF BRDIS in 2015 further confirms the growing importance of trademarks relative to patents (see table 59 in https://ncses.nsf.gov/pubs/nsf18313/#&). In 11 industries, the percentage of firms ranking trademarks as very important exceeds the percentage ranking patents as very important by double digits: beverage and tobacco products (gap of 54.9%), finance and insurance (46.6%), food (45.9%), miscellaneous manufacturing (28.6%), wood products (25.0%), transportation and warehousing (23.2%), information (20.0%), machinery (17.4%), wholesale trade (16.2%), textile, apparel, and leather products (15.6%), and other nonmanufacturing (11.1%).

[16] Trademarks registered in service classes increased from 26.7% of all trademarks in 1992 to over 39.0% in 2009 (Graham et al. 2013).

[17] These small sample studies are less appropriate for studying stock return predictability, which is known to be driven by firm size (Fama and French 1993), industry (Fama and French 1997), and country (Hou et al. 2011).

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

[19] We follow the matching procedure of Hsu et al. (2017).

[20] We collect the subsidiaries of U.S. public firms in the following steps: first, we convert all public firms' GVKEY into Capital IQ's firm identifier; second, we input all these matched identifiers in the "Watch Lists" on the Capital IQ platform (https://www.capitaliq.com); and, third, we then use the "Screening" procedure, select "Companies", and add the "Current Subsidiaries" criteria.

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

[22] This follows the practice of the literature. For example, Chan et al. (2001) and Chambers et al. (2002) assign all firms without reported R&D expenditures to a separate group. Similarly, Hirshleifer et al. (2018) assign all firms without newly granted patents into a specific group.

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

[24] As a robustness check, we also form decile TRAT portfolios and report their returns and alphas in online appendix Table IA3.

[25] Chen et al. (2018) show that factor-adjusted returns and characteristic-adjusted returns can be drastically different.

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

[27] The results (untabulated) are robust if we use the logarithmic transformation of TRAT, *Ln(TRAT)*, instead of TRAT rank. The slopes on *Ln(TRAT)* are 0.15% and 0.12% (t = 2.41 and 3.66) in models 1 and 3, respectively, in Table 4.

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

[29] We assign observations into high versus low sentiment subperiods using the median Baker-Wurgler sentiment index (Baker and Wurgler 2006) and re-run the portfolio sort analyses for the separate subperiod samples. The alphas of the hedge portfolios do not differ between the high versus low sentiment subperiods.

[30] In the future profitability test of Section 5.1 and the analyst forecast error test of Section 5.2, we run weighted panel regressions and use market equity at the end of year t as the weight to match the value-weighted returns that we report in portfolio sorts.

[31] Following Cheong and Thomas (2011), we start the sample in 1993 because, before the regime shift in the early 1990s, I/B/E/S did not always adjust actual EPS for items that analysts did not forecast, which would cause a mismatch between forecasted EPS and actual EPS (Cohen et al. 2007). In addition, we keep only firm-years that are followed by at least five analysts.

[32] Fitzgerald et al. (2020) show that exploitative patents are positively associated with earnings surprises, which they infer as evidence for investors' underreaction to news about firms' exploitative innovation. In unreported tests, we find that TRAT also significantly predicts *AFE* in year $t + 2$ (based on two-year ahead forecasts of annual earnings), which helps explain TRAT's two-year ahead return predictability in alphas shown in Table 3. Because IBES provides few forecasts of annual earnings beyond the two-year ahead horizon, we are unable to examine the consistency of *AFE* predictability with the stock return predictability over longer horizons. However, TRAT's predictability for fundamental performance and stock returns are weaker and not uniformly significant for longer horizons.

[33] To protect their intellectual property and market positions, firms register trademarks to prevent piracy and mimicking behaviors. The registration does not protect against potential trademark dilution where another entity can use a logo or symbol that is similar to the firm's trademark but for a product/service that is not directly competing with the product/service that is covered by the original trademark. Famous examples including Kodak pianos, DuPont shoes, and Buick aspirin (Morrin et al. 2006). However, it is often difficult for the owner to prove economic loss in the court in such trademark dilution scenario, which nonetheless hurts the owner's IP.

[34] The FTDA protection may vary with higher protection for famous and valuable trademarks. Courts decide the economic value on a case-by-case basis. New trademarks enhance a firm's trademark portfolio, so the FTDA is expected to increase the value of a firm's overall trademark portfolio.

[35] Brauneis and Heald (2011) search and match names that appear in trademark databases and advertisements in *New York Times*, *Washington Post*, and *Wall Street Journal* for potential trademark dilution cases, and find a significant decrease in these cases after the FTDA's enactment, consistent with the law conferring greater protection against dilution. Heath and Mace (2020) show that ROA increased for firms with trademarks after the FTDA.

[36] Because some years in the FTDA subperiod coincide with the Internet bubble years, we examine the robustness of I_{FTDA} by dropping the 1998–2000 period. Online appendix Table IA8 shows that the results are robust.

[37] The Moseley period ended when the Trademark Dilution Revision Act (TDRA) was signed into law in 2006 to clarify confusions in the FTDA and the Moseley v. V Secret Catalogue case.

[38] New trademarks are announced by the USPTO in the weekly *Official Gazette* only on Tuesdays. To ensure that the registration event returns are not a day of the week effect, we examine Tuesday event abnormal returns from one to four weeks before the trademark registration event. In this test, we limit the sample to those events with no other new trademark registrations in the prior one to four weeks. None of the CARs around these pseudo-Tuesday events are statistically significant or substantial in magnitude.

[39] 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.

[40] A trademark can be opposed before it is officially registered. The average opposition rate is 1.31% at the trademark level in our sample.

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