THREE ESSAYS ON INNOVATION, CORPORATE CONTROL AND HOUSEHOLD CONSUMPTION-BASED ASSET PRICING

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by

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TABLE OF CONTENTS

LIST OF FIGURES

Chapter I

Chapter II

Chapter III

LIST OF TABLES

Chapter I

Chapter II

Chapter III

Academic Abstracts: Chapter I

BLAZE NEW TRAILS FOR OTHERS TO FOLLOW: EVIDENCE FROM SCANNER DATA

Ruixiang Wang

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ABSTRACT

Tracking more than 100 billion weekly transactions of two million products at the barcode level from 2007 to 2017, we identify and categorize new products as pioneers, followers and improvers to study corporate exploratory and/or exploitative innovation strategies. Firms introducing "pioneer" products are associated with greater future profitability and stock returns than those introducing "improver" and "follower" products. Price elasticity of demand explains pioneering (exploratory) innovation's operating success. Meanwhile, limited investor attention accounts for pioneering firms' superior stock performance. We exploit two exogenous shocks to firms' new product development decisions to address endogeneity concerns.

Academic Abstracts: Chapter II

FAMILY TRUSTS, CORPORATE CONTROL, AND INNOVATION

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ABSTRACT

This paper explores the long-run consequences of concentrating super-voting shares within family trusts. Dual-class shares are widely regarded as entrenching ownership structures that provide total control for top managers and engender excessive agency costs. In contrast, family-owned firms are often praised for instilling a long-run vision that limits self-dealing. In our data, 75% of family firms employ a dual-class ownership structure and 46% of these companies do so by holding these shares within a trust. We find that enhanced voting control through family trusts leads to larger investments into research and development and greater patent output. This patent production is perceived as more valuable by the market. Traditional investment is similarly perceived as more valuable. Firms controlled by trusts are more profitable and earn higher stock-returns. Super-voting shares held by family members outside of this structure have no effect and dual-class shares held by non-family investors lead to worse outcomes. These results reverse in a natural experiment that leverages the staggered adoption of state laws that weaken the control authority of family trusts.

Academic Abstracts: Chapter III

ASSET PRICES AND PARTISANSHIP: EVIDENCE FROM DAILY SHOPPER DATA

Ruixiang Wang

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ABSTRACT

We propose a novel consumption measure that has a daily frequency and is based on real time shopping data. Our measure explains the joint equity-premium–risk-free rate puzzle with a risk aversion coefficient much lower than any other consumption measures. It explains the cross-sectional variation of expected returns on various portfolios and is the only consumption measure that passes Kleibergen and Zhan (*Journal of Finance*, 2020) robust tests. Our model decomposes consumption shocks into different frequencies of volatility and shows that ignoring short-term dynamics and intra-annual fluctuations explains the much higher risk aversion from low-frequency consumption measures. At zip-code level daily consumption, (a) consumption in blue areas suggests higher risk aversion than that in red areas; (b) only Democratic consumption beta explains a variation of cross-sectional returns, and is more sensitive to overall industry performance.

Chapter I

1. Introduction

Innovation activity is the prime engine of long-run economic growth (Solow 1957) and original innovations can keep improving firm value for several years after they are generated (Hall, Jaffe and Trajtenberg 2005). However, researchers have found significant heterogeneity in innovation investments and thus cast doubt upon the degree to which existing measures can reflect firms' innovation efforts (Reeb and Zhao 2019). Since the goal of corporate innovation is to introduce cutting-edge products, a measure derived on products and their sales can better assess overall innovation success. Using detailed retail transactions data that track each new product's entry from 2007 to 2017, we investigate *how and why* innovation strategies differentially affect firm operating and stock performance.

To gain competitive advantages, businesses either offer different products from rivals or improve certain aspects on existing products (Porter 1996). This is consistent with the notion that when designing a strategy for product innovation, firms generally choose exploration and/or exploitation[1] (March 1991, Gao, Hsu and Li 2018). We follow this logic by categorizing firms into three types of new product innovators, including those that tend to lead the market by introducing pioneer products (pure exploration); those that follow the pioneering firms by offering products that are similar to existing products but in new business lines to the firm (exploration and exploitation), and those that offer new versions of existing products in the same business line as existing products (pure exploitation). To

[1] According to March (1991), an exploratory innovation strategy is vertical innovation that virtually creates a new business segment, whereas an exploitative strategy learns from existing technology to make new products within the same business line.

the best of our knowledge, this is the first paper that studies the heterogenous strategies of corporate innovation based on new product introduction decisions.

Evaluating how innovation strategies affect firm performance is of interest, yet investing in a particular intangible asset is the result of a firm's optimization problem (Argente, Baslandze, Moreira and Hanley 2019). As such, a single proxy is insufficient to represent the whole innovation process from idea generation to product manufacturing because, for example, some firms could use trade secrets to protect their manufacturing process while others apply for patents to defend their products (Reeb and Zhao 2019). By linking patent to product, Argente *et al.* (2019) show that firms use patents in protective or productive ways, depending on their size. They also find that non-patenting firms in fact offer many innovative new products. That there are various ways to measure innovation could plausibly explain the finding that assets with technical uncertainty in innovation are difficult to value and lead to underpricing or over-discounting[2]. This paper fills the void by focusing on new products that represent firms' ultimate payoff for innovation efforts to evaluate corporate innovation. Indeed, by combining our sample with patent and trademark, Figure 1 reveals that more than half of our sample firms do not apply for patents or trademarks.

In innovation search literature, researchers using different patent-based proxies have found that exploratory or exploitative innovations all lead to superior performance.[3] Our paper's categorization method aims to comprehensively investigate these strategies using a unified product-based measure. In Figure 2, we link the product-based innovation search

[2] See Eberhart, Maxwell and Siddique (2004); Hall (1993), Chan, Lakonishok and Sougiannis (2001); Lev (2001), Hirshleifer, Hsu and Li (2013, 2018) and Hsu, Li, Li, Teoh andTseng (2020)
[3] See, for example, Hirshleifer, Hsu and Li (2018) and Fitzgerald, Balsmeier, Fleming and Manso (2019)

strategies to traditional measures and profitability. Specifically, we divide sample firms into leaders and laggards[4] by each strategy based on Hoberg and Phillips (2010, 2016) industry groups ("H&P industry" hereafter) and compare their return on equity (ROE), R&D investment, innovation efficiency, and trademark introduction rate.

A cross-sectional comparison among the three product strategies reveals that: (1) Compared to laggards, leaders invest *less* in R&D, yet they are *more* efficient in turning R&D into patents; (2) leaders in pioneer and improver products generate greater ROE than laggards; (3) leaders in pioneer and follower products introduce more new trademarks than laggards, which are understandable as they seek to introduce vertically new products (pioneers are vertical to the whole market, and followers vertical within itself). Interestingly, improver leaders apply *fewer* trademarks than laggards, which is probably because they tend to focus on innovating existing brands. A key conclusion drawn is that, first, not all innovatively efficient strategies will yield better ROE. Second, although improvers do not apply for many trademarks, they demonstrate superior profitability by optimizing existing product lines through innovation efficiency.

Motivated by these patterns, we hypothesize that firms focusing on pioneer innovations tend to have *higher* future profitability due to launching radically new products that are highly exploratory, thereby making them industry leaders that retain monopolistic profits. Second, while follower products exploit other pioneer products, the associated firms are demonstrating exploratory innovation since the business segment is new to them. Given the monopoly of pioneer products by market leaders, firms introducing follower products have to find their own niche. Therefore, these firms need to spend significant

[4] A firm is a leader (laggards) when its product innovation rate is above (below) its H&P industry average

amount of time and resources differentiating themselves from pioneers, which can harm their profitability. As such, the contribution to profitability by follower products is *unclear*. Last but not least, improver firms are exploiting their knowledge based on existing product portfolios to innovate similar products with improvements. Presumably, if firms want to improve an existing product, it must be a successful one. To make an improvement, firms collect customers' feedback, either through questionnaire or data analysis of product transactions. As such, firms focusing on improving products will solidify their product line's popularity, thus leading to *better* future profitability.

Our empirical results show that pioneer and improver products are associated with superior future profitability. For example, one-standard-deviation increase in the pioneer product introduction rate, which is the sales of pioneer products divided by those of total new products in a particular year, is associated with a 0.5% increase in the next year's ROA that is slightly higher than that of the Innovation Originality (0.46%[5]), Patent based Innovation Efficiency (0.45%), but lower than Trademark (0.939%), which is a tercile variable instead of a continuous one. Meanwhile, improving product introduction rate is associated with a 1.2% increase in future ROE, while follower product introduction does not have any significant contribution to future profitability.

We are cautious that innovation strategy is a choice by firms, thus subject to endogeneity concerns. Firms that have more liquidity should be able to take risk and afford the high research and development expenses that consequently generate new breakthrough innovations. To address these concerns, we first explore the exogenous variation of

[5] Although we standardize the independent variable to make it directly comparable with the Innovation Originality (Hirshleifer *et al.*2018), readers should be cautious in interpreting the magnitude of coefficients because our sample is shorter and contains fewer firms than that used for Originality Measure.

innovation activities induced by the staggered changes in state-level corporate tax rates that will reduce innovation activities in affected states (Mukherjee Singh and Žaldokas 2017). A set of difference-in-difference (DiD) experiments supports our findings. Second, motivated by the marketing literature on new product diffusion through word-of-mouth advertising (Horsky and Simon 1983), we identify an instrument, the local firm's average advertising expense per new product, to use it in a two-stage-least-squares (2SLS) analysis. The empirical relation still holds when using the instrumented variable.

Next, we propose elasticity of demand to explain firms' innovation success. We find that pioneer products and firms manufacturing such products are consistently associated with lowest demand elasticity among their respective counterparts. For example, pioneer products are associated with 21% absolute value of price elasticity of demand, as compared to 24% and 27% for improvers and followers. This suggests that consumers tend to keep buying pioneer products despite their high prices, which explains why firms focusing on pioneer products gain superior operating performance.

In the second part of this paper, we investigate if the stock market can incorporate different sets of information contained in product innovation strategies, especially for pioneer and improver products that can lead to better future profitability. Using portfolio analysis, we find that a strategy of purchasing the top 70th percentile of pioneer introduction rate and shorting the bottom 30th percentile consistently generates 0.61% monthly alpha from a Fama French 3 factor plus momentum, which is higher than the alpha generated from the same strategy based on the Innovation Originality (Hirshleifer *et al.* 2018) of

0.35%.[6] On the other hand, a trading strategy involving improvers generates significant alphas only in traditional asset price models. However, they are correctly priced after controlling for an innovative efficiency factor (Hirshleifer, Hsu and Li 2013). This could be because traditional models still fail to fully understand improver products by some high-tech firms, which are exposed to specific innovation risk proxied by innovation efficiency.

Further, we investigate whether the underpricing is due to unobserved risk factors or a behavioral-based investor inattention theory. Our first proxy for limited attention is advertising expense, which is found to attract investor attention[7]. It is particularly relevant to this study because our focus is on products while advertising increases product exposure. If firms invested heavily on advertising their new products, especially ex ante, analysts would find them easier to value than those who tend to "surprise" the market by offering new products without notice. The second proxy is the number of patents. Since stock market is very responsive to patent approval (Kogan *et al.* 2017), it should have little uncertainty to value the pioneer products associated with these breakthrough patents. On the other hand, if a firm does not apply for any patents related to a newly launched pioneer product, the market would not have any signal about this pioneer product, thus having uncertainty valuing it.

We perform portfolio and predictability analyses in subsamples of high and low advertising firms as well as patenting and non-patenting firms. We find that the underpricing effect is stronger in firms that invest less in advertising and those that do not apply for any patents. This shows that without information released through advertising or

[6] Although the alpha is greater than the Innovation Originality (Hirshleifer *et al.*2018), it should be interpreted with caution because they have a longer sample period (1982-2007) while mine is shorter (2008 to 2018).
[7] See Grullon, Kanatas and Weston (2004); Lou (2014)

patents, the market is even more uncertain to value pioneer products. We also tested if the superior stock performance of pioneer innovation is driven by unknown systematic risks or that pioneer innovation is exposed to some state variables that represent risks associated with technological changes. We create risk factors[8] to proxy for such risk and find that the risk premia are insignificant, indicating that the findings are unlikely to be driven by risk-based explanations.

Our paper contributes to the literature in four ways. First, we document a novel channel of how and why corporate innovations *differentially* create value. Finance and economic researchers have shown a strong relation between innovative activities and firm performance and economic growth[9]. Our paper decomposes the aggregate innovation activity and finds that pioneer or improver innovations are driving firm profitability due to low price elasticity of demand. On the other hand, followers are difficult to compete with pioneer peers to gain meaningful superior performance.

Second, we advance the literature of valuation of innovation that identifies it as a premium or mispricing with different measures. Hsu (2009) finds that innovation as a priced risk that carries a premium in the cross-section. Conversely, the underpricing of innovation efficiency, originality and trademark is due to investor inattention. With product-level data, we confirm that the innovation premium is time-varying, that it is priced at the beginning stage and is mispriced (or correctly priced with more information transparency) at the product commercialization stage.

[8] The factors are constructed by forming long-short hedging portfolio formed by longing top 30th and shorting bottom 70th of firms conducting pioneer/follower/improver product innovation
[9] See Aghion and Howitt (1990), Hsu, Tian and Xu (2014)

Third, we contribute to the innovation search literature by employing a nuanced categorization method of corporate innovation to evaluate explorative and/or exploitative strategies while demonstrating how product innovations differentially affect industry competition[10]. Extant research mainly categorizes exploratory v. exploitative innovation based on patent or trademark classes and scholars have found conflicting results using different measures. By leveraging product-market modules, our method evaluates explorative and exploitative innovations at a finer level based on market pioneer (exploratory), follower (exploitative and exploratory) and improver (purely exploitative). We show that firms should adopt either an exploratory or purely exploitative strategy as followers on average cannot compete with pioneers.

Finally, we introduce a dataset that captures firms' innovation activities at the product level. Researchers have called for more refined proxies because firms conduct different innovative efforts in different dimensions (Kerr and Nanda 2015, He and Tian 2018). On the one hand, new proxies are being developed based on traditional patent and citation measures[11]. On the other hand, a growing number of papers look at alternative sources, such as brand or trademark (Hsu *et al.* 2020). This paper contributes to this debate by showing that the final products, supported by different innovation proxies, have different impacts on firm performance.

This paper proceeds as follows: section 2 describes data, section 3 investigates product innovation strategies and firm future profitability, while section 4 examines stock market's valuation on such strategies. Section 5 concludes the paper.

[10] See March (1991), Porter (2008, 1996)
[11]For example, Trajtenberg (1990), Hall, Jaffe and Trajtenberg (2001, 2005), Hirshleifer *et al* .(2013, 2018), Kogan, Papanikolaou, Seru and Stoffman (2017)

2. Data Description, Product Innovation Measures and Summary Statistics

2.1 Nielsen Retail Scanner Dataset

We start with the Nielsen Retail Scanner Dataset (RSD) provided by the Kilts-Nielsen Data Center at the University of Chicago Booth School of Business. RSD is generated by the point-of-sale systems from more than 90 participating retail chains with 40,000 unique stores across all U.S. markets (See Figure 3). Each store reports product selling prices and quantities per week by scanning the barcode of each product on Saturday of each week. The barcode is a 12-digit Universal Product Code (UPC), which represents the finest level of product identification because it is unique to every product and any change in product attributes will result in a new barcode.[12]

Currently, RSD reports around 2.6 million UPCs' weekly sales from 2006 to 2017 that consists of more than 100 billion transactions at the UPC-weekend-store level with a total of 2 trillion in product sales. The participating stores are in grocery, drug, mass merchandise and others that take up to more than 50% of total sales volume of U.S. grocery and drug stores and more than 30% of U.S. mass merchandiser sales volume.[13]

2.2 GS1 U.S. Data Hub

To connect firms with products, we link RSD to GS1 U.S. Data Hub (GS1) as GS1 is the only official source of UPCs and provides firm name of all UPC owners. If a firm wants to get UPCs for its products, it will contact GS1 to purchase a company prefix, which will

[12] One possible concern is that a new UPC might not always represent a new product. However, Nielsen notes that if they detect a new UPC in this scenario, they would assign this to its prior UPC.
[13] Source : https://www.chicagobooth.edu/research/kilts/datasets/nielsen

be combined with the unique product number to form a 12-digit UPC code. The company prefix varies from five- to ten-digits to identify unique firms and their products. Intuitively, the digits of company prefix determine the maximum number of products a firm can launch because the total number of UPC digits is 12. From Figure 4, we see that if a firm purchases a nine-digit company prefix (right side), this firm can launch at most 100 products with 00 to 99 as the two digits product number. On the contrary, if a firm purchases a six-digit prefix, this firm can launch up to 100,000 products because six-digits as product number allows 10^5 possible combinations. Naturally, the nine-digit company prefix is cheaper to obtain than a six-digit prefix.

Because GS1 links firm name to firm prefix, we connect firm prefix with UPCs from Nielsen to obtain the ultimate owner's name of the UPCs. We perform all the matching at the parent level because some firms can own many firm prefixes through merger and acquisition. GS1 also further provides this firm's address, city, state and zip code.

2.3 Merge RSD/GS1 with CRSP/COMPUSTAT

Next, we merge the combined RSD/GS1 to CRSP/COMPUSTAT to obtain firm financial and stock information. Because GS1 does not provide unique firm identifier such as Gvkey or Permno, we use fuzzy matching between firm name in GS1 and that in CRSP, with additional checks on address, state and zip code. After matching, we are able to identify 442 unique firms at the intersection of RSD/GS1/CRSP/COMPUSTAT from 2006 and 2017. In addition to the firm year level tests, we match the CRSP individual firm return data at monthly level and Compustat data at quarterly level in monthly return predictability tests.

2.4 Identification and Categorization of New Products

Following the economics literature (Argente *et al.* 2018, Broda and Weinstein 2010), a new product is defined as the first time a UPC has recorded sales in the RSD data in that particular week. However, the way to identify new products suffers from a truncation bias. Nielsen started collecting data for RSD in 2006 and the latest available sample year is 2017, with updating occurring every two years. The issue is that for products identified as new in 2006, they could be entering into the data in 2006 for the first time, or they could already be in the market but the data starts from 2006. To address this issue, we delete all data from 2006, and our final data set is from 2007 and 2017.

RSD organizes them into more than 1100 time-varying modules that belong to 125 groups that are further segmented into 10 departments. To model the heterogeneities in firm innovation and follow the exploratory and/or exploitative strategies, we identify all new products as (1) pioneer when its introduction was so new that RSD had to create a new module; (2) follower when the firm introduced it for the first time although there has already been pioneer products in related modules; (3) improver when it is an improvement to the focal firm's existing product module.

Appendix 2 shows a set of pioneer, follower and improver product examples. For pioneers, Nielsen added three new modules about electronic cigarettes to account for their mass-commercialization around 2013. We categorize all the products associated with these modules as pioneer products. For followers, Tyson Foods, a company primarily specializing in prepared meats, acquired the brand "Three Happy Cows" in 2014, announcing its entry into the yogurt market. We regard all these products as follower

products. For improver products, Apple keeps introducing new version of iPhone and all of these versions are improver products.

We calculate the total weekly sales of each product as (price/prmult) *units sold, in which "prmult" is a promotion variable, such as 3 for $1. Following standard economics literature (Broda and Weinstein 2010), we seasonally adjust the weekly sales by regressing it on monthly dummies to collect residuals. We then scale the total sales of pioneer/follower/improver products by the total new products sales by firm *i* in the same period *t*:

$$Pioneer/Follower/ImproverProductIntroduction\ Rate_{i,t} = \frac{\sum Sales\ of\ Pioneer/Follower/ImproverProducts_{i,t}}{TotalNewProduct\ Sales_{i,t}}$$

As the total number of new products is the sum of pioneer, follower, and improver products, these measures reflect a firm's strategic focus in their product innovation toward exploration and/or exploitation. An avid reader might caution that the sales of these new products might be small percentage of the company's total sales and thus should not create significant incremental value to a firm. To address this comment, we replace the total sales of new products in a denominator to total sales of a firm. The results remain intact.

2.5 Samples Construction and Control Variables

To ensure that our results are not driven by other innovation inputs, we control for two innovation-related variables, including innovation efficiency (Hirshleifer *et al.*2013) and trademarks (Hsu *et al.*2020), in all the models except for portfolio tests. For trademarks, RSD provides brand information for each product. We calculate new brand introduction

rate to proxy for the trademark application.[14] In portfolio analysis, we control for patent-based innovation efficiency factor EMI1 in obtaining alphas.[15]

First, we examine different product introductions' impact on future profitability proxied by COP, ROA, and ROE. We control for common variables used in the literature that affect future profitability, including log-transformed market equity and firm age, as well as advertising expense, R&D expense, capital expenditure, and M/B ratio. The final dataset for regression has 338 firm and 2,096 firm and year observations.

In the second part of the paper, we conduct portfolio and return predictability analyses. Because our sample size is limited, we sort firms into tercile portfolios based on three product introduction rates to avoid under-diversification. Next, we conduct monthly Fama-MacBeth predictive regression and control for common predictors related to innovation, including size, book to market ratio, momentum, patent scaled by assets, short-term return reversal, asset growth, capital expenditure scaled by assets, R&D to market value of equity, ROA, and a multi-segment firm dummy. The merged sample of return prediction has 347 firms with 24,308 firm months observations.

2.6 Summary Statistics

The general product introduction statistics are in Panel A of Table 1. On average, sample firms have 291 products and introduce 40 new products per year. Out of these new products, 4.4% are pioneer products, while 3.5% are followers. The majority of new products are improvers. The reason the sum of the three rates is not one is because some

[14] Here, we assume that when a firm launches a brand, it has already applied for a trademark. This is reasonable as firms will benefit from legal protection from trademark application for their products (Bereskin *et al.*2020, Millot 2009)
[15]We do not use citation-based innovative efficiency (EMI2) because the associated citation data ends in 2006

firms do not have any new products for the entire year. For product information, the average product price is $15 while selling quantity is 11 at a given store in a certain week. Sample firms' products on average obtain $5,632 sales per week.

Next, we present means of firm characteristics in (1) the main sample, and (2) splitting the sample by pioneer, follower, and improver rates above or below the H&P industry average. We also calculate the differences of these three groups. We use bold font to indicate differences that are significant at the 5% level.

On average, firms have 3% annual ROA. They have $17 billion in total assets and $14 billion in total sales, indicating that they are large firms. Their innovation efficiency is 15% and they apply for 63 patents on average in a particular year. Regarding the subsample analysis, generally firms with product innovations above the industry average have better profitability, lower market value of equity and lower sales than those below. Interestingly, these firms also have lower R&D expense, but better innovation efficiency and trademarks (except for improvers) than those below. This shows that although industry leaders are smaller than laggards, they are very efficient in innovating new products.

3. How and Why do Product Innovations Differentially Affect Future Operating Performance?

In this section, we address the first part of our research question by investigating the impact of new product introductions on firm operating performance In Section 3.1, we run Fama-MacBeth annual cross-sectional regressions to predict next year COP, ROA and ROE. We address the potential endogeneity issues in 3.2. In Section 3.3, we provide an economic channel between product innovation and future profitability through elasticity of

demand. In all tables, we winsorize variables at the 1% and 99% levels and standardize all independent variables to have zero mean and one standard deviation, except for dummies, to avoid outliers and to simplify interpretation.

3.1 How do product Innovations differentially affect Future Profitability?

We first run Fama and MacBeth (1973) annual cross-sectional regressions of the next year's operating profitability proxies on current product introduction for firm *i* at time *t*. The regress specification is as follows:[16]

$$COP, ROA\ and\ ROE_{i,t+1} = \alpha + \beta_1 Pioneer_{i,t} + \beta_2 Follower_{i,t} + \beta_3 Improver_{i,t} + \lambda' \boldsymbol{X_{i,t}} + \sum_{f=1}^{48} \varphi_f Industry_f + \varepsilon_{i,t}$$

where β_1 to β_3 measure the effects of pioneer/follower/improver product introduction rates on future operating performance. λ' is a vector of coefficients for control set $\boldsymbol{X_{i,t}}$. We include industry dummies according to Fama and French (1997) 48 industries and φ_f represents the coefficients of these dummies. Furthermore, we repeat the three tests by comparing industry leaders in executing each strategy with industry laggards according to H&P industry classifications based on product similarities.

In accounting for how exploratory and/or exploitative innovations affect profitability and industry competition, we examine firms' manufacturing pioneer, follower and improving products individually and across H&P industry. We focus on firm operating performance using cash-based operating profit (COP), return on assets (ROA), and return on equity (ROE). According to Ball *et al.*(2016), cash-based operating profits outperform

[16] We also scale pioneer/follower/improver by total product sales, as well as run the specification without industry dummies, the results remain the same. See Appendix 3.

other profitability measures and predict the cross section of average returns. On the other hand, ROE and ROA incorporate broad information about a firm's overall profitability.

Because COP, ROA and ROE represent a firm's profitability as a whole while a firm can have three kinds of product innovation activities at the same time, we include three product innovation rates together to reflect firm-level total innovation strategies that match firm-level profitability measures. We control for common variables described in section 2.5 and also include industry dummies based on Fama and French (1997) 48 industries. We use Newey-West (1986) autocorrelation adjusted heteroscedasticity robust t statistics to derive the significance of the coefficients.

Table 2 shows how different innovation strategies affect firms' future profitability. Models (1), (3) and (5) regress future COP, ROA and ROE on contemporaneous product introduction rates. The slope of the pioneer product introduction rate is significantly positive, controlling for the other two rates and other variables. Economically, one-standard-deviation increase in pioneer introduction rate is associated with 0.2% increase in COP (0.5% increase in ROA) next year. Given the COP (ROA) has a mean of 5% (3%), this is a 4% (13%) increase around the mean. At the same time, improvers are associated with 1.2% increase in future ROE.

In Models (2), (4) and (6) of Table 2, we regress future profitability on a dummy that equals 1 if the focal firm's product introduction rates are above industry average defined by H&P. The slope thus compares industry leaders with laggards in different product introduction strategies. On average, firms leading the industry in introducing pioneer products are associated with 0.6% greater future COP than laggards. Meanwhile, improver product leaders on average have 0.5% higher future ROA than laggards. For follower

products, industry leaders actually underperform laggards by 1%. In sum, pioneers are consistently associated with better future profitability, improvers in some cases can improve performance, while followers generally don't experience any improvement. We also replicate mean reversion and future volatilities models in Hirshleifer *et al.*2018 and get similar results, which are in Appendix 4.

3.2 Endogeneity issues of product innovation strategies and future profitability

The choice of a certain product innovation strategy is not random. For example, some large firms with ample liquidity tend to have strong cash flows that allow them to invest more in pioneer product innovation; thus pioneer product introductions are determined by inherent firm characteristics. On the other hand, some young entrepreneurial firms can launch pioneer products due to their ability to find favorable VC funding, while others may not find investors to finance such risky projects. In this case, a pioneer product is correlated with unobservable factors, such as VC taste or a founder or manager's personal charisma.

To address these endogeneity concerns, we first explore an exogenous variation in new product development and introduction caused by the staggered changes in state-level corporate tax rates. Heider and Ljungqvist (2015) first propose that state level tax changes have a first-order effect on capital structure. Mukherjee *et al.*(2017) find that firms reduced innovation and product introduction (from textual analysis of 10-K filings) following an increase in state-level corporate tax. Guided by their finding, we exclusively focus on states that raised taxes in our sample period. We identify six states that have increased taxes during our sample period.[17]

[17] The six states are: Maryland (2008), Michigan (2008, 2012), Connecticut (2004, 2012), North Carolina (2009), Oregon (2009) and Illinois (2011)

Since a tax increase discourages corporate innovation activities, it presents an exogenous shock to the firms' innovation strategies. Specifically, if the findings in 3.1 hold, the reduced innovation activities will lead to a decrease in profitability of firms located in states with a tax increase. Importantly, this relationship is not affected by unobservable heterogeneities or individual firm decision because it is a state-wide variation in innovation activities caused by changes in corporate tax.

We assign firms in treatment group if they are headquartered in one of the six states that experienced tax rise. Heider and Ljungqvist (2015) as well as Mukherjee *et al.*(2017) both note a problem about Compustat's location data, which suffer from a flaw that Compustat only reports the address of a firm's current principal executive office, rather than its historic headquarter location that is time-varying due to changes of headquarter states. They search the 10-K to extract historic headquarter data because the only available historic headquarter data is provided by CRSP that starts in 2007. Since our data exactly starts from 2007, we are able to use the CRSP location data to correctly identify headquarter states.

We use a DiD specification, which first relies on an important parallel assumption that, without exogenous shocks there should be no difference in the outcome variable between the treatment and control groups. When the exogenous shock happens, the treatment group should experience significant changes in the outcome variable compared to the control group. In our setting, we expect the treatment firms underperform control firms in profitability *only after* the states raise the corporate income tax.

We regress future profitability proxies on a dummy of treatment vs control, along with same control used on Table 2's original models. We plot yearly coefficients in a [-2,2]

window and their 95% confidence interval. Figure 5 shows the parallel trends for COP, ROA and ROE. In the event year, the treatment firms significantly underperformed the control firms, indicating that only treatment firms experienced this shock because other coefficients are insignificantly different from 0.

We then run the following Fama-MacBeth regression to conduct our DiD regression:

$$Y_{i,t+1} = \alpha + \beta_1 Treatment * After * Pioneer\ Introduction\ Ratio_{i,t} +$$
$$\beta_2{}' All\ Interaction\ Terms_{i,t} + \lambda' \boldsymbol{X}_{i,t} + \sum_{f=1}^{48} \varphi_f Industry_f + \varepsilon_{i,t}$$

where Y is future COP, ROA or ROE, β_1 is the DiD coefficient that measures the difference between the treatment and control firms before and after the tax increase. $\beta_2{}'$ is a vector of coefficients that represent the interaction terms. λ' is the coefficients of control vector $\boldsymbol{X}$ used in the main models. φ represents coefficients of industry dummies. t is annual and f represents one of 48 industries. Since the pioneer product introduction rate is the focus of this paper, we treat this variable as the endogenous variable.[18]

Panel A of Table 3 shows the DiD result. In models (1)-(3), the DiD coefficients are negative and significant, indicating that the treatment firms on average have lower future operating profitability caused by a reduction in pioneer product innovation compared to control firms after their states increased corporate income tax.

Second, we identify an instrumental variable that is associated with product innovation. The marketing literature has proposed that advertising of new products can inform other innovators of the existence and value of other firms' new products through an

[18] We find similar results for the improver introduction rate. For brevity, we do not report these results.

innovation diffusion process (Horsky and Simon 1983). Presumably, if a firm has observed many new products' advertisements, such as on billboards or social media, launched by other companies in the same city, it will feel pressured or inspired to introduce more products to blend with the local innovative culture. Empirically, we calculate average advertising expenditure per one new product[19] of sample firms, except for the focal firm, located in each city. Importantly, we also exclude all the firms that share the same industry with the focal firm because these firms' advertising and new products' sales can correlate with focal firm's profitability, thus violating exclusion condition. We use this measure to instrument the endogenous product introduction rate in a two stage least square analysis (2SLS).

Panel B of Table 3 shows the 2SLS results. Model (1) is the first stage model in which we regress the pioneer product introduction rate on instrumental variable, advertising expenditure of other firms locating in the same city as the focal firm. The instrumental variable is positive and significant, indicating that the higher advertising expenditure by other firms, the more likely the focal firm to conduct pioneer product innovation, thus satisfying relevance conditions. The R^2 of the first stage model is 33.1% while F statistics is 9.625, indicating the stability of the model.

In models (2)-(4) we regress future profitability on the predicted or instrumented pioneer introduction rate, along with the same set of controls. For example, the coefficient of the instrumented pioneer rate is 0.001 or 0.1%, meaning that one-standard-deviation increase in the instrumented pioneer rate will increase future ROA by 0.1%.

[19] For all sample firms (excluding the focal firm and same-industry firms) located in the same city as the focal firm we divide average total advertising spending by average number of new products.

In sum, the DiD and 2SLS approaches alleviate the endogeneity concern that pioneer introduction rate is correlated with unobservable characteristics (omitted variables) or pioneer introduction rate is determined by the highly persistent profitability of growth firms (reverse causality). Notwithstanding, the endogeneity problem can never be fully addressed. We acknowledge the limitation with which available empirical tools can solve such problem.

In addition, one might question if the way Nielsen assigns products into module is endogenous. The way that Nielsen determines modules is based on product characteristics, such as bottles, lotion or accessory.[20] As such, it is unlikely that the construction of modules was correlated with firm-level characteristics, including size, sales or other unobservable factors.

3.3 Why do Product Innovations Differentially Affect Future Profitability?

Having shown the superior performance of pioneer and improver products as well as addressed the endogeneity concerns, we provide an economic channel through which product innovations affect profitability. With price and quantity sold data for each product, we derive the price elasticities of demand for pioneer, follower and improver as well as other existing products. The price elasticity of demand is the percent change of demand in response to one percent change in price. Intuitively, a product with low price elasticity of demand indicates its demand is inelastic to change in price. Furthermore, firms

[20] From discussions with the data vendor regarding module classification, classifications are by product type, and are unrelated to the firm. For example, the "Health and Beauty/Baby Needs" category contains subcategories such as bottles, accessories, and lotions, among other subcategories. These subcategories (are new subcategory classifications) are unrelated to the particular firm.

manufacturing such low elasticity of demand products should keep a high demand or sales with increase in their products' prices, thus maintaining a high profitability.

The economics literature documents a canonical double-log regression whose beta is the price elasticity of demand (Nicholson 1992). For each product *i* at week *t*, we run this pooled OLS regression at product-week level:

$$Ln(Quantity\ Demanded)_{i,t} + = \alpha + \beta_1\ Ln\ (Price)_{i,t} + \varepsilon_{i,t}$$

where β_1 is the price elasticity of demand.

In addition, we design another specification that includes control variables to account for unobservable heterogeneities in firm characteristics that may covary with quantities sold and controls for time trend of new product introduction. These variables include product price standard deviation, quantity demanded standard deviation and total sales as well as firm age, beginning value of total asset, total sales as reported by Compustat and Herfindahl index based on the three-digit SIC code. The specification is as follows:

$$Ln(Quantity\ Demanded)_{i,t} + = \alpha + \beta_2\ Ln\ (Price)_{i,t} + \beta_3{}'Controls_{i,t} + \lambda'\boldsymbol{X}_{i,t} + \varepsilon_{i,t}$$

where β_2 is the price elasticity of demand, β_3 is a vector of coefficients of control variables and λ is a vector of coefficients of fixed effects X, including firm and year. We separately run this regression for pioneer, follower and improver products.

Next, we first obtain the β_1 from the canonical double log regression and assign it to corresponding product, thus aggregating it at the product-firm-year level. We regress all the products' absolute value of price elasticity of demand on pioneer, follower and

improver dummies with product and firm level controls. To properly track each firm's product innovation strategies, we use multiplicative fixed effects of firm by year and industry by year in this specification:

$$Individual\ product's\ absoulute\ value\ of\ price\ elasticity\ of\ demand_{i,t} = \alpha + \varphi_{1-3}\ Pioneer/Follower/Improver\ Dummies_{i,t} + \varphi_4{}' Controls_{i,t-1} + \lambda' \boldsymbol{X}_{i,t-1} + \varepsilon_{i,t-1}$$

where φ_1 to φ_3 are coefficients of the three dummy variables. Because the universe of products includes pioneer, follower, improver and existing products, each dummy's coefficient is a comparison of absolute value of price elasticity of demand between pioneer/follower/improver and existing products.

Last but not least, we aggregate all the individual product's absolute value of price elasticity of demand into firm-year level by value weighting them by their respective annual sales. We then univariately compare firms with and without pioneer, follower and improver products as well as firms that are above the HP industry mean in terms of pioneer/follower/improver introduction.

Table 4 presents the price elasticity of demand results. Panel Aa presents the canonical price elasticity of demand regression at product-weekend level. The pioneer, follower and improver products respectively have -21.3%, -26.8% and -23.8% raw price elasticity of demand. This means that for a pioneer product, its demand on average declines by 21.3% with one percent increase in its price as compared to 26.5% decline for follower and 23.8% for improver, making pioneer the most inelastic new product. Panel Ab shows the regression with controls and fixed effects. The raw price elasticities show the same pattern for three kinds of new products.

Panel B shows the product-firm-year level regression of absolute value of each product on pioneer, follower and improver dummies with controls and firm by(and) year or industry by(and) year fixed effects. Because the pioneer, follower and improver are dummies compared to existing products, the coefficients are the difference. Economically, model (1) for example shows that, on average, a pioneer product's absolute value of price elasticity of demand is 7.334% lower than that of an existing product, controlling for follower and improver product as well as other variables. For followers and improvers, they are 5.495% and 6.351% lower than existing products, thus making pioneers the lowest elasticity of demand among all products. This conclusion is robust to every firm's pioneer products, every year's pioneer products' introduction, and every industry's pioneer products as well as all the pioneers introduced by each firm in each year or each industry in every year.

Panel C presents the univariate compassion of firm level absolute value of elasticity of demand. We report the mean values of firms with or without each product categories as well as above or below HP industry average with Satterthwaite T statistics for the difference in mean. We find that only pioneer products show significant difference. For example, on average, pioneer firms' aggregate absolute value of price elasticity of demand is 34% lower than non-pioneer firms. Further, industry leaders in pioneer introduction have 22% lower absolute value of price elasticity of demand than industry laggards.

Taken together, these panels comprehensively analyze how price elasticity of demand explains product innovation success. We first document a fact that pioneer products are most price inelastic. Next, aggregating these absolute price elasticities of demand at product level, we find that pioneers still have lowest price elasticity of demand after controlling for various controls and most importantly this empirical finding is robust to

firm by year or industry by year fixed effects. Furthermore, after aggregating all products into a firm level absolute value of price elasticity of demand, we find that pioneer firms are more price inelastic than non-pioneer firm, or industry leaders in pioneer have lower value than laggards. These findings show that pioneer products can help firms maintain a high quantity sold (demanded) with price increase, which translate into superior operating profitability.

4. How and Why Do Product Innovations Affect Stock Performance?

In this section, we test the second part of our research question on how product innovations differentially affect stock performance. In particular, we design our tests based on investor inattention literature in valuing intangible assets (Hirshleifer *et al.*2013, 2018, Hsu *et al.*2020). We first sort firms into portfolios based on three product introduction rates to test their alphas against different risk models. Then We use contemporaneous product introduction rates to predict next month stock returns.

4.1 Portfolio Analysis

We run portfolio analysis to test product innovation and firm stock performance. Because of the limited sample size, we use tercile portfolios to avoid portfolio under-diversification. At the end of June of year 2008 to 2018, We sort firms into three portfolios based 30th and 70th percentiles of pioneer product introduction rate in July of year t-1. We repeat the same process for follower and improver and hold these portfolios for one year and calculate their average monthly excess returns based on beginning market value of equity. For each group of tercile portfolios, we form a long-short portfolio based on the differences of top 70 and bottom 30 portfolios. Next, we run time-series regressions of each

portfolio's excess returns on (1) Fama-French 3 Factors Plus Momentum; (2) Fama-French 3 Factors Plus Momentum, Profitability (RMW) and Investment (CMA). In addition, since the new product measures are related to firm innovation efforts, we control for Fama-French 3 Factors Plus Momentum and Patent Innovation Efficiency Factor (EMI1). We report all the portfolios' excess returns and alphas.

In Panel A, Table 5, we show the excess returns for three groups of tercile portfolios. The pioneer firms display a decreasing trend of excess returns from high to low portfolios. The long-short portfolio has an excess monthly return of 0.58%, significant at 5% level. Follower and improver firms do not have any significant excess returns.

In the right columns, we report long-short portfolios' alphas against different risk models. Pioneer long-short portfolio consistently generates positive and significant alphas, ranging from 0.58 to 0.61%. Interestingly, improving portfolio has weak alphas from Fama-French 3 factor models plus momentum (0.48%) or investment and profitability (0.52%). However, when controlling for innovation efficiency factor EMI1, its significant alpha disappears. This could be because some improver products of high-tech firms cannot be fully explained by conventional asset pricing models. However, when adding a factor that is specifically correlated with corporate innovation efficiency, this underpricing disappears because highly innovative efficient firms tend to earn a good return from their improver products.

In sum, we find that firms with more pioneer products tend to be underpriced relative to those introducing fewer pioneer products. This indicates that the stock markets will have difficulty processing the information of these ultra-new products. Follower products do not have any significant alphas, meaning that financial analysts can correctly value these

products due to there being a precedent. Improver products are still associated with mispricing possibly due to high-tech firms in our sample as these mispricing disappears when adding the innovation efficiency factor that specifically controls for technological innovation efficiency.

4.2 Return Predictability

The portfolio analyses show that pioneer products are undervalued from all risk models, improver products show weak mispricing while follower products tend to be correctly priced. Next, we investigate if product innovations can predict the cross section of stock returns.

To this end, we aggregate product information at monthly level to predict future monthly returns. However, since pioneer product introduction is a rare event, monthly pioneer product introduction variable is predominately populated by zeros, thus this variable's explanatory power is significantly limited. To address this, we calculate a firm i's sum of past 12 months' total pioneer products, follower products and improver products [-11,0] to create three product innovation variables to predict next month return in a rolling fashion:

$$PastPioneer/Follower/Improver\ Introdution_{i,t-11\rightarrow t}$$
$$= \sum_{t=-11}^{t} Numher\ of\ Pioneer/Follower/Improver\ Products_{i,t}$$

Following the innovation literature, we include an extensive set of variables that are found to predict returns. We winsorize all variables at 1% and 99% and standardize all independent variables to have zero mean and one standard deviation to avoid the impact of

outliers and make interpretation easy. We also include the industry dummies according to Fama and French (1997) 48 industries and use Newey-West t statistics. We report the time-series average slopes in percentage. The Fama-MacBeth regression model is as follows:

$$MonthlyReturns_{i,t+n} = \alpha + \beta_1 Past\ Pioneer\ Introduction_i + \beta_2 Past\ Follower\ Introduction_i + \beta_3 Past\ Improver\ Introduction_i + \lambda' \boldsymbol{X_{i,t}} + \sum_{f=1}^{48} \varphi_f * Industry_f + \varepsilon_{i,t}$$

Panel B, Table 5, reports the return prediction results. Only past pioneer product introduction can significantly predict next month returns after controlling for other known predictors. Specifically, in model (1), one-standard-deviation increase in past pioneer introduction can increase next month return by 0.288%, significant at 1% level. Furthermore, models (2)-(4) show that the return predictive power tends to dissipate in three months.

4.3 Why Are Firms Focusing on Pioneer Products Underpriced?

4.3.1 Behavioral Explanation: Limited Investor Attention

The results so far suggest that firms introducing pioneer products are undervalued with positive alphas and exhibit strong return predictability. In this section, we examine if the underpricing is driven by limited investor attention theory (Hirshleifer and Teoh 2003, Hirshleifer, Lim and Teoh 2009). Researchers have found several firm characteristics and intangible assets that are hard to process by investors, including advertising expense, patents, R&D, analyst coverage and earnings surprise[21]. In our setting, if a firm introduces

[21] See Grullon, Kanatas and Weston 2004; Lou 2014, Aboody and Lev 2000, Chan, Lakonishok and Sougiannis 2001, Lev and Sougiannis 1996, Eberhart, Maxwell and Siddique 2004, Bereskin *et al.*2020, Fitzgerald, Balsmeier, Fleming and Manso 2019, Hirshleifer *et al.*2018

a pioneer product, analysts or investors have to value them. Since there are no historical examples of pricing or sales that helps understand this product, such products entail great valuation complexity and uncertainty. We choose advertising expenditure and patent applications[22] proxy for the reduction in complexity of pioneer new products. The rationale for these two proxies is that (1) firms investing more to broadcast their new products are more likely to attract investors' attention and make them easier to value because analysts can gather more information; (2) patent approval is usually a well-known event and markets can form a basic understanding about the focal firm's innovation focus, helping them value future products associated with these patents.

To test the investor inattention and valuation uncertainty using these two proxies, we perform double sorting and run return predictability in splitting samples. First, at the end of June of year 2008 to 2018, we sort sample firms into two groups based on (1) above and below the median of last year's advertising expense and (2) if the sample firms have at least one patent and those having zero patent last year. Next, we sort each group's firms into three portfolios based 30th and 70th percentiles. In addition to the six portfolios, we calculate a high-minus-low portfolio for each product introduction rate group.

In panel A, Table 6, we report results for advertising double sorting portfolio excess returns and alphas. In low advertising group, there is a decreasing trend in portfolio excess returns, although medium and bottom excess returns are not significant. The hedging portfolios have positive excess returns, and they exhibit positive alphas against all risk models, all significant at 1% level. This indicates that firms investing little in advertising their pioneer products will lead to investor inattention and underpricing. For pioneer

[22] We find qualitatively same results using analyst coverage and earnings surprise. The results are in appendix 5

products in high advertising spending group, there are no significant excess returns and alphas, nor is there any trend in the excess returns.

In Table 6, Panel B, we report patent double sorting portfolio results. In non-patenting firms' group, the hedging portfolio has positive and significant excess return and alphas, indicating that financial markets are surprised by the firms introducing pioneer products without previous patent applications. On the contrary, in patenting firms' group, there are no significant excess return and alphas, indicating that with previous patents application and approval, the market has fully incorporated their potential at the time of pioneer product introduction.

Further, we perform Fama-MacBeth regression in the split subsamples. We regress next month returns on current product introduction measure that incorporate past 12-month total new products. In panel C, Table 6, we report advertising and patent subsample results. The pioneer introduction in firms with low advertising expense is driving the return predictability. One-standard-deviation increase in such rate can lead to a 0.553% increase in next month's return. For firms without patents, pioneer introduction rate can significantly predict next month returns 0.377% per one-standard-deviation increase in such rate.

Taken together, this section finds that firms introducing pioneer product tend to be undervalued with positive alphas and exhibit return predictability, indicating that stock markets have difficulty valuing these products' potential. To understand why pioneer products are undervalued, we split sample firms by advertising expense and patents. We find that valuation uncertainty is driving the mispricing. When firms have more

information and transparency of their pioneer products from advertisement campaign or previous patent approval, stock markets tend to value these products correctly.

4.3.2 Is Pioneer Product Innovation Priced? A Risk-based Test

Although the evidence has favored the limited attention theory, we investigate a risk-based explanation in this section. It could be possible that the return predication of pioneer innovations is associated with some unknown investment-related technological change risk that is not captured by the common risk factors such as Fama French three factors, or investment and profitability factors as well as innovation factor. To this end, we perform two pass procedure in a Fama-MacBeth cross-sectional regression framework.

We first construct a pioneer factor, which is the long-short hedging portfolio formed by longing top 30th and shorting bottom 70th [23] of firms conducting pioneer product innovation. Follower and improver factors are constructed in a similar vein. We also add follower and improver factors, in addition to commonly known risk factors including market risk premium, size (SMB), value (HML), profitability (RMW) and investment (CMA) introduced in Fama and French (2015).

For testing assets, we use 25 Fama-French (1993) size and book-to-market portfolios. To increase the dimensionality of the cross-section and address the concerns of Lewellen, Nagel and Shanken (2010), we add 10 industry portfolios. The selection of testing assets thus shows an economically important cross-section. In addition, in response to Jegadeesh *et al.*(2019) that portfolios might mask the risk-return characteristics based on individual stocks, we use the universe of CRSP individual stocks as testing assets. Following Boguth

[23] Following Hirshleifer *et al.*(2017), we sort firms into 30th and 70th percentile. We also tried decile portfolios and the results remain qualitatively the same.

and Kuehn (2013), we add market value of equity and book to market ratio in individual stock cross-sectional regressions.

Table 7, panel A, reports two-pass FMB cross-sectional regression results. The coefficient of pioneer factor beta is the price of risk or known as lambda. There are no significant lambdas of pioneer factor in model (1), (3) and (5), indicating that the pioneer innovation rate is not priced in the cross-section with or without controlling for other known risk factors. In models (2), (4) and (6), we estimate the first and second pass without intercepts and the results remain insignificant. The individual stock results in panel B show qualitatively similar insignificant lambdas.

Overall, this section finds that the risk-based explanation is unlikely to be the underlying mechanisms behind the return predication. Although all the evidence has pointed to a behavioral based story, we can't completely rule out risk explanations.

5. Conclusion

In this paper, we study how and why firms' explorative and/or exploitative innovation strategies differentially affect corporate operating and stock performance. We find that when firms focus on exploration over exploitation to introduce pioneer products, they can earn higher and persistent profitability. Concurrently, pursuing pure exploitation pays dividends too as improver products also lead to better performance. However, the innovation strategy emphasizing exploitation over exploration does not seem to pay off as follower products are unable to create value. We then provide an economic channel of why pioneer and improver outperform based on price elasticity of demand. For stock performance, investors are able to correctly price followers and most improver products,

yet pioneer products are still undervalued. A further set of analyses confirms that the underpricing and return predictability is driven by limited attention.

Our paper has highlighted the benefits of original and pioneering product introduction. If firms are lacking such ideas, they should focus on improving their existing business lines, which can bring in steady profitability.

References

Aboody, D., & Lev, B. (2000). Information asymmetry, R&D, and insider gains. *The journal of Finance*, *55*(6), 2747-2766.

Argente, D., Lee, M., & Moreira, S. (2018). Innovation and product reallocation in the great recession. *Journal of Monetary Economics*, *93*, 1-20.

Aghion, P., & Howitt, P. (1990). *A model of growth through creative destruction* (No. w3223). National Bureau of Economic Research.

Argente, D., Baslandze, S., Moreira, S., & Hanley, D. (2019). *Patents to Products: Innovation, Product Creation, and Firm Growth*. Working paper.

Ball, R., Gerakos, J., Linnainmaa, J. T., & Nikolaev, V. (2016). Accruals, cash flows, and operating profitability in the cross section of stock returns. *Journal of Financial Economics*, *121*(1), 28-45.

Bereskin, F. L., Hsu, P. H., Latham, W. R., & Wang, H. (2020). So Sue Me! Stock Market Reactions to Alleged Patent Infringers. Stock Market Reactions to Alleged Patent Infringers (June 25, 2020).

Boguth, O., & Kuehn, L. A. (2013). Consumption volatility risk. *The Journal of Finance*, *68*(6), 2589-2615.

Broda, C., & Weinstein, D. E. (2010). Product creation and destruction: Evidence and price implications. *American Economic Review*, *100*(3), 691-723.

Chan, L. K., Lakonishok, J., & Sougiannis, T. (2001). The stock market valuation of research and development expenditures. *The Journal of Finance*, *56*(6), 2431-2456.

Eberhart, A. C., Maxwell, W. F., & Siddique, A. R. (2004). An examination of long-term abnormal stock returns and operating performance following R&D increases. *The Journal of Finance*, *59*(2), 623-650.

Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of political economy*, *81*(3), 607-636.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of*.

Fama, E. F., & French, K. R. (1997). Industry costs of equity. Journal of financial economics, 43(2), 153-193.

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. Journal of financial economics, 116(1), 1-22.

Fitzgerald, T., Balsmeier, B., Fleming, L., & Manso, G. (2019). Innovation search strategy and predictable returns. *Management Science, forthcoming*.

Gao, H., Hsu, P. H., & Li, K. (2018). Innovation strategy of private firms. *Journal of Financial and Quantitative Analysis*, *53*(1), 1-32.

Grullon, G., Kanatas, G., & Weston, J. P. (2004). Advertising, breadth of ownership, and liquidity. *The Review of Financial Studies*, *17*(2), 439-461.

Hall, B. H. (1993). The stock market's valuation of R&D investment during the 1980's. *The American Economic Review*, *83*(2), 259-264.

Hall, B. H., Jaffe, A. B., & Trajtenberg, M. (2001). *The NBER patent citation data file: Lessons, insights and methodological tools* (No. w8498). National Bureau of Economic Research.

Hall, B. H., Jaffe, A., & Trajtenberg, M. (2005). Market value and patent citations. *RAND Journal of economics*, 16-38.

He, J., & Tian, X. (2018). Finance and corporate innovation: A survey. *Asia-Pacific Journal of Financial Studies*, *47*(2), 165-212.

Heider, F., & Ljungqvist, A. (2015). As certain as debt and taxes: Estimating the tax sensitivity of leverage from state tax changes. *Journal of financial economics*, *118*(3), 684-712.

Hirshleifer, D., & Teoh, S. H. (2003). Limited attention, information disclosure, and financial reporting. *Journal of accounting and economics*, *36*(1-3), 337-386.

Hirshleifer, D., Hsu, P. H., & Li, D. (2013). Innovative efficiency and stock returns. *Journal of Financial Economics*, *107*(3), 632-654.

Hirshleifer, D., Hsu, P. H., & Li, D. (2018). Innovative originality, profitability, and stock returns. *The Review of Financial Studies*, *31*(7), 2553-2605.

Hirshleifer, D., Lim, S. S., & Teoh, S. H. (2009). Driven to distraction: Extraneous events and underreaction to earnings news. *The Journal of Finance*, *64*(5), 2289-2325.

Hoberg, G., & Phillips, G. (2010). Product market synergies and competition in mergers and acquisitions: A text-based analysis. *The Review of Financial Studies*, *23*(10), 3773-3811.

Hoberg, G., & Phillips, G. (2016). Text-based network industries and endogenous product differentiation. *Journal of Political Economy*, *124*(5), 1423-1465.

Horsky, D., & Simon, L. S. (1983). Advertising and the diffusion of new products. *Marketing Science*, *2*(1), 1-17.

Hsu, P. H. (2009). Technological innovations and aggregate risk premiums. *Journal of Financial Economics*, *94*(2), 264-279.

Hsu, P. H., Li, D., Li, Q., Teoh, S. H., & Tseng, K. (2020). Valuation of New Trademarks. *Available at SSRN 3224187*.

Hsu, P. H., Tian, X., & Xu, Y. (2014). Financial development and innovation: Cross-country evidence. *Journal of Financial Economics*, *112*(1), 116-135.

Jegadeesh, N., Noh, J., Pukthuanthong, K., Roll, R., & Wang, J. (2019). Empirical tests of asset pricing models with individual assets: Resolving the errors-in-variables bias in risk premium estimation. *Journal of Financial Economics*, *133*(2), 273-298.

Kerr, W. R., & Nanda, R. (2015). Financing innovation. *Annual Review of Financial Economics*, *7*, 445-462.

Kogan, L., Papanikolaou, D., Seru, A., & Stoffman, N. (2017). Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics*, *132*(2), 665-712.

Lev, B. (2000). Intangibles: Management, measurement, and reporting. Brookings institution press.

Lev, B., & Sougiannis, T. (1996). The capitalization, amortization, and value-relevance of R&D. *Journal of accounting and economics*, *21*(1), 107-138.

Lewellen, J., Nagel, S., & Shanken, J. (2010). A skeptical appraisal of asset pricing tests. *Journal of Financial economics*, *96*(2), 175-194.

Lou, D. (2014). Attracting investor attention through advertising. *The Review of Financial Studies*, *27*(6), 1797-1829.

Manso, G. (2011). Motivating innovation. *The Journal of Finance*, *66*(5), 1823-1860.

March, J. G. (1991). Exploration and exploitation in organizational learning. *Organization science*, *2*(1), 71-87.

Millot, V. (2009). Trademarks as an indicator of product and marketing innovations.

Mukherjee, A., Singh, M., & Žaldokas, A. (2017). Do corporate taxes hinder innovation?. *Journal of Financial Economics*, *124*(1), 195-221.

Newey, W. K., & West, K. D. (1986). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix.

Nicholson, W. (1992), *Microeconomic Theory: Basic Principles and Extensions*, Fifth Edition, Fort Worth: Dryden Press.

Porter, M. E. (2008). The five competitive forces that shape strategy. Harvard business review, 86(1), 25-40. Porter, M. E. (1996). What is strategy?. *Harvard business review*, *74*(6), 61-78.

Reeb, D. M., & Zhao, W. (2019). Patents Do Not Measure Innovation Success.

Solow, R. M. (1957). Technical change and the aggregate production function. *The review of Economics and Statistics*, 312-320.

Trajtenberg, M. (1990). A penny for your quotes: patent citations and the value of innovations. *The Rand Journal of Economics*, 172-187.

Figure 1: Coverage of Patent and/or Trademarks by the Sample Firms

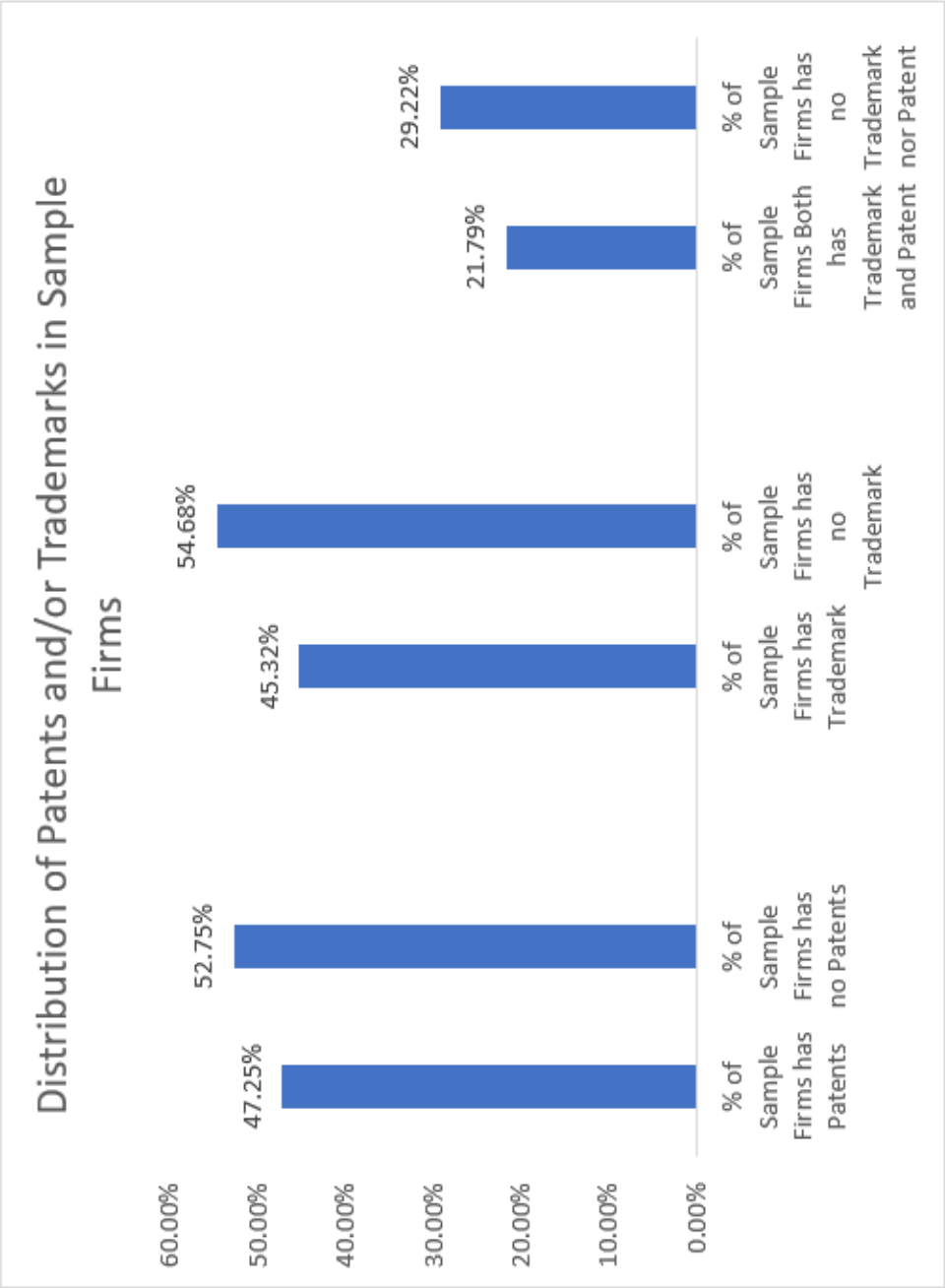
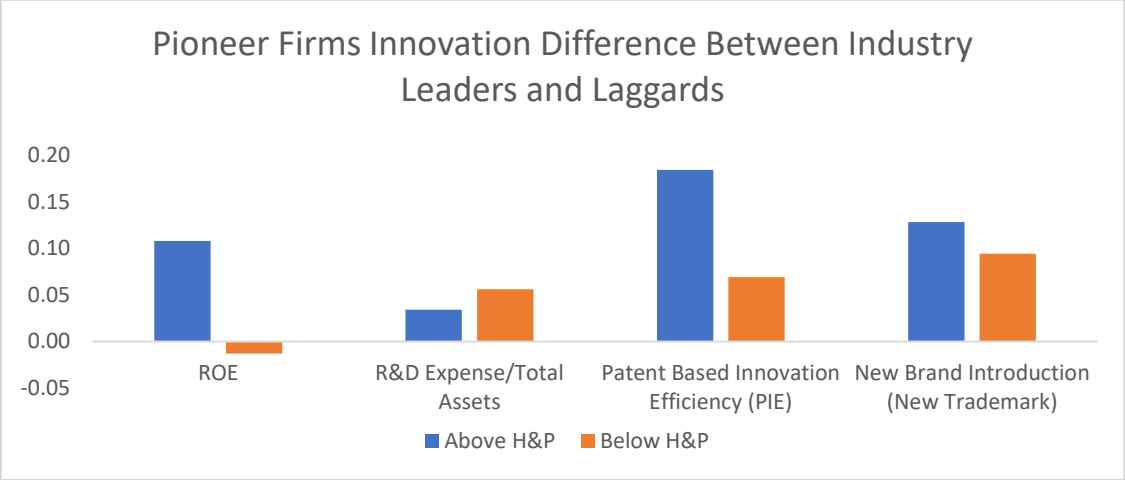
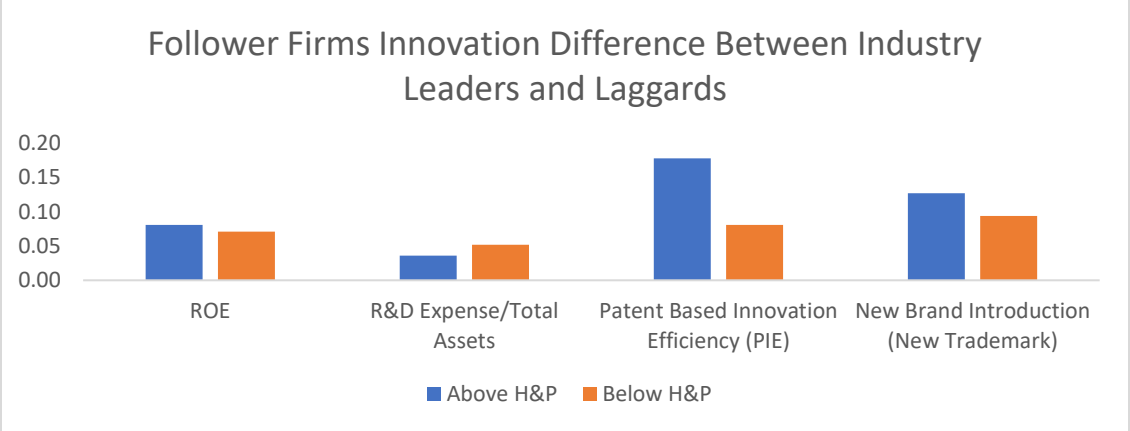


Figure 2: Univariate Comparison of Three Product Innovation Strategies Between Industry Leaders and Laggards





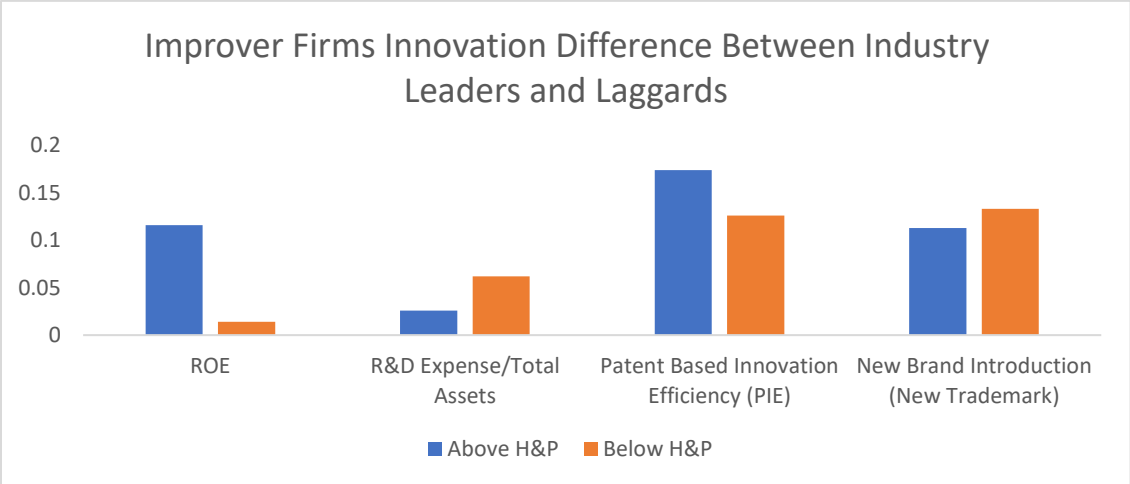


Figure 3: RSD U.S. Market Penetration. Source: https://slideplayer.com/slide/5736272/

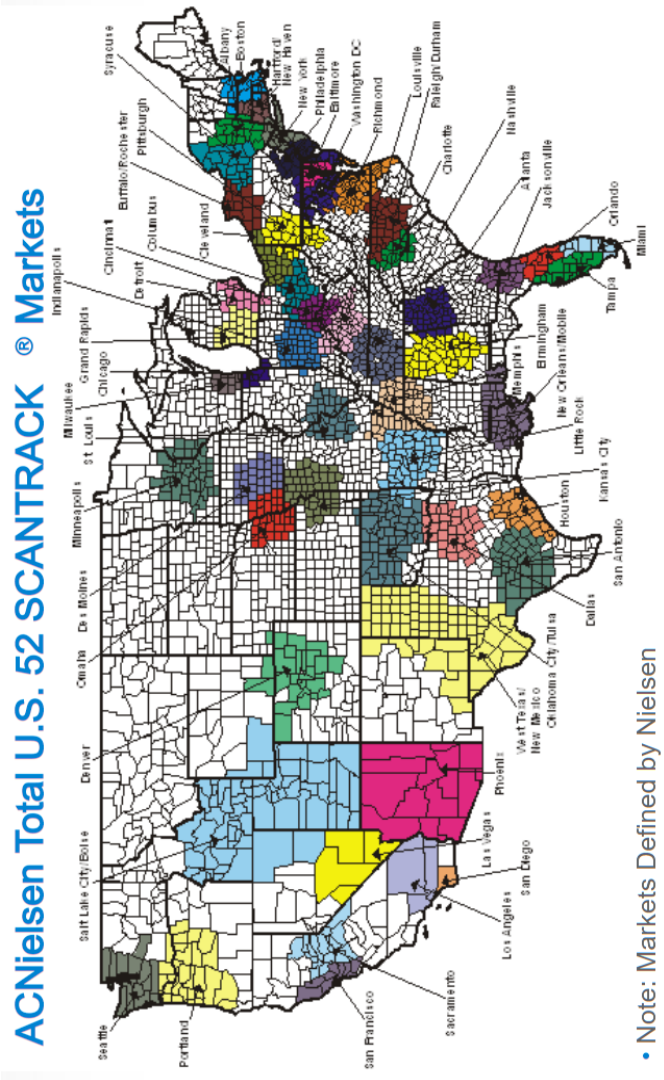


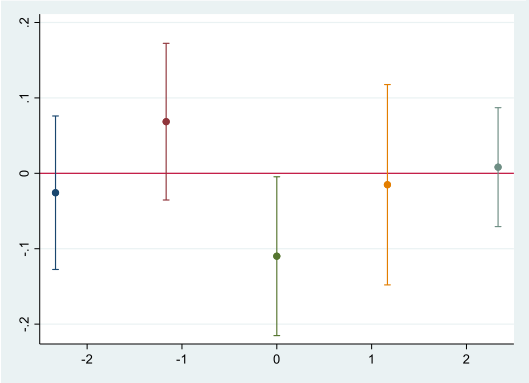
Figure 4: Examples of GS1 Company Prefix and UPC code

This figure shows two common UPC codes' composition. One is applied by the firm with six digit firm prefix and other with nine digit firm prefix. Source: https://www.gs1-us.info/gs1-company-prefix/

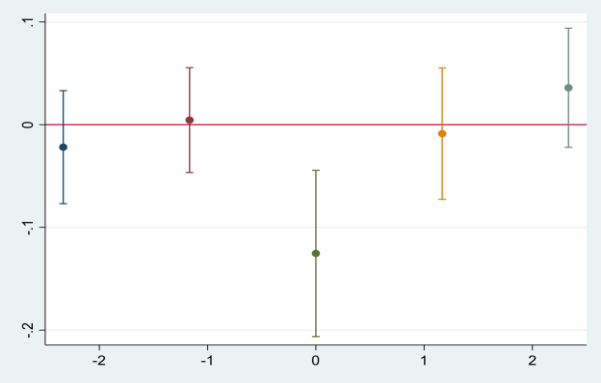
Figure 5: Parallel Trends for Difference in Difference Tests

These graphs are generated by running a first difference regressions of outcome variables on a dummy indicating control or treatment, along with original controls. Treatment firms are headquartered in the states that have risen corporate tax while control firms are headquartered in the states that do not have a corporate tax increase. The coefficient is the dummy of treatment and control, indicating the difference of these two groups with regards to the outcome variable. We report the coefficients for five years around the state tax change event year [-2, 2], along with their 95 percent confidence intervals. X axis is event year and year 0 is when the states raised the corporate tax. Y axis is the outcome variable, including COP (t+1), ROA (t+1) and ROE (t+1).

Panel A: COP (T+1)



Panel B: ROA (T+1)



Panel C: ROE(t+1)

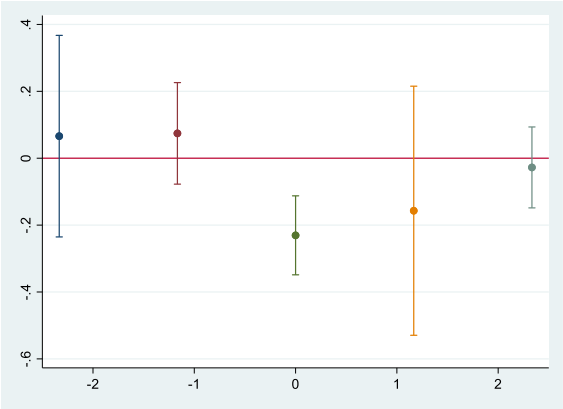


Table 1: Summary Statistics

This table shows two sets of summary statistics. **Panel A** shows the general product by firm-year characteristics. **Panel B** shows the firm-year means in general sample, and samples split by pioneer, follower and improvers. Within each new product group, we divide the sample into industry leaders (above H&P) and laggards (below H&P) and calculate the differences. We bold the difference if they are significant at or above 5% level. For brevity, we only report the main firm-year sample that convers

Panel A: Product Characteristics

	Mean	Std Dev	p25	Median	P75
Number of Pioneer Products	0.36	1.63	0	0	0
Number of Follower Products	0.23	0.99	0	0	0
Number of Improver Products	39.47	137.61	0	2	19
Total New Products	40.06	137.95	0	2	20
Pioneer Product Introduction Rate	0.035	0.18	0	0	0
Follower Product Introduction Rate	0.044	0.16	0	0	0
Improver Product Introduction Rate	0.58	0.48	0	0.96	1
Past 12 Month Pioneer Product Introduction Rate	0.019	0.065	0.000	0.000	0.023
Past 12 Month Pioneer Product Introduction Rate	0.013	0.042	0.000	0.000	0.000
Past 12 Month Pioneer Product Introduction Rate	0.562	0.280	0.000	0.760	1.000
Total Products	290.56	895.95	3	21	138
Firm Average Weekly Product Price (in dollars)	14.76	35.35	3.6	6.96	14.31
Firm Average Weekly Product Quantities Sold	11.36	128.58	1.42	2.23	4.98
Firm Average Weekly Product Sales (In dollars)	5652.34	11248.5	97.22	897.87	5525.89

Panel B: Firm Characteristics Based on 2,096 Firm-Year Observations or 338 Unique Firms	Sample Mean	Sample Median	Pioneer Means			Follower Means			Improver Means		
			Above H&P	Below H&P	Difference	Above H&P	Below H&P	Difference	Above H&P	Below H&P	Difference
ROA	0.03	0.05	0.03	0.01	**0.02**	0.03	0.02	0.01	0.04	0.01	**0.03**
ROE	0.079	0.12	0.11	-0.01	**0.12**	0.08	0.07	0.01	0.12	0.01	**0.10**
Cash Based Operating Profitability (COP)	0.048	0.00	0.05	0.04	0.01	0.05	0.05	-0.01	0.05	0.05	0.00
Market Value of Equity (ME)	19340.3	1823.53	17455.24	25379.36	**-7924.12**	17755.19	24853.27	**-7098.08**	19497.39	19065.74	431.65
Firm Age	45.74	46.90	45.67	45.98	-0.32	45.90	45.20	0.70	47.34	42.95	**4.39**
Advertising Expense/Total Assets	0.03	0.01	0.03	0.03	0.00	0.03	0.04	**-0.01**	0.03	0.04	0.00
R&D Expense/Total Assets	0.039	0.01	0.03	0.06	**-0.02**	0.04	0.05	**-0.02**	0.03	0.06	**-0.04**
Capital Expenditure / Total Assets	0.04	0.03	0.04	0.04	0.00	0.04	0.04	**0.00**	0.04	0.04	0.00
Market to Book Ratio	4.04	2.59	3.97	4.26	-0.30	4.11	3.76	0.35	4.11	3.90	0.21
Number of Patents	63.38	0.00	68.53	46.94	**21.58**	64.68	58.87	5.81	66.62	57.74	8.87
Patent Based Innovation Efficiency (PIE)	0.15	0.00	0.18	0.07	**0.12**	0.18	0.08	**0.10**	0.17	0.13	**0.05**
New Brand Introduction (New Trademark)	0.12	0.00	0.13	0.09	**0.03**	0.13	0.09	**0.03**	0.11	0.13	**-0.02**
Size (In Million)	17399.4	1890.61	16992.20	18699.09	-1706.89	16216.64	21495.81	**-5279.17**	17923.32	16487.24	1436.08
Sales	14489.35	2186.73	12087.22	22146.89	**-10059.6**	12199.74	22410.61	**-10210.8**	13838.24	15623.70	-1785.4

Table 2: Profitability Tests

This table shows profitability tests for product innovation measures. We use Fama-MacBeth (1973) predictive regression of future Cash-Based Operating Profitability (COP), ROA and ROE on three product introduction rates in models (1), (3) and (5). We then regress these profitability measures on a dummy which equals 1 if the firm's product innovation rate is above H&P industry mean in models (2), (4) and (6). In all models, we report average slopes and Newey-West (1987) autocorrelation-adjusted heteroscedastic robust standard errors in parentheses from annual Fama and MacBeth (1973) cross-sectional regressions. We include industry fixed effect in models (1), (3) and (5). *, ** and *** indicate the significance levels of 10%, 5% and 1%, respectively.

Future Operating Performance						
Dependent Variable	COP (T+1)		ROA (T+1)		ROE (T+1)	
	(1)	(2)	(3)	(4)	(5)	(6)
Pioneer Product Introduction Rate (t)	0.002*		0.005**		0.011***	
	(0.011)		(0.002)		(0.002)	
Follower Product Introduction Rate (t)	0.014		0.003		-0.037	
	(0.009)		(0.006)		(0.039)	
Improver Product Introduction Rate (t)	0.004		0.000		0.012**	
	(0.004)		(0.001)		(0.014)	
Pioneer Product Introduction Rate above H&P Average (t)		0.006***		0.013**		0.125**
		(0.002)		(0.006)		(0.055)
Follower Product Introduction Rate above H&P Average (t)		0.001		-0.010*		-0.017
		(0.002)		(0.004)		(0.035)
Improver Product Introduction Rate above H&P Average (t)		-0.005		0.005*		0.040
		(0.004)		(0.002)		(0.030)
COP (t)	0.764***	0.786***				
	(0.023)	(0.039)				
ROA(t)			0.862***	1.281***		
			(0.071)	(0.067)		
ROE (t)					0.253**	0.318***
					(0.101)	(0.061)
Ln (ME) (t-1)	0.002**	0.001**	0.004***	0.002***	0.027***	0.057***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.006)	(0.015)
Ln (Firm Age) (t)	-0.001	-0.004	0.005*	0.007*	-0.030	0.067
	(0.004)	(0.003)	(0.003)	(0.004)	(0.021)	(0.042)
Advertising Expenditure (t)	-0.012	0.010	0.103**	0.131***	-0.438*	-0.045
	(0.021)	(0.021)	(0.038)	(0.021)	(0.218)	(0.947)
R&D Expenditure (t)	0.011	0.054	-0.039	-0.422***	-2.117***	-1.050
	(0.077)	(0.064)	(0.125)	(0.132)	(0.647)	(1.148)
Capital Expenditure (t)	-0.051	-0.064***	0.150*	0.026	0.314	1.672*
	(0.047)	(0.019)	(0.079)	(0.043)	(0.484)	(0.866)
Market to Book (t)	0.002**	0.001	-0.000	-0.002	0.022***	-0.049
	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.058)
Patent Based Innovation Efficiency	0.009	0.005*	-0.008***	0.151	-0.007	-0.018
	(0.006)	(0.003)	(0.002)	(0.135)	(0.016)	(0.014)
New Trademark Introduction	0.004	-0.002	-0.031***	-0.025*	0.058	0.004
	(0.004)	(0.004)	(0.007)	(0.011)	(0.050)	(0.041)
Constant	0.020	0.010	-0.047**	-0.064***	-0.146	-0.661**
	(0.016)	(0.006)	(0.016)	(0.017)	(0.204)	(0.209)
Observations	2,096	2,096	2,096	2,096	2,096	2,096
R-squared	0.699	0.733	0.840	0.747	0.655	0.572
F statistics	29.597	35.119	12.972	79.108	2.593	7.970
NW Robust Standard Errors	Y	Y	Y	Y	Y	Y
Industry Dummies	Y	N	Y	N	Y	N

Table 3: Identification Tests

This table shows two methods to address endogeneity concerns. **Panel A** is a quasi-natural experiment in Difference in Difference setting. We regress future COP, ROA and ROE on pioneer rate interacting with treatment and after, as well as all the terms supporting the interaction terms and control variables. In all models, we report average slopes and Newey-West (1987) autocorrelation-adjusted heteroscedastic robust standard errors in parentheses from annual Fama and MacBeth (1973) cross-sectional regressions. We include industry dummies in each regression. **Panel B** shows two stage least square analysis. Model (1) is the first stage in which we regress endogenous variable, pioneer product introduction rate, on instrumental variable, local average advertising spending. Models (2), (3) and (4) are future COP, ROA and ROE models using instrumented pioneer product introduction rate. We use firm and year fixed effects and report Stock-Yogo statistics F value. Controls are similar to those in Table 3). *, ** and *** indicate the significance levels of 10%, 5% and 1%, respectively.

Panel A: Difference in Difference			
Dependent Variables	COP(t+1)	ROA (T+1)	ROE (T+1)
	(1)	(2)	(3)
Pioneer Rate* Treatment * After	-0.043**	-0.002*	-0.077**
	(0.019)	(0.001)	(0.030)
Pioneer Rate* Treatment	0.051	-0.325**	-2.480***
	(0.037)	(0.120)	(0.729)
Pioneer Rate* After	-0.012	0.161	9.020
	(0.010)	(0.100)	(8.366)
Treatment * After	0.006	-0.007	-0.201*
	(0.006)	(0.008)	(0.095)
Treatment	-0.006	-0.003	0.126
	(0.003)	(0.002)	(0.092)
After	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Pioneer Product Introduction Rate (t)	-0.001	0.012	-0.037
	(0.004)	(0.015)	(0.106)
Follower Product Introduction Rate (t)	0.001	-0.007	0.143
	(0.009)	(0.024)	(0.147)
Improver Product Introduction Rate (t)	0.003	0.001	0.108
	(0.004)	(0.003)	(0.073)
COP(t)	0.640***		
	(0.047)		
ROA (t)		0.756***	
		(0.037)	
ROE(t)			0.173**
			(0.071)
Ln(ME) (t-1)	0.002***	0.007**	0.050*
	(0.000)	(0.002)	(0.028)
Ln(Firm Age) (t)	-0.008***	-0.000	-0.169
	(0.002)	(0.003)	(0.117)
Advertising Expenditure (t)	0.014	0.004	-0.675
	(0.031)	(0.036)	(0.546)
R&D Expenditure (t)	0.063	-1.003***	-4.154**
	(0.076)	(0.102)	(1.375)
Capital Expenditure (t)	-0.039	0.317**	0.332
	(0.032)	(0.127)	(0.788)
Market to Book (t)	0.001	-0.000	0.010
	(0.001)	(0.002)	(0.061)
Patent Based Innovation Efficiency	0.143	0.285	3.548**
	(0.084)	(0.205)	(1.185)
New Brand Introduction (Trademark)	-0.000	-0.027*	-0.310
	(0.004)	(0.014)	(0.231)
Constant	0.043	-0.017	0.347
	(0.029)	(0.022)	(0.605)
Observations	2,054	2,054	2,054
R-squared	0.702	0.638	0.511
F statistics	5.134	10.131	1.719
NW Robust Standard Errors	Y	Y	Y

Panel B: 2SLS	First Stage	Second Stage		
Dependent Variables	Pioneer Product Introduction Rate (t)	COP (T+1)	ROA (T+1)	ROE (T+1)
	(1)	(2)	(3)	(4)
Pioneer Product Introduction Rate (t)		0.018**	0.001**	0.024***
		(0.007)	(0.000)	(0.007)
Local Average Advertising Spending	0.012**			
	(0.006)			
COP(t)	-0.124***	0.066***		
	(0.047)	(0.002)		
ROA (t)			0.822***	
			(0.021)	
ROE(t)				0.010***
				(0.003)
Ln(ME) (t-1)	-0.000	0.000***	-0.005	0.005***
	(0.003)	(0.000)	(0.005)	(0.001)
Ln(Firm Age) (t)	-0.017	-0.000	0.000	-0.005
	(0.012)	(0.000)	(0.000)	(0.003)
Advertising Expenditure (t)	0.188	-0.003	0.272***	0.008
	(0.116)	(0.004)	(0.056)	(0.032)
R&D Expenditure (t)	-0.342***	0.002	-0.515***	-0.259***
	(0.122)	(0.002)	(0.059)	(0.021)
Capital Expenditure (t)	-0.054	-0.009	0.139	0.079
	(0.195)	(0.006)	(0.094)	(0.055)
Market to Book (t)	0.000	0.000	0.000	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Patent Based Innovation Efficiency	-0.000	-0.005	0.001	0.001
	(0.011)	(0.011)	(0.005)	(0.003)
New Brand Introduction (Trademark)	0.349***	-0.003*	-0.042***	0.005
	(0.020)	(0.001)	(0.013)	(0.013)
Constant	0.050	-0.001	0.003	-0.020
	(0.067)	(0.002)	(0.027)	(0.019)
Observations	1,206	1,206	1,206	1,206
R-squared	0.331	0.554	0.775	0.421
F statistics	9.625	32.591	14.661	14.108
Industry and Year Fixed Effects	Y	Y	Y	Y
Stock-Yogo F Statistics	N/A	14.576	8.429	7.055

Table 4: Elasticity of Demand Tests

In this table, we present elasticity of demand tests. **Panel Aa** presents the pooled OLS regression that calculates the elasticity of demand in this specification: Ln (Demand) = β*Ln (Price) + α where the β is the original price elasticity of demand. In **Panel Ab**, we control for more variables at both product level and firm level. We also use firm and year fixed effects. In **Panel B**, we first run Ln (Demand) = β*Ln (Price) + α for each product and collect β. Next, we value weight the βs of all products by sales at firm level to generate a firm-level aggregated elasticity of demand measure. For interpretation convenience, we present the absolute values. In Panel C, we regress all the βs of all products on pioneer, follower and improver dummies to allow for more controls and fixed effects, including firm and(by) year as well as industry and(by) year.

Panel Aa: Pooled OLS Regression, Product-Weekend Level			
Dependent Variable	Ln (Quantity Demanded Each Weekend)		
	Pioneer Products	Follower Products	Improver Products
Ln (Price)	-0.213***	-0.268***	-0.238***
	(0.003)	(0.001)	(0.000)
Constant	1.015***	1.058***	1.081***
	(0.005)	(0.002)	(0.000)
Observations	50,111	242,699	10,442,465
R-squared	0.106	0.148	0.117

Panel Ab: Regression with Controls and Fixed Effects, Product-Weekend Level			
Dependent Variable	Ln (Quantity Demanded Each Weekend)		
	Pioneer Products	Follower Products	Improver Products
Ln (Price)	-0.165***	-0.234***	-0.185***
	(0.003)	(0.001)	(0.000)
Price Std	-0.000	-0.012***	-0.004***
	(0.001)	(0.001)	(0.000)
Ln (Product Annual Sales)	0.163***	0.176***	0.204***
	(0.006)	(0.002)	(0.000)
Quantity Demanded Std	0.014***	0.002***	0.023***
	(0.000)	(0.000)	(0.000)
Firm Level Industry Competition	-0.480***	-0.009	0.007***
	(0.021)	(0.009)	(0.001)
Ln (Firm Age)	0.004***	-0.001***	0.002***
	(0.000)	(0.000)	(0.000)
Ln (Total Asset)	-0.076***	-0.020***	-0.007***
	(0.005)	(0.002)	(0.000)
Ln (Firm Total Sale)	0.065***	0.016***	0.030***
	(0.005)	(0.002)	(0.000)
Constant	0.914***	1.119***	0.588***
	(0.016)	(0.006)	(0.001)
Year Fixed Effect	Y	Y	Y
Firm fixed effect	Y	Y	Y
Observations	50,866	244,167	10,209,194
R-squared	0.277	0.191	0.353

Panel B: Regression Analysis, Product-Firm-Year Level				
Dependent Variable	Absolute Value of Price Elasticity of Demand (%) of Each Product			
Pioneer Dummy	-7.334***	-6.945***	-6.692***	-6.941***
	(2.372)	(2.434)	(2.342)	(2.403)
Follower Dummy	-5.495***	-5.585***	-5.221***	-5.592***
	(1.097)	(1.109)	(1.070)	(1.081)
Improver Dummy	-6.351***	-6.730***	-6.041***	-6.417***
	(0.257)	(0.261)	(0.257)	(0.260)
Quantity Demanded Std	-0.636***	-0.695***	-0.703***	-0.760***
	(0.013)	(0.014)	(0.013)	(0.014)
Ln (Product Annual Sales)	-2.893***	-2.863***	-2.984***	-2.945***
	(0.042)	(0.042)	(0.042)	(0.042)
Firm Level Industry Competition	-1.101		1.928	-37.072***
	(2.162)		(2.030)	(9.019)
Ln (Firm Age)	-14.663***		-9.099***	-9.361***
	(1.647)		(0.360)	(0.386)
Ln (Total Asset)	-1.970***		0.718*	1.558***
	(0.756)		(0.418)	(0.536)
Ln (Firm Total Sale)	0.972		-1.676***	-2.469***
	(0.860)		(0.467)	(0.586)
Constant	35.644***	-29.710***	14.295***	24.203***
	(7.014)	(0.482)	(1.364)	(2.509)
Observations	521,225	521,225	521,225	521,225
R-squared	0.115	0.124	0.106	0.112
Fixed Effects	Firm and Year	Firm by Year	Industry and Year	Industry by Year

Panel C: Univariate Analysis, Firm-Year Level	Absolute Value of Price Elasticity of Demand (%) of Each Firm			
	Yes	No	Difference	Satterthwaite T Statistics
Pioneer Firms	26%	59%	-34%	-2.21
Follower Firms	24%	55%	-31%	-1.25
Improver Firms	58%	42%	16%	1.27
Pioneer Above HP Industry Average	46%	68%	-22%	-1.83
Follower Above HP Industry Average	53%	44%	10%	0.72
Improver Above HP Industry Average	54%	46%	9%	0.79

Table 5: Portfolio Analysis and Return Predictability

In **Panel A**, we report portfolio excess returns and alphas. At the end of June of year 2008 to 2018, We sort firms into three portfolios based 30th and 70th percentiles of pioneer product introduction rate in July of year t-1. We repeat the same process for follower and improver and hold these portfolios for one year and calculate their average monthly excess returns based on beginning market value of equity. For each group of tercile portfolios, we form a long-short portfolio based on the differences of top 70 and bottom 30 portfolios. Next, we run time-series regressions of each portfolio's excess returns on (1) Fama-French 3 Factors Plus Momentum; (2) Fama-French 3 Factors Plus Momentum, Profitability (RMW) and Investment (CMA). In addition, since the new product measures are related to firm innovation efforts, we control for Fama-French 3 Factors Plus Momentum and Patent Innovation Efficiency Factor (EMI1). In **Panel B**, we regress next month's return on contemporaneous product introduction that incorporates past 12 months total product introduction activities. We report average slopes (in %) and standard errors from monthly Fama and MacBeth cross-sectional regressions. Industry dummies are included in each model but not reported to save space. ***, **, and * present 1%, 5%, and 10% significance level, respectively.

Panel A: Portfolio Analyses	Portfolio Excess Returns	Alphas from Different Risk Models		
		4F	4F+RMW+CMA	4F+EMI1
Pioneer Firms				
Top 30%	1.021***	0.405*	0.187	0.403*
	(0.330)	(0.209)	(0.200)	(0.212)
Medium 40%	1.124***	0.351***	0.277**	0.403***
	(0.336)	(0.119)	(0.118)	(0.116)
Bottom 30%	0.409	-0.247	-0.431*	-0.227
	(0.349)	(0.234)	(0.233)	(0.236)
High-Low	0.576**	0.614**	0.581**	0.591**
	(0.251)	(0.260)	(0.269)	(0.263)
Follower Firms				
Top 30%	0.983***	0.443*	0.277	0.499**
	(0.332)	(0.228)	(0.224)	(0.228)
Medium 40%	1.026***	0.245**	0.129	0.277**
	(0.335)	(0.118)	(0.112)	(0.118)
Bottom 30%	0.599	0.020	-0.227	0.022
	(0.365)	(0.278)	(0.274)	(0.282)
High-Low	0.347	0.385	0.466	0.437
	(0.324)	(0.333)	(0.341)	(0.336)
Improver Firms				
Top 30%	0.992***	0.404**	0.231	0.424**
	(0.312)	(0.187)	(0.183)	(0.194)
Medium	1.094***	0.308**	0.204*	0.222*
	(0.341)	(0.127)	(0.120)	(0.128)
Bottom 30%	0.558	-0.116	-0.323	0.002
	(0.356)	(0.235)	(0.231)	(0.240)
High-Low	0.397	0.483*	0.516*	0.383
	(0.254)	(0.261)	(0.269)	(0.268)

Panel B: Return Prediction				
Dependent Variable	Next Month Return	M+2	M+3	M+4
	(1)	(2)	(3)	(4)
Past Pioneer Introduction	0.288***	0.185**	0.160*	0.125
	(0.098)	(0.093)	(0.093)	(0.093)
Past Follower Introduction	0.048	0.022	0.015	-0.005
	(0.108)	(0.105)	(0.101)	(0.107)
Past Improver Introduction	-0.022	-0.071	-0.117	-0.042
	(0.166)	(0.150)	(0.145)	(0.127)
Ln (Total Products)	-0.053	-0.020	-0.006	-0.045
	(0.073)	(0.074)	(0.071)	(0.066)
Size	-0.092	-0.117*	-0.111*	-0.119**
	(0.064)	(0.061)	(0.059)	(0.059)
Book to Market	-0.055**	-0.055**	-0.085**	-0.051*
	(0.021)	(0.025)	(0.039)	(0.028)
Momentum	-5.670	-12.696**	-14.687**	-9.908*
	(5.603)	(5.071)	(6.269)	(5.411)
Patents/Assets	-11.341*	-14.073*	-12.367*	-13.894*
	(6.599)	(7.167)	(6.333)	(7.721)
Short-Term Return Reversal	-3.153***	1.068	-1.408	-2.952**
	(1.022)	(1.061)	(1.456)	(1.468)
Asset Growth	2.665***	2.410***	2.243***	1.910***
	(0.583)	(0.547)	(0.543)	(0.469)
Capx/Assets	-4.344	-4.236	-3.873	-4.715
	(3.177)	(3.322)	(3.204)	(3.243)
R&D/Market Equity	0.245*	0.244*	0.200	0.085
	(0.138)	(0.134)	(0.132)	(0.123)
ROA	4.060***	3.793***	3.783***	3.596***
	(0.796)	(0.862)	(1.002)	(0.992)
Multi-Segment Firm	-0.030	-0.022	0.055	0.090
	(0.167)	(0.170)	(0.163)	(0.149)
Patent Based Innovation Efficiency	0.136	0.102	-0.106	0.307
	(0.319)	(0.309)	(0.211)	(0.381)
New Trademark Introduction	-1.133**	-0.725	-1.141**	-0.805
	(0.535)	(0.508)	(0.505)	(0.556)
Constant	1.586*	1.902**	1.958**	1.994**
	(0.827)	(0.846)	(0.882)	(0.828)
Observations	24,038	24,026	24,010	23,987
R-squared	0.280	0.276	0.280	0.275
F statistics	2.872	2.325	2.190	1.971
NW Robust Standard Errors	Y	Y	Y	Y
Industry Dummies	Y	Y	Y	Y

Table 6: Portfolio Analysis and Return Predictability in Split Samples

This table reports double-sorting portfolio and return predictability in split sample analyses. In **Panel A,** at the end of June of year 2008 to 2018, we sort sample firms into high and low Ad spending groups based on the median of last year's advertising expense. Then, for every product introduction rate, we sort each group's firms into three portfolios based 30th and 70th percentiles, resulting in six portfolios for each rate. In addition, we calculate a high-minus-low portfolio. In **Panel B,** we repeat same process by sorting sample firms into two groups based on whether there they have at least one patent approved last year. In **Panel C**, we report average slopes (in %) and standard errors from monthly Fama and MacBeth cross-sectional predictive regressions in two subsamples split by advertising expense and patents. Controls are similar to those in Table 6 Panel B. ***, **, and * present 1%, 5%, and 10% significance level, respectively.

Panel A: Portfolio Analysis: Ad Spending

Low Ad Spending Group	Excess Return	Alphas			**High Ad Spending Group**		Panel B: Alphas		
		4F	4F+RMW+CMA	4F+EMI1			4F	4F+RMW+CMA	4F+EMI1
Pioneer Firms					**Pioneer Firms**				
Top 30%	1.281***	0.688*	0.443	0.689*	Top 30%	0.818**	0.337	0.082	0.365
	(0.432)	(0.356)	(0.358)	(0.360)		(0.331)	(0.248)	(0.239)	(0.250)
Medium 40%	0.475	-0.397**	-0.408**	-0.384**	Medium 40%	0.995**	0.233	0.161	0.221
	(0.396)	(0.182)	(0.188)	(0.183)		(0.406)	(0.276)	(0.286)	(0.279)
Bottom 30%	0.158	-0.612**	-0.782**	-0.614**	Bottom 30%	0.753**	0.190	-0.061	0.245
	(0.430)	(0.306)	(0.311)	(0.310)		(0.338)	(0.257)	(0.250)	(0.257)
High-Low	1.123***	1.300***	1.225***	1.303***	High-Low	0.065	0.147	0.143	0.120
	(0.427)	(0.433)	(0.448)	(0.438)		(0.285)	(0.291)	(0.301)	(0.293)

Panel B: Portfolio Analysis: PATENT

Non-Patenting Firms	Excess Return	Alphas			**Patenting Firms**	Excess Return		Alphas	
		4F	4F+RMW+CMA	4F+EMI1			4F	4F+RMW+CMA	4F+EMI1
Pioneer Firms					**Pioneer Firms**				
Top 30%	1.448**	0.997*	0.782	0.786	Top 30%	0.788**	0.331	0.160	0.366
	(0.601)	(0.579)	(0.596)	(0.570)		(0.370)	(0.301)	(0.304)	(0.303)
Medium 40%	0.290	-0.524	-0.656	-0.679	Medium 40%	1.034***	0.248**	0.136	0.284**
	(0.560)	(0.458)	(0.473)	(0.453)		(0.339)	(0.125)	(0.120)	(0.124)
Bottom 30%	1.308***	0.602*	0.370	0.671*	Bottom 30%	0.799**	0.247	-0.030	0.287
	(0.446)	(0.356)	(0.359)	(0.358)		(0.365)	(0.281)	(0.272)	(0.282)
High-Low	1.158*	1.521**	1.438**	1.465**	High-Low	-0.010	0.084	0.190	0.079
	(0.673)	(0.674)	(0.699)	(0.682)		(0.396)	(0.403)	(0.413)	(0.407)

Panel C: Return Prediction

Dependent Variable	Next Month Return%			
	High Ad Spending	Low Ad Spending	Patenting Firms	Non-Patenting Firms
Past 12-month Total Pioneer Introduction	0.142	0.553***	-0.129	0.377**
	(0.104)	(0.169)	(0.130)	(0.174)
Past 12-month Total Follower Introduction	0.194	-0.278	-0.038	0.080
	(0.186)	(0.184)	(0.237)	(0.178)
Past 12-month Total Improver Introduction	0.102	0.180	0.097	0.227
	(0.212)	(0.329)	(0.159)	(0.440)
Total Number of Products	-0.094	-0.124	-0.014	-0.092
	(0.110)	(0.138)	(0.084)	(0.138)
Size	-0.102	0.004	-0.050	-0.041
	(0.130)	(0.070)	(0.063)	(0.096)
Book to Market	-0.049**	-0.049	-0.043**	-0.104***
	(0.024)	(0.069)	(0.020)	(0.038)
Momentum	-9.197	-3.482	-4.082	-4.788
	(7.851)	(8.612)	(7.377)	(6.175)
Patents/Assets	7.768	-4.266	-3.761	0.000
	(15.637)	(15.667)	(8.681)	(0.000)
Short-Term Return Reversal	-7.913***	-2.397	-6.648***	-1.696
	(1.951)	(2.265)	(1.659)	(1.288)
Asset Growth	2.586**	1.689	1.846***	3.451***
	(1.079)	(1.252)	(0.539)	(0.903)
Capx/Assets	-12.184**	-9.403*	-3.258	-5.466
	(4.888)	(5.496)	(5.473)	(4.009)
R&D/Market Equity	0.010	1.138	-0.018	1.155**
	(0.237)	(0.925)	(0.096)	(0.481)
ROA	10.457***	4.989**	6.469***	5.509***
	(1.881)	(2.073)	(2.031)	(0.876)
Multi-Segment Firm	0.280	-0.334	0.113	-0.061
	(0.326)	(0.437)	(0.175)	(0.237)
Patent Based Innovation Efficiency	-0.057	-0.496	-0.101	0.000
	(1.073)	(0.690)	(0.191)	(0.000)
New Trademark Introduction	-1.222	-0.475	-0.588	-1.013
	(1.164)	(1.060)	(0.844)	(0.844)
Constant	2.001	1.409*	0.991	1.354
	(1.344)	(0.794)	(0.884)	(0.965)
Observations	9,476	9,916	12,480	13,838
R-squared	0.516	0.551	0.443	0.398
F statistics	2.694	1.150	1.561	2.753
NW Robust Standard Errors	Y	Y	Y	Y
Industry Dummies	Y	Y	Y	Y

Table 7: Risk-based tests

This table shows the second pass results of cross-sectional tests in a two-path procedure. We create the pioneer product innovation factor, which is a hedging portfolio that longs top 30 percentile firms in pioneer innovation and shorts the bottom 70 percentile. In the first pass, we run time series regression of each asset's monthly return on pioneer innovation factor return, and other risk factor portfolios in other remaining models, and in the second pass, we regress the expected asset return on the beta of pioneer innovation factor, and betas of other risk factors in the remaining models. The results below show the second pass in which all the independent variables are coefficients obtained from first pass timer series regressions and the dependent variables are expected asset returns. Econometrically, we include intercepts in models (1), (3) and (5) and we impose a no intercept condition in models (2), (4) and (6). In **panel A**, the testing assets are 25 portfolios sorted by size and B/M and 10 industry portfolios. In panel B, the testing assets are all CRSP individual stocks, whose screening process follows Jegadeesh *et al.*(2019). In addition, we follow Boguth and Kuehn (2013) to control for log-transformed market value of equity and B/M ratio. We report Newey-West (1987) adjusted standard errors with 3 lags. ***, **, and * present 1%, 5%, and 10% significance level, respectively.

Panel A:35 Portfolios as Testing Assets

	Intercept	βPioneer Factor	βImprover Factor	βFollower Factor	βMKT	βSMB	βHML	βRMW	βCMA
Model (1)	1.121***	0.009							
	(0.406)	(0.217)							
Model (2)		-0.232							
		(0.142)							
Model (3)	1.128***	0.107	-0.115	-0.440					
	(0.405)	(0.314)	(0.254)	(0.291)					
Model (4)		-0.225	-0.135	-0.319					
		(0.267)	(0.233)	(0.266)					
Model (5)	0.902***	0.201	-0.046	-0.514	0.208	0.078	-0.108	0.127	0.066
	(0.207)	(0.276)	(0.242)	(0.373)	(0.320)	(0.190)	(0.246)	(0.137)	(0.122)
Model (6)		0.134	0.021	-0.143	0.985***	0.024	-0.276**	-0.045	-0.162*
		(0.283)	(0.245)	(0.276)	(0.087)	(0.107)	(0.131)	(0.121)	(0.084)

Panel B: Individual Stock as Testing Assets

	Intercept	βPioneer Factor	βImprover Factor	βFollower Factor	βMKT	βSMB	βHML	βRMW	βCMA	βLn(Market Value of Equity t-1)	βB/M Ratio
Model (1)	1.442***	-0.011								-0.001**	-0.000
	(0.535)	(0.015)								(0.001)	(0.000)
Model (2)		-0.007								-0.005**	-0.000
		(0.011)								(0.001)	(0.000)
Model (3)	1.464***	-0.039	0.007	0.019						-0.001	-0.000
	(0.535)	(0.042)	(0.045)	(0.062)						(0.001)	(0.000)
Model (4)		-0.042	-0.013	-0.004						-0.004**	-0.000
		(0.036)	(0.041)	(0.052)						(0.001)	(0.000)
Model (5)	1.299***	-0.110	-0.031	0.017	0.098	0.107	0.045	-0.039	0.003	-0.001	-0.000
	(0.439)	(0.078)	(0.085)	(0.118)	(0.135)	(0.078)	(0.069)	(0.049)	(0.044)	(0.001)	(0.000)
Model (6)		-0.159	-0.043	0.025	0.422	0.241***	0.179	-0.095	0.047	-0.006**	-0.000
		(0.122)	(0.124)	(0.135)	(0.241)	(0.069)	(0.114)	(0.068)	(0.026)	(0.003)	(0.000)

Appendix 1: Variable Definitions

Firm Year Level Tests	
Number of Pioneer Products	Total number of pioneer products introduced in year T
Number of Follower Products	Total number of follower products introduced in year T
Number of Improver Products	Total number of improver products introduced in year T
Total New Products	Total new products introduced in year T
Pioneer Product Introduction Rate	Sales of pioneer products/total new product sales
Follower Product Introduction Rate	Sales of follower products/total new products
Improver Product Introduction Rate	Sales of improver products/total new products
Size	Total Assets (AT)
Sale	Total Sales (SALE)
Firm age	Firm Age using Founding Date (Field and Ritter)
Innovation Efficiency	Patents scaled by past 5-year cumulative R&D expense assuming 20% depreciation rate
New Trademark Introduction	New brands introduced in year T scaled by total brands owned in year t
ROE	Net Income (NI)/Shareholder's Equity Total (SEQ t-1)
ROA	Earnings Before Interest (EBITDA)/Total Assets (AT t-1)
COP	Revenue (REVT)-Cost of Goods Sold (COGS)-Administrative Expenses (XSGA-XRD)-Δ(Accounts Receivable (RECT))-Δ(Inventory (INVT))-Δ(Prepaid Expenses (XPP))+Δ(Deferred Revenue (DRC+DRLT))+ Δ(Trade Accounts Payable (AP))+Δ(Accrued Expenses (XACC))
Advertising Expense/Total Assets	Advertising Expense (XAD)/Total Assets (AT t-1)
R&D Expense / Total Assets	Research and Development Expense (XRD)/ Total Assets (AT t-1)
Capital Expenditure / Total Assets	Capital Expenditures (CAPX)/ Total Assets (AT t-1)
Market to Book Ratio	(Common Share Outstanding* Price Close (CSHO * PRCC_F) / Common Equity (CEQ)
Market Value of Equity	Common Share Outstanding* Price Close (CSHO * PRCC_F)
Firm-Month Predictability Tests	
Size	Total Assets (AT)
Momentum	Past 11 month returns
Patents/Assets	Number of Patents (t-1) / Total Assets (AT t-1)
Short-Term Return Reversal	Monthly return in the previous month
Asset Growth	Total Assets (AT)/AT (T-1)-1
Capx/Assets	Capital Expenditure (CAPX)/ Total Assets (AT t-1)
R&D/Market Equity	[Research and Development Expense (XRD)/ Common Share Outstanding* Price Close (CSHO * PRCC_F t-1)
Multi-Segment Firm	More than one business segment

Appendix 2: Detailed Examples of How Pioneer, Follower and Improver Products are Assigned based on Modules

Pioneer Example (1):
In year 2013, Nielsen added three modules: "ELECTRONIC CIGARETTES – SMOKING; ELECTRONIC CIGARS – SMOKING; ELECTRONIC REM ACCESSORY – SMOKING". Anecdotally, 2013 and 2014 saw the start of mass commercialization and sales of E-Cigarette, especially favored by teenagers, which caused a big concern to the policy makers. Since the entry of these products was so new that Nielsen had to add three modules, all the products that belong to these three modules are regarded as pioneers.

Picture credit: https://images.app.goo.gl/JwKinovXKoDbqaYs9

Picture credit: https://images.app.goo.gl/JwKinovXKoDbqaYs9

Pioneer Example (2):
In 2014, Nielsen added a new module “RBC BLENDER APPLIANCE”, which accounts for a high-performance blender series. This kind of blender seeks to provide the best flavor of smoothies while maintaining the nutrients contained in the fruits or vegetables through a technology of “pulverization”, which can chop and pulverize the nutrition in skins and seeds and other parts into a very smooth and drinkable manner.

Picture credit: https://images.app.goo.gl/RBMXtWVgZKcCzU698

Pioneer Example (3):
In year 2013, Nielsen added a specific module named “PAIN RELIEVING DEVICE”. All the products in this module are regarded as Pioneers. For example, the product “Icy Hot SmartRelief TENS Therapy”, which based on our limited knowledge integrates a key technology, Transcutaneous Electrical Nerve Stimulation (TENS), it into a non-prescription, low cost, portable over-the-counter machine.

Picture credit: https://images.app.goo.gl/qkdk2CHmVkTapXfJ6

Follower Product Example (1)

Tyson Foods, a company primarily specializing in prepared meats, acquired the brand "Three Happy Cow" in 2014, announcing its entry into the yogurt market. Nielsen categorizes it as "YOGURT-REFRIGERATED". However, Tyson discontinued the operation in 2015 and according to a report, an insider believed that "*Tyson obviously don't know or understand the dairy business…or especially organic or Non-GMO food*." Source: https://www.foodnavigator-usa.com/Article/2015/02/11/Production-ceases-at-Greek-Yogurt-brand-Three-Happy-Cows

Picture credit: https://www.innit.com/nutrition/three-happy-cows-greek-vanilla-yogurt/p/00043038000116

Follower Product Example (2)
Anheuser Busch Inbev introduced the Margrita spiked tea beverage and made its entry into the sweet tea market. Nielsen categorizes it into module “TEA – LIQUID”

Picture credit: https://images.app.goo.gl/RiufgiVGba8ieXsy7

Follower Product Example (3)

Starbucks, a firm focusing on coffee, introduced Teavana brand that entered into tea drink market, including both packaged (and freshly brewed) tea products. Nielsen categories it as “TEA – PACKAGED”

Picture credit: http://www.fitfoodiemegha.com/2017/03/Teavana-new-tea-menu-starbucks-india-kothrud-reviewed.html

Improver Example (1)
Apple keeps introducing new versions of iPhone every year. The module's name is "CELLULAR PHONE". Picture credit: https://techcrunch.com/2017/09/12/this-is-how-much-the-new-iphones-will-cost/

Improver Example (2)
Anheuser Busch Inbev expands its product lines based on successful models. For example, it introduced Lime flavored beer named Bud Light Lime. The name of module is "BEER". Picture credit: https://images.app.goo.gl/qYZj2f7oXnfFsnDT7

Improver Example (3)
IROBOT CORP has a variety of vacuum products that suit for different households. The module is named "VACUUM AND CARPET CLE" Picture credit: https://www.irobot.com/roomba

Appendix 2a: A Cross-sectional Comparison Among Pioneer, Follower and Improver

Readers might be interested in how pioneer, follower and improver products are in the same business line. Here are some examples:

Example 1:
Pioneer: iPhone: https://en.wikipedia.org/wiki/IPhone_(1st_generation)

Follower: Google Pixel:
https://en.wikipedia.org/wiki/Pixel_(1st_generation)#:~:text=They%20were%20announced%20during%20a,the%20Pixel%204%20in%202019.

Improver: Other Generations of iPhones

Example 2:
Pioneer: Altra's MarkTEN

Follower: Viporesso
https://www.directvapor.com/vaporesso-xros-16w-vape-pod-starter-kit/

Improver: MarkTEN Elite
https://www.cspdailynews.com/tobacco/altria-introducing-closed-vapor-system

Example 3:

Pioneer: Vitamix
https://www.vitamix.com/us/en_us/Shop/5200-Getting-Started?skuId=001372-1093#overview

Follower: Oster Blender
https://www.amazon.com/Oster-Blender-24-Ounce-Smoothie-Brushed/dp/B00XHXN54K

Improver: More Advanced Vitamix Models
https://www.vitamix.com/us/en_us/shop/classic-blenders

Appendix 3: Profitability Tests Based on Total Sales as Scaler and Without Industry Dummies

Future Operating Performance						
Dependent Variable	COP (T+1)		ROA (T+1)		ROE (T+1)	
	(1)	(2)	(3)	(4)	(5)	(6)
Pioneer Product Introduction Rate **Based on Total Sales (t)**	0.004**		0.007**		0.023**	
	(0.001)		(0.003)		(0.007)	
Follower Product Introduction Rate **Based on Total Sales (t)**	0.887		0.002		-0.004	
	(0.867)		(0.006)		(0.006)	
Improver Product Introduction Rate **Based on Total Sales (t)**	0.001		0.004*		0.004	
	(0.002)		(0.002)		(0.008)	
Pioneer Product Introduction Rate **No Industry Dummy Models**		0.003*		0.004*		0.008**
		(0.002)		(0.002)		(0.003)
Follower Product Introduction Rate **No Industry Dummy Models**		0.001		0.001		-0.015
		(0.001)		(0.006)		(0.012)
Improver Product Introduction Rate **No Industry Dummy Models**		0.001		0.001		0.011**
		(0.002)		(0.001)		(0.004)
COP (t)	0.880***	0.881***				
	(0.031)	(0.028)				
ROA(t)			0.857***	0.854***		
			(0.066)	(0.068)		
ROE (t)					0.254**	0.277**
					(0.102)	(0.096)
Ln(ME) (t-1)	0.002***	0.002***	0.004***	0.004***	0.029***	0.026***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.006)	(0.005)
Ln(Firm Age) (t)	0.004	0.004	0.005**	0.006***	-0.031	-0.007
	(0.004)	(0.003)	(0.002)	(0.002)	(0.021)	(0.017)
Advertising Expenditure (t)	-0.014	-0.007	0.088*	0.102*	-0.415*	-0.410
	(0.022)	(0.016)	(0.041)	(0.050)	(0.211)	(0.264)
R&D Expenditure (t)	-0.135	-0.123	-0.068	-0.141	-2.111***	-1.971***
	(0.129)	(0.087)	(0.132)	(0.083)	(0.640)	(0.611)
Capital Expenditure (t)	-0.040	-0.058*	0.140	0.136**	0.231	-0.057
	(0.057)	(0.026)	(0.084)	(0.058)	(0.474)	(0.291)
Market to Book (t)	0.000	0.000	-0.000	-0.000	0.022***	0.022***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.003)
Patent Based Innovation Efficiency	0.004	0.005**	-0.008***	-0.003	-0.011	0.007
	(0.003)	(0.002)	(0.002)	(0.003)	(0.016)	(0.019)
New Brand Introduction (New Trademark Proxy)	0.013	0.021	-0.042***	-0.023**	0.046	0.124**
	(0.032)	(0.028)	(0.012)	(0.008)	(0.052)	(0.055)
Constant	0.020	-0.023*	-0.038	-0.060***	-0.065	-0.137
	(0.016)	(0.011)	(0.036)	(0.013)	(0.181)	(0.086)
Observations	2,096	2,096	2,096	2,096	2,096	2,096
R-squared	0.717	0.686	0.843	0.816	0.653	0.564
F statistics	15.933	84.441	13.909	57.139	2.781	8.747
NW Robust Standard Errors	Y	Y	Y	Y	Y	Y
Industry Dummies	Y	N	Y	N	Y	N

Appendix 4: Replication of future volatilities and future mean reversion tests in Hirshleifer et al. 2018

This table shows replicates future volatilities and future mean reversion tests in Hirshleifer *et al.*2018. In **Panel A**, models (1)-(4) regress the standard deviation of future four years of ROA on three rates separately and altogether. Models (6)-(8) regress the same dependent variable on above H&P industry average dummies separately and altogether. We repeat the same process for ROE from models (9) to (16). In **Panel B**, models (1)-(3) regress change in ROA from t to t+1, on interaction between three rates and change in ROA from t-1 to t., we regress the same dependent variable on the interaction between above H&P industry average dummies and change in ROA from t-1 to t. We repeat the same process for ROE in models (7)-(12). In all models, we report average slopes and Newey-West (1987) autocorrelation-adjusted heteroscedastic robust standard errors in parentheses from annual Fama and MacBeth (1973) cross-sectional regressions. We include industry dummies in each regression. Asterisks *, ** and *** indicate the significance levels of 10%, 5% and 1%, respectively.

Panel A: Future ROA and ROE Volatility

Dependent Variable	Volatility of ROA (t+1 to t+4)								Volatility of ROE (t+1 to t+4)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Pioneer Product Introduction Rate (t)	-0.004*	-0.008*							-0.022*	-0.024*						
	(0.002)	(0.004)							(0.008)	(0.010)						
Follower Product Introduction Rate (t)	0.006		-0.005						0.463		0.370					
	(0.007)		(0.014)						(0.290)		(0.300)					
Improver Product Introduction Rate (t)	0.046			0.049					0.125			0.095				
	(0.036)			(0.034)					(0.089)			(0.079)				
Pioneer Product Introduction Rate above H&P Average (t)					-0.016*	-0.056*							-0.035*	-0.054*		
					(0.008)	(0.019)							(0.013)	(0.017)		
Follower Product Introduction Rate above H&P Average (t)					-0.074		-0.052						-0.030*		-0.044	
					(0.041)		(0.029)						(0.016)		(0.030)	
Improver Product Introduction Rate above H&P Average (t)					0.058			0.015					0.000			-0.023*
					(0.077)			(0.054)					(0.008)			(0.007)
Volatility of ROA (t-4 to t)	0.221	0.211	0.214	0.227	0.328	-0.059	-0.047	-0.037								
	(0.135)	(0.142)	(0.139)	(0.139)	(0.211)	(0.429)	(0.553)	(0.401)								
Volatility of ROE (t-4 to t)									0.104	0.190	-0.032	-0.003	0.147	0.153	0.175	0.188
									(0.218)	(0.254)	(0.343)	(0.396)	(0.262)	(0.241)	(0.268)	(0.239)
Observations	2,096	2,096	2,096	2,096	2,096	2,096	2,096	2,096	2,096	2,096	2,096	2,096	2,096	2,096	2,096	2,096
R-squared	0.269	0.260	0.259	0.265	0.218	0.203	0.201	0.210	0.260	0.247	0.250	0.248	0.152	0.145	0.145	0.140
F statistics	2.028	2.892	2.963	2.042	3.726	3.892	2.051	6.405	2.707	2.163	2.625	3.305	3.209	4.295	2.263	3.962
NW Robust Standard Errors	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry Dummies	Y	Y	Y	Y	N	N	N	N	Y	Y	Y	Y	N	N	N	N

Panel A: Future ROA and ROE Mean Reversion												
Dependent Variable	Change in ROA (T+1)						Change in ROE (T+1)					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Pioneer Product Introduction Rate (t)	0.002	0.008	0.009				-0.031	-0.041	-0.041			
	(0.016)	(0.015)	(0.018)				(0.039)	(0.043)	(0.039)			
Follower Product Introduction Rate (t)	0.011	0.008	0.007				-0.004	-0.030	-0.017			
	(0.019)	(0.016)	(0.019)				(0.031)	(0.040)	(0.029)			
Improver Product Introduction Rate (t)	-0.003	-0.003	-0.003				-0.004	-0.003	0.001			
	(0.002)	(0.002)	(0.002)				(0.015)	(0.016)	(0.014)			
Pioneer Product Introduction Rate above H&P Average (t)				0.003	0.006	0.004				0.087	0.096	0.093*
				(0.007)	(0.006)	(0.007)				(0.062)	(0.059)	(0.050)
Follower Product Introduction Rate above H&P Average (t)				0.000	-0.002	-0.001				-0.004	0.009	-0.003
				(0.004)	(0.004)	(0.005)				(0.025)	(0.026)	(0.029)
Improver Product Introduction Rate above H&P Average (t)				0.008***	0.007**	0.009***				0.003	-0.000	0.011
				(0.002)	(0.003)	(0.002)				(0.021)	(0.023)	(0.020)
Pioneer Product Introduction Rate * Change ROA (t)	0.007***						0.013**					
	(0.001)						(0.005)					
Follower Product Introduction Rate *Change ROA (t)		0.004						0.006				
		(0.002)						(0.005)				
Improver Product Introduction Rate * Change ROA (t)			0.002**						0.001			
			-0.001						(0.001)			
Pioneer Product Introduction Rate above H&P Average * Change ROA (t)				0.012**						0.013***		
				(0.004)						(0.004)		
Follower Product Introduction Rate above H&P Average * Change ROA (t)					0.015						-0.002	
					(0.030)						(0.002)	
Improver Product Introduction Rate above H&P Average * Change ROA (t)						0.004*						0.020**
						(0.002)						(0.009)
Change ROA (t)	-0.041**	-0.042**	-0.042**	-0.043**	-0.053**	-0.056**						
	(0.005)	(0.006)	(0.005)	(0.006)	(0.009)	(0.006)						
ROA (t)	-0.077	-0.090	-0.084	-0.096	-0.129*	-0.128*						
	(0.053)	(0.064)	(0.052)	(0.082)	(0.065)	(0.069)						
Change ROE (t)							-0.125**	-0.120*	-0.116**	-0.262*	-0.183**	-0.273**
							(0.038)	(0.041)	(0.035)	(0.090)	(0.055)	(0.060)
ROE (t)							-0.269**	-0.265**	-0.254**	-0.586**	-0.59***	-0.583**
							(0.064)	(0.057)	(0.057)	(0.076)	(0.072)	(0.089)
Ln(ME) (t-1)	0.003**	0.003**	0.003**	0.003**	0.004***	0.004***	0.008***	0.007**	0.006**	0.042**	0.046**	0.044**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.017)	(0.016)	(0.016)
Ln(Firm Age) (t)	0.001	0.003	0.001	-0.001	0.001	-0.001	0.018***	0.015**	0.015*	0.055	0.051	0.048
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.006)	(0.008)	(0.047)	(0.049)	(0.047)
Advertising Expenditure (t)	-0.003	0.001	-0.016	0.055	0.067	0.052	0.142	0.026	0.032	0.187	0.227	0.241
	(0.018)	(0.016)	(0.018)	(0.053)	(0.057)	(0.045)	(0.116)	(0.100)	(0.112)	(0.714)	(0.750)	(0.722)
R&D Expenditure (t)	-0.009	0.032	-0.034	-0.076	-0.103	-0.091	0.524***	0.519***	0.519***	-0.720	-0.824	-0.768
	(0.086)	(0.060)	(0.090)	(0.052)	(0.075)	(0.084)	(0.102)	(0.086)	(0.083)	(0.927)	(0.889)	(0.935)
Capital Expenditure (t)	0.053	0.064	0.058	0.131**	0.129**	0.118*	-0.071	-0.061	-0.123	1.223	1.163	1.073
	(0.053)	(0.050)	(0.053)	(0.057)	(0.052)	(0.064)	(0.239)	(0.269)	(0.277)	(1.045)	(0.906)	(0.910)
Market to Book (t)	-0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.004**	0.005***	-0.045	-0.045	-0.045
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)	(0.001)	(0.060)	(0.061)	(0.060)
Patent Based Innovation Efficiency	-0.008**	-0.011**	-0.010**	-0.005**	-0.006**	-0.008**	0.013	0.012	0.012	-0.016	-0.008	-0.011
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.013)	(0.013)	(0.013)	(0.016)	(0.018)	(0.016)
New Trademark Introduction	-0.025*	-0.017	-0.020	-0.014*	-0.009	-0.02***	0.003	0.019	0.020	-0.053	-0.077	-0.076
	(0.013)	(0.010)	(0.012)	(0.007)	(0.007)	(0.006)	(0.025)	(0.027)	(0.022)	(0.075)	(0.068)	(0.069)
Constant	-0.005	-0.028*	-0.008	-0.031	-0.038	-0.018	-0.259*	-0.286**	-0.181**	-0.454*	-0.471*	-0.439*
	(0.020)	(0.015)	(0.020)	(0.025)	(0.023)	(0.027)	(0.125)	(0.099)	(0.078)	(0.240)	(0.235)	(0.224)
Observations	2,096	2,096	2,096	2,096	2,096	2,096	2,096	2,096	2,096	2,096	2,096	2,096
R-squared	0.872	0.870	0.869	0.855	0.862	0.843	0.422	0.395	0.410	0.704	0.687	0.694
F statistics	4.307	2.238	3.213	7.174	5.675	10.990	2.596	3.449	2.408	6.668	6.879	6.155
NW Robust Standard Errors	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry Dummies	Y	Y	Y	N	N	N	Y	Y	Y	N	N	N

Appendix 5: Investor Inattention Tests: Other Proxies

Panel A: Subsample Portfolio Double Sorting

Earnings Surprise

Low Earnings Surprise	Excess Return	Alphas 4F	4F+RMW+CMA	4F+EMI1	**High Earnings Surprise**	Excess Return	Alphas 4F	4F+RMW+CMA	4F+EMI1
Pioneer Firms					**Pioneer Firms**				
Top 30%	0.956***	0.546**	0.253	0.550**	Top 30%	0.980***	0.420	0.140	0.442
	(0.337)	(0.259)	(0.245)	(0.262)		(0.369)	(0.279)	(0.270)	(0.282)
Medium 40%	1.204***	0.422**	0.336*	0.468**	Medium 40%	1.106***	0.318	0.249	0.302
	(0.387)	(0.187)	(0.191)	(0.185)		(0.419)	(0.294)	(0.304)	(0.297)
Bottom 30%	0.803**	0.145	0.069	0.130	Bottom 30%	0.269	-0.440	-0.749**	-0.404
	(0.371)	(0.258)	(0.266)	(0.260)		(0.405)	(0.300)	(0.289)	(0.302)
High-Low	0.153	0.402	0.183	0.420	High-Low	0.711*	0.859**	0.889**	0.846**
	(0.331)	(0.321)	(0.323)	(0.324)		(0.373)	(0.377)	(0.391)	(0.381)

Analyst Coverage

Low Analyst Coverage	Excess Return	Alphas 4F	4F+RMW+CMA	4F+EMI1	**High Analyst Coverage**	Excess Return	Alphas 4F	4F+RMW+CMA	4F+EMI1
Pioneer Firms					**Pioneer Firms**				
Top 30%	0.988***	0.496**	0.218	0.519**	Top 30%	1.212**	0.426	0.398	0.322
	(0.318)	(0.225)	(0.209)	(0.226)		(0.600)	(0.516)	(0.534)	(0.516)
Medium 40%	1.106***	0.318	0.249	0.302	Medium 40%	0.743	-0.100	-0.078	-0.086
	(0.419)	(0.294)	(0.304)	(0.297)		(0.461)	(0.210)	(0.217)	(0.212)
Bottom 30%	0.412	-0.243	-0.438*	-0.228	Bottom 30%	0.625	-0.136	-0.256	-0.166
	(0.355)	(0.245)	(0.243)	(0.247)		(0.486)	(0.306)	(0.314)	(0.308)
High-Low	0.577**	0.739**	0.657**	0.748**	High-Low	0.587	0.562	0.654	0.488
	(0.291)	(0.295)	(0.304)	(0.298)		(0.552)	(0.565)	(0.581)	(0.568)

Panel B: Return Prediction

Dependent Variable	Next Month Return			
	High Earnings Surprise	Low Earnings Surprise	High Analyst Coverage	Low Analyst Coverage
Past 12-month Total Pioneer Introduction	0.224*	0.089	0.191*	0.845*
	(0.125)	(0.177)	(0.113)	(0.488)
Past 12-month Total Follower Introduction	0.169	0.317*	0.014	0.109
	(0.159)	(0.185)	(0.127)	(0.362)
Past 12-month Total Improver Introduction	-0.028	0.201	-0.017	-1.917
	(0.344)	(0.161)	(0.052)	(2.003)
Total Number of Products	-0.107	-0.079	-0.016	-0.006
	(0.102)	(0.097)	(0.067)	(0.187)
Size	-0.125	-0.079	-0.017	0.000
	(0.125)	(0.072)	(0.081)	(0.168)
Book to Market	-0.061*	-0.033	-0.045**	-0.211**
	(0.034)	(0.030)	(0.019)	(0.090)
Momentum	-5.071	-11.215	-12.028	-3.327
	(7.604)	(8.665)	(8.328)	(8.460)
Patents/Assets	-25.079	-20.441	2.681	-13.626
	(22.947)	(16.482)	(13.505)	(17.711)
Short-Term Return Reversal	-3.351*	-3.159**	-1.330	-2.308
	(1.810)	(1.542)	(1.662)	(2.347)
Asset Growth	5.959***	3.455***	1.900**	5.621***
	(1.479)	(1.080)	(0.748)	(1.404)
Capx/Assets	-11.740***	-7.087	-9.835*	-4.485
	(4.355)	(4.421)	(5.263)	(5.513)
R&D/Market Equity	0.462	0.376	-1,453.589	505.622
	(0.299)	(0.345)	(4,844.432)	(2,642.953)
ROA	8.412***	3.563**	7.390***	7.527***
	(2.135)	(1.748)	(1.894)	(1.904)
Multi-Segment Firm	0.218	-0.086	-0.183	-0.183
	(0.279)	(0.303)	(0.195)	(0.658)
Patent Based Innovation Efficiency	-0.541	0.659	0.063	-1.502
	(0.958)	(0.493)	(0.430)	(0.919)
New Brand Introduction (Trademark)	0.427	-1.798	-0.385	-1.760
	(0.709)	(1.085)	(0.608)	(1.465)
Constant	1.763	1.917**	1.079	0.943
	(1.231)	(0.918)	(1.039)	(1.537)
Observations	12,037	11,178	11,658	11,557
R-squared	0.458	0.482	0.470	0.483
F statistics	1.757	1.334	1.534	1.784
NW Robust Standard Errors	Y	Y	Y	Y

Chapter II

1. Introduction

On October 17, 2018, *The Wall Street Journal* reported that a broad coalition of asset managers was seeking to strip the Chairmanship from Facebook's CEO, Mr. Mark Zuckerberg, for his alleged mishandling of controversies that included a major data breach and the spread of misinformation on the platform.[24] The shareholder proposal calling for the splitting of the CEO and Chairman roles was initially put forth by Trillium Asset Management and had the support of the New York City pension fund as well as the state treasurers of Connecticut, Illinois, Massachusetts, Oregon, Pennsylvania, Rhode Island, and Vermont. Despite having widespread backing from numerous public pension funds and institutional investors, the proposal was roundly defeated due to Mr. Zuckerberg's iron grip on the voting control of the company.[25] He protected his role as Chairman because of Facebook's dual class ownership structure, where holders of the company's Class B common stock enjoy a ten-to-one voting advantage over the publicly traded Class A shares. An overwhelming majority of these shares are held by Mr. Zuckerberg's philanthropy (CZI Holdings, LLC), which in turn is solely controlled by The Mark Zuckerberg Trust.[26]

In this paper, we study how super-voting shares affect innovative outcomes and long-run shareholder value at founder-led and family-owned companies. Dual class ownership is quite common among well-established old economy businesses. In most of these firms, insiders enjoy substantial control over their companies by holding a non-publicly traded "superior" class of stock that gives them more votes per share than the publicly traded "inferior" class.

[24] https://www.wsj.com/articles/funds-back-proposal-to-remove-zuckerberg-as-facebook-chairman-1539789440
[25] https://www.wsj.com/articles/more-state-treasurers-back-split-of-facebooks-ceo-and-chairman-roles-11559233188
[26] https://www.sec.gov/Archives/edgar/data/1326801/000132680119000025/facebook2019definitiveprox.htm

As a result, these share structures create a divergence or "wedge" between voting and cash flow rights that further separates the ownership and control of public companies. The controlling principals of Brown-Forman, Ford Motor Co., News Corp, CBS/Viacom, Hershey, Levi Strauss, and Nike all hold dual class shares. Governance experts have frequently criticized dual class ownership structures as entrenching and a threat to the long-run future of the companies employing them (Gompers, Ishii and Metrick, 2010; Bebchuk and Kastiel, 2017; Bebchuk, Kraakman and Triantis, 2000).

Despite these concerns, dual class share structures have become a dominant ownership form for some of the world's most innovative companies. Alphabet, Facebook, and Zillow as well as upstarts such as Lyft, Snap, Pinterest, and Zoom are all organized in this fashion. The number of U.S. companies with dual-class stock structures increased from 487 in 2005 to 778 in 2020.[27] This surge in dual-class firms is likely to continue. As of June 2019, approximately 7% of Russell 3000 companies have dual class share structures.[28] We note that this structure is particularly prevalent at founder and family-led companies (Anderson, Ottolenghi, Reeb, and Savor 2018), that are often praised for their long-term orientation (Villalonga, Amit, and Trujillo, 2015). Indeed, our data shows that 75% of family firms are dual class firms.

Interestingly, the managers of founder or family-led companies typically do not hold the majority of their shares individually. Instead, they often collectively consolidate their shares within a family trust. The primary focus of our paper is on how family firms use these entities to control the firms they manage and on the consequences for doing so. While there are several tax advantages for creating a family trust,[29] we study the implications for corporate control.

[27] https://www.sec.gov/spotlight/investor-advisory-committee-2012/recommendation-on-dual-class-shares.pdf
https://site.warrington.ufl.edu/ritter/files/IPOs-Dual-Class.pdf
[28] https://www.cravath.com/a/web/13094/CG20_Chapter%201%20-%20Cravath,%20Swaine%20and%20Moore-B.pdf
[29] The known primary motivation for establishing family trusts is tax avoidance, for example, families can transfer millions of dollars to their children without paying any gift tax. .

Absent any formal organization, family shares would consist of factionalized holdings of several potentially competing family members with differing objectives. Prior theoretical literature predicts that consolidating ownership positions among dispersed shareholders can resolve collective action problems and improve the efficiency of managerial decision-making (Bennedsen and Wolfenzon, 2000; Gomes and Novaes, 2005). We argue that family trusts offer such a vehicle into which family insiders can pool their shares together into a single entity that executes their control over the firm in a unified fashion.

It is important to recognize that the consolidation of voting power within a family trust has the potential for abuse, particularly at dual class firms. The collective voting power is substantially enhanced when the concentrated shares have superior voting rights, and in these circumstances the potential for managerial entrenchment and rent extraction is exacerbated. However, unlike individual stockholders, family trusts are perpetual entities, and this feature might assuage the exploitation of enhanced corporate control to serve short-term interests. Rather, voting control organized in this fashion might alternatively favor long-run value creation in a way that serves all the trust's benefactors for generations.

This paper seeks to reconcile the conflicting predictions regarding managerial rent extraction and long-run value creation. To do so, we assemble a sample of 1,313 firm-year observations from 184 U.S. dual class public companies listed in the S&P 1500 index from 1994 to 2010. Within this dataset, we hand-collect whether our sample companies are family owned, the control rights of their super-voting shares, and whether these shares are held within a family trust. Our empirical approach is to proxy for long-run value creation by examining the marginal returns on investment and innovative outcomes such as R&D

spending, patent generation, and patent citations for companies holding dual class shares inside and outside of family trusts.

We find that nearly 50% of family firms in our sample have at least one family trust and these trusts typically have voting rights that are substantially larger than what their economic interest might suggest. The average family trust has a voting power that is 2.9 times greater than the cash flow rights for the shares held within the trust. By comparison, the typical control-to-cash flow rights ratio (hereafter referred to as the "wedge") of non-family dual class firms is 2.6. The wider wedge is attributable to family members putting more super voting than inferior cash shares into family trusts that achieve a unified control.

Overall, we find that family trusts offer a unique way of organizing shares that appears to enhance the wealth of all the company's shareholders. We regress contemporaneous long-run size and book-to-market (B/M) adjusted stock returns on the wedge for dual class shares held within and outside of family trusts. We show that shareholders earn greater stock returns when the family trust has a higher control wedge. The economic impact is relevant. For example, a one standard deviation increase in family trust's wedge is associated with 2.4% increase in risk-adjusted stock returns. Interestingly, we find the opposite effect when these shares are instead held by individual shareholders and not within the trust. Economically, a one standard deviation increase in the wedge held outside of the trust is associated with a 1.5% decline in stock returns.

Our results are confirmed when examining contemporaneous operating performance, as measured by the industry-adjusted return on assets (ROA). Operating performance is increasing with the control rights of the family trust. We find that a one standard deviation increase in the family trust wedge is associated with a 0.4% increase in industry-adjusted

ROA. Again, dual class shares held outside of the trust or at firms where no family ownership exists are associated with sub-par performance.

The sample data suggests the source of the accounting and stock market outperformance. Investors appear to more highly value the physical investment activities of firms when a family trust can exert unified control over the company. Following the marginal value of investment methods in Masulis, Wang, and Xie (2009), we find that investors, on average, associate the marginal dollar spent on capital expenditures with a net increase in value of 37 cents when the trust's wedge increases by one standard deviation. Our results also replicate the work of Masulis *et al*. (2009) regarding dual class ownership at large. Dual class shares held outside of a trust and the dual class wedge overall is associated with negative investment returns. We find that the marginal value of capital expenditure investment falls by 27 cents for a one standard deviation increase in the dual class wedge.

Consolidating voting power within family trusts leads to more investments in innovation. Our empirical results further reveal that the family trust wedge is positively associated with R&D spending, the number of patents produced, the market value of those patents, and the number of patent citations. Once again, at the same time, we find that at large dual class shareholdings consistently reduce these innovation outputs. For example, a one standard deviation increase in trust wedge will increase raw patent count by 1.19. Given the mean of raw patents is 11.08, it is a 11% increase. Meanwhile, a one standard deviation increase in dual class ratio will decrease the patent by 1.1, which is a 10% decrease.

We are careful to recognize that the choice of creating a trust and putting the specific number of voting shares into a trust is not random. Although we control for various covariates

and use a battery of fixed effects in each model, we can't fully rule out unobservable heterogeneities that could be correlated with the family trust's wedge, such as unique family firm history, interrelation among family members, or family firms' relation with local government.[30] On the other hand, instead of the family trust wedge positively contributing to firm value, it could also be that family insiders, disappointed by lackluster performance, consolidate their shares into the trust to steer the firm out of trouble.

To address this, we identify a plausible exogenous shock induced by a "model law" regarding the establishment of trusts in the United States. This sample regulation, known as the Uniform Trust Code (UTC), was drafted by the National Conference of Commissioners on Uniform State Laws and seeks to standardize the establishment of trusts by requiring trustees to properly diversify trust investment in a way consistent with portfolio theory.[31] It was codified in 2000 and is being adopted in a staggered fashion by many states. Family firms headquartered in the adopting states must diversify their trust holdings so they do not concentrate investment within their firms, thus relaxing their control.

Using a difference-in-difference (DiD) natural experiment, we find that, following the adoption of the UTC, firms located in those states suffer declines in the marginal value of CAPX, profitability, stock performance, R&D intensity, and patent production. Event study evidence confirms these results as investors react negatively to news of the adoption. Family firms with trusts experience negative announcement returns of around negative four

[30] For example, Hormel Foundation, which is trustee of various Hormel family trusts that hold 48% voting control, states that "contributions from the Hormel Foundation directly benefit the Austin, MN area."
[31] https://www.uniformlaws.org/committees/community-home?CommunityKey=193ff839-7955-4846-8f3c-ce74ac23938d

percent. In contrast, family firms without trusts experience small negative returns and non-family firms experience positive returns.

Our paper contributes to the literature on family firms by researching an unstudied internal family governance mechanism. Villalonga *et al.* (2015) argue that the complexity of family ownership engenders a host of agency conflicts among family insiders, family outsiders, outside shareholders, and creditors. To resolve these issues, they document that family firms employ several alternative governance mechanisms such as family councils or assemblies to enable coordination of decision making among members (Amit and Villalonga, 2013; Davis, 2007; Blumentritt, Keyt, and Astrachan, 2007). Our paper adds to this line of inquiry by studying an important facet of the family ownership structure. To our knowledge, no paper exists on the accumulation of their ownership stakes into family trusts. Our empirical results confirm the theoretical predictions of Bennedsen and Wolfenzon (2000) and Gomes and Novaes (2005) that firm value benefits from coordinated control through family trusts. We find supporting evidence that family trusts serve as a governance mechanism *within* family firms and it helps create more value to their companies under dual class share structures.

Secondly, we contribute to the literature on anti-takeover provisions (ATP) and the effect they have on firm value and innovative outcomes. Our work builds directly upon research by Masulis *et al.* (2009) documenting that a greater wedge between cash flow and voting rights at dual class firms is associated increased agency problems, impaired expected investment returns, and lower firm value. Our paper also fits in with Atannasov (2013), which shows that firm value and corporate innovation is decreasing with takeover protection afforded by the passage of state-wide business combination laws. Our results

confirm the primary results of these two papers that, for the average firm (i.e., family and non-family firms combined), ATPs are associated with value destruction and less innovation. However, more recent research by Chemmanur and Tian (2018) and Baran, Forst and Via (2020) challenge these views by examining charter and bylaw-based ATPs and dual class shareholdings, respectively. Their work suggests that enhanced control rights may lead to more innovation by insulating risk-averse managers from the hazards of lottery-like investment projects, especially when facing financial constraints.

We refine the inferences of the Masulis *et al*. (2009) and Atannasov (2013) papers by documenting a subset of firms within their results where our understanding regarding ATPs is actually reversed. We show that when the super-voting shares are concentrated among a group of family owners within a family trust, a long-run view dominates the rent-seeking motives from entrenching control. This results in higher shareholder wealth and greater innovative outcomes. Our research complements Chemmanur and Tian (2018) and Baran *et al*. (2020) by providing an alternative to the myopia channel explored in their papers. Instead, our paper exploits the large intersection between dual-class ownership structures and family firms and that is a distinguishing feature of our paper.

We explicitly test the theoretical predictions of Bennedsen and Wolfenzon (2000) and Gomes and Novaes (2005) that collective controlling ownership from affiliated shareholders is value enhancing. In our data, the beneficial effects of corporate control for innovation are driven completely by the super-voting shares held collectively by the family trusts. Super-voting shares held outside of these trusts (even if held by family members) are associated with less innovation and lower firm value, as predicted by Atannasov (2013).

Given the popularity of dual class structure and unique ownership of family firms, it is meaningful to understand how family control performs under a dual class framework.

Finally, our paper contributes to the literature on the influence that outside blockholders have on corporate outcomes. Consolidated shareholdings by dispersed investors are not a unique phenomenon; mutual or pension fund holdings are ubiquitous at U.S. public companies and the costs and benefits of large blockholders are widely studied (see Edmans, 2014 for a review). However, the blockholdings we study differ from their institutional counterparts due to the shareholders' common affiliation and the potential for involvement in the management of the company itself. Therefore, we believe that ownership through trusts is different and worthy of individual study.

This paper proceeds as follows: section 2 reviews the extant literature and sets up our empirical predictions, section 3 describes data and research design, while section 4 reports our empirical results. Section 5 deals with concerns over endogeneity. Section 6 concludes the paper.

2. Literature Review and Hypothesis Development

In corporate finance, the innovating owner-manager faces a classic problem where their need to raise capital via new share issuances is set against the control dilution consequence resulting from bringing in outside equity investors. A common resolution to this dilemma is the creation of multiple classes of stock with differential voting rights. One share class is sold to the investing public. This class is typically granted cash flow rights such as the right to a proportional share in paid out dividends and residual claims in the event of liquidation. The other share class sometimes has weaker cash flow rights but

enjoys stronger control rights. These superior voting shares, sometimes called "founder's shares," are generally privately held and retained by the founding management team. Their superior control rights are usually expressly denominated as a voting multiple relative to those of the publicly held common stock when deciding upon matters brought forth to shareholders at the annual meeting (e.g., who will serve on the board, shareholder proposals, and the approval of corporate takeover offers).

Although a dual class share structures permit founding families to raise equity capital while simultaneously retaining creative control over their companies, it exacerbates the separation of economic ownership and voting control, which is at the heart of the managerial agency problem (Harris and Raviv, 1988; Grossman and Hart, 1980). Several papers argue that dual-class shares violate the corporate democracy precept of "one share one vote" and provide a channel for shareholder expropriation by corporate insiders. In this vein, Gompers *et al.* (2010) show that firm value is inversely associated with the wedge between voting and cash-flow rights and Masulis *et al.* (2009) find a positive association between such a wedge and a variety of agency problems.

Some scholars have argued that the entrenching features of super voting shares are a risk to both established old economy firms and young, new economy companies alike. Smart, Thirumalai, and Zutter (2008) study dual class initial public offerings (IPOs) and show that dual-class firms trade at lower prices than single-class firms, both at the IPO and over the five subsequent years. Atanassov (2013) argues that managers protected from competitive pressures by state anti-takeover laws are less inclined to innovate due to shirking or career concern related risk-aversion. Following the promulgation of business combination laws, companies in these states produce future patents and the patents they do produce are less

influential. Following this argument, dual class structure can be seen as one of anti-takeover provisions (ATPs) that discourages managers to conduct long-term value creation projects. Therefore, we hypothesize that firm value will suffer when the control wedge represented at the firm by the company's super-voting shares is greater. We argue that the mechanism will be due to less innovation.

H1: Control enhancing provisions are associated with worse innovative outcomes and lower firm value.

On the other hand, advocates suggest that anti-takeover provisions could enhance firm performance if it helps companies avoid myopic cost saving strategies such as cutting research and development (Govindarajan and Srivastava, 2018). Lehn, Netter, and Poulsen (1990) find that firms with greater growth opportunities and lower agency costs are more likely to consolidate control through dual-class recapitalization than through LBOs. Chemmanur and Tian (2018) study bylaw and charter-based ATPs, arguing they lessen the pressures arising from short-term stock price fluctuations. The ATPs they study are positively associated with patent output. Baran *et al.* (2020) specifically study super-voting share structures by comparing the innovative outcomes of single class v. dual class firms and present similar results. They argue that the enhanced control rights insulate managers from myopic distractions allowing their companies to innovate more. The effect is strongest for firms facing financial constraints or strong product market competition.

A possible resolution to these conflicting results regarding myopia and entrenchment v. long-run innovation may come from an understanding that family and founder-managed firms are the most frequent users of dual class ownership structures (Anderson, Ottolenghi, Reeb, and Savor 2018). Family managers have special attachment to their firms and family insiders

usually hold controlling stakes in their companies. This makes them relatively free from short-term pressures (Chen, Chen, Cheng and Shevlin, 2010). Family ownership is quite prevalent across U.S. public companies. Anderson and Reeb (2003) find that around a third of S&P 500 firms are family controlled and they have a higher valuation than non-family firms on average. Fahlenbrach (2009) similarly finds that founder CEOs are associated with better stock performance and Anderson *et al.* (2017) show this effect persists even among dual class family firms. Villalonga and Amit (2006) also document that first-generation family firms (i.e., founder firms) tend to outperform. Consistent with the view that family firms are less myopic, Kim, Park and Shin (2017) show that family firms seek to maintain a long-term relationship with suppliers and other stakeholders while Fahlenbrach (2009) documents that founder-led firms invest more in R&D, capital expenditures, and engage in more focused M&A activity.

However, family firms are not immune to agency problems altogether. Rather, they often take a different form (Villalonga *et al.* 2015). While their extensive ownership tends to mitigate the classic principal-agent problem between managers and all outside shareholders (Jensen and Meckling,1976; Fama and Jensen, 1983), family firms suffer from concerns such as nepotism, the expropriation of minority shareholders, and excessive risk aversion. Indeed, Villalonga and Amit (2006) show that, while first generation family firms outperform, descendent-CEOs tend to destroy value. Family managers often take advantage of their controlling position in the firm to divert corporate resources to their own private interests. This so called “tunneling” is a documented problem in several settings (Johnson, La Porta, Lopez-de-Silanes, and Shleifer, 2000; Bertrand, Mehta and Mullainathan, 2002; Caprio and Croci, 2008; Villalonga and Amit, 2010). Anderson,

Mansi, and Reeb (2003) document that family firms are often more concentrated on long-run survival than growth and innovation. While this does benefit the company's creditors, this view can lead to prioritizing firm value maximization over shareholder wealth maximization. Naturally, super-voting shares empower family managers to further pursue their own interests over those of shareholders with impunity.

Family managers are aware of the complexity that their ownership engenders and the myriad of governance problems that can result from it. Accordingly, family firms often take special steps to resolve these concerns between managers, family and non-family shareholders, and other outside stakeholders. This includes family board representation (Gonzalez *et al*, 2014), voting agreements among family members (Villalonga and Amit, 2009), and multi-level governance through the use of family councils (Davis, 2007; Amit and Villalonga, 2013).

Our paper specifically studies one of these coordination mechanisms to resolve potential conflicts, namely family trusts. When shareholdings from disparate family members are held collectively within a family trust, family members can consolidate their voting control over the company and act with a single strong voice about the direction of the company. Further, because these vehicles are perpetual in nature, they engender a more long-run vision for the firm than other forms of large collective ownership observed at U.S. public firms (e.g., mutual or pension fund blockholdings).

To our knowledge, no studies exist on the consequences of organizing the family's ownership holdings into family trusts, but we can look to the theoretical literature for predictions. Bennedsen and Wolfenzon (2000) argue that by grouping shareholdings together, the controlling coalition takes more efficient actions than might otherwise be

expected if the individual owners acted on their own. The analysis by Gomes and Novaes (2005) predicts that collective control eliminates intra-shareholder bargaining problems and results in more efficient corporate investment decisions. Obviously, super-voting shares would only serve to strengthen that collective voice.

For these reasons, we predict that dual-class shareholdings might exacerbate the agency problems facing family firms. However, when those shareholdings are concentrated in family trusts, we expect an improvement in firm value and performance as well as more efficient investments in corporate innovation.

H2: Super-voting shares held within a family trust will have a positive effect on innovation and value.

H3: Control enhancing shares held outside of the trust will be associated with worse outcomes.

3. Data and Research Design

3.1 Sample Construction

To test our hypotheses, we assemble a sample using the universe of U.S. publicly traded companies listed in the S&P 1,500 index from Execucomp. We start our sample in 1994 because this is the first year when company filings are widely available on the Securities and Exchange Commission's (SEC) Electronic Data Gathering, Analysis, and Retrieval (EDGAR) website. A primary focus of our paper is on how coordinated family shareholdings affect innovative outcomes. We obtain data on patent production, impact,

and value used by Kogan, Papanikolaou, Seru and Stoffman (2017) and their data is available from 1926 until 2010.[32] Therefore, our initial sample is from 1994 to 2010.

Because there are substantial differences between dual class and single class firms, we follow Masulis *et al.* (2009) and Gompers *et al.* (2009) by restricting our analysis to dual class firms to increase the heterogeneity of our sample and mitigate endogeneity concerns. This restriction is relaxed later in the paper for robustness. We obtain our listing of dual class firms from the Institutional Shareholder Services (ISS) governance database, retaining only those firms listed in that resource. Masulis *et al.* (2009) report that approximately 6% of public companies from 1994 to 2002 are dual class. We similarly find that 5.24% of Execucomp / ISS companies are dual class in our sample period.

We identify founder or family-managed companies by examining the sample firms' proxy statement (DEF14A) filings on EDGAR. Following Anderson and Reeb (2003, 2004) and Villalonga and Amit (2006), we classify any firm as a family firm if the total combined ownership collectively exceeds five percent among the managers, directors, and blockholders affiliated with the firm's founder either by blood or by marriage. We identify founders by searching the company histories on their official websites and on FundingUniverse.com. Among these companies, we hand-collect the ownership positions of the family members, whether the company has a family trust, and the voting rights of the shares held within and outside of the trust.

We collect data on Research and Development (R&D) expenditures and other financial accounting data from COMPUSTAT database. Finally, we merge these observations with the University of Chicago's Center for Research on Securities Prices

[32] This data is graciously provided by the authors and is publicly available on Noah Stoffman's website: https://host.kelley.iu.edu/nstoffma/

(CRSP) database to compute long-run abnormal stock returns. Observations with incomplete data from either of these two sources are dropped. We winsorize all continuous variables at the 1st and 99th percentiles to mitigate the influence of outliers. Our final dataset consists of 1,313 observations from 184 unique firms. Appendix A shows the variable definitions.

3.3 Identification of Family Trusts

Next, we identify the presence of the family trust(s), and then collect their cash holdings and superior voting holdings within each family firm. We web-crawl key words including "family trust", "family trusts" "voting trust" "voting trusts" in all DEF14A filings for S&P1500 firms. We read each firm's Definitive 14A filing that is indicated by our algorithm to contain the target word combination to confirm that the trust is created and owned by the family that controls the firm.

In such filling, if there exist words "family trust" and/or their variations, they are usually located in the footnote of the "beneficial ownership" sector. Whenever we find family members (from the steps mentioned in the previous paragraph) who are associated with a trust, we read the footnotes about that trust, which usually has detail information about the trust's holding, cash flow rights and voting rights. We record the presence of trust, the total percentage claim of cash flow rights and voting rights. Appendix B provides a detailed discussion of identification method.

After assembling the dataset, Figure 1A shows that 46% of family dual class firms have at least one family trust, whereas only 29% of family firms don't have family trusts. In addition, for the dual class sample, only 25% of firms are professionally managed, indicating 75% are family owned. Using the ending sample year's total market

capitalization as a measure of firm size, Figure 1B shows that in aggregate, family firms with a trust have approximately same size as family firms without a trust. The total family dual class firms' size is bigger than their non-family counterparts.

3.4 Computing the "Wedge": Voting Control for Super-Voting Shares

In a general[33] dual class structure, common stocks have one vote per share whereas the superior voting stocks have many votes per share. The voting rights are calculated as dividing the total votes controlled by insiders, including both common share votes and superior share votes, by the total votes available or created by both classes. The total cash flow rights are calculated as dividing the total cash shares controlled by insiders, including both common shares and superior voting shares, by the total shares. In a single class firm, the voting rights and the cash flow rights should be equal because all shares have one vote per share. On the other hand, in dual class firms, superior voting shares bear more than one vote per share, causing a difference between cash flow rights and voting rights.

Lemmon and Lins (2003), Harvey, Lins and Roper (2004), Gompers *et al.* (2010) and Masulis *et al.* (2009) introduce two ways of calculating the wedge. In the first method, the difference captures the degree of separation of ownership and control. The second method is to divide the voting rights by the cash flow rights, which is called dual-class ratio or dual-class leverage in Masulis *et al.* (2009) and other studies. In this paper, we calculate trust wedge ratio by dividing the voting rights by the cash flow rights held by the trusts in aggregate.

Traditionally, literature uses dual class ratio to examine the agency cost at dual class firms (Gompers *et al.* 2010, Masulis *et al.* 2009). We follow the literature to collect all cash

[33] There are other variations, such as 3 classes, 4 classes, or one vote per share and 0.1 vote per share, among others

flow and superior voting shares held by insiders for all the sample firms and calculate the dual class ratio in the same way as trust wedge ratio.

In Table 1, we show summary statistics for variables in different tests. The key explanatory variables are dual class ratio and trust wedge ratio. The dual class ratio is calculated following Masulis *et al.* (2009) and has a mean of 2.6, which is close to theirs (2.208). The 25th, 50th and 75th quartiles of ratios between theirs and ours are also very similar. We calculate family trust in the same way as dual class ratio. The mean is 2.9, higher than dual class ratio.

Our key independent variable "Trust Wedge Ratio" is completely conditional on the presence of the family trust(s) created by family firms. Intuitively, trust wedge ratio is a subset of dual class ratio as the latter represents all the cash and voting shares held by insiders whereas trust wedge ratio only represents the cash and voting shares held by family trust(s). However, it should be noted that trust wedge ratio need not necessarily be smaller than dual class ratio in all cases. For a theoretical example, if a firm has a total of 100 cash shares and 1,000 votes held by all insiders, the dual class ratio is 10. Meanwhile, a family trust can hold 1 cash share and 999 votes, thus the trust wedge ratio is 999.

Since we seek to investigate why dual class ratio and family trust wedge differentially affect firm performance, we decompose the dual class ratio to see which parts of this ratio are driving the positive and negative effects. We first test if the "excess wedge", defined as out of trust wedge ratio yet inside the dual class ratio, is driving the negative effect on firm performance. We calculate the "excess wedge" as the difference between dual class ratio and family trust wedge. Thus, in family trust firms, the excess wedge is the difference,

but in dual class firms without a family trust, the excess wedge is zero. We name this variable as "*Outside the Trust-Ratio*".

Furthermore, we want to test if the dual class ratio will further decrease value in firms without the family trust(s). We define the "*No Trust Exist-Ratio*" that equals dual class ratio when the firm doesn't have any family trusts and equals to zero when there is at least one family trust.

3.5 Research Design: Firm Value and Operating Performance

For firm stock performance, we regress the size and B/M adjusted annual stock returns directly on dual class ratio and wedges. This annual stock returns are the difference between one-year buy and hold return for the sample company and that of a size and book-to-market matched benchmark over 12 months ending at the fiscal year-end date. Following Fama and French (1993), the sample firms are assigned to one of 25 value-weighted size and book-to-market benchmark portfolios as of June of each year, which are formed from five size quintiles using the market cap of NYSE firms as of June 30 of each year and five book-to-market quintiles are formed from NYSE firms as of December of the prior year. In addition, to examine the effect of different ratios and wedges on operating performance, we use Fama and French (1997) 48 industry adjusted return on asset as the dependent variable. Further, we follow Masulis *et al.* (2009) by regressing the size and B/M adjusted annual stock returns on change in CAPX interacting with family trust wedges and dual class ratio with a set of controls. For key dependent variables based on the final sample of 1,313 observations[34], excess stock return is the size and B/M adjusted stock

[34] All the summary statistics described and reported thereafter are all based on the final sample of 1,313 observations

return for the firm i in year t, averaging 2.4 percent. In the sample firms, the average return on asset (ROA) adjusted by industry median is 0.3% per year.

3.6 Research Design: Innovation Outcomes

We use innovation measures to proxy for long-run value creation, including R&D scaled by sales and patent-related measures provided by Kogan *et al.* (2017), on trust wedges and dual class ratios with a set of controls. The R&D measures the intensity of investment in innovation, while the three patent variables proxy for innovation success. Kogan *et al.* (2017)'s data include number of patents, which is simply the total patents a firm has applied in the fiscal year. The second measure is TSM, which is the total dollar increase in market capitalization based on stock market reaction in a [0,2] window upon patent issuance in a firm year. The third measure is TCW, which is the log transformed sum of a citation measure in which each patent's citation is scaled by the average forward citations received by all the patents that were grated in the same year as this patent, in order to adjust for citation truncation lags. Following convention (Hirshleifer, Hsu and Li 2017), any firms missing patent data don't have any material innovation programs and we accordingly set missing values to zero.

For innovation outputs, the R&D intensity is 0.036, indicating that 3.6% of sales is devoted to R&D expenditure. Firms on average apply for 11 patents per year. They averaged $158.6 million in market cap appreciation in response to all patent approvals in a year while at the same time these firms have 18 average citations (truncation adjusted) for each patent. Following innovation literature, we log-transform all three innovation measures in empirical analyses.

3.7 Control variables

We have two sets of controls variables. In marginal value of CAPX model, we use standard control variables for this framework following Faulkender and Wang (2006), including changes in (1) capital expenditure (CAPX), (2) R&D expense, (3) earnings before interest and extraordinary items, (4) total assets net of cash, (5) interest expense, (6) total dividends, as well as (7) net amount of external financing. All firm level control variables are normalized by the beginning of period market capitalization. We construct such variables from firm fundamentals and stock returns data provided by Compustat and the Center for Research in Security Prices (CRSP).

The second set of control variables is used in other models from firm stock and operating performance to innovation outputs. We control for variables that can affect firm short- and long-term value by following Mukherjee, Singh and Žaldokas (2017) as well as Custódio, Ferreira and Matos (2019). Specifically, we include R&D intensity (R&D scaled by sales), Herfindahl-Hirschman Index based on three digits SIC code, logarithm of firm sales, a dummy that indicates if a firm carries S&P debt rating, change in profitability, asset tangibility, logarithm of capital to labor ratio, leverage, Tobin's Q, CAPX, firm age and firm size. Because our research examines the different impact of family trust's wedge from dual class ratio, we additionally control for family firm and family trust dummies.

In terms of control variables, sample firms on average record $7.6 billion in annual sales, 23% of total asset is financed by debt. Firms invest 5% of asset in capital expenditure and their average age is 28 years.

4. Empirical Results

4.1 How do different ratios affect firm operating and stock performance?

In our first set of tests, we regress proxies of firm value on trust wedge ratio and dual class ratios with a set of controls. The main model specification is as follows:

$$Firm\ Value\ outputs_{i,t} = \gamma_0 + \gamma_1 Trust\ Wedge\ Ratio\ or\ Dual\ Class\ Ratio_{i,t-1} + \gamma^{'}\phi_{\boldsymbol{i,t-1}} + \omega_{i,t-1} + \lambda_{i,t-1} + \varepsilon_{i,t-1} \quad (1)$$

where the coefficient $\gamma_1$is the coefficient of interest that measures the contribution of one-standard-deviation increase in the wedge or ratio to the value outputs. ϕ represents the second set of control variables while γ' is the vector of their coefficients. $\omega_{i,t-1}$ and $\lambda_{i,t-1}$ are industry and year or firm and year fixed effects.

To make sure our results are not affected by unobserved heterogeneities in some particular industries or firms, we use industry and year as well as firm and year fixed effects. To ensure that the coefficient standard errors are not biased by heteroscedasticity, we report robust heteroscedastic-consistent standard errors clustered by firm. To make interpretation easy, we standardize all the independent variables to have mean of zero and standard deviation of one. For marginal value model, we only standardize the wedge and ratio variables because the change in CAPX is already standardized by the beginning book value of asset.

Table 2 reports the results of stock return. In model (1) and (2), the trust wedge ratio is positively related to stock performance. For example, one-standard-deviation increase in trust wedge ratio leads to a 2.4% increase in annual stock return, supporting hypothesis 2. Dual class ratio doesn't have a significant relation with stock returns. After decomposing the wedge, we find that the portion of dual class ratio outside the trust wedge ratio is negatively related to stock return with 1.5% reduction per one-standard-deviation increase in industry and year fixed effect models, which is consistent with hypothesis 3.

Next, we use industry adjusted ROA as a measure of firm operating performance to test different ratios. Model (1) and (2) of Table 3 show that trust wedge ratio is associated with 0.4% to 0.6% increase in future adjusted ROA per standard deviation. On the other hand, models (3) and (4) reveal that future ROA tend to decrease by 0.1% or 1.1% with one-standard-deviation increase in dual class ratio. Decomposition of dual class ratio shows that the reduction in profitability is aggravated with excess wedge outside trust wedge or pure dual class wedge without family trust presence. In profitability models, all of our three hypotheses are supported that dual class control enhancing provisions decrease value while trust wedge increases value. Further, the negative value effect is driven by wedge held outside of trust.

4.2 Trust Wedge Ratio, Dual Class Ratio and Marginal value of Capital Expenditure

In this section, we test the interaction effect between marginal value of CAPX and family trust wedge as well as dual class ratio with its variations. We regress the size and B/M adjusted annual stock returns on the change in CAPX. The main model specification is as follows:

$$r_{i,t} - R_{i,t}^{B} = \beta_0 + \beta_1 Trust\ Wedge\ Ratio\ or\ Dual\ Class\ Ratio_{i,t-1} + \beta_2 \frac{\Delta Capx_{i,t}}{M_{i,t-1}} \times$$

$$Trust\ Wedge\ Ratio\ or\ Dual\ Class\ Ratio_{i,t-1} + \beta_3 \frac{\Delta Capx}{M_{i,t-1}} + \gamma' \mathrm{X}_{\boldsymbol{i,t-1}} + \omega_{i,t-1} + \lambda_{i,t-1} + \varepsilon_{i,t-1}$$

(2)

where the coefficient β_3 is the original marginal value variable in the framework of Faulkender and Wang (2006) that measures the marginal value of one dollar increase in CAPX spending as perceived by shareholders. β_2 is our main coefficient of interest that measures the effect of one-standard-deviation increase in the family trust or dual class ratio on the marginal value of CAPX, which is used in Masulis *et al.* (2009). γ' is a vector that

shows the coefficients of control variables in set X , which represents the control variables for marginal value models by Faulkender and Wang (2006). $\omega_{i,t-1}$ and $\lambda_{i,t-1}$ are industry and year or firm and year fixed effects.

The results are in Table 4. There are four blocks of models in which we interact Trust Wedge Ratio, Dual Class Ratio, Outside the Trust-Ratio and No Trust Exist-Ratio with change in capital expenditure. Models (1), (3), (5) and (7) use industry and year fixed effects while (2), (4), (6) and (8) use firm and year fixed effects. According to marginal value framework, model (1)'s coefficient of the interaction term means that for one-standard-deviation increase in trust wedge with $1 increase in capital expenditure, the capital expenditure will worth 37 cents more as perceived by shareholders. This supports our hypothesis 2 that when trusts hold super-voting shares, they can help increase value. The dollar effect is stronger in firm-year fixed effects, which is 41.2 cents. For model (3), we can see that the coefficient is negative for dual class ratio. This means that for $1 increase in capital expenditure coupled with one-standard-deviation increase in dual class ratio, the value of capital expenditure will worth 27 cents less. It supports the hypothesis 1 that control enhancing provisions, proxied by dual class ratio, lead to reduction in value.

Next, we disentangle the value-enhancing wedge from the value-destroying ratio. We create the non-trust ratio, which is the dual class ratio *if* the firm doesn't report a family trust in that fiscal year, and the excess wedge, which is the difference between the dual class ratio and family trust wedge. Naturally, the excess wedge would be dual class ratio if the firm doesn't report a family trust. From models (5) to (6), we can see that the negative effect comes entirely from the excess portion outside of trust wedge but inside the dual class ratio. For example, in model (5), if the excess wedge increases by one standard

deviation with capital expenditure up by $1 dollar, the shareholders will discount this $1 dollar increase by 35 cents. In models (7) and (8), the main independent variable is the pure dual class ratios without any trust wedge ratio, we can see that the agency problem exacerbates as the marginal value of capital expenditure decreases by 40 cents, which are greater than that of ratio outside the trust (model 5) and of dual class ratio with trust wedge (model 3). These results in aggregate support hypothesis 3 that super-voting shares held outside of trust will decrease value.

4.3 R&D Expenditures

In previous sector, we show that in general, family trust wedge is positively associated with stock and operating performance, while dual class ratio is decreasing value. We find that the driving factor of value destruction is the wedge portion owned by insiders, rather than by family trust.

Since the wedge represents excess control rights over economic rights, its magnitude measures the agency problem in which entrenched managers can use control rights to derive private benefits without bearing corresponding economic consequence. Our empirical evidence supports this conjecture by showing that when the wedge is exclusively held by managers or insiders as dual class ratio, it destroys value at a greater scale.

However, it begs to question why family trust wedge is associated with better performance. We propose one economic channel in this section: corporate investment with a long-term focus and innovation outputs as a result of such investment. Family firms are known for their long-term orientation. Since family trust is a vehicle that pools family members' shares, its voting decision represents family trustees' decision. Thus, we expect family members will support more long-term value creating projects.

We use R&D/sales to proxy for the investment of long-term value creation, and innovation for the outputs, which would be an economic channel contributing to the better performance. The main model specification is as follows:

$$R\&D\ or\ Innovation\ Outputs_{i,t} = \gamma_0 + \gamma_1 Trust\ Wedge\ Ratio\ or\ Dual\ Class\ Ratio_{i,t-1} + \gamma' \phi_{\boldsymbol{i,t-1}} + \omega_{i,t-1} + \lambda_{i,t-1} + \varepsilon_{i,t-1} \quad (3)$$

where the coefficient $\gamma_1$is the coefficient of interest that measures the contribution of one-standard-deviation increase in the wedge or ratio to the R&D or innovation outputs. ϕ represents the second set of control variables while γ' is the vector of their coefficients. $\omega_{i,t-1}$ and $\lambda_{i,t-1}$ are industry and year or firm and year fixed effects.

The empirical evidence is supportive of our hypotheses. Table 5 shows the R&D/sales results. In model (1) and (2), trust wedge ratio is positively related to R&D/Sales. At the same time, dual class ratio tends to lead managers to lower R&D investment. Further, we confirm that the negative impact of dual class ratio is driven by the portion outside the trust or without trust's existence.

4.4 Patent Production

Next, we examine the outputs of long-term oriented projects from patent-based measures. Table 6, model (1) and (2), show that trust wedge is positively related to log transformed patents. One-standard-deviation increase in trust wedge ratio is associated with 0.178 increase in patents. Given the log-transformed patent has a mean of 0.518, this is a 34% increase around the mean. At the same time, one-standard-deviation increase in dual class ratio will decrease patents by 0.087, which is a 17% reduction. The two additional wedges decomposed from dual class ratio and trust wedge ratio display the same decreasing patterns.

Table 7 regresses the average citations (truncation adjusted) a sample firm receives during a year. In industry and year fixed effect models, one-standard-deviation increase in trust wedge ratio leads to 0.219 increase in log-transformed citations, or a 33% increase around the mean. At the same time, dual class ratio is associated with 0.102 decrease or 15% reduction around the mean. Additionally, outside the trust-ratio variable tends to reduce citations by 36% while no trust exist-ratio leads to a 16% decrease around the mean.

Lastly, we examine how the stock market reacted to the news of patent applications' approval that accrued to sample firms. Table 8 regresses the appreciation of stock capitalization to patent approval on different ratios. We find that stock market reacts positively to patents approvals by firms with high trust wedge ratio. On the contrary, it seems to discount the patents approval events by firms with high dual class ratios.

In sum, this section proposes and confirms an economic channel through which trust wedge contributes to better stock and operating performance. The long-term orientation by family firm is in contrast to short-termism by professional managers and this is amplified in dual class structure that gives managers or insiders more controls than corresponding economic investment. We use long-term investment and outputs to show that family insiders will use this control-enhancing tools to strengthen the long-term view while individual insiders use them to enhance the short-termism or to derive private benefits. Specifically, we confirm our hypothesis 1 that control enhancing provision is associated with agency problem in terms of less long-term investment and innovation outputs. However, this control enhancing power held in family trust can increase long-run investment and innovation outputs as predicted by hypothesis 2. Lastly, we validate hypothesis 3 that the negative effect is caused by excess power held outside of trust.

5. Endogeneity Issues and Robustness

5.1 Identification Strategy

The choice of establishing family trust(s) and putting certain number of shares into the trust is not random. For example, in order to strengthen family members' objective of long-term focus by increasing R&D investment, or applying more patents, family insiders can set up a trust to consolidate their control. On the other hand, inside family firm, some members may have more say than others due to personal charisma or family history. These people might be able to determine the shares held in trust, making the trust wedge ratio correlated with unobservable heterogeneities unique to family firm, which is impossible to control by firm-level variables or fixed effects.

To address this, we explore an exogenous change induced by the adoption of a law in staggered fashion across the U.S. Known as the Uniform Trust Code, this model law was codified in 2000 that seeks to standardize the establishment of trusts across states to a greater extent in response to the trusts' increased use by the affluent. The purpose is to "create a uniform, comprehensive, easy-to-find body of trust law". The states can adopt it to supplement and revise their existing laws regarding trusts. Prior to its passage, trust laws were very different among states.

Table 9, Panel A, shows the states that have adopted this law. There are currently 24 states passing this law from 2000 to 2011. Since our sample period is from 1992 to 2010, we identify the year in our sample in which the states had adopted the law. We use the state headquarters because the trusts that we can identify registration location are with the state of corporate headquarters rather than the state of incorporation. For example, Hershey

Family Trust is registered in the state of Pennsylvania while Hershey is a Delaware corporation.

5.2 How Would Uniform Trust Code Affect Innovation?

The impact of this law on family trust is heatedly debated in legal research community. On appearance, this law seeks to standardize the establishment of trust, thus making it more applicable. However, the focus of the debate centers on the investment management directives of trusts. It requires the managers of the trusts to diversify the trust fund consistent with portfolio theory, instead of concentrating all the fund on buying shares of family business.

Proponents of this rule say that it can help beneficiaries of the trust to maximize the return, thus meeting settlor's purpose of most trusts (Langbein 2010). On the other hand, Cooper (2008) argues that this rule has eroded into trustees' flexibility in investment. In fact, many trust documents have directed trustees to retain a certain investment in business, yet this law will disrupt the objectives and may weaken family members' power in their own firm.

From finance perspective, if this law limits the trust fund's investment in its own firm and requires the trustees to achieve portfolio diversification, we should expect the family firms' control through trust will decrease following this law. In other words, we expect the coefficients of DiD variable to be negative, indicating that compared to control firms, the treatment firms would experience a drop in performance and long-term project investment or outputs after the states adopted the law.

5.3 Event-study Evidence

We first show how the stock market reacted to the adoption of this law in table 9, panel B, in an event study that measures the cumulative abnormal return two days before and after the law's enactment for our sample firms headquartered in these states. We find that on average, family firms lost 2.5% after the law's passage. Then we divide the sample group into family firm with trust vs non-family firm and family firm without trust vs family firm with trust. We find that the negative effect was driven by family firm with trust. For example, the mean return of family firm with trust was a 4.09% loss, compared to 1.28% gain for non-family firm. On the other hand, family firms without trust do not seem to lose much, averaging 0.44%.

5.4 Difference in Difference (DiD) Quasi-Natural Experiment

Next, we conduct a quasi-natural experiment of DiD approach. Specifically, we assign firms in treatment group if they are headquartered in states that have adopted the trust code and firms in control group if in states that haven't adopted the law. In a difference in difference study, we run this regression:

$$Annual\ Excess\ Returns = \alpha + \beta_1 Treatment * After * Trust\ Wedge\ Ratio * Change\ in\ Capx + \beta_2{}' All\ interaction\ terms + \lambda' \boldsymbol{X_{i,t}} + \omega_{i,t} + \varphi_{i,t} + \varepsilon_{i,t}$$

$$Performance/Innovation\ Outputs = \alpha + \beta_1 Treatment * After * Trust\ Wedge\ Ratio + \beta_2{}' All\ interaction\ terms + \lambda' \boldsymbol{X_{i,t}} + \omega_{i,t} + \lambda_{i,t} + \varepsilon_{i,t}$$

where β_1 is the DiD coefficient that measures the difference between the treatment and control firms before and after the tax rise. $\beta_2{}'$ is a vector of coefficients that represent the interaction terms required for the interactive term for the DiD coefficient. λ' is the coefficients of same control vector $\boldsymbol{X}$ used in main models. $\omega_{i,t}$ and $\lambda_{i,t}$ indicate firm and year or industry and year fixed effects.

Table 9, Panel C, shows the DiD results. We conduct this experiment for all of our previous models. The DiD coefficients are all negative, meaning that compared to control firms, treatment firms experienced reductions in marginal value of CAPX, operating and stock performance as well as innovation outputs after states have adopted the law. This first supports the empirical relation reported previously. Specifically, because the family firms' control-enhancing power in trust has been exogenously reduced by the trust law, the firm performance and innovation outputs have decreased. Second, this finding upholds the argument against the law in legal research as family firms have reduced long-term value creation activities.

5.5 Parallel Trends

Difference in Difference (DiD) relies on an important parallel assumption that only the treatment group should experience a change due to the exogenous shock, while the control group should keep its trend before and after the event. To show this, we regress all the outputs on a dummy of treatment vs control, along with same control. We plot yearly coefficients 3 years before and after the event in a [-3,3] window and their 95% confidence interval.

Figure 2 shows the parallel trend of all models. In the event year, the treatment firms significantly underperformed the control firms, indicating that only treatment firms experienced this shock because other coefficients are insignificantly different from 0.

5.6 Additional Robustness Test

In this section, we repeat our analysis in full S&P 1,500 firm sample by regressing R/D intensity, patent, Tsm, Tcw, industry adjusted ROA and annual size and B/M adjusted stock returns on family trust dummy and trust holding. Table 10 reports the results. We

find that although family trust dummy loads negatively only in innovation outputs, trust holding loads positively for all dependent variables except for R&D intensity. This further strengthens our argument that it is the consolidation of power by trust that matters, and if the trust doesn't hold a meaningful number of shares, or power, there is no significant effect.

6. Conclusion

In this paper, we identify a unique family firm governance mechanism, family trust, in dual class firms. Since dual class structure creates a wedge that enhances insiders' control over their economic commitment, it aggravates agency problem, for which we find supportive evidence that total dual class ratio destroys value. However, the wedge created by family trust, a subset of total dual class ratio, can increase firm performance through marginal value of CAPX, industry adjusted ROA, annual abnormal stock return. Consistent with the literature, we find that family firms' long-term orientation has been amplified by the control-enhancing tool created by family trust that helps the firm invest more in R&D, which results in more patents, citations and stock market reaction. As such, we find evidence that dual class structure is not always value-destroying, it depends on who is in control.

References

Anderson, R. C., & Reeb, D. M. (2003). Founding-family ownership and firm performance: evidence from the S&P 500. *The journal of finance*, *58*(3), 1301-1328.

Anderson, R. C., Mansi, S. A., & Reeb, D. M. (2003). Founding family ownership and the agency cost of debt. *Journal of Financial economics*, *68*(2), 263-285.

Anderson, R. C., Ottolenghi, E., Reeb, D. M., & Savor, P. (2018). The control risk premium. *Fox School of Business Research Paper*, (17-021).

Atanassov, J. (2013). Do hostile takeovers stifle innovation? Evidence from antitakeover legislation and corporate patenting. *The Journal of Finance*, *68*(3), 1097-1131.

Baran, L., Forst, A., & Via, M. T. (2020). Dual class share structure and innovation. *Available at SSRN 3183517*.

Bebchuk, L. A., & Kastiel, K. (2017). The untenable case for perpetual dual-class stock. *Va. L. Rev.*, *103*, 585.

Bebchuk, L. A., Kraakman, R., & Triantis, G. (2000). Stock pyramids, cross-ownership, and dual class equity: the mechanisms and agency costs of separating control from cash-flow rights. In *Concentrated corporate ownership* (pp. 295-318). University of Chicago Press.

Bennedsen, M., & Wolfenzon, D. (2000). The balance of power in closely held corporations. *Journal of financial economics*, *58*(1-2), 113-139.

Bertrand, M., Mehta, P., & Mullainathan, S. (2002). Ferreting out tunneling: An application to Indian business groups. *The Quarterly Journal of Economics*, *117*(1), 121-148.

Blumentritt, T. P., Keyt, A. D., & Astrachan, J. H. (2007). Creating an environment for successful nonfamily CEOs: An exploratory study of good principals. *Family Business Review*, *20*(4), 321-335.

Caprio, L., & Croci, E. (2008). The determinants of the voting premium in Italy: The evidence from 1974 to 2003. *Journal of Banking & Finance*, *32*(11), 2433-2443.

Chemmanur, T. J., & Tian, X. (2018). Do anti-takeover provisions spur corporate innovation? A regression discontinuity analysis. *Journal of Financial and Quantitative Analysis, Forthcoming*.

Chen, S., Chen, X., Cheng, Q., & Shevlin, T. (2010). Are family firms more tax aggressive than non-family firms?. *Journal of financial economics*, *95*(1), 41-61.

Cooper, J. A. (2008). Empty Promises: Settlor's Intent, the Uniform Trust Code, and the Future of Trust Investment Law. *BUL Rev.*, *88*, 1165.

Custódio, C., Ferreira, M. A., & Matos, P. (2019). Do general managerial skills spur innovation?. *Management Science*, *65*(2), 459-476.

Davis J. 2007. Governance of the business family. Harv. Bus. Sch. Note 807-020, BostonFama, E. F., & Jensen, M. C. (1983). Separation of ownership and control. *The journal of law and Economics*, *26*(2), 301-325.

Edmans, Alex, 2014, Blockholders and Corporate Governance, *Annual Review of Financial Economics* 6, p. 23-50.

Fahlenbrach, R. (2009). Founder-CEOs, investment decisions, and stock market performance. *Journal of financial and Quantitative Analysis*, 439-466.

Gomes, A. R., & Novaes, W. (2005). Sharing of control as a corporate governance mechanism. *Available at SSRN 277111*.

Gompers, P. A., Ishii, J., & Metrick, A. (2010). Extreme governance: An analysis of dual-class firms in the United States. *The Review of Financial Studies*, *23*(3), 1051-1088.

Govindarajan, V., & Srivastava, A. (2018). Reexamining dual-class stock. *Business Horizons*, *61*(3), 461-466.

González, M., Guzmán, A., Pombo, C., & Trujillo, M. A. (2014). Family involvement and dividend policy in closely held firms. *Family Business Review*, *27*(4), 365-385.

Griliches, Z. (1998). Patent statistics as economic indicators: a survey. In *R&D and productivity: the econometric evidence* (pp. 287-343). University of Chicago Press.

Grossman, S. J., & Hart, O. D. (1980). Takeover bids, the free-rider problem, and the theory of the corporation. *The Bell Journal of Economics*, 42-64.

Harris, M., & Raviv, A. (1988). Corporate governance: Voting rights and majority rules. *Journal of financial economics*, *20*, 203-235.

Hall, B. H., Jaffe, A., & Trajtenberg, M. (2005). Market value and patent citations. *RAND Journal of economics*, 16-38.

Harvey, C. R., Lins, K. V., & Roper, A. H. (2004). The effect of capital structure when expected agency costs are extreme. *Journal of financial economics*, *74*(1), 3-30.

Hirshleifer, D., Hsu, P. H., & Li, D. (2018). Innovative originality, profitability, and stock returns. *The Review of Financial Studies*, *31*(7), 2553-2605.

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of financial economics*, *3*(4), 305-360.

Johnson, S., La Porta, R., Lopez-de-Silanes, F., & Shleifer, A. (2000). Tunneling. *American economic review*, *90*(2), 22-27.

Kim, S. Y., Park, S. S., & Shin, H. H. (2017). Do family firms care for their stakeholders? Evidence from the customer-supplier relationship. *Korean Finance Association Conference*, 788-813.

Kogan, L., Papanikolaou, D., Seru, A., & Stoffman, N. (2017). Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics*, *132*(2), 665-712.

Lehn, K., Netter, J., & Poulsen, A. (1990). Consolidating corporate control: Dual-class recapitalizations versus leveraged buyouts. *Journal of Financial Economics*, *27*(2), 557-580.

Langbein, J. H. (2010). Burn the Rembrandt-Trust Law's Limits on the Settlor's Power to Direct Investment. *BUL Rev.*, *90*, 375.

Masulis, R. W., Wang, C., & Xie, F. (2009). Agency problems at dual-class companies. *The Journal of Finance*, *64*(4), 1697-1727.

Mukherjee, A., Singh, M., & Žaldokas, A. (2017). Do corporate taxes hinder innovation?. *Journal of Financial Economics*, *124*(1), 195-221.

Quigley, J., Torre, N. G., Amit, R., Villalonga, B., & Contigiani, A. (2013). A Primer on Governance of the Family Enterprise.

Smart, S. B., Thirumalai, R. S., & Zutter, C. J. (2008). What's in a vote? The short-and long-run impact of dual-class equity on IPO firm values. *Journal of Accounting and Economics*, *45*(1), 94-115.

Solow, R. M. (1957). Technical change and the aggregate production function. *The review of Economics and Statistics*, *39*(3), 312-320.

Villalonga, B., & Amit, R. (2009). How are US family firms controlled?. *The Review of Financial Studies*, *22*(8), 3047-3091.

Villalonga, B., & Amit, R. (2010). Family control of firms and industries. *Financial Management*, *39*(3), 863-904.

Villalonga, B., Amit, R., Trujillo, M. A., & Guzmán, A. (2015). Governance of family firms. *Annual Review of Financial Economics*, *7*, 635-654.

Figure 1A: Distribution of dual class firms, family trust firms and nonfamily trust family firms:

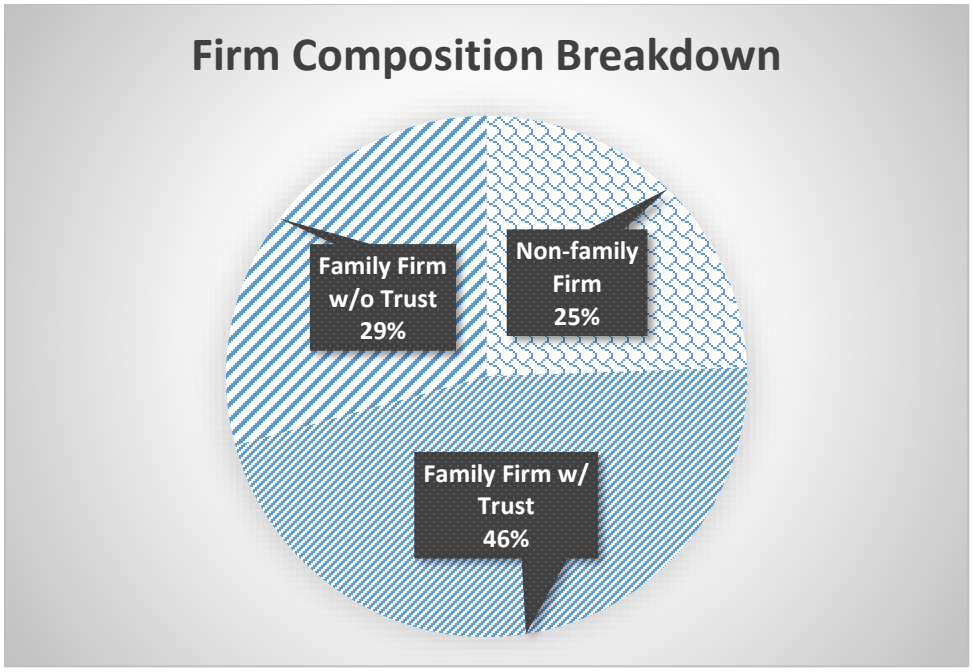


Figure 1B: Market Cap of dual class firms, family trust firms and nonfamily trust family firms in 2010:

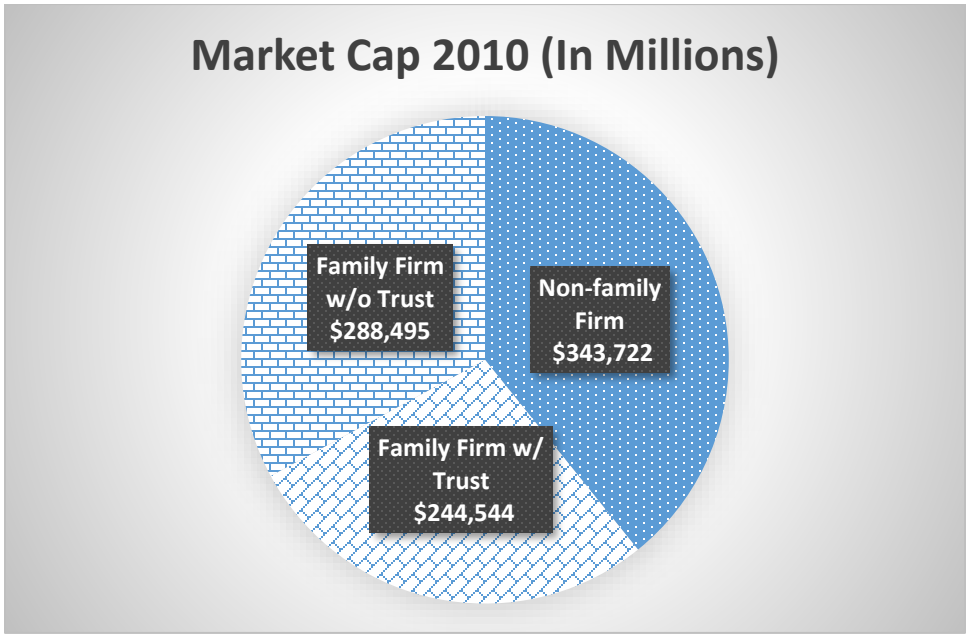
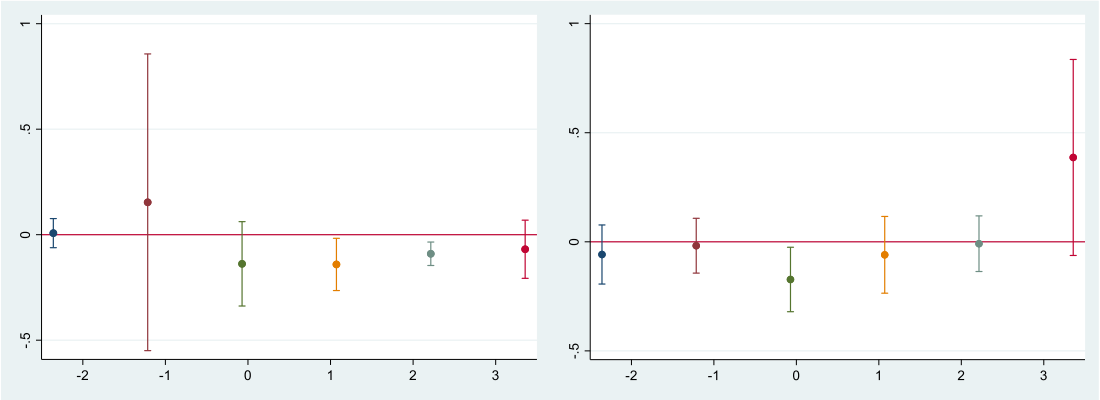


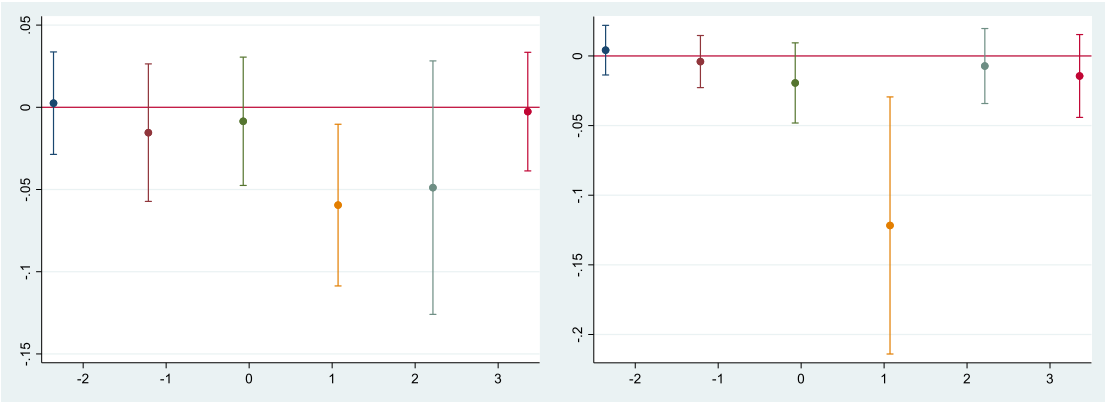
Figure 2:

These figures respectively show the parallel trends of our main tests, including marginal value of CAPX, R&D, abnormal ROA, patent, tsm and tcw models. Specifically, we draw the coefficients on the interaction term between a dummy of the firm being a treatment or a control firm and the trust wedge in a total of six-year window. The X axis shows the 3 years before (including the event year) and 3 years after the law adoption window, whereas the Y axis shows the magnitude of the outcome variables. The coefficient measures the differential effect of trust wedge on CAPX and innovation between the treatment and control firms when the Uniform Trust Code became effective. 95% confidence intervals are shown for each coefficient.

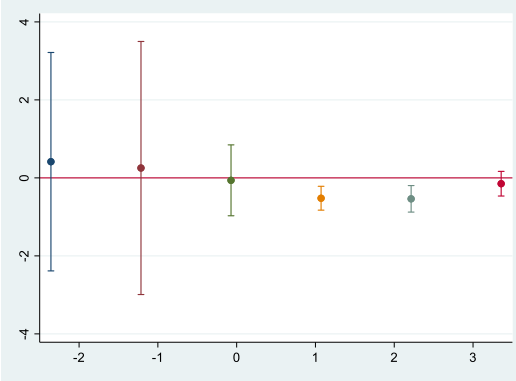
Marginal Value of CAPX (left) and Long Run Stock Return (right)

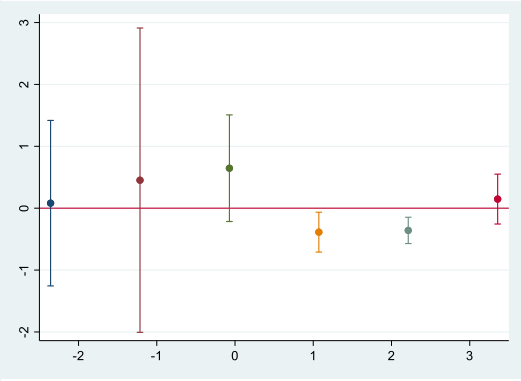


Abnormal ROA (left) and R&D intensity (right)



Patent (left) and TSM (right)





TCW

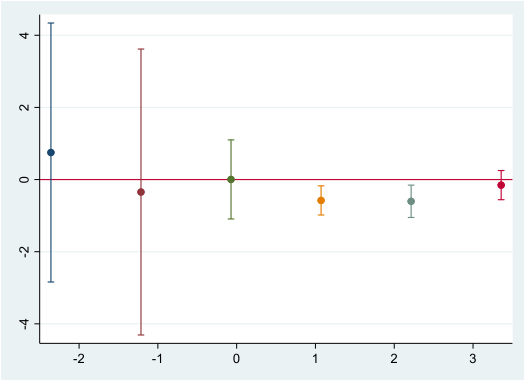


Table 1: Summary Statistics

This table shows summary statistics of several sets of variables, including dual class firm ownership structure, family trust information, excess stock returns, variables for innovation models and marginal value models. The final sample has 1,313 observations that cover 184 unique dual class firms from 1992 to 2010.

	Mean	Std.	Q1	Median	Q3
Dual class firm ownership structure					
Insiders' cash flow rights	0.342	0.122	0.246	0.336	0.478
Insiders' voting rights	0.658	0.122	0.522	0.664	0.754
Dual Class Ratio	2.604	3.449	1.093	1.978	3.062
Family trust information					
Family Trust	0.432	0.496	0.000	0.000	1.000
Family Trust cash flow rights	0.040	0.150	0.000	0.000	0.001
Family Trust voting rights	0.093	0.356	0.000	0.000	0.003
Trust Wedge Ratio	2.857	2.774	1.000	1.843	3.511
Size and B/M adjusted stock returns during the fiscal year					
(r-Rb)	0.024	0.423	-0.216	-0.037	0.192
Variables used for profitability and innovation models					
Number of patents	11.078	61.437	0.000	0.000	1.000
TSM	158.610	943.001	0.000	0.000	0.575
TCW	18.314	97.446	0.000	0.000	1.000
Ln (1+Number of Patents)	0.518	1.144	0.000	0.000	0.000
Ln (1+TSM)	0.907	1.925	0.000	0.000	0.454
Ln(1+TCW)	0.668	1.396	0.000	0.000	0.693
Industry Adjusted ROA	0.030	0.102	-0.003	0.029	0.068
R&D Intensity	0.036	0.251	0.000	0.000	0.008
Herfindahl Index	0.193	0.176	0.086	0.138	0.240
Sales	7693.286	24737.02	670.842	1498.035	3746.3
Debt Rating	0.551	0.498	0.000	1.000	1.000
Change in Profitability	0.149	0.237	0.098	0.149	0.214
Asset Tangibility	0.249	0.187	0.116	0.204	0.341
Ln (Capital to Labor)	3.873	0.999	3.251	3.764	4.467
Leverage	0.233	0.217	0.052	0.181	0.350
Tobin's Q	1.872	1.149	1.157	1.514	2.219
Capex	0.050	0.056	0.022	0.039	0.063
Firm Age	27.515	17.817	13.000	25.000	37.000
Total Assets	11,628	41,490.31	664.16	1,543.61	3,943.54
Family Firm	0.746	0.44	0.00	1.00	1.00
Variables for marginal value models, scaled by the mkt value of equity at t-1					
Cash t-1	0.178	0.654	0.018	0.058	0.168
R&D expenditure t-1	0.015	0.054	0.000	0.000	0.007
Change in cash t	0.025	0.229	-0.013	0.003	0.034
Change in earnings t	0.013	0.772	-0.012	0.007	0.031
Change in Net Assets t	0.045	1.375	-0.019	0.034	0.125
Change in R&D t	0.000	0.013	0.000	0.000	0.000
Change in Interest t	-0.002	0.191	-0.002	0.000	0.003
Change in Dividends t	-0.001	0.028	0.000	0.000	0.001
Net Financing t	0.002	0.190	-0.030	0.000	0.016

Table 2: Annual Stock Return Tests

This table reports regression results of long-run stock return on wedge creating mechanisms. The dependent variable is long run size and B/M adjusted buy and hold stock return. Econometrically, Models (1), (3), (5) and (7) use industry and year fixed effect; Models (2), (4), (6) and (8) use firm and year fixed effect. White heteroscedastic-consistent robust standard errors in parentheses are clustered at firm level (White 1980). Asterisks *, ** and *** indicate the significance levels of 10%, 5% and 1%, respectively.

Dependent Variable	Size and B/M Adjusted Annual Returns							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Trust Wedge Ratio	0.024**	0.042***						
	(0.011)	(0.010)						
Dual Class Ratio			-0.001	0.003				
			(0.002)	(0.008)				
Outside the Trust-Ratio					-0.015**	-0.035***		
					(0.007)	(0.011)		
No Trust Exist-Ratio							0.003	0.003
							(0.002)	(0.006)
Family Firm	-0.516***	-0.299*	-0.450***	-0.358**	-0.490***	-0.367***	-0.475***	-0.212*
	(0.155)	(0.173)	(0.115)	(0.145)	(0.140)	(0.136)	(0.127)	(0.119)
Family Trust	0.057	0.107	0.087	0.076	0.053	0.093	0.085	0.094
	(0.086)	(0.166)	(0.099)	(0.177)	(0.094)	(0.170)	(0.100)	(0.172)
R&D Intensity	-0.064**	-0.097	-0.081***	-0.091	-0.073***	-0.109	-0.077***	-0.053
	(0.027)	(0.085)	(0.029)	(0.086)	(0.028)	(0.083)	(0.028)	(0.092)
HHI	0.071**	0.087	0.064*	0.083	0.063*	0.089	0.063*	0.083
	(0.035)	(0.077)	(0.036)	(0.076)	(0.035)	(0.076)	(0.036)	(0.077)
Firm Sale	0.103	0.350	0.089***	0.298	0.103	0.357	0.084	0.083
	(0.106)	(0.326)	(0.031)	(0.310)	(0.103)	(0.310)	(0.101)	(0.377)
Debt Rating	0.095	-0.173	0.109	-0.163	0.105	-0.136	0.110	-0.193
	(0.110)	(0.433)	(0.108)	(0.481)	(0.107)	(0.475)	(0.110)	(0.432)
Change in Profitability	-0.021	-0.001	-0.023	0.012	-0.023	0.000	-0.023	0.016
	(0.022)	(0.061)	(0.023)	(0.063)	(0.023)	(0.063)	(0.023)	(0.061)
Asset Tangibility	-0.295***	-0.802***	-0.257***	-0.691***	-0.270***	-0.672***	-0.262***	-0.837***
	(0.093)	(0.168)	(0.091)	(0.154)	(0.090)	(0.151)	(0.090)	(0.171)
Capital to Labor	0.101***	0.172***	0.104***	0.243***	0.103***	0.244***	0.103***	0.176***
	(0.026)	(0.052)	(0.026)	(0.048)	(0.026)	(0.047)	(0.026)	(0.053)
Leverage	0.000	-0.000	0.000	-0.000	0.000	-0.000**	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tobin's Q	-0.001	0.000	-0.002	0.002	-0.001	0.001	-0.002	0.001
	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)
Investment (CAPX)	0.043	-0.082	0.065**	-0.065	0.056**	-0.061	0.064**	-0.096
	(0.027)	(0.080)	(0.029)	(0.081)	(0.027)	(0.078)	(0.029)	(0.083)
Firm Age	0.010	-0.082	0.011	-0.087	0.012	-0.081	0.010	-0.088
	(0.033)	(0.061)	(0.033)	(0.061)	(0.033)	(0.061)	(0.033)	(0.066)
Firm Size	-0.047	-0.072	0.026	0.044	-0.023	-0.056	0.014	0.045
	(0.039)	(0.051)	(0.026)	(0.046)	(0.032)	(0.056)	(0.027)	(0.048)
Constant	0.111	1.227**	0.065	0.807	0.114	1.043*	0.053	0.970
	(0.117)	(0.556)	(0.124)	(0.565)	(0.118)	(0.551)	(0.124)	(0.614)
Observations	1,313	1,313	1,313	1,313	1,313	1,313	1,313	1,313
R-squared	0.168	0.320	0.162	0.328	0.166	0.333	0.161	0.313
F statistics	4.636	12.757	4.793	9.746	4.576	12.198	4.656	9.865
Industry	Y	N	Y	N	Y	N	Y	N
Year	Y	Y	Y	Y	Y	Y	Y	Y
Firm	N	Y	N	Y	N	Y	N	Y

Table 3: Abnormal Return on Asset Tests

This table reports regression results of abnormal return on assets on wedge creating mechanisms. The dependent variable is return on assets adjusted by industry median according to Fama French 48 industry categories. Econometrically, Models (1), (3), (5) and (7) use industry and year fixed effect; Models (2), (4), (6) and (8) use firm and year fixed effect. White heteroscedastic-consistent robust standard errors in parentheses are clustered at firm level (White 1980). Asterisks *, ** and *** indicate the significance levels of 10%, 5% and 1%, respectively.

Dependent Variable	Industry Adjusted Return on Asset							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Trust Wedge Ratio	0.004***	0.006***						
	(0.001)	(0.002)						
Dual Class Ratio			-0.001**	-0.011**				
			(0.001)	(0.005)				
Outside the Trust-Ratio					-0.002**	-0.005*		
					(0.001)	(0.003)		
No Trust Exist-Ratio							-0.003**	-0.004*
							(0.001)	(0.002)
Family Firm	-0.356***	-0.186***	-0.325***	-0.182***	-0.324***	-0.182***	-0.322***	-0.141***
	(0.070)	(0.029)	(0.081)	(0.031)	(0.081)	(0.031)	(0.085)	(0.017)
Family Trust	-0.023	0.015	-0.029*	0.020	-0.031*	0.018	-0.023	0.020
	(0.016)	(0.040)	(0.015)	(0.040)	(0.016)	(0.040)	(0.017)	(0.040)
R&D Intensity	0.002	0.034***	0.010	0.035***	0.009	0.035***	0.010	0.053***
	(0.008)	(0.011)	(0.008)	(0.011)	(0.008)	(0.011)	(0.009)	(0.016)
HHI	0.001	0.017	0.001	0.017	0.001	0.017	0.001	0.016
	(0.008)	(0.011)	(0.008)	(0.012)	(0.008)	(0.012)	(0.008)	(0.011)
Firm Sale	0.063**	0.175**	0.198***	0.177**	0.198***	0.177**	0.192***	0.137
	(0.029)	(0.081)	(0.053)	(0.085)	(0.053)	(0.085)	(0.053)	(0.090)
Debt Rating	0.061***	0.022	0.044**	0.011	0.042**	0.015	0.040**	0.002
	(0.021)	(0.061)	(0.020)	(0.063)	(0.021)	(0.063)	(0.020)	(0.065)
Change in Profitability	-0.004	0.010	-0.004	0.009	-0.003	0.009	-0.002	0.013
	(0.004)	(0.010)	(0.004)	(0.010)	(0.004)	(0.010)	(0.004)	(0.010)
Asset Tangibility	-0.099***	-0.079**	-0.100***	-0.091***	-0.097***	-0.090***	-0.093***	-0.096***
	(0.017)	(0.031)	(0.016)	(0.030)	(0.016)	(0.031)	(0.016)	(0.031)
Capital to Labor	0.022***	0.023***	0.019***	0.016***	0.019***	0.016***	0.018***	0.017***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)
Leverage	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tobin's Q	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.001
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Investment (CAPX)	0.004	-0.048***	-0.005	-0.050***	-0.004	-0.049***	-0.006	-0.060***
	(0.008)	(0.014)	(0.009)	(0.015)	(0.009)	(0.015)	(0.009)	(0.018)
Firm Age	0.012	0.019*	0.010	0.019*	0.011	0.019*	0.012	0.016
	(0.009)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Firm Size	-0.017***	-0.016*	-0.028***	-0.032**	-0.018***	-0.018*	-0.012	-0.041**
	(0.007)	(0.010)	(0.008)	(0.013)	(0.007)	(0.010)	(0.007)	(0.016)
Constant	-0.048	0.030	-0.046	0.044	-0.051	0.039	-0.057*	-0.019
	(0.031)	(0.106)	(0.032)	(0.106)	(0.031)	(0.107)	(0.030)	(0.094)
Observations	1,313	1,313	1,313	1,313	1,313	1,313	1,313	1,313
R-squared	0.391	0.579	0.413	0.578	0.412	0.577	0.410	0.571
F statistics	19.260	9.248	15.385	9.866	15.046	9.045	16.579	8.740
Industry	Y	N	Y	N	Y	N	Y	N
Year	Y	Y	Y	Y	Y	Y	Y	Y
Firm	N	Y	N	Y	N	Y	N	Y

Table 4: Marginal Value of CAPX Tests

This table reports regression results for marginal value of CAPX models. Econometrically, Models (1), (3), (5) and (7) use industry and year fixed effect; Models (2), (4), (6) and (8) use firm and year fixed effect. White heteroscedastic-consistent robust standard errors in parentheses are clustered at firm level (White 1980). Asterisks *, ** and *** indicate the significance levels of 10%, 5% and 1%, respectively.

Dependent Variable	Size and B/M Adjusted Annual Returns							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Trust Wedge Ratio * Change in CAPX	0.370**	0.412***						
	(0.150)	(0.132)						
Dual Class Ratio * Change in CAPX			-0.268*	-0.518*				
			(0.140)	(0.302)				
Outside the Trust-Ratio * Change in CAPX					-0.354**	-0.442***		
					(0.152)	(0.141)		
No Trust Exist-Ratio * Change in CAPX							-0.403**	-0.419*
							(0.166)	(0.224)
Trust Wedge	0.011***	0.008			-0.006	0.000		
	(0.004)	(0.008)			(0.005)	(0.011)		
Dual Class Ratio	-0.001	-0.000	0.003	0.016	0.001	-0.000	-0.006	-0.005
	(0.002)	(0.008)	(0.006)	(0.015)	(0.003)	(0.008)	(0.004)	(0.012)
Change in CAPX	0.617**	0.868***	-0.191	-0.389	0.535**	0.820***	-0.174	-0.184
	(0.269)	(0.273)	(0.370)	(0.739)	(0.263)	(0.270)	(0.359)	(0.410)
CAPX tm1	0.815***	1.796***	0.572**	0.997***	0.824***	1.810***	0.553**	0.730**
	(0.307)	(0.564)	(0.236)	(0.332)	(0.310)	(0.563)	(0.236)	(0.304)
Leverage	-0.692***	-1.403***	-0.624***	-1.356***	-0.677***	-1.407***	-0.626***	-1.327***
	(0.090)	(0.159)	(0.086)	(0.157)	(0.092)	(0.160)	(0.085)	(0.147)
Change in Earnings	0.382***	0.305***	0.798***	0.723***	0.382***	0.302***	0.801***	0.335***
	(0.071)	(0.072)	(0.129)	(0.121)	(0.071)	(0.072)	(0.129)	(0.070)
Change in Net Assets	0.124***	0.103**	0.103**	0.068	0.123***	0.101**	0.104**	0.115**
	(0.047)	(0.050)	(0.051)	(0.056)	(0.047)	(0.050)	(0.051)	(0.052)
Change in R&D	-4.906**	-4.776*	-4.554*	-5.426*	-4.821**	-4.800*	-4.604*	-4.705***
	(2.296)	(2.692)	(2.711)	(3.217)	(2.369)	(2.751)	(2.698)	(0.895)
Change in Interest	-1.785	-1.332	-1.566	-0.845	-1.902	-1.418	-1.480	-1.139
	(1.145)	(1.163)	(1.311)	(2.247)	(1.159)	(1.180)	(1.338)	(2.314)
Change in Dividends	1.189	1.114	0.724	0.069	1.195	1.107	0.745	0.790
	(0.786)	(0.761)	(2.301)	(0.455)	(0.790)	(0.758)	(2.310)	(0.654)
Net Financing	-0.042	-0.055	-0.059	-0.064	-0.046	-0.056	-0.056	-0.033
	(0.042)	(0.042)	(0.047)	(0.046)	(0.042)	(0.042)	(0.047)	(0.041)
Constant	0.097***	0.201***	0.098***	0.210***	0.102***	0.211***	0.115***	0.267***
	(0.023)	(0.048)	(0.026)	(0.057)	(0.023)	(0.045)	(0.022)	(0.037)
Observations	1,313	1,313	1,313	1,313	1,313	1,313	1,313	1,313
R-squared	0.234	0.359	0.235	0.356	0.231	0.359	0.236	0.350
F statistics	13.408	16.967	19.732	23.422	12.884	14.998	19.610	35.041
Industry	Y	N	Y	N	Y	N	Y	N
Year	Y	Y	Y	Y	Y	Y	Y	Y
Firm	N	Y	N	Y	N	Y	N	Y

Table 5: R&D Tests

This table reports regression results of R&D intensity on wedge creating mechanisms. The dependent variable is R&D expenditure scaled by sales. Econometrically, Models (1), (3), (5) and (7) use industry and year fixed effect; Models (2), (4), (6) and (8) use firm and year fixed effect. White heteroscedastic-consistent robust standard errors in parentheses are clustered at firm level (White 1980). Asterisks *, ** and *** indicate the significance levels of 10%, 5% and 1%, respectively.

Dependent Variable	R&D expenditure scaled by sales							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Trust Wedge Ratio	0.030**	0.001**						
	(0.015)	(0.000)						
Dual Class Ratio			-0.015*	-0.000**				
			(0.008)	(0.000)				
Outside the Trust-Ratio					-0.017*	-0.000**		
					(0.009)	(0.000)		
No Trust Exist-Ratio							-0.002*	-0.005**
							(0.001)	(0.002)
Family Firm	-0.016	-0.010	-0.006	-0.003	-0.005	-0.003	-0.005	0.029
	(0.031)	(0.006)	(0.028)	(0.004)	(0.032)	(0.004)	(0.005)	(0.027)
Family Trust	-0.086	-0.012	-0.178**	-0.003	-0.184*	-0.003*	-0.003	0.072
	(0.059)	(0.009)	(0.081)	(0.002)	(0.105)	(0.001)	(0.002)	(0.054)
HHI	-0.019	0.001	-0.031	0.003	-0.021	0.003	-0.003	-0.014
	(0.019)	(0.004)	(0.021)	(0.002)	(0.020)	(0.002)	(0.002)	(0.010)
Firm Sale	-0.886**	-0.010	-0.993**	0.003	-0.999**	0.003	-0.021**	-0.865***
	(0.383)	(0.007)	(0.450)	(0.004)	(0.447)	(0.006)	(0.010)	(0.095)
Debt Rating	0.037	0.020	0.015	0.000	0.130	0.001	-0.004	-0.085*
	(0.084)	(0.019)	(0.049)	(0.005)	(0.120)	(0.004)	(0.006)	(0.050)
Change in Profitability	0.011	-0.004	-0.000	-0.000*	-0.011	-0.001	0.000	0.000**
	(0.014)	(0.003)	(0.000)	(0.000)	(0.025)	(0.001)	(0.000)	(0.000)
Asset Tangibility	-0.085**	-0.026**	0.040	0.000	-0.045	-0.000	0.000	-0.037
	(0.038)	(0.013)	(0.052)	(0.002)	(0.040)	(0.002)	(0.005)	(0.034)
Capital to Labor	0.044**	-0.008	0.090**	0.000	0.061**	0.000	0.007***	0.028***
	(0.017)	(0.006)	(0.035)	(0.000)	(0.027)	(0.000)	(0.001)	(0.006)
Leverage	0.000***	0.000	0.323	0.004	0.000**	-0.000	0.012	0.090**
	(0.000)	(0.000)	(0.229)	(0.004)	(0.000)	(0.000)	(0.013)	(0.043)
Tobin's Q	-0.001*	-0.000	-0.001	0.000	-0.001*	0.000	-0.000	0.000
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Investment (CAPX)	0.074	0.008	0.168**	0.001*	0.163*	0.001	0.004**	-0.002
	(0.055)	(0.010)	(0.076)	(0.001)	(0.097)	(0.001)	(0.002)	(0.034)
Firm Age	-0.014	-0.004*	-0.010	-0.003**	-0.007	-0.003**	0.001	-0.028
	(0.018)	(0.002)	(0.017)	(0.001)	(0.019)	(0.001)	(0.002)	(0.021)
Firm Size	-0.024	0.006***	0.026	0.002**	0.019	0.003***	0.000	0.022*
	(0.021)	(0.002)	(0.024)	(0.001)	(0.020)	(0.001)	(0.003)	(0.012)
Constant	0.191**	0.090**	0.133**	0.018*	0.320*	0.022***	-0.007	-0.407**
	(0.097)	(0.045)	(0.058)	(0.009)	(0.172)	(0.008)	(0.009)	(0.185)
Observations	1,313	1,313	1,313	1,313	1,313	1,313	1,313	1,313
R-squared	0.515	0.976	0.490	0.969	0.471	0.969	0.708	0.963
F statistics	1.929	1.656	1.938	0.953	1.224	0.981	2.216	8.839
Industry	Y	N	Y	N	Y	N	Y	N
Year	Y	Y	Y	Y	Y	Y	Y	Y
Firm	N	Y	N	Y	N	Y	N	Y

Table 6: Patent Tests

This table reports regression results of number of patents on wedge creating mechanisms. The dependent variable is log-transformed number of patents. Econometrically, Models (1), (3), (5) and (7) use industry and year fixed effect; Models (2), (4), (6) and (8) use firm and year fixed effect. White heteroscedastic-consistent robust standard errors in parentheses are clustered at firm level (White 1980). Asterisks *, ** and *** indicate the significance levels of 10%, 5% and 1%, respectively.

Dependent Variable	Ln (1+Number of Patents)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Trust Wedge Ratio	0.178**	0.038*						
	(0.089)	(0.023)						
Dual Class Ratio			-0.087***	-0.105*				
			(0.030)	(0.060)				
Outside the Trust-Ratio					-0.155***	-0.038*		
					(0.055)	(0.021)		
No Trust Exist-Ratio							-0.141**	-0.048*
							(0.055)	(0.027)
Family Firm	0.240*	-0.012	0.292*	0.022	0.254*	-0.003	0.300**	-0.009
	(0.144)	(0.035)	(0.151)	(0.038)	(0.137)	(0.036)	(0.151)	(0.033)
Family Trust	-0.528**	-0.078	-0.093	-0.014	-0.485***	-0.087	-0.408**	-0.104
	(0.229)	(0.078)	(0.136)	(0.061)	(0.176)	(0.081)	(0.181)	(0.094)
R&D Intensity	0.138***	0.043	0.129***	0.012	0.149***	0.045	0.131***	0.046
	(0.037)	(0.033)	(0.037)	(0.051)	(0.035)	(0.034)	(0.037)	(0.033)
HHI	1.056	0.114	1.132**	-0.047	0.765	0.146	1.202**	0.151
	(0.853)	(0.405)	(0.464)	(0.635)	(0.814)	(0.598)	(0.463)	(0.272)
Firm Sale	0.359*	-0.006	0.068	0.066	0.300*	0.007	0.083	0.071
	(0.184)	(0.073)	(0.117)	(0.085)	(0.164)	(0.072)	(0.113)	(0.087)
Debt Rating	-0.357**	-0.027	-0.344**	-0.029	-0.426**	-0.018	-0.341**	-0.013
	(0.174)	(0.092)	(0.139)	(0.105)	(0.175)	(0.094)	(0.137)	(0.096)
Change in Profitability	-0.100	-0.024	-0.286	-0.028	-0.105	-0.030	-0.306*	-0.457**
	(0.096)	(0.026)	(0.181)	(0.023)	(0.094)	(0.027)	(0.180)	(0.195)
Asset Tangibility	-0.200	-0.479	0.156	-0.754	-0.125	-0.393	0.210	-0.505
	(0.577)	(0.523)	(0.402)	(0.688)	(0.573)	(0.497)	(0.400)	(0.524)
Capital to Labor	0.126	0.047	0.016	0.068	0.104	0.045	0.004	0.061
	(0.111)	(0.052)	(0.076)	(0.062)	(0.106)	(0.046)	(0.073)	(0.048)
Leverage	0.185	-0.252	0.193	-0.241	0.355	-0.246	0.182	-0.292
	(0.367)	(0.186)	(0.333)	(0.211)	(0.373)	(0.183)	(0.331)	(0.182)
Tobin's Q	0.122	-0.015	0.128*	-0.026	0.135*	-0.023	0.123*	-0.018
	(0.085)	(0.016)	(0.067)	(0.026)	(0.079)	(0.024)	(0.066)	(0.025)
Investment (CAPX)	-0.001	0.000	0.001	-0.000	-0.001	-0.000	0.001	-0.000
	(0.001)	(0.000)	(0.002)	(0.000)	(0.001)	(0.000)	(0.002)	(0.000)
Firm Age	0.012***	0.101	0.007	0.002	0.014***	0.000	0.006	0.001
	(0.004)	(0.099)	(0.006)	(0.003)	(0.004)	(0.002)	(0.006)	(0.002)
Firm Size	0.052	0.110	0.261**	0.062	0.134	0.090	0.231*	0.051
	(0.142)	(0.102)	(0.130)	(0.133)	(0.127)	(0.106)	(0.119)	(0.106)
Constant	-3.981***	-0.741	-2.776***	-0.247	-3.780***	-0.263	-2.525***	-0.412
	(0.956)	(0.914)	(0.725)	(0.756)	(0.862)	(0.638)	(0.675)	(0.692)
Observations	1,313	1,313	1,313	1,313	1,313	1,313	1,313	1,313
R-squared	0.468	0.845	0.479	0.882	0.488	0.845	0.478	0.846
F statistics	3.330	1.004	3.207	1.020	3.651	0.975	3.326	1.611
Industry	Y	N	Y	N	Y	N	Y	N
Year	Y	Y	Y	Y	Y	Y	Y	Y
Firm	N	Y	N	Y	N	Y	N	Y

Table 7: TCW Tests

This table reports regression results of citation–weighted patents (tcw) on wedge creating mechanisms. The dependent variable is TCW in log transformed form, which has adjusted for citation truncation lags. Econometrically, Models (1), (3), (5) and (7) use industry and year fixed effect; Models (2), (4), (6) and (8) use firm and year fixed effect. White heteroscedastic-consistent robust standard errors in parentheses are clustered at firm level (White 1980). Asterisks *, ** and *** indicate the significance levels of 10%, 5% and 1%, respectively.

Dependent Variable	Ln(1+TCW)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Trust Wedge Ratio	0.219**	0.276**						
	(0.103)	(0.130)						
Dual Class Ratio			-0.102***	-0.138**				
			(0.036)	(0.065)				
Outside the Trust-Ratio					-0.239***	-0.068*		
					(0.088)	(0.041)		
No Trust Exist-Ratio							-0.108***	-0.056*
							(0.041)	(0.032)
Family Firm	0.291	-0.023	0.345*	-0.020	0.333*	-0.042	0.370	0.045
	(0.181)	(0.082)	(0.187)	(0.081)	(0.186)	(0.080)	(0.243)	(0.095)
Family Trust	-0.695**	0.028	-0.155	0.032	-0.403**	-0.082	-0.825***	-0.125
	(0.273)	(0.085)	(0.167)	(0.085)	(0.192)	(0.123)	(0.294)	(0.143)
R&D Intensity	0.175***	0.015	0.166***	0.019	0.169***	0.049	0.259***	0.069
	(0.047)	(0.064)	(0.048)	(0.052)	(0.050)	(0.043)	(0.064)	(0.056)
HHI	1.514	-0.009	1.457***	-0.169	1.550***	-0.037	1.627	0.733
	(1.055)	(0.431)	(0.548)	(0.689)	(0.555)	(0.256)	(1.325)	(0.989)
Firm Sale	0.438**	0.028	0.132	-0.014	0.137	-0.043	0.585**	0.112
	(0.212)	(0.093)	(0.149)	(0.099)	(0.144)	(0.119)	(0.259)	(0.145)
Debt Rating	-0.376*	0.068	-0.364**	0.062	-0.359**	0.083	-0.540**	0.051
	(0.203)	(0.128)	(0.167)	(0.131)	(0.165)	(0.130)	(0.255)	(0.220)
Change in Profitability	-0.133	-0.024	-0.356	-0.022	-0.373*	-0.007	-0.179	-0.022
	(0.121)	(0.033)	(0.226)	(0.032)	(0.223)	(0.062)	(0.202)	(0.057)
Asset Tangibility	-0.123	-0.566	0.234	-0.390	0.306	-0.193	0.192	-0.680
	(0.694)	(0.705)	(0.519)	(0.675)	(0.510)	(0.589)	(0.983)	(0.767)
Capital to Labor	0.144	0.090	0.034	0.072	0.018	0.047	0.082	0.111
	(0.133)	(0.069)	(0.097)	(0.061)	(0.095)	(0.054)	(0.174)	(0.080)
Leverage	0.038	-0.504**	0.068	-0.520**	0.027	-0.532**	0.453	-0.522*
	(0.429)	(0.245)	(0.395)	(0.242)	(0.394)	(0.217)	(0.537)	(0.310)
Tobin's Q	0.150	-0.028	0.153*	-0.040	0.151*	-0.026	0.332**	0.008
	(0.102)	(0.023)	(0.080)	(0.033)	(0.080)	(0.023)	(0.130)	(0.051)
Investment (CAPX)	-0.001	-0.000*	0.001	-0.000	0.001	-0.000	-0.002	-0.000**
	(0.001)	(0.000)	(0.002)	(0.000)	(0.002)	(0.000)	(0.001)	(0.000)
Firm Age	0.016***	0.100	0.010	0.000	0.010	-0.000	0.026***	0.003
	(0.005)	(0.146)	(0.007)	(0.004)	(0.007)	(0.004)	(0.007)	(0.005)
Firm Size	0.050	0.060	0.265	0.110	0.258*	0.108	0.212	0.136
	(0.170)	(0.145)	(0.160)	(0.158)	(0.154)	(0.150)	(0.224)	(0.180)
Constant	-4.781***	-0.125	-3.434***	0.225	-3.350***	0.195	-7.000***	-1.444
	(1.109)	(1.328)	(0.869)	(0.971)	(0.857)	(0.953)	(1.368)	(1.084)
Observations	1,313	1,313	1,313	1,313	1,313	1,313	1,313	1,313
R-squared	0.464	0.881	0.469	0.881	0.466	0.843	0.492	0.843
F statistics	3.420	1.155	3.115	1.099	3.140	1.391	4.031	0.870
Industry	Y	N	Y	N	Y	N	Y	N
Year	Y	Y	Y	Y	Y	Y	Y	Y
Firm	N	Y	N	Y	N	Y	N	Y

Table 8: TSM Tests

This table reports regression results of stock market return weighted patents (tsm) on wedge creating mechanisms. The dependent variable is TSM in log transformed form, which measures the total dollar value of patents issued to a given firm in year t based on stock market reaction in the [0, +2] window. Econometrically, Models (1), (3), (5) and (7) use industry and year fixed effect; Models (2), (4), (6) and (8) use firm and year fixed effect. White heteroscedastic-consistent robust standard errors in parentheses are clustered at firm level (White 1980). Asterisks *, ** and *** indicate the significance levels of 10%, 5% and 1%, respectively.

Dependent Variable	Ln(1+TSM)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Trust Wedge Ratio	0.293**	0.106*						
	(0.139)	(0.064)						
Dual Class Ratio			-0.126**	-0.187*				
			(0.050)	(0.096)				
Outside the Trust-Ratio					-0.239***	-0.070*		
					(0.088)	(0.041)		
No Trust Exist-Ratio							-0.224**	-0.091*
							(0.099)	(0.051)
Family Firm	0.349	0.012	0.420	0.055	0.370	0.055	0.432*	0.025
	(0.252)	(0.064)	(0.256)	(0.097)	(0.243)	(0.092)	(0.256)	(0.087)
Family Trust	-0.941**	-0.228	-0.221	0.028	-0.825***	-0.140	-0.720**	-0.171
	(0.379)	(0.191)	(0.232)	(0.117)	(0.294)	(0.146)	(0.313)	(0.176)
R&D Intensity	0.241***	0.139	0.226***	0.047	0.259***	0.071	0.230***	0.051
	(0.066)	(0.092)	(0.069)	(0.066)	(0.064)	(0.056)	(0.070)	(0.063)
HHI	2.062	0.397	2.026***	0.469	1.627	0.397	2.124***	0.870
	(1.398)	(0.422)	(0.712)	(0.961)	(1.325)	(0.420)	(0.709)	(0.631)
Firm Sale	0.681**	0.198	0.337	0.125	0.585**	0.133	0.353	0.292
	(0.280)	(0.127)	(0.223)	(0.149)	(0.259)	(0.160)	(0.215)	(0.180)
Debt Rating	-0.435*	0.030	-0.412*	0.012	-0.540**	0.055	-0.416*	0.049
	(0.256)	(0.206)	(0.213)	(0.223)	(0.255)	(0.220)	(0.212)	(0.224)
Change in Profitability	-0.174	0.007	-0.595*	-0.047	-0.179	-0.026	-0.621*	-1.127***
	(0.203)	(0.061)	(0.330)	(0.075)	(0.202)	(0.064)	(0.325)	(0.419)
Asset Tangibility	0.072	-1.566*	0.460	-0.959	0.192	-0.803	0.557	-1.161
	(0.964)	(0.902)	(0.778)	(0.915)	(0.983)	(0.819)	(0.778)	(0.956)
Capital to Labor	0.115	0.184**	0.004	0.132	0.082	0.120	-0.018	0.179*
	(0.178)	(0.089)	(0.138)	(0.089)	(0.174)	(0.082)	(0.132)	(0.096)
Leverage	0.169	-0.446	0.157	-0.584*	0.453	-0.533*	0.148	-0.700**
	(0.548)	(0.321)	(0.500)	(0.337)	(0.537)	(0.302)	(0.493)	(0.335)
Tobin's Q	0.312**	0.001	0.287**	-0.001	0.332**	0.002	0.280**	0.014
	(0.138)	(0.050)	(0.113)	(0.052)	(0.130)	(0.032)	(0.111)	(0.034)
Investment (CAPX)	-0.001	-0.000	0.001	-0.000	-0.002	-0.000**	0.002	-0.000
	(0.001)	(0.003)	(0.003)	(0.000)	(0.001)	(0.000)	(0.003)	(0.000)
Firm Age	0.024***	0.314	0.017*	0.005	0.026***	0.003	0.016	0.006
	(0.007)	(0.224)	(0.010)	(0.005)	(0.007)	(0.005)	(0.010)	(0.005)
Firm Size	0.082	0.160	0.302	0.162	0.212	0.101	0.268	0.073
	(0.238)	(0.284)	(0.232)	(0.195)	(0.224)	(0.184)	(0.214)	(0.194)
Constant	-7.295***	-2.260	-5.556***	-1.351	-7.000***	-1.270	-5.159***	-2.219*
	(1.496)	(1.555)	(1.223)	(1.149)	(1.368)	(1.025)	(1.143)	(1.274)
Observations	1,313	1,313	1,313	1,313	1,313	1,313	1,313	1,313
R-squared	0.478	0.823	0.479	0.879	0.492	0.843	0.480	0.880
F statistics	3.902	1.039	3.471	1.097	4.031	1.030	3.659	1.455
Industry	Y	N	Y	N	Y	N	Y	N
Year	Y	Y	Y	Y	Y	Y	Y	Y
Firm	N	Y	N	Y	N	Y	N	Y

Table 9: Natural Experiment

Panel A reports the states that have adopted the Uniform Trust Code (UTC) as well as effective date, statutory citation and law code with data obtained at: Source: http://dccode.elaws.us/code?no=19-13. We define a firm to be a treatment if it is headquartered in the state that has adopted the law. Panel B shows the 5-day cumulative abnormal returns around the Uniform Trust Code's effective date for firms incorporated in the adopting states. We use Fama French 3 factor model as the benchmark model. We divide the firms into family firm and non-family firm, as well as firms with a family trust and firms without a family trust. Then we test the significance of difference in means and medians. Panel C presents the DiD regression results.

Panel A

Jurisdiction	Laws	Effective Date	Statutory Citation
Alabama	2006, c. 216	1/1/2007	Code 1975, §§ 19-3B-101 to 19-3B-1305.
Arizona	2008, c. 247	1/1/2009	A.R.S. §§ 14-10101 to 14-11102.
Arkansas	2005, c. 1031	8/12/2005	A.C.A. §§ 28-73-101 to 28-73-1105.
District of Columbia	2004, c. 15-104	3/10/2004	D.C. Official Code, 2001 Ed. §§ 19-1301.01 to 19-1311.03.
Florida [FN1]	2006, c. 217	7/1/2007	West's F.S.A. §§ 736.0101 to 736.1303.
Kansas	2002, c. 133	1/1/2003	K.S.A. 58a-101 to 58a-1107.
Maine	2004, c. 618	7/1/2005	18-B M.R.S.A. §§ 101 to 1104.
Michigan	2009, No. 46	4/1/2010	M.C.L.A. §§ 700.7101 to 700.8206.
Missouri	2004, H.B. No. 1511	1/1/2005	V.A.M.S. §§ 456.1-101 to 456.11-1106.
Nebraska [FN2]	2003, LB 130	1/1/2005	R.R.S. 1943, §§ 30-3801 to 30-38,110.
New Hampshire	2004, c. 130	10/1/2004	RSA 564-B:1-101 to 564-B:12-1205.
New Mexico	2003, c. 122	7/1/2003	NMSA 1978, §§ 46A-1-101 to 46A-11-1105.
North Carolina	2005, c. 192	1/1/2006	G.S. §§ 36C-1-101 to 36C-11-1104.
North Dakota	2007, c. 549	8/1/2007	NDCC 59-09-01 to 59-19-02.
Ohio	2006, H.B. 416	1/1/2007	R.C. §§ 5801.01 to 5811.03.
Oregon	2005, c. 348	6-29-2005 [FN*]	ORS 130.001 to 130.910.
Pennsylvania	2006, c. 98	11/6/2006	20 Pa.C.S.A. §§ 7701 to 7799.3.
South Carolina	2005, c. 66	1/1/2006	Code 1976, §§ 62-7-101 to 62-7-1106.
Tennessee	2004, c. 537	7/1/2004	T.C.A. §§ 35-15-101 to 35-15-1103.
Utah	2004, c. 89	7/1/2004	U.C.A. 1953, 75-7-101 to 75-7-1201.
Vermont	2009, P.A. 20	7/1/2009	14A V.S.A. §§ 101 to 1204.
Virginia	2005, c. 935	7/1/2006	Code 1950, §§ 55-541.01 to 55-551.06.
West Virginia	2011, c. 66	6/10/2011	W. Va. Code §§ 44D-1-101 to 44D-11-1105.
Wyoming	2003, c. 124	7/1/2003	Wyo.Stat.Ann. §§ 4-10-101 to 4-10-1103.

[FN*] Approval date.

[FN1] Enacts the Uniform Trust Code and repeals the Uniform Trustees' Powers Act effective July 1, 2007.

[FN2] Repealed the Uniform Prudent Investor Act (R.R.S. 1943, §§ 8-2201 to 8-2213) and the Uniform Trustees' Powers Act (R.R.S. 1943, §§ 30-2819 to 30-2826), and enacted the Uniform Trust Code (R.R.S. 1943, §§ 30-3801 to 30-38,110) by L.2003, LB 130, operative January 1, 2005.

Panel B:

This table compares the average [-2, 2] Cumulative Abnormal Return (CAR) difference around the day when the Uniform Trust Code took effect for the non-family firm, family firm as well as family firm with or without trust that are headquartered in the affected states. There is a total of *73* firms affected by this law, in which there are *43* family firms and *30* non-family firms. Among the family firms, *19* firms have a family trust while *24* family firms don't have family trust.

Differences in CARs before and after the Uniform Trust Code Became Effective

		Non-Family Firm	Family Firm	Difference	P value
Difference in means test	Mean [-2,2] CAR	1.28%	-2.50%	3.78%***	0.00
Wilcoxon Median Test	Median [-2,2] CAR	0.30%	-2.80%	3.10%***	0.00
		Non-Family Firm	Family Firm w/ Trust	Difference	P value
Difference in means test	Mean [-2,2] CAR	1.28%	-4.09%	5.37%***	0.01
Wilcoxon Median Test	Median [-2,2] CAR	0.30%	-3.81%	3.82%***	0.00
		Family Firm w/ Trust	Family Firm w/o Trust	Difference	P value
Difference in means test	Mean [-2,2] CAR	-4.09%	-0.44%	-4.1%***	0.00
Wilcoxon Median Test	Median [-2,2] CAR	-3.81%	-0.76%	-3.05%**	0.04

Panel C:

This table shows the Difference in Difference (DiD) experiment for marginal value of CAPX, R&D/Sales, Abnormal ROA, Patent, TSM and TCW models. Only DiD coefficients are reported to save space. Models (1) and (2) include all the variables that support the four-way interaction term as well as all the standard controls used in Table 2. The coefficient of four-way interaction term compares the change of Family Trust Wedge's marginal value of CAPX before and after the Uniform Trust Code's passage between adopting states and non-adopting states. Similarly, Models (3) to (12) include all the variables that support the three-way interaction and standard controls used in table 3 to 7. The coefficient of three-way interaction compares the change in innovation outputs before and after the code's passage between the adopting states and non-adopting states. Econometrically, each block of coefficients represents two fixed effects, including industry, year fixed effect, as well as firm and year fixed effect. White heteroscedastic-consistent robust standard errors in parentheses are clustered at firm level (White 1980). Asterisks *, ** and *** indicate the significance levels of 10%, 5% and 1%, respectively.

Dependent Variable	Annual Excess Returns		LR Stock Return		R&D/Sales		Abnormal ROA		Ln(1+Patent)		Ln(1+TSM)		Ln(1+TCW)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Trust Wedge Ratio * Change in CAPX * After * Treatment	-1.32**	-1.213*												
	(0.441)	(0.429)												
Trust Wedge Ratio * After * Treatment			-0.034*	-0.35*	-0.01	-0.08*	-0.05	-0.07*	-0.322*	-0.148*	-0.47*	-0.17*	-0.47*	-0.17*
			(0.013)	(0.014)	(0.06)	(0.004)	(0.03)	(0.004)	(0.117)	(0.052)	(0.185)	(0.066)	(0.185)	(0.066)
Interaction Terms	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1,313	1,313	1,313	1,313	1,313	1,313	1,313	1,313	1,313	1,313	1,313	1,313	1,313	1,313
R-squared	0.252	0.373	0.186	0.361	0.667	0.960	0.526	0.688	0.493	0.886	0.491	0.880	0.491	0.880
F statistics	17.862	27.193	6.286	14.943	1.198	7.628	25.03	17.162	2.903	1.337	4.134	1.358	4.134	1.358
Industry	Y	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y	N
Year	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y

Table 10: Family Trust in single class sample

This table reports regression results for family trust on various outcome variables. The dependent variables are stock return, ROA, R&D intensity, patent, TSM and TCW while the independent variables are trust wedge and family trust. Note that in the single class firm, trust wedge is 1. All models use industry and year fixed effects. White heteroscedastic-consistent robust standard errors in parentheses are clustered at firm level (White 1980). Asterisks *, ** and *** indicate the significance levels of 10%, 5% and 1%, respectively.

Dependent Variables	(1) R/D Intensity	(2) Patent	(3) Tsm	(4) Tcw	(5) ROA	(6) Stock Return	(7) R/D Intensity	(8) Patent	(9) Tsm	(10) Tcw	(11) ROA	(12) Stock Return
Trust Holding							-0.004	0.031***	0.043**	0.035***	0.001*	0.001*
							(0.005)	(0.012)	(0.018)	(0.013)	(0.001)	(0.000)
Family Trust	0.003	-0.108***	-0.151***	-0.129***	-0.001	-0.003	0.053	-0.156***	-0.217***	-0.183***	-0.003	-0.005**
	(0.002)	(0.037)	(0.057)	(0.045)	(0.002)	(0.002)	(0.056)	(0.037)	(0.056)	(0.045)	(0.002)	(0.002)
Family Firm	0.000	-0.013	0.074	-0.009	0.001	0.002	-0.010	-0.015	0.072	-0.012	0.001	0.001
	(0.002)	(0.044)	(0.066)	(0.051)	(0.002)	(0.002)	(0.020)	(0.043)	(0.065)	(0.051)	(0.002)	(0.002)
R/D Intensity		3.634***	4.632***	4.718***	-0.449***	-0.065***		5.331***	6.963***	6.963***	-0.449***	-0.064***
		(0.381)	(0.536)	(0.493)	(0.026)	(0.018)		(0.365)	(0.502)	(0.447)	(0.026)	(0.018)
HHI	-0.026***	-0.058	-0.098	-0.070	-0.016***	-0.009	0.014	-0.027	-0.054	-0.029	-0.016***	-0.009
	(0.005)	(0.119)	(0.178)	(0.141)	(0.005)	(0.005)	(0.060)	(0.117)	(0.176)	(0.138)	(0.005)	(0.005)
Sales	-0.024***	0.139***	0.217***	0.145***	0.019***	-0.003**	0.160	0.139***	0.219***	0.146***	0.019***	-0.003**
	(0.002)	(0.025)	(0.040)	(0.029)	(0.002)	(0.002)	(0.125)	(0.024)	(0.039)	(0.029)	(0.002)	(0.002)
S&P Rating	-0.002	-0.011	-0.046	-0.026	-0.007***	-0.003*	-0.031	-0.006	-0.041	-0.020	-0.007***	-0.003
	(0.002)	(0.037)	(0.055)	(0.044)	(0.001)	(0.002)	(0.020)	(0.036)	(0.054)	(0.043)	(0.001)	(0.002)
Profitability	0.000	-0.000	-0.000	0.000	0.000**	-0.000	-0.632***	-0.001	-0.001	-0.001	0.000**	-0.000
	(0.000)	(0.001)	(0.002)	(0.002)	(0.000)	(0.000)	(0.084)	(0.001)	(0.002)	(0.001)	(0.000)	(0.000)
Asset Tangibility	-0.073***	-0.311**	-0.734***	-0.528***	-0.026***	-0.001	-0.255	-0.218*	-0.608***	-0.404***	-0.026***	-0.001
	(0.005)	(0.125)	(0.191)	(0.149)	(0.005)	(0.007)	(0.224)	(0.123)	(0.188)	(0.146)	(0.005)	(0.007)
Capital to Labor	0.009***	0.075***	0.138***	0.108***	0.006***	-0.000	0.123**	0.061***	0.119***	0.090***	0.006***	-0.000
	(0.001)	(0.019)	(0.031)	(0.024)	(0.001)	(0.001)	(0.060)	(0.019)	(0.030)	(0.023)	(0.001)	(0.001)
Leverage	-0.029***	-0.604***	-1.212***	-0.736***	-0.111***	0.067***	0.069	-0.569***	-1.166***	-0.690***	-0.111***	0.067***
	(0.003)	(0.080)	(0.119)	(0.093)	(0.004)	(0.006)	(0.107)	(0.079)	(0.117)	(0.091)	(0.004)	(0.006)
Tobin's Q	0.004***	0.019**	0.123***	0.038***	0.029***	-0.002***	0.030**	0.016**	0.119***	0.035***	0.029***	-0.002***
	(0.001)	(0.008)	(0.017)	(0.010)	(0.001)	(0.001)	(0.013)	(0.008)	(0.016)	(0.010)	(0.001)	(0.001)
Capx	-0.000	0.001	0.004	-0.000	0.000	-0.046***	-0.115	-0.001	0.001	-0.003	0.000	-0.047***
	(0.001)	(0.002)	(0.003)	(0.003)	(0.000)	(0.009)	(0.265)	(0.002)	(0.003)	(0.003)	(0.000)	(0.009)
Firm age	0.000***	0.012***	0.018***	0.013***	-0.000***	0.000	-0.001*	0.012***	0.017***	0.012***	-0.000***	0.000
	(0.000)	(0.001)	(0.002)	(0.002)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)	(0.002)	(0.000)	(0.000)
Firm Size	0.018***	0.197***	0.448***	0.245***	-0.010***	-0.014***	-0.139	0.201***	0.452***	0.249***	-0.010***	-0.014***
	(0.002)	(0.027)	(0.043)	(0.031)	(0.002)	(0.002)	(0.115)	(0.026)	(0.043)	(0.031)	(0.002)	(0.002)
Constant	0.054***	-2.348***	-4.715***	-2.668***	-0.047***	0.292***	-0.412*	-2.395***	-4.783***	-2.733***	-0.047***	0.292***
	(0.006)	(0.150)	(0.208)	(0.167)	(0.005)	(0.007)	(0.229)	(0.148)	(0.206)	(0.165)	(0.005)	(0.007)
Observations	34,549	34,549	34,549	34,549	34,549	34,549	34,549	34,549	34,549	34,549	34,549	34,549
R-squared	0.565	0.464	0.499	0.466	0.474	0.638	0.843	0.472	0.505	0.475	0.475	0.638
F statistics	45.303	40.231	74.407	45.068	32.55	55.516	30.072	42.933	76.026	49.290	30.54	52.241
Industry and Year fixed effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm standard error clustered	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Appendix A: Variable Definition

Variable	Definition
Key independent variables:	
Insider's Cash Flow Rights	Total Cash Flow Rights Held by a firm in a particular year; Source: Definitive 14A
Insider's Voting Rights	Total voting rights held by a firm in a particular year; Source: Definitive 14A
Ratio	Total Voting Rights/Total Cash Flow Rights; Source: Definitive 14A
Family Trust	Takes 1 if a family firm in our sample mentions holding shares in a family trust or trusts; Source: Definitive 14A
Family Trust Wedge	Voting rights held by family trust(s)/Cash flow rights held by family trust(s); Source: Definitive 14A
Variable for marginal value models:	
r-Rb	Long-Run Monthly (-11,0) Net of Value Weighted FF (1993) 25 Size/Book to Market Benchmark Portfolio BHARs; Source: CRSP
Capex t-1	Capex (t-1) to Beginning Market Value of Equity; Source: Compustat
R&D expenditure t-1	R&D expenditure (t-1) to Beginning Market Value of Equity; Source: Compustat
Change in Capex t	Change in Capex to Beginning Market Value of Equity; Source: Compustat
Change in earnings t	Change in Earnings to Beginning Market Value of Equity; Source: Compustat
Change in Net Assets t	Change in Net Assets to Beginning Market Value of Equity; Source: Compustat
Change in R&D t	Change in R&D to Beginning Market Value of Equity; Source: Compustat
Change in Interest t	Change in Interests to Beginning Market Value of Equity; Source: Compustat
Change in Dividends t	Change in Dividends to Beginning Market Value of Equity; Source: Compustat
Net Financing t	New Finance to Beginning Market Value of Equity; Source: Compustat
Variable for innovation models:	
Number of patents	Number of patents from Kogan et al (2017)
TSM	Stock Market Value weighted patent measure; Source: Kogan et al (2017)
TCW	Truncation adjusted patent citation measure; Source: Kogan et al (2017)
Patent Generality	This shows if the citatitions *received* by the patents of the firm in our sample are from a wide technological classes; Source: Hall et el (2001)
Patent Originality	This shows if the citatitions *made* by the patents of the firm in our sample are from a wide technological classes; Source: Hall et el (2001)
R&D Intensity	R&D expenditure scaled by sales; Source: Compustat
Herfindahl Index	Sum of the share of firm's sales based on a three digit SIC industry code in a calendar year; Source: Compustat
Sales	Firm sales; Source: Compustat
Debt Rating	If a firm has S&P debt rating; Source: Compustat
Profitability	Earnings before interest and tax scaled by sales; Source: Compustat
Asset Tangibility	Plant, property and equipment scaled by total assets; Source: Compustat
Ln(Capital to Labor)	Plant, property and equipment scaled by total number of employees; Source: Compustat
Leverage	Total debt scaled by total assets; Source: Compustat
Tobin's Q	Total assets plus market value of equity minus book value of equity scaled by total assets; Source: Compustat
Capex	Capital expenditures; Source: Compustat
Firm Age	Firm age based on the first appearance of total asset in Compustat; Source: Compustat
Total Assets	Total assets; Source: Compustat
Family Firm	If a firm is a family firm according to Anderson and Reeb (2003)

Appendix B: Family Trust Data Collection and Trust Wedge Calculation

Founding family members usually establish family trust(s) to consolidate voting shares to retain family control of the firm. In most cases, these trusts directly hold shares and/or some family controlling shareholders put part or all of their shares in trust(s). In other cases, trust(s) can hold certain interests in family foundation and/or family limited partnership that holds shares in the firm. The holding information is available in Definitive 14A.

The information about trust holding is usually in the "beneficial ownership" section of DEF 14A, in which a trust is listed as a beneficial owner with all its holding details. It is also common that trust holding information appears in footnotes of "beneficial ownership" section for major family shareholders, who own a significant amount of shares that are both held in various trusts and by themselves. DEF 14A's footnotes generally give detailed number of shares held in trust and by themselves. In a minority of cases, family foundation or partnership will hold shares as shown in DEF 14A. In the footnotes of such holding, if there is a trust or trusts that hold interests in the foundation or partnership, we calculate the corresponding holding for the trust(s).

We use web-crawler to identify if a DEF 14A filing contains "trust" "trusts" "family trust" "family trusts", without cap sensitive. We then search through each definitive 14A for crawled firms, collecting total number of common shares and voting shares outstanding, as well as common shares and voting shares held by trust(s).

For total dual class wedge, we follow Masulis *et al.* (2009) that calculate the ratio of total voting rights controlled by all insiders to the total cash flow rights controlled by all insiders.

Then we calculate the trust wedge following Villalonga and Amit (2008). Specifically, we calculate the total common shares and superior voting shares held by trust(s). Then we calculate cash flow rights by dividing the total cash rights made possible by both common and superior voting shares by the total cash rights available in the firm's outstanding shares, including common and superior voting shares. We calculate voting rights by dividing the total voting rights made possible by the common shares (usually one vote per share) and superior voting shares (usually 10 votes per share, although it can vary) by the total votes made possible by the firms' common and superior shares' outstanding. Then we take a ratio of trust voting rights to trust cash flow rights as the trust wedge.

Chapter III

1. Introduction

Can consumption risk explain the equity premium well? The past dozens of years have witnessed an explosion of studies attempting to answer this question. Early empirical evidence offers little support for the canonical consumption-based capital asset pricing model (CCAPM).[35] The limited success of the classic model has led to the development of consumption-based asset pricing models that allow for a more general representation of investors' preferences, or impose new restrictions on the dynamics of cash-flow fundamentals, or new market structures.[36] Alternatively, a simple remedy for the deficiencies of the classic model might be a new measure of consumption.

We propose a novel consumption measure that tracks shopping trips within same day, and thus argue that deficiencies of the classic model stem from the data. Our measure captures instantaneous consumption at a point in time as required by the theoretical concept, whereas existing consumption measures fail to achieve. They represent flows over a period of time, and then is used to construct consumption growth over a discrete interval.

Our daily scanned and tracked consumption measure is able to explain observed equity premium with constant relative risk aversion (CRRA) preferences with a relative risk aversion of 9.219, which is much smaller than those of 15.630 for garbage and 22.530 for

[35] See Hansen (1982), Hansen and Singleton (1982, 1983), Chen et al. (1986), Mankiw and Shapiro (1986), Breeden et al. (1989), and Hansen and Jagannathan (1991), among others.
[36] See Epstein and Zin (1989), Sundaresan (1989), Constantinides (1990), Abel (1990), Heaton (1995), and Campbell and Cochrane (1999) for more general preferences for consumption at different points in time; See Restoy and Weil (2011), Bansal and Yaron (2004), and Bansal, Kiku and Yaron (2012) for long-run risks; See Constantinides and Duffie (1996) for market incompleteness; See Mankiw and Zeldes (1991) for limited market participation.

unfiltered National Income and Product Accounts (NIPA). Including the risk-free rate as a test asset widens the gap further: a point estimate for the coefficient of relative risk aversion for daily consumption measure remains similar (about 11.477), whereas that for garbage is 28.720 and for unfiltered NIPA is 50.840. Moreover, daily consumption generates substantially low risk-free rate of 1.255% versus 17.250% for garbage, and 30.090% for unfiltered NIPA. Not only does it imply a lower order estimate, but it also derives implied risk-free rate consistent with real interest rate. In a joint pricing test, the daily-consumption-based model fits the equity premium and risk-free rate at a low risk aversion of 5.464 with the mean absolute error (MAE) of 0.537%. This result highlights the success of daily consumption measure in explaining the equity premium puzzle and risk-free rate puzzle.

We then assess the daily-consumption-based model performance in fitting the cross-section of stock returns. The test portfolios include the 25 Fama and French (1996) size and book-to-market portfolios and 10 industry portfolios. Our daily-consumption-based model performs well. The test shows a positive and significant premium for daily consumption growth as a risk factor with a low mean absolute pricing error (MAPE). Similar results also hold when the test portfolios include individual stocks or 30 portfolios sorted by size, value and investment, with an additional equity premium portfolio.[37] Kleibergen and Zhan (2020) emphasize two fundamentals of the reliability asset pricing test: the correlations between stock returns and factors and the time series sample size T

[37] Jegadeesh et al. (2019) suggests that using portfolios as the test assets may mask relevant risk- or return related features of individual assets, and proposes using individual assets as test assets with an instrumental variables approach.

that is large enough relative to the number of assets. They propose two statistical tests based on these criteria and we are the only consumption measure that passes both tests.

We present an AR-spline-GARCH model to formally explain that the success of our daily consumption-based model is attributed to the high frequency of the data. On one hand, daily consumption measure avoids time aggregation bias, interpolation, filter process and other statistical issues. It records households' daily consumption instantaneously and is equally detailed every day. Savov (2011) and Kroencke (2017) provide detailed discussion regarding how different sources of measurement error "distort" the measure of consumption. Daily consumption measure is more puristic and does not undergo any complex procedures. On the other hand, daily consumption measure captures slowly-evolving macroeconomic effects (low-frequency volatility), which includes intra-annual fluctuations and long-term trend. Low frequency consumption measure is only able to characterize long-term trend, but not intra-annual fluctuations. Long-term trend alone is smooth, and this could lead to incredibly large risk aversion. In contrast, daily consumption measure catches time series dynamics (short-term fluctuations), which is ignored in low-frequency consumption measure. Noise shocks are an important source of short-term fluctuations. Households continuously receive information about the future, which sometimes is news and sometimes just noise. Based on this information, households choose consumption and investments. If the information turns out to be fundamentals ex post, the economy adjusts gradually to that information, which is represented by low-frequency volatility. If it turns out to be noise, the economy returns to its initial state, which is captured

by short-term dynamics. Considering the pricing implication of news and noise in stock returns,[38] daily consumption, which captures both short-run dynamics and more low-frequency fluctuations, is able to produce better results compared with other low-frequency measures.

In the classical model with those low-frequency aggregate consumption, inordinately high degrees of risk aversion are necessary to reconcile the low variability of consumption with the high volatility of stock returns, as low-frequency consumption loses a majority part of information during the aggregation and moves little with unpredictable returns. To better understand why our daily-consumption-based model is able to explain the puzzle, we break down consumption volatility (high-frequency volatility) into short-run dynamics and low-frequency volatility, and show that ignoring either component could decrease consumption volatility, stock market covariances, and raise estimates of relative risk aversion.

While we focus on daily *total* consumption, we also conduct additional analyses on the consumption of two particular products: Magnet product, and non-food grocery and general merchandise.[39] We have proposed that daily shopper spending captures consumption in real time. As a result, one would expect spending growth on products more prone to instantaneously consuming to perform better than the growth rate of spending on

[38] See Brogaard et al. (2019), and Ang et al. (2021) for the role of news and noise in stock price movements.

[39] Magnet products include fruits, vegetables, meats and in-store baked-goods, which could be considered as strictly nondurable goods. On the other hand, non-food grocery and general merchandise include detergent, diapers, fresheners/deodorizers, household cleaners, laundry supplies, pet care, batteries/flashlights, candles, computer/electronic, cookware, film/cameras, insecticides, lawn & garden, motor vehicle, and office supplies, which could be considered as relatively durable goods in our data. We would like to emphasize that household spending on these relatively durables goods only accounts for a small proportion of our daily consumption, and it does not include standard durables such as furniture and mobile homes.

relatively slowly consuming products in asset pricing tests. We find that is indeed the case. Concentrating on the Magnet product, which measures the most instantaneous consumption, lowers the estimated risk-aversion coefficient further from 9.219 to 7.960. On the other hand, daily consumption growth on the non-food grocery and general merchandise implies a higher risk-aversion coefficient estimate.

Additionally, our daily consumption measure provides households' demographic information. Using these information, we can investigate heterogeneity across different groups of households. More specifically, we explore how the model using consumption of households on opposite sides of the political spectrum differs in the estimates of relative risk aversion and explanatory power in the cross-section of assets. This is an understudied aspect of consumption-based asset pricing model. However, it is important because of the "obvious ties" between political risk and financial markets. Partisan differences in risk preferences may affect which political party wins elections, and ultimately translate into different political platforms. In a partisan view, Democrats prioritize growth and high tax, while Republicans prefer low inflation and low tax. These policy preferences therefore lead to difference in stock returns and economic growth. To our knowledge, our paper is the first one providing an empirical test to investigate this question.

Allowing for partisan heterogeneity, we document the significant difference in the risk preferences of Democrats and Republicans: Democrats are more risk averse than Republicans. This confirms the traditional partisan view that Republicans are in favor of business. Moreover, Democratic consumption beta well explains the cross-sectional

variation in the asset returns. It is consistent with higher risk aversion demanding high compensation for risk, which translates into the higher average returns. We proceed further to investigate how the partisan consumption beta relates to the cross-sectional variation in the average returns of industry portfolios. We find that Democratic consumption beta is more correlated with the average returns of 10 industry portfolios and it is consistently larger than Republican consumption beta in each industry. The similar results hold when we use 17 industry portfolio.

Overall, our results suggest that daily consumption performs better than the existing consumption measure in explaining the equity premium, the risk-free rate, and the cross-section of asset returns. Moreover, we provide two useful tools, a consumption-risk-hedging portfolio and a traded consumption factor, to help households hedge consumption risk and develop innovative investment strategies. Our mimicking factors can explain the cross-sectional variation of stock returns in the same way as the daily consumption growth. The data is publicly available from the authors' websites. Furthermore, our measure also passes out of sample test from 2016-2018 period.

In terms of heterogeneity, consistent with people with different political ideologies responding to uncertainty differently, we document substantial risk preference gap between Democrats and Republicans, and further show that Democratic consumption beta is priced in the cross-sectional variation of returns, while Republican consumption beta is not.

This paper draws on several strands of literature. In order to improve the performance of consumption-based models, a growing literature has proposed alternative measures of

consumption risk. Ait-Sahalia et al. (2004) find that luxury goods have greater pricing ability than aggregate consumption. Jagannathan and Wang (2007) show that the consumption-based capital asset pricing model performs better with fourth-quarter NIPA consumption. Savov (2011) finds that garbage growth, as a proxy of consumption growth, is priced in the cross-sectional portfolio returns. Chen et al. (2020) and Da, Yang, and Yun (2016) report similar results using carbon dioxide emissions and electricity consumption to proxy for consumption. Using the information in household data, Yogo (2006) studies the pricing role of durable consumption. Malloy et al. (2009) use stockholder consumption to price the size and value portfolios. Qiao (2013) and Kroencke (2017) address the shortcomings of NIPA consumption using filtered consumption and unfiltered consumption respectively. Existing literature supports the need for a cleaner consumption measure for asset valuation. Our contribution to this strand of literature is to show that the CCAPM using daily consumption measure matches the equity premium with a low relative risk-aversion and implies a risk-free rate consistent with the real interest rate, leading to a formal resolution of the joint equity premium-risk-free rate puzzle.

This paper also relates to an extensive literature studying the underlying stochastic process of consumption growth. Bansal et al. (2014) and Campbell et al. (2018) both argue that volatility shocks are priced, even conditional on those shocks to the mean. Tedongap (2007) estimates the conditional volatility of consumption through a GARCH model, and shows that its innovations lead to risk premium in the value stocks. Bandi and Tamoni

(2015) and Boons and Tamoni (2015) decompose the process for consumption growth into different frequency specific, components.

They find that the shock with a half-life of about 4 years explains the cross-section of returns. Dew-Becker and Giglio (2016) instead argue that the extremely low-frequency shocks are most important for explaining the joint dynamics of macroeconomic fundamentals and asset returns. In contrast, Zviadadze (2018) argues that shocks to the variance of consumption growth, and to the long-run mean of volatility, justify most of the time-series variation of the market discount rate.

Our paper incorporates low-frequency volatility and short-run dynamics together into conditional high-frequency volatility of consumption. Furthermore, we show that both components contribute to the covariance of asset returns and consumption growth, and justify the good performance in the cross-section of assets.

This paper expands the literature that studies the relationship between finance and political economy. Bittlingmayer (1998) establishes political events as the main source of financial volatility during the transition from Imperial to Weimar Republic. Belo et al. (1992) and Leblang and Mukherjee (2005) document the effects of political processes on stock returns. Bekaert et al. (2014) show that political uncertainty has a positive marginal impact on sovereign bond spreads, and Caporale and Caporale (2008) show that it also affects the term premium between the 3and 6-month US Treasury rates. Pagliardi, Poncet, and Zenios (2019) construct a political factor, which well explains the cross-sectional returns. P*a*stor and Veronesi (2020) find evidence that political uncertainty carries a risk

premium in time-series returns with a general equilibrium model and shows that time-varying risk aversion is a driving force. Specifically, in the cross-section, more risk-averse Americans tend to vote for Democrat when the expected stock return is high, and less risk-averse ones vote for Republican when the expected stock return is low. Our paper complements P*a*stor and Veronesi (2020) by revealing the political identity of more risk averse Americans, and more importantly, by showing the explanatory power in the cross-section of assets.

This paper also contributes to a literature connecting household finance to political economy. Kaustia et al. (2015) show that right-wing voting is significantly and positively associated with stock ownership. Mian, Sufi, and Trebbi (2015), Kempf and Tsoutsoura (2018) and Meeuwis et al. (2019) explore how individuals with different political convictions respond to political events. Akey et al. (2018) examine how changes in political power affect consumers' credit access. Our paper emphasizes the interaction between household consumption, household political party affiliation, and consumption-based models.

The remainder of this paper proceeds as follows. Section 2 describes the data. Section 3 presents the relative risk aversion estimates and results for cross-sectional asset pricing tests. We propose a decomposition for consumption shocks classified by frequency of volatility, which justifies better performance relative to other low-frequency consumption measure. Section 4 provides additional robustness analyses. Section 5 discusses partisan heterogeneity. Section 6 conducts the out-of-sample tests and Section 7 constructs a

consumption-risk-hedging portfolio and traded consumption factor. Section 8 concludes the paper.

2. Data

We use the Consumer Panel Dataset (CPD) provided by the Kilts-Nielsen Data Center at the University of Chicago Booth School of Business.[40] The CPD data is a panel of approximately

40,000 to 60,000 households geographically dispersed and demographically balanced across the United States. This dataset records the specific product and its price a household buys during a trip in a particular day. The markets covered by CPD consist of 52 Nielsen-Defined Scantrack areas that encompass around 30% households consumption in the U.S., while at the same time, Nielsen assigns each household a projection factor so the consumption by covered households can be projected to represent the whole U.S. household consumption. Figure 1 shows the geographic markets covered by CPD.

The product purchased is identified at the barcode level, which is a 12-digit Universal Product Code (UPC) representing the finest level of product identification. Each product has a unique barcode and any change in product attributes will result in a new barcode.[7] Panelists participated in CPD data use in-home scanners to track all the products they purchase in one trip with price and quantities information. Importantly, a trip could also be

[40] Researcher(s) own analyses calculated (or derived) based in part on data from The Nielsen Company (US), LLC and marketing databases provided through the Nielsen Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the Nielsen data are those of the researcher(s) and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

made online and households would follow the same process of scanning the products they purchased online. The scanner given to the panelists is optical that is similar to what is used in a supermarket, thereby ensuring the accuracy of product information scanned by the households. Hence, the unit of each observation is the price of a particular product bought by a household during one specific trip in a day. The product includes groceries, drug products, small appliances, and electronics.

Importantly, panelists also report their total expenditure in that particular trip, besides the spending only on grocery products tracked by UPC. For a hypothetical example, in one trip during a particular day, a household bought a gallon of milk for $6 and a computer software for $30 in the supermarket. Then this household spent another $50 dining in a restaurant. As a participant enrolled in CPD program, the household head would scan the milk and software that have two UPCs, but report $86 as the total expenditure. Therefore, CPD would have two rows for this single trip with two tracking UPCs and their prices ($6 and $30), and also list the total expenditure $86 for these two rows.

To ensure the precision of the data, Nielsen implements a number of methods. First, Nielsen validates the reported consumer spending with the scanner data of retailers on a quarterly frequency to ensure high data quality. Second, Nielsen forms weekly sample reports to compare the current week data and historical data. Meanwhile, Nielsen checks the sample characteristics on a weekly basis and uses traditional mailing methods to performs adjustments to guarantee balancing whenever deemed necessary. Lastly, Nielsen deletes households who don’t report the required minimum consumption in the past 12

months. On the other hand, Nielsen uses various incentives to retain panelists and thus far has been able to maintain a 80% retention rate. The incentives include monthly price drawings, gift points awarded for weekly transmission of data and sweepstakes. Nielsen structures the incentives to not bias the shopping behavior of their panelists.

To capture as many dimensionalities of household consumption as possible, we use the total expenditure as our raw measure to proxy for household consumption per trip in a day. Unfortunately, the sources of spending beyond those tractable UPC grocery products are unidentifiable: they could be a dinning bill, an expense for service or purchases of durable goods, which cannot be tracked and is impossible to record at household daily trip-product level. Consequently, it is possible that CPD not only tracks the expenditure of services as the main purpose in a trip, but also records UPCs and corresponding prices on a way a household drops by a grocery store to buy some beverages. To make the best use of our data, we adopt the total expenditure to measure the broadest level of consumption possibly tracked by the data. Moreover, using total expenditure may also alleviate the concerns that we are only tracking household consumption on grocery products.

CPD data also provides households' demographic information, such as household size, income, education, age, race and geography, among others. In the conditional analyses, we sort households into different groups or portfolios based on political regions and income level to address our research questions. By doing so, we are able to circumvent the annual level data on household characteristics, thus we observe households' daily consumption behaviors with different characteristics. Importantly, to avoid the possibility that some

households are more likely to be selected due to their household characteristics compared to the population, Nielsen assigns a projection factor or sampling weight to each household. [41] We average all trips' total expenditure per household per day adjusted by its projection factor to obtain our daily total consumption measure. We end with 4,370 days with total expenditure from 2004 to 2015 for in-sample test and 1094 days with total expenditure from 2016 to 2018 for out-of-sample test. We deflate the daily total spending based on monthly inflation rate.

To observe how the household's consumption behavior affects stock return, we link the daily consumption data to CRSP daily stock index return. The excess market return is daily CRSP value weight index return minus daily risk-free rate reported in the French Data Library. To conduct cross-sectional tests, we further merge our data with Fama-French 25 size and book-to market portfolios as well as 10 industry portfolios from the French Data Library. As a robustness check, we also merge our date with 10 size, 10 book-to-market and 10 investment growth portfolios plus a market portfolio as used in Kroencke (2017).

An issue with merging convention is worth noting. We merge the daily consumption data with daily stock return data by excluding the weekends, as there is no trading during the weekends. However, since the consumption during weekend contains richest information about households' spending activities, we modify the Monday's consumption

[41] The projection factor represents the weight of each household relative to the U.S. population. In other words, the sum of the weights (projection factors) is the total household population (i.e. number of households) in the U.S. We weight each household's daily consumption using its unique projection factor. In constructing this projection factor, Nielsen apply their proprietary linear programming optimization routine to estimate projector weight. Please consult with Nielsen at Chicago Booth School of Business for further question about their methodology and data collection.

growth in a way that reflects weekend consumption information while matching the Monday's stock return information.[42]

Table 1 shows the summary statistics of our daily consumption measure in percent. Panel A shows our daily consumption growth in daily and annual levels from 2004 to 2015. To facilitate comparison, we also report the summary statistics of unfiltered NIPA, three-year consumption growth (P-J) and fourth-quarter consumption (Q4-Q4) within the same sample period. Panel B reports the summary statistics for the postwar sample period (1960-2014). However, as Garbage data is not available beyond 2007, we only report its summary statistics from 1960 to 2007.[43]

In Table 1, Panel A, households on average spend around 0.17% more on a next day, adjusted for inflation. To make our daily consumption measure comparable to other annual measures, we aggregate our daily measure into annual level, yielding a mean of 6.226%, which is higher than other consumption measures, such as 0.93% from Q4-Q4 or 1.05% unfiltered NIPA (Kroencke, 2017) from 2004 to 2015. This difference could come from the household heterogeneities and properties of purchase. Our data tracks both daily grocery spending and other activities in a trip, which could include from any outdoor activities to service and nondurables, thus our measure is more comprehensively reflecting households' daily spending. In addition, this high growth rate could be driven by high

[42] Specifically, a stock's return on Monday is calculated by the closing price of Monday and the closing price of Friday minus one. On the other hand, Monday's consumption growth is Monday's consumption growth divided by Sunday's consumption growth minus one. We further obtain Sunday's consumption growth (Sunday/Saturday-1) and Saturday's consumption growth (Saturday/Friday)-1. Then we calculate these three growth rates' geometric average to make it new Monday's consumption growth, which incorporates consumption information from Saturday to Monday. We match this with Monday's stock return.

[43] In table 1 and 6, we put Garbage under 1960-2014 group to simplify the table, although it is from 1960-2007.

income households that have top 10% or above median income levels or households that have more family members, which reflects household heterogeneity, unlike those per-capita aggregate consumption. The standard deviation of daily consumption measure is 6.164%, indicating significant volatility of consumptions in our household samples. Daily consumption shows significantly negative autocorrelation, suggesting that households' current spending is negatively correlated with past. This could be because households are cautious about their everyday spending.

Our daily consumption measure at annual level has volatility 18.16% and covariance with the market 0.342%, which are both higher than all other measures, suggesting our measure in annual form covaries more with the market excess return. The correlation with the stock return is 10.222% at annual level, slightly lower than that of garbage (19.705%) and much lower than other measures. However, our covariance with the market is highest compared to other measures at annual frequency. This is attributed to the fact that our measure has the highest volatility (18% compared to on average the volatility of 2% from other measures).

However, readers should be cautious comparing our daily consumption measure with other annual consumption measures, because of different sample period and data frequency. Daily consumption measure spans from 2004 to 2015 with much more observations, whereas NIPA-based consumption has much longer sample period with less observations. Our advantage is granularity that enables us to match households' daily consumption with daily stock return, which reveals more information in terms of

households' daily consumption decision. This also suggests that the comparison between the daily consumption measure annual level and other annual consumption measures could be unfair.

3. Asset Pricing with Daily Consumption

3.1. The Equity Premium and Risk-Free Rate

We consider a representative agent with additive CRRA preference in our economy. Empirical evidence suggests that with power utility, implausibly high-risk aversion is required to fit the equity premium given the measured consumption being too smooth. This high-risk aversion also leads to an higher implied risk free rate. So the equity premium puzzle is closely related to the risk-free rate puzzle. However, high volatility in our daily consumption measure and the positive correlation between daily consumption growth and stock returns suggests that daily consumption growth could reconcile the equity premium with reasonable risk aversion, and potentially could solve risk-free rate puzzle simultaneously.

We first test the classic model using our consumption data with the Euler equation of consumption:

$$E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma} R^e_{t+1}] = 0 \tag{1}$$

where C_t is daily consumption at time t, β is subjective discount factor, γ is relative risk aversion coefficient, R^e_{t+1} is next day stock return in excess of daily risk-free rate. Following the literature (Hansen, Heaton and Li, 2008; Savov, 2011), we set β to be 0.95,

and focus on γ. Given the relative risk aversion (γ) and the discount factor (β), we obtain the risk-free rate as follows:

$$R^f = E[\beta(\frac{C_{t+1}}{C_t})^{-\gamma}]^{-1} \tag{2}$$

We also report this implied risk-free rate when we test the Euler equation. To further increase testing power and precision, we include the observed risk-free rate as an additional test asset: (3)

$$E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma} R^e_{t+1}] = 0$$
$$E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma} R^f_{t+1}] = 1. \tag{4}$$

and we also introduce instruments to test conditioning information model:

$$E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma} R^e_{t+1} \otimes Z_t] = 0 \tag{5}$$

where we follow the literature (Kroencke, 2017; Savov, 2011) to include a constant, lagged consumption growth, one plus the lagged excess market return and the detrended logged log price to dividend ratio.

Table 2, Panel A shows the results of an exactly identified GMM test of the Euler equation for the excess market return. The only test asset is the equity premium. We find that our daily measure generates a risk-aversion estimate of 9.219 with standard error of 3.028. This implies a risk-free rate of 1.255%, which is significantly lower than the risk-free rate estimated from existing measures, but also is consistent with what we observe

from the real world. For comparison, garbage yields a risk-aversion estimate of 15.630 and risk-free rate of 17.250%. Similarly, unfiltered NIPA matches excess return with a relative risk-aversion coefficient of 22.53 and risk-free rate of 30.09%. The mean absolute error for all these models is 0.

In Panel B, we augment the exactly identified model with an additional moment restriction of risk-free rate. These two-moment restrictions will force the gamma to match our daily consumption measure with excess return and a traded risk-free T-bill asset. The relative risk-aversion coefficient is 11.477, which is similar to the coefficient estimated by the exactly identified model with standard error of 2.215. In Panel C, we use conditioning information at time $t-1$ with the instruments. The relative risk-aversion coefficient is 5.464. This result seems to reconcile with the differences in the estimates of risk aversion between the household finance literature and empirical asset pricing literature. The mean absolute error of moment restriction increases to 0.537%, however. This could be driven by the return predictability contained in the instruments, which are well-known predictors.

Overall, we find that daily consumption measure explains well the equity premium with a reasonable relative risk-aversion coefficient. After fitting the risk-aversion coefficient with the consumption data, the implied risk-free rate is much lower than those from existing consumption measures at the annual level. The superior performance of our daily measure ascribes to its high frequency and volatility. We describe in detail in the next section.

3.2. The Cross-section of Returns

Another key insight of the model is that an asset's consumption beta, covariance between asset return and consumption growth, determines its expected return. We test this cross-sectional implication of the model by running Fama-MacBeth (1973) regression. The basic one-factor return-beta representation is:

$$E[R^e_{i,t+1}] = \lambda + \lambda_c \beta_i \tag{6}$$

where the left-hand side is the expected excess return per period of testing assets. λ is pricing error, which should be zero if excess returns are dependent variable while risk free rate if raw returns are used. λ_c is the price of consumption risk that measures the risk premium per unit exposure to consumption risk.

We first perform a time series regression on monthly asset excess returns to obtain time-varying consumption beta:

$$R^e_{i,t+1} = \alpha_i + \beta_{i,c} \log(\frac{C_{t+1}}{C_t}) + \epsilon_{i,t+1} \tag{7}$$

By doing so, we allow the first path to vary across months, which is suggested by Cochrane (2005). Then we run cross-sectional regressions of asset excess returns on their consumption betas during each period:

$$E[R^e_{i,t+1}] = \lambda_c \beta_{i,c} \tag{8}$$

Lastly, we average the time-varying λ_c to get the price of risk over time as specified in Fama and MacBeth (1973).

As the standard test assets for cross-sectional asset pricing, we choose the 25 Fama-French (1993) size and book-to-market portfolios. Additionally, we include another 10

industry portfolios as our test assets in order to increase the dimensionality of the cross-section and address the concerns raised by Lewellen, Nagel and Shanken (2010). This selection of testing assets thus shows an economically important cross-section. Moreover, in response to Jegadeesh et al. (2019) that portfolios might mask the risk-return characteristics based on individual stocks, we also use the universe of CRSP individual stocks as testing assets. Following Boguth and Kuehn (2013), we add market value of equity and book to market ratio in individual stock cross-sectional regressions. For comparison purposes, we also examine the asset pricing implication with 10 size, 10 book to market, 10 profitability and one equity premium as testing assets (Kroencke, 2017). In each model, we report three-lag Newey-West t-statistics for portfolio models (Savov, 2011) and twelve lag Newey-West t-statistics for individual asset models (Boguth and Kuehn 2013).

In Table 3, we report results with the intercept from testing assets of 31 portfolios that include 30 portfolios sorted by size, value and investment. Savov (2011) documents that omitting the intercept imposes a restriction of the model and delivers more power. Considering the results remain qualitatively similar and including intercept terms is a more standard procedure (Lettau and Ludvigson, 2002; Jagannathan and Wang, 2007), we only report the results with the intercept.[44]In addition, we report first stage beta loadings from time-series regressions.

[44] The results without the intercept are qualitatively same, and are available upon request.

Model (1), λ_c is 0.012%, significant at 5% level. This shows that for one unit of risk exposure to households' daily consumption risk, the price is 0.012% per day, which roughly translates into 3.036% annual rate given 253 trading days in a year. The mean absolute pricing error is 0.033% for daily returns. In models (2) to (4), we control for market excess return, small-minus-big factor return, high-minus-low, robust-minus-weak and conservative minus aggressive as well as q-factors in Hou, Xue and Zhang (2015). λ_c are consistently positive and significant at 5% level. These results suggest that our daily consumption measures are able to explain the cross-section of returns. Furthermore, the factor loading of consumption risk is positive and ranges from 0.039 to 0.372. This shows that consumption risk is positively correlated with stock returns.

We run cross-sectional regression using testing assets of 25 portfolios sorted on size and book to market as well as 10 industry portfolios, with an additional equity premium portfolio. The results are qualitatively same. In Model (1), λ_c is 0.012%, which is almost the same as the 35 portfolios as testing assets after rounding, and all the remaining λ_c in Model (2) to Model (4) are significant at 5% or 10% level, indicating a positive return beta relationship. The first stage betas show the similar results

We repeat the cross-sectional regression with individual stocks as testing assets and report the results in Table 4. Although Black, Jensen and Sholes (1972) raise the concern regarding that first stage betas are measured with errors and thus it is better to use portfolios as test assets, other scholars argue that portfolios may mask the risk-return relationships among individual stocks and propose using individual assets as test assets. Following this

strand of literature, we also test the asset pricing implication of consumption beta with individual stocks. In Model (1), λ_c is 0.002% in one factor model, which is slightly lower than the portfolio models. This might be the volatility of individual stock returns and those of portfolios. All λ_c in Models (1)-(4) are positive and significant, indicating that our daily consumption is priced in the cross-sectional variation of individual asset returns. Moreover, the first stage betas for consumption growth are all positive and significant.

In addition, we replicate the cross-sectional tests using existing consumption measures of PJ, Q4-Q4, Unfiltered NIPA and Garbage using both 31 portfolios and 35 portfolios. The results are reported in Appendix 1. We find that with 35 portfolios, all other consumption measures are priced. Furthermore, we follow Giglio and Xiu (2020) to use 167 portfolios to represent the cross section. The 167 portfolios include 25 portfolios sorted on size and operating profitability, 25 portfolios on size and momentum, two sets of 25 portfolios on size and short/long term reversal, 25 portfolios on operating profitability and investment, 25 portfolios on size and book-to-market and 17 industry portfolios. We repeat the models (1) and (4) using these assets and all $\lambda_c s$ are significant at 5% level. For brevity, we don't report these results, which are available upon request.

3.3. Kleibergen and Zhan (2020) Test

Kleibergen and Zhan (2020) (KZ thereafter) casts doubt about the measures proposed in the current CCAPM literature. Specifically, they question the credibility of these measures in two aspects: (a) the strength of identification as represented by the beta, which measures the correlation between risk factors and returns on testing assets. The essence of

this argument is that all the betas in the first-path should be statistically different from zero; (b) the number of testing assets versus the frequency or the number of time series observations in what is known as "Limited *T* versus Large *N*" problem. This problem is raised because most consumption measures are at annual frequency, whereas the testing assets are usually 35 or 40 portfolios. In a time-series of around 60 years in a usual case of CCAPM measures, 60 observations in time-series (*T*) is not very different from the number of testing assets (*N*), thus threatening the credibility of the risk factor.

To this end, they provide two tests: the first test is a rank test that examines if the timeseries betas are statistically and jointly different from zero, and the second test provides a 95% confidence interval of true risk premium in a GRS-FAR test. In a set of tests on the existing measures, including reported filtered NIPA, P-J, Q4-Q4, Garbage and Unfiltered NIPA, KZ shows that only Garbage passes the first rank test, but fails the second test. All other measures fail both tests.[45]

We apply these two tests to our measure. Table 5 presents the KZ tests' statistics for daily consumption measure, along with other measures for comparison. Panel A reports the results using 31 portfolios, and Panel B reports the results with 35 portfolios. We find that, with 35 portfolios, daily consumption is the only consumption measure that passes both KZ Test I and Test II. The true λ_c derived from this daily consumption is not only bounded, but also has confidence interval between 0.029 to 0.112, which suggests that

[45] See their table III where they use 31 portfolios as testing assets.

there is sufficient variation in the betas to identify risk premium and this risk premium is identified.

Panel B, Column (1) shows that daily consumption measure generates a p-value in the rank test close to 0, which indicates that we can reject the null that all betas are jointly zero. As such, our measure passes the first KZ test of the strength of identification. Except for Garbage, all the p-values for reported NIPA, P-J, Q4-Q4 and Unfiltered NIPA in column (2), (3), (4) and (6) are above 0.1, suggesting that these measures' first-path betas are not statistically different from zero. Daily measure, although bounded, fails the second KZ test because the confidence interval contains 0. Comparing to others, virtually all the consumption measures fail the second test. For garbage, although its risk premium is bounded, the confidence interval contains zero, thus the risk premium could be zero. The same situation happens to unfiltered NIPA, whose risk premium also contains zero, though it is bounded.

Overall, we show that daily measure passes both KZ rank test and test of identification strength with 35 portfolios. The first-path betas are not jointly zero, thus reflecting a strong correlation between daily factor and portfolio returns in the time-series. Moreover, the true λ_c is bounded and does not contain zero, thus indicating the strength of identification.

3.4. A Model of Daily Consumption Dynamics

Consumption dynamics are hard to measure accurately in the data, and their underlying stochastic process has been the subject of a long-standing debate. A common empirical practice to identify and test the stochastic process of consumption growth is to

use low-frequency consumption data. Consequently, in order to match low-frequency consumption growth, a large fraction of the high frequency asset returns data is required to throw away to construct time-aggregated returns. This raises a major concern regarding the error caused by time aggregation both in consumption growth and stock returns.[46]

However, we are able to get rid of time aggregation problem and other statistical errors because of the availability of daily consumption data, considered as comparatively high-frequency macroeconomic data in the literature. This daily consumption enables us to explore a wealth of information contained in high-frequency data, and further investigate the canonical consumption-based asset pricing model. Bansal and Yaron (2004) and Chaudhuri and Lo (2016) imply that consumption risk produces distinct effects on financial assets over different time horizon. It is crucial to determine at which frequency consumption risk factor operates. In this paper, we focus on daily consumption volatility, and conduct empirical analysis to understand the features of the data.

Figure 2 shows how daily consumption growth changes over time. According to Figure 2, no significant upward or downward time trend occurs in the data, but we do observe strong high frequency fluctuations around the constant level near zero.

Figure 3 displays the sample autocorrelation and partial autocorrelation for daily consumption growth, which clearly shows significant ACFs and PACFs and suggests that the ACF is dominant. Therefore, at the daily frequency, consumption growth is negatively

[46] Breeden, Gibbons and Litzenberger (1989) and Ait-Sahlia, Mykland, and Zhang (2005) show time aggregation leads to significant error in consumption growth and stock returns, respectively.

autocorrelated, and an autoregressive component is recommended instead of a moving average component in the mean process.

Considering that strong high-frequency fluctuations exist in the time-series data and consumption usually relates to slowly-moving macroeconomics environment, it is reasonable to assume that high-frequency variance has the following form:

$$h_t = \tau_t g_t \tag{9}$$

where g_t measures the short-run dynamics of high-frequency variance, and τ_t is the low-frequency variance. With this form, we decompose the high-frequency volatility into two parts in the spirit of Engle and Rangel (2008).

Short-run fluctuations are usually ignored in the low-frequency consumption measure because of negative autocorrelation exhibited in the high-frequency consumption growth. On the other hand, low-frequency volatility determines the unconditional volatility of daily consumption growth and can be interpreted as a trend around which the conditional volatility fluctuates. It can capture the long-memory component of the volatility process associated with slowly varying deterministic conditions in the economy, or random variables that are highly persistent and move slowly.

Based on the guess of high-frequency variance, the conditional variance of consumption growthis

$$var_{t-1}(\Delta c_t) = h_{t-1} \tag{10}$$

$$= \tau_{t-1} g_{t-1} \tag{11}$$

Therefore, the conditional covariance between conditional consumption growth and stock returns can be written as:

$$\mathrm{cov}_{t-1}(\Delta c_t, r_{it}) = \rho\sigma_{t-1}(\Delta c_t)\sigma_{t-1}(r_{it}) \tag{12}$$

$$= \rho\sqrt{\tau_{t-1}g_{t-1}}\sigma_{t-1}(r_{it}) \tag{13}$$

In order to disentangle short-run dynamics from low-frequency volatility, we apply logarithmic transformation to both sides:

$$\log(\mathrm{cov}_{t-1}(\Delta c_t, r_{it})) = \log(\rho) + \frac{1}{2}\log(\tau_{t-1}) + \frac{1}{2}\log(g_{t-1}) + \log(\sigma_{t-1}(r_{it})) \tag{14}$$

Although logarithm transformation is not a linear function, it is monotonic function, which suggests that the proportion of low-frequency volatility and short-run dynamics in total volatility shall almost be kept before and after logarithm transformation. Meanwhile, the central insight of the CCAPM models is that the risk of any asset should depend on the covariance of its returns with consumption growth and if we assume that both consumption growth and stock returns are conditionally jointly lognormal, we obtain

$$E_{t-1}(r_{i,t} - r_{f,t}) + \frac{\mathrm{var}(r_{i,t})}{2} = \gamma\mathrm{cov}_{t-1}(\Delta c_t, r_{it}) \tag{15}$$

where $var(r_{i,t})$ is the conditional variance of asset returns. Considering these observed negative autocorrelation, it is obvious that, using aggregated low-frequency consumption measure, short-run dynamics are suppressed. Based on (14), we find that ignoring short-run dynamics will decrease $\log(\mathrm{cov}_{t-1}(\Delta c_t, r_{it}))$, equivalently decrease $\mathrm{cov}_{t-1}(\Delta c_t, r_{it})$, and ultimately increase the relative risk-aversion coefficient γ. Therefore, short-run fluctuations

could justify why daily consumption growth performs better than existing low-frequency consumption growth.

Next, we construct a full model and estimate the parameters. We propose an AR-spline-GARCH model for the daily consumption growth. High-frequency volatility is decomposed into a product of two components. One is the short-run dynamics of conditional volatility associated with transitory effects of volatility innovations and the other one describes slower variations in the volatility process associated with more

$$\Delta c_t = \sum_{i=1}^{p} \alpha_i \Delta c_{t-i} + \epsilon_t, \quad \epsilon_t | \mathcal{F}_{t-1} \sim \mathbb{N}(0, h_t) \tag{16}$$

$$h_t = \tau_t g_t \tag{17}$$

$$g_t = 1 + \sum_{j=1}^{n} \omega_j g_{t-j}, \quad \sum_j \omega_j = 0 \tag{18}$$

$$\tau_t = \exp(f_1(t)) \tag{19}$$

permanent effects. As we know, this unique decomposition implies that we can separate the covariance between growth and asset returns into horizon-matched covariances between each component and returns.[47] Following Engle and Rangel (2008), we allow the data to provide the functional form of this low-frequency volatility.

We approximate the low-frequency volatility nonparametrically using an exponential spline, which generates a smooth curve describing the low-frequency component based exclusively on data evidence. From the equation, it is clear that we do not impose structure on how the macroeconomic indicators affect volatility, as the sampling frequency prevents

[47] Boons and Tamoni (2015) and Bandi and Tamoni (2017) decompose the consumption growth into parts of varying persistence and find that the shock with the business-cycle frequency plays a significant role in explaining the cross-section of returns. However, even the high-frequency components in these papers are quarter units, we focus on daily consumption growth and its volatility components.

the direct inclusion of macroeconomic variables. However, using a spline to model the low-frequency component implies a hidden structural assumption that macro effects cannot cause a sharp jump in low-frequency volatility. This appears reasonable because sharp jumps in volatility are captured through the high-frequency component. With the imposed restriction $^{P}{}_{j}\,\omega_j = 0$, the unconditional variance of consumption growth is

$$E(\epsilon_t^2) = \tau_t \tag{20}$$

Therefore, the unconditional volatility of consumption growth coincides with the low-frequency volatility.

More specifically, $f_1(t)$ is a smooth function of time t, which captures the long-term trend. It is represented using smoothing splines with smoothing parameters selected by restricted maximum likelihood. Using smoothing splines circumvents the problem of knot selection and simultaneously controls for overfitting by shrinking the coefficients of the estimated function.

Figure 4 shows the fitted values of low-frequency variance. The plots have a very odd looking rise-and-fall pattern, which suggests a strong intra-annual fluctuations exist. Therefore, it is important to introduce a cyclical smoother when we model low-frequency variance. Therefore, we revise the low-frequency component as follows:

$$\tau_t = \exp(f_1(t) + f_2(d)), d = t \bmod 250 \tag{21}$$

where $f_2(d)$ is a smooth function of d, which represents day 1, day 2, ..., day 250, and therefore characterizes the intra-annual fluctuations.

We re-estimate the parameters and Table 6 shows the results. Table 6 reports the model parameter estimates and standard errors. We first fit the model with unit root test and minimization of the BIC and MLE to obtain the best ARIMA model for daily consumption growth. We find AR(5) model fits the data best, which confirms our initial guess for the mean process. For volatility process, we try to search the best model by reducing the model until it contains only significant terms, while keeping the model simple. We find four lag terms meet the requirement. From the table, we conclude that all coefficients are significant.

Figure 5 shows the fitted value of two smooth functions and the fitted value of low-frequency variance. We can see that the cyclical smoother is picking up intra-annual fluctuations in the low-frequency volatility. The wiggle is much stronger in the beginning and in the end of each year, and during the middle of each year, we observe mild fluctuations. For the long-term trend, it is relatively stable but still significant. Overall, Figure 5 shows strong intra-annual fluctuations exist in the low-frequency variance.

Figure 6 shows how this AR-spline-GARCH model fits high- and low-frequency patterns of volatility during the sample period and plots the logarithm of high- and low-frequency volatility.

From the graph, we find strong intra-annual fluctuations and short-run dynamics. Based on the fit of the model, we conclude that besides that short-run dynamics are easily ignored in the low frequency consumption growth, those intra-annual fluctuations can be ignored as well. Those low-frequency consumption growth rates usually only have one

observation for each year, thus they are not able to capture intra-annual fluctuations as our daily consumption growth.

To further illustrate the superiority of high-frequency consumption growth, we aggregate the daily consumption into annual, monthly and weekly consumption growth. Table 7 reports the results. We find that, consistent with our argument, low-frequency aggregate consumption growth performs worse compared with daily consumption growth. Among these three alternative consumption measures, weekly consumption growth generates the significant risk aversion estimate of 17.96, while monthly and annual consumption don't show a significant risk aversion. We notice that the results derived from the annual consumption growth suffer from a small sample size limitation, so we shall cautiously compare the annual consumption growth aggregated from daily consumption growth with the existing annual consumption growth.

Overall, the underlying stochastic process of daily consumption growth strongly indicates that aggregating high-frequency consumption growth to low-frequency consumption growth could lose large amount of information, such as short-run dynamics and intra-annual fluctuations in the low frequency volatility. Ignoring these components results in too smooth measured consumption and a much higher relative risk aversion. With a model involving slow-moving macroeconomic effects and short-run dynamics, we understand the results with our daily consumption measure better.

4. Robustness Analyses

4.1. Magnet, and Non-Food Grocery and General Merchandise

We have proposed that daily shopper spending captures consumption in real time because it tracks each purchase whenever it occurs. As a result, one would expect spending growth on instantaneous consumption to perform better than the growth rate of spending on relatively slowly consuming products in asset pricing tests. We find that it is indeed the case with the help of the Magnet products, and non-food grocery and general merchandise.

Nielsen constructs a unique product group, Magnet group, which includes those products that don't have regular UPC codes. For example, fruits in a supermarket are usually tracked by weight, same as vegetables, meats and in-store backed goods. Therefore, the Magnet products could be considered as strictly nondurable goods, as they are immediately perishable items. We expect the model with only Magnet product consumption to generate lower estimate of risk-aversion coefficient, as spending on these strictly nondurable goods serves as a good proxy of the extremely instantaneous consumption.

In contrast to Magnet group, non-food grocery and general merchandise include detergent, diapers, fresheners/deodorizers, household cleaners, laundry supplies, pet care, batteries/flashlights, candles, computer/electronic, cookware, film/cameras, insecticides, lawn & garden, motor vehicle, and office supplies, which could be considered as relatively durable goods in our data. We emphasize that spending on these groups are relatively durable from two perspectives. First, some components, such as candles and diapers, are typical nondurable goods, although majority products can be categorized as durables. Secondly, even for those products that are considered as durables, their periods between

successive purchases are much shorter compared with those typical durables, such as furniture and mobile homes, as they are sold in the retail chains.

Overall, relatively durable goods account for a small proportion of our daily consumption, and Nielsen does not provide a special product group for them. Therefore, instead of arguing that the spending on non-food grocery and general merchandise is a proxy for spending on durables, we consider the spending on these groups as a mix of spending on relatively durable goods and nondurables with heavier weight on relatively durable goods. Therefore, the model with spending on non-food grocery and general merchandise shall perform less well compared with the one with only spending on Magnet products. This expectation also aligns with the results in Yogo (2006), where he investigates CCAPM with durable goods and assume households derive utility from service flow of durable goods that is a constant fraction of the stock. He finds that the durable consumption model requires high risk aversion to fit the high level and volatility of expected stock returns.

Table 8 shows the results and confirms our expectation. We first find that spending on non-food grocery and general merchandise are more closely correlated with the excess market return than magnet products, which echos Julliard and Paker (2005). Meanwhile, we find that the model with spending on Magnet generates the estimate of risk aversion coefficient 7.960, lower than the risk aversion coefficient 9.219 in the daily-consumption-based model and the risk aversion coefficient 9.698 in the model with spending on non-food grocery and general merchandise.

4.2. Long-horizon Returns

We have witnessed the good performance with *contemporaneous* daily consumption growth, and to confirm the robustness of our results, we test if our daily consumption risk in the long-run can still be correlated with the excess market return. Parker and Julliard (2005) argue that ultimate consumption, or consumption growth over several quarters, is better correlated with the market return and is a better fit with equity premium with a reasonable risk aversion coefficient. We test this conjecture using our daily measure. We construct weekly growth measures up to 26 weeks and calculate each consumption growth.

Table 9 presents the result. We find that the risk aversion indeed decreases with longer period, up to 8 weeks. From 16 to 26-week horizons, however, the risk averse coefficients become either negative or insignificant. This shows that at a daily frequency, the optimal ultimate consumption period is up to 8 weeks. Or households incorporate consumption information up to 8 weeks into their contemporaneous portfolio choice.

5. Partisanship and Consumption Risk

Daily consumption measure provides households' demographic information and allows us to categorize households into different groups based on their characteristics. Among all these characteristics, we are particularly interested in household's political spectrum because of the increasing influence exerted by political risk on the financial markets. To understand the interplay between individual ideology, political landscape, and financial returns, we explore whether and how the model using consumption of households

on opposite sides of the political spectrum differs in the estimates of relative risk aversion and explanatory power in the cross-section of assets.

We classify households' partisan affiliation based on their residence under the rationale that those residing in the same region with stronger support for a party are more likely to be affiliated with that party (Meeuwis et. al., 2019). We use campaign finance data from the Federal Election Commission, which records the number of donors and amount of donation to a certain party in the presidential elections at zip code level. Following Meeuwis et al (2019), we consider individual contributions to party committees, campaign committees and political action committees during our sample period.

We first link the donation zip code to our household residential address and then calculate two groups of measures to infer whether a zip-code is predominately supporting Democrats or Republican party. Specifically, we first obtain two individual donation share measures to two parties (Republican and Democrats) by count of individual donors in each zip code area. Second, we calculate sum of donation dollar amounts in each zip code area to these two parties, thus generating two dollar amount donation share measures.

We use 0.8 as the threshold to classify the partisan affiliation. This means that, for example, if the individual donation share of Democratic party is equal to or above 0.8 (80%), then we conclude that this zip-code area is dominated by residents who support Democratic party. Conversely, if the individual donation share of Republican party is equal to or above 0.8, then this zip-code is a Republican controlled area. If both parties'

individual donation share measures are below 0.8, then we declare that this zip-code is a divided area.

In the main analysis, we use partisan affiliation based on individual donation share measures because they focus on individual residents, which align with our individual household level consumption data. On the other hand, dollar amount could be biased as one individual could donate a significant amount of money. Despite this, we find qualitatively similar results using dollar amount measure, which is not reported for brevity but available upon request.

5.1. Partisanship and Risk Aversion

We start by examining whether there exists substantial heterogeneity in the risk-aversion coefficient between households residing in the different party-controlled states. We report the results of a GMM test of the Euler equation for the excess market return in Table 10.

Table 10, Column 1 shows the relationship between consumption and investment for households living in Democratic party-controlled states. The relative risk-aversion coefficient is 9.179, which is reasonable, though a little higher than that in the main model. The standard error is 3.085, indicating a 1% level significance. Table 10, Column 2 shows that households in Republican Party controlled states have an average relative risk aversion of −7.524 with the standard error of 2.560, which suggests insignificant result. This shows that households in these states are actually risk loving that they derive utility from exposing themselves in risk without requiring corresponding return. This could also indicate that

they are not rational investors. Table 10, Column 3 shows for those households in divided states, coefficient of relative risk aversion is 9.371 with 1% level significance.

Meanwhile, we observe positive implied risk-free rates in all three areas. Democratic party-controlled states show a risk-free rate of 1.246% while Republican Party controlled states and divided states have 3.013% and 1.376% respectively.

5.2. Partisanship and Cross-section of Returns

Next we examine how the consumption risks of households on opposite sides of the political spectrum are priced in the cross-section. We run Fama-MacBeth cross-sectional regressions for the three portfolios representing households residing in three states. For testing assets, we use 35 portfolios, including 25 size-book to market portfolios and 10 industry portfolios, 31 portfolios, as well as individual stocks.

Table 11, Panel A shows the results using 31 portfolios as testing assets. Model (1) presents λ, or risk premium, of consumption risk by households. λ of consumption risk by households in Democratic-controlled states is 0.013% daily, significant at 5% level. Conversely, consumptions of households in Republican- and Divided-controlled states are not priced in the cross section. Table 8, Panel B represents the results using 35 portfolios that show similar effects. Table 8, Panel C, shows individual stocks results that suggest λ of consumption risk by households in Democratic controlled states is still significant even controlling for market cap and book-to-market ratio.

The results taken together indicate that only the consumption by households in Democratic controlled states is priced consistently and drive the overall superior results

shown in Table 3. This is consistent with the traditional partisan view that Democrats are usually more financially educated and have easier access to financial market, brokerage firms and fund firms. Therefore, the investors in Democratic-controlled states require a risk premium when holding assets that expose to their consumption growth. On the other hand, Republican- and Divided-controlled states don't display a significant λ. Alternatively, we can interpret the finding as that investors just do not require a risk premium in their investment while considering their contemporaneous consumption decisions.

5.3. Income and Risk Aversion

In this section, we further explore the partisan samples' results by investigating what drive the Democrats' reasonable risk aversion. We group the households based on their annual labor income conditional on political party affiliation. Table 12 presents the results of an exactly identified GMM test of the Euler equation. Each block shows one double-sorted household portfolio based on partisanship and above/below median or top/bottom deciles income level. Comparing across three panels, we find that all those high-income households show significantly positive relative risk-aversion coefficients, whereas almost other households (below median or bottom decile) do not have significant coefficients.

Within top 10 percent high- income group, we find that households in Democratic-controlled areas have highest risk aversion coefficients. These results indicate that high income households living in Democratic-controlled areas are more risk averse than their counterparts in Republican-controlled areas. This could also suggest that high income households in Democratic-controlled states tend to invest more in stock market than those

in Republican party-controlled areas. On the other hand, the relative risk-aversion coefficient for bottom 10 percent income households in divided states is not significant, showing that the results for households in divided-states are mostly driven by the high income households in those areas.

5.4. Income and Cross-section of Returns

We then repeat Fama-MacBeth cross-sectional regressions for these households grouped by labor income level and political party affiliation. We not only run consumption growth risk of each portfolio, but also pool households at the same income level but belong to different areas of partisan controls. Both tests return qualitatively similar results, and for simplicity, we only report the tests with pooled consumption beta. [48] The testing assets are the same as in all the partisanship models that include 35 portfolios, 31 portfolios and individual assets.

Table 13, Panel A, shows the cross-sectional regression results for partisanship and income level with 31 portfolios. Model (1) shows households residing in Democratic, Republican and

Divided states with top 10 and bottom 10 income level. Model (2) shows households residing in Democratic, Republican and Divided states with above median and below median income level. Among the different consumption growth factors, only Democratic-controlled areas consistently show a significant λ, or risk premium. For example, for the high-income households at top decile in Democratic-controlled states, they require 0.019%

[48] The results with individual households consumption beta are available upon request.

risk premium for assets that have one-unit exposure to their consumption growth per day. For those above median (Model 2), they require 0.004%, lower than the top decile households. However, Republican-controlled states show no significant consumption beta, which is consistent with the results in Table 8 suggesting that households in Republican areas are less risk averse. Moreover, high income households in divided areas also do not demand a significant risk premium. Moreover, Models (1) and Model (2) indicate that low income people, including those at bottom decile or below median, do not require a statistically meaningful risk premium when making a decision between consumption and investment.

Table 13, Panel B, shows the results with 35 portfolios. Overall, the results are similar as those in Table 9, Panel A, except Republican-controlled areas with income above median. Their consumption risk is also priced.

Table 13, Panel C, shows the results when using the universe of individual stocks. Model (1) presents the risk premiums required by households with top 10 and bottom 10 income level. Model (2) shows results from households residing in Democratic, Republican and Divided states with above median and below median income level. Controlling for size factor and book-to-market ratio, only risk premiums of households residing in high income Democratic-controlled and divided areas are significantly positive, while all others are significantly negative. Model (1) shows a 0.002% daily risk premium per one-unit exposure to the consumption risk for top decile Democrats, same for that in top income divided areas. Model (2) shows similar results as those in Model (1).

Putting together, Table 13 finds that income level plays a significant role in explaining the risk aversion of households in the whole sample and in the subsamples conditional on partisanship. We first find that Democrats are contributing to our whole sample's superior risk aversion results, possibly due to a more pro-stock market economic policy by the Democratic Party (Blinder and Watson, 2016) or a population of high financial sophistication. Then we find that the high-income people are the main drivers for the possible connection between investment and consumption risk. Thus, our results connect to the literature that studies the relationship between political party affiliation and household finance.

5.5. Partisanship and Industry Characteristics

After investigating the relation between investment and consumption, we examine how the consumption of households across political spectrum relates to the industries' performance. This exercise will help us deepen our understandings about the degree of political connection across industries. As consumption data is not tradable, we can't directly test if α are jointly zero using a GRS test. We run time-series regressions to collect consumption betas, and then compare the industry betas with the corresponding industry mean returns, as well as betas among three partisan-controlled states.

Table 14 shows the results with 10 Fama and French industries as the testing assets. First, we can see that Democratic-controlled states consistently show the biggest betas across all the industries than those of other two. This indicates that households in Democratic-controlled states are more sensitive to industry performance, or business

cycles when experiencing consumption fluctuations. Consumption fluctuates a lot over the business cycle. Households in those states could be quite sensitive to business cycle and tend to cut their consumption significantly. Specifically, they tend to require higher return when they realize a great growth in their consumption during expansions than their counterparts in Republican- and divided- states. Or conversely, when households in Democratic areas find out that their consumption drops significantly during recessions, the stocks for these industries will fall at a larger scale than the cases for Republican and divided households. Second, for the Telcm industry, Democratic areas show a positive beta while other two display a negative association. Third, we find that all three consumption measures are negatively correlated with mean returns across industries. The Democratic Party states show a highest level of absolute correlation compared to other two.

Taken together, we show that our measure can modestly explain industry return. More importantly, Democratic areas show the greatest sensitivity. Last but not least, the results show that households' consumption beta in democratic areas is negative for high tech industries.

6. Out-of-Sample Tests

To check out-of-sample robustness, we re-run all tests on a new sample period from 2016 to 2018. Table 15, Panel A shows the results of an exactly identified GMM test of the Euler equation for the excess market return; Table 15, Panel B provides the results with an additional moment restriction of risk-free rate; Table 15, Panel C reports the results with the instruments.

We find that the relative risk-aversion coefficient using out-of-sample data is 17.954, significant at 1% level, compared with the coefficient of 9.219 using in-sample data. Including additional moment decrease the risk-aversion coefficient to 13.6, whereas considering the instruments lowers the risk-aversion coefficient further to 11.957. Additionally, Table 15 shows low implied risk-free rates: 1.626 in Panel A and 1.28 in Panel C. Overall, Table 15 is consistent with Table 2: daily consumption measure delivers a lower risk-aversion coefficient while lowering the implied risk-free rate.

Then we examine the cross-sectional implication of the model by re-running Fama-MacBeth (1973) regression with out-of-sample data. Panels A, B and C report the price of consumption risk using 31 portfolios, 35 portfolios and individual stocks respectively.

We find that, with 31 portfolios, λ_c is 0.007% compared with 0.012% in Table 3; With 35 portfolios, we observe λ_c 0.008% versus 0.012% with in-sample data; With individual stocks as testing assets, λ_c increases from 0.001% in Table 4 to 0.002%. Meanwhile, all λ_cs are significant at either 5% or 1% levels across all panels. In summary, we can conclude that with out-of-sample data, the daily-consumption-based model performs well in fitting the cross-section of stock returns.

In this section, we conduct out-of-sample tests with data from 2016 to 2018, and we find overall, Table 15 and Table 16 strengthen our results in Section 3 and provide strong evidence for the continuing explanatory power of our daily consumption measures with the most recent data.

7. Factor Mimicking Portfolio

7.1. Hedging Consumption Risk

In this section, we aim to build a portfolio that specifically hedges consumption fluctuation risk. Households or investors make a decision between consuming and investing every day, thus their consumption should be closely related to stock returns at daily level. As such, constructing a portfolio that pays when investors' marginal utility is high due to high consumption fluctuation will help investors hedge this particular consumption risk.

We construct the consumption hedging portfolio using a Factor Mimicking Portfolio (FMP) approach, which projects the non-traded time-series consumption growth data onto a set of factors that drive the cross-section of stock return. The resultant FMP spans all the risk factors driving returns. For the traded factors, we first choose ten industry portfolios from the French Data Library because consumption should be related to business cycle or performance across different industries. In addition, our consumption measure is based on daily grocery and non-grocery shopping trips covering products and services across industries. Furthermore, we follow Engle et al. (2020) to include a market portfolio (excess market return or MKT), small-minus-big portfolio (SMB) for size and high-minus-low portfolio (HML) for value.

7.1.1. Factor Mimicking Portfolio and Out-of-Sample Test

We first run time series regression of consumption growth on chosen projecting factors, including Fama-French three factors, MKT, SMB and HML, and ten industry

portfolios. Table 17, Panel A, reports the projection results from our normal sample period from 2004 to 2015. We then use the estimated coefficients to construct the factor mimicking portfolio. A good FMP strategy should deliver excellent hedging effect out of sample. Therefore, we do not attempt to construct the factor mimicking portfolio within the normal sample period (2004-2015). Rather, we seek to use the estimated factor exposures in-sample to construct a factor mimicking portfolio out-of-sample (2016-2018).

Specifically, we use the estimated coefficients in Panel A from 2004-2015 to fit a time series of consumption growth based on the portfolios in the projection regression but from 2016-2018. This time series of returns can be regarded as the traded version of consumption growth out of sample. Following Engle et al. (2020), we test the FMP's out of sample fit by showing the correlation between the FMP from 2016 to 2018 using 2004-2015 data and real consumption growth from 2016 to 2018. Panel B of Table 17 shows that the correlation between the out-of-sample FMP and real time consumption is 10%, significant at 1% level. This indicates that our FMP can match the future consumption growth by 10%. This strategy can be implemented as investors can construct this FMP by assigning weights from Panel A of Table 17 to three factors and ten industry portfolios, thus effectively hedging the consumption fluctuation risk.

7.2. Traded Consumption Factor

Since we find that our consumption growth is priced cross-sectionally, we seek to construct a traded factor that can compare with other factors in pricing stock returns in time-series analysis. Unlike other consumption measures that are at annual level, our

measure is at daily level that enables us to perform factor projection to create a high-frequency and traded version of consumption growth.

We use this traded consumption factor to check the alphas in explaining asset returns. In addition, we run cross sectional tests to verify and compare the prices of risk between traded and non-traded version of consumption growth.

7.2.1. Constructing the Traded Consumption Factor

We construct the traded consumption factor using the similar method in section 7.1.1 of factor mimicking portfolio approach. But the objective here is to construct a traded time series in the full sample to test its asset pricing implications. Therefore, we project the consumption growth from 2004 to 2018 onto the same set of factors and assets. Then we collect the coefficient estimates and normalize them so the sum of the coefficients is one. We assign these weights to the projected assets to construct the traded version of consumption factor.

Panel A, Table 18, shows the projection regression and estimated coefficients. The consumption growth loads positively on SMB factor while negatively on Durables industry. It is also significantly positively related to manufacturing and telecommunication industries.

7.2.2 Factor Mimicking Portfolio and Asset Pricing Tests

After constructing the traded factor, we conduct time series and cross-sectional tests. We report alphas and risk premiums using the same testing assets in previous sectors, including 35 assets that comprise of 25 size and book-to-market sorted portfolios and 10

industry portfolios as well as 31 assets consisted of 10 size, 10 book-to-market, 10 investment growth and one market portfolios.

Panel B, a and b, Table 18, respectively report the risk premium and alphas using abovementioned two sets of assets. We calculate the significant level using the Gibbons-Ross-Shanken (1986) F-statistics that tests if all the alphas of all testing assets are jointly zero. The average alpha of traded consumption factor is higher than Fama-French 3 factor or Fama-French 3 factor plus a momentum factor when using the 31 portfolios. Likewise, the consumption alpha is higher than both Fama-French 3 factor with and without momentum factor if using 35 portfolios. On the other hand, the consumption factor carries a significant risk premium, which ranges from 0.08% to 0.101% per day, significant at 5% level. The R squared of the consumption as a single factor to explain the cross-section of returns range from 29% to 35%.

Taken together, we show that our traded consumption measure still carries a risk premium that explains 29% to 35% of variation in cross-sectional returns. Furthermore, its alphas are comparable to those from Fama-French 3-factor model with or without a momentum factor.

8. Conclusion

This paper uses daily consumption to re-evaluate consumption Euler equations in the standard consumption-based capital asset pricing model. We find that the CCAPM with daily consumption matches the equity premium with a relative risk-aversion coefficient of 9.219. Similarly, low risk aversion coefficient of 11.477 also emerges from a joint pricing

tests, which suggests that daily consumption does a better job than Garbage and Unfiltered NIPA in resolving the equity-premium puzzle and risk-free-rate puzzle. The daily-consumption-based model also well explains the cross-sectional dispersion in average returns.

We further investigate partisan heterogeneity, and reveal the significant difference in the risk preferences of Democrats and Republicans. Democrats are not only more risk averse than Republicans, but also their consumption beta does a better job in fitting cross-sectional asset pricing moments.

In addition to demonstrating the asset pricing performance of the daily consumption Euler equations, our paper also illustrates the importance of short-term component and intra-annual dynamics in conditional high-frequency consumption volatility. For future research, it is interesting to study whether incorporating asymmetric correlation between short-term dynamics and low-frequency volatility or a fat-tailed distribution of daily consumption growth can proxy the consumption volatility dynamic better and strengthen the asset pricing implication further. Alternatively, it is worth investigating the implications of daily consumption measure for asset pricing models that go beyond CRRA preferences, which could generate new insights about the true-properties of consumption growth.

References

Abel, A.B., 1990, "Asset Prices under Habit Formation and Catching up with the Joneses." National Bureau of Economic Research working paper.

Ait-Sahalia, Y., Parker, J.A., and Yogo, M., 2004, "Luxury Goods and the Equity Premium." *Journal of Finance*, 59(6), 2959-3004.

Ait-Sahalia, Y., Per, A.M., and Zhang, L., 2005, "A Tale of Two Time Scales: Determining Integrated Volatility with Noisy High-Frequency Data." *Journal of the American Statistical Association*, 100(472), 1394-1411.

Ang, A., Hodrick, R.J., Xing, Y., and Zhang, X., 2021, "The Cross-Section of Volatility and Expected Returns." National Bureau of Economic Research working paper.

Bandi, F., and Tamoni, A., 2017, "Business-Cycle Consumption Risk and Asset Prices." working paper.

Bansal, R., and Yaron, A., 2004, "Risks for the Long Run: A Potential Resolution of Asset Pricing Puzzles." *Journal of Finance*, 59(4), 1481-1509.

Bansal, R., Kiku, D., and Yaron, A., 2012, "Risks for the Long Run: Estimation with Time Aggregation." National Bureau of Economic Research working paper.

Bekaert, G., Ehrmann, M., Fratzscher, M., and Mehl, A., 2014, "The Global Crisis and Equity Market Contagion." *Journal of Finance*, 69(6), 2597-2649.

Bittlingmayer, G., 1998, "Output, Stock Volatility, and Political Uncertainty in a Natural Experiment: Germany, 1880–1940."*The Journal of Finance*, 53(6), 2243-2257.

Blinder, A., Watson, M., 2016, "Presidents and the US Economy: An Econometric Exploration." *American Economic Review*, 106(4), 1015-1045.

Boguth, O., and Kuehn, L.A., 2013, "Consumption Volatility Risk." *Journal of Finance*, 68(6), 2589-2615.

Boons, M., and Tamoni, A., 2015, "Horizon-Specific Macroeconomic Risks and the Cross-Section of Expected Returns." working paper.

Breeden, D.T., Gibbons, M.R., and Litzenberger, R.H., 1989, "Empirical Tests of the Consumption-Oriented CAPM." *The Journal of Finance*, 44(2), 231-262.

Brogaard, J., Nguyen, H., Putnins, T., and Wu, E., 2019, “What Moves Stock Prices? The Role of New, Noises, and Information.” working paper.

Campbell, J.Y., and Cochrane, J.H., 1999, “By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior.”*Journal of Political Economy*, 107(2), 205-251.

Campbell, J.Y., 2017, “Financial Decisions and Markets: A Course in Asset Pricing.” Princeton University Press, NJ.

Campbell, J.Y., Giglio, S., Polk, C., and Turley, R., 2018, “An Intertemporal CAPM with Stochastic Volatility.” *Journal of Financial Economics*, 128(2), 207-233.

Caporale, B., and Caporale T., 2008, “Political Risk and the Expectations Hypothesis.” *Economics Letters*, 100, 178-180.

Chen, N.F., Roll, R., and Ross, S.A., 1986, “Economic Forces and the Stock Market.” *Journal of Business*, 383-403.

Chen, Z., Liu, J., Lu, A., and Tao, L., 2020, “Carbon Dioxide and Asset Pricing: Evidence from International Stock Markets. ”working paper.

Cochrane, J.H., 2005, “Asset Pricing” Princeton University Press. Princeton New Jersey.

Constantinides, G.M., and Duffie, D., 1996, “Asset Pricing with Heterogeneous Consumers.” *Journal of Political Economy*, 104(2), 219-240.

Constantinides, G.M., 1990, “Habit Formation: A Resolution of the Equity Premium Puzzle.” *Journal of Political Economy*, 98(3), 519-543.

Da, Z., Yang, W., and Yun, H., 2016, “Household Production and Asset Prices.” *Management Science*, 62(2), 387-409.

Dew-Becker, I., and Giglio, S., 2016, “Asset Pricing in the Frequency Domain: Theory And Empirics.” *Review of Financial Studies*, 29(8), 2029-2068.

Engle, R.F., and Rangel, J.G., 2008, “The Spline-GARCH Model for Low-Frequency Volatility and Its Global Macroeconomic Causes.” *Review of Financial Studies*, 21(3), 1187-1222.

Engle, R.F., Giglio, S., Kelly, B., Lee, H. and Stroebel, J., 2020, “Hedging climate change news. ”*Review of Financial Studies*, 33(3), 1184-1216.

Epstein, L.G., and Zin, S.E.V., 1989, “Risk Aversion, and the Temporal Behavior Of Consumption and Asset Returns: A Theoretical Framework.” *Econometrica*, 57(4), 937.

Fama, E.F., and French, K.R., 1996, “Multifactor Explanations of Asset Pricing Anomalies.” *Journal of Finance*, 51(1), 55-84.

Fama, E.F., and Macbeth, J.D., 1973, “Risk, Return, and Equilibrium: Empirical Tests.” *Journal of Political Economy*, 81(3), 607-636.

Giglio, S. and Xiu, D., 2020, “Asset pricing with omitted factors. ”*Journal of Political Economy*, forthcoming.

Hansen, L.P., and Jagannathan, R., 1991, “Implications of Security Market Data for Models of Dynamic Economies.” *Journal of Political Economy*, 99(2), 225-262.

Hansen, L.P., and Singleton, K.J., 1982, “Generalized Instrumental Variables Estimation of Nonlinear Rational Expectations Models.”*Econometrica: Journal of the Econometric Society*, 1269-1286.

Hansen, L.P., and Singleton, K.J., 1983, “Stochastic Consumption, Risk Aversion, and the Temporal Behavior of Asset Returns.” *Journal of Political Economy*, 91(2), 249-265.

Heaton, J., 1995, “An Empirical Investigation of Asset Pricing with Temporally Dependent Preference Specifications.”*Econometrica: Journal of the Econometric Society*, 681-717.

Hendershott, T., Livdan, D., and R¨osch, D., 2020, “Asset Pricing: A Tale of Night and Day.” *Journal of Financial Economics*, 138(2020), 635-662.

Hou, K., Xue, C., Zhang, L., 2015, “Digesting anomalies: An investment approach.” *The Review of Financial Studies*, 29(3), 650-705.

Jagannathan, R., and Wang, Y., 2007, “Lazy Investors, Discretionary Consumption, and the Cross-Section of Stock Returns.” *Journal of Finance*, 62(4), 1623-1661.

Jegadeesh, N., Noh, J., Pukthuanthong, K., Roll, R., and Wang, J., 2019, “Empirical Tests of Asset Pricing Models with Individual Assets: Resolving the Errors-In-Variables Bias in Risk Premium Estimation.” *Journal of Financial Economics*, 133(2), 273-298.

Jensen, M.C., Black, F., and Scholes, M.S., 1972, “The Capital Asset Pricing Model: Some Empirical Tests.

Kaustia, M., and Rantala, V., 2015, “Social Learning and Corporate Peer Effects.” *Journal of Financial Economics*, 117(3), 653-669.

Kaustia, M., Kn¨*u*pfer, S., and Torstila, S. 2015, “Stock Ownership and Political Behavior: Evidence from Demutualizations.”*Management Science*, 62(4), 945-963.

Kempf, E., and Tsoutsoura, M., 2018, “Partisan Professionals: Evidence from Credit Rating Analysts.” National Bureau of Economic Research working paper.

Kleibergen, F., and Zhan, Z., 2020, “Robust Inference for Consumption-Based Asset Pricing.” *Journal of Finance*, 75(1), 507-550.

Kroencke, T.A., 2017, “Asset Pricing without Garbage.” *Journal of Finance*, 72(1), 47-98.

Leblang, D., and Mukherjee, B., 2005, “Government Partisanship, Elections, and the Stock Market: Examining American and British Stock Returns, 1930–2000.”*American Journal of Political Science*, 49(4), 780-802.

Lettau, M., and Ludvigson, S., 2002, “Consumption, Aggregate Wealth, and Expected Stock Returns.” *Journal of Finance*, 56(3), 815-849.

Lewellen, J., Nagel, S., and Shanken, J., 2010, “A Skeptical Appraisal of Asset Pricing Tests.” *Journal of Financial Economics*, 96(2), 175-194.

Malloy, C.J., Moskowitz, T.J., and Vissing-Jorgensen, A., 2009, “Long-Run Stockholder Consumption Risk and Asset Returns.” *Journal of Finance*, 64(6), 2427-2479.

Mankiw, N.G., and Shapiro, M.D., 1986, “Do We Reject Too Often?: Small Sample Properties of Tests of Rational Expectations Models.” *Economics Letters*, 20(2), 139-145.

Mankiw, N.G., and Zeldes, S.P., 1991, “The Consumption of Stockholders and Nonstockholders.”*Journal of Financial Economics*, 29(1), 97-112.

Meeuwis, M., Parker, J.A., Schoar, A., and Simester, D.I., 2019, “Belief Disagreement and Portfolio Choice.” National Bureau of Economic Research working paper.

Mian, A., Sufi, A., and Trebbi, F., 2015, “Foreclosures, House Prices, and the Real Economy.” *Journal of Finance*, 70(6), 2587-2634.

Pagliardi, G., Poncet, P., and Zenios, S.A., 2019, “A Political Capital Asset Pricing Model.” working paper.

Parker, J. A., Julliard, C. 2005, “Consumption risk and the cross section of expected returns.” *Journal of Political Economy*, 113(1), 185-222

Pastor, L., and Veronesi, P., 2017, “Political Cycles and Stock Returns.” National Bureau of Economic Research working paper.

Qiao, 2013, “Cross-Sectional Evidence in Consumption Mismeasurement.” working paper.

Restoy, F. and Weil, P., 2011, “Approximate Equilibrium Asset Prices.” *Review of Finance*, 15(1), 1-28.

Savov, A., 2011, “Asset Pricing with Garbage.” *Journal of Finance*, 66(1), 177-201.

Sundaresan, S.M., 1989, “Intertemporally Dependent Preferences and the Volatility of Consumption and Wealth.” *Review of Financial Studies*, 2(1), 73-89.

Svarstad, H., Benjaminsen, T.A., and Over˚*a*, R., 2018, “Power Theories in Political Ecology.

T´*e*dongap, R., 2015, “Consumption Volatility and the Cross-Section of Stock Returns.” *Review of Finance*, 19(1), 367-405.

Yogo, M., 2006, “A Consumption-Based Explanation of Expected Stock Returns.” *Journal of Finance*, 61(2), 539-580.

Zviadadze, I., 2018, “Term Structure of Risk in Expected Returns.” working paper.

Figure 1: Nielsen Market Penetration

Nielsen-defined Scantrack markets where Consumer Panel Data (CPD) tracks the consumption of participating households.

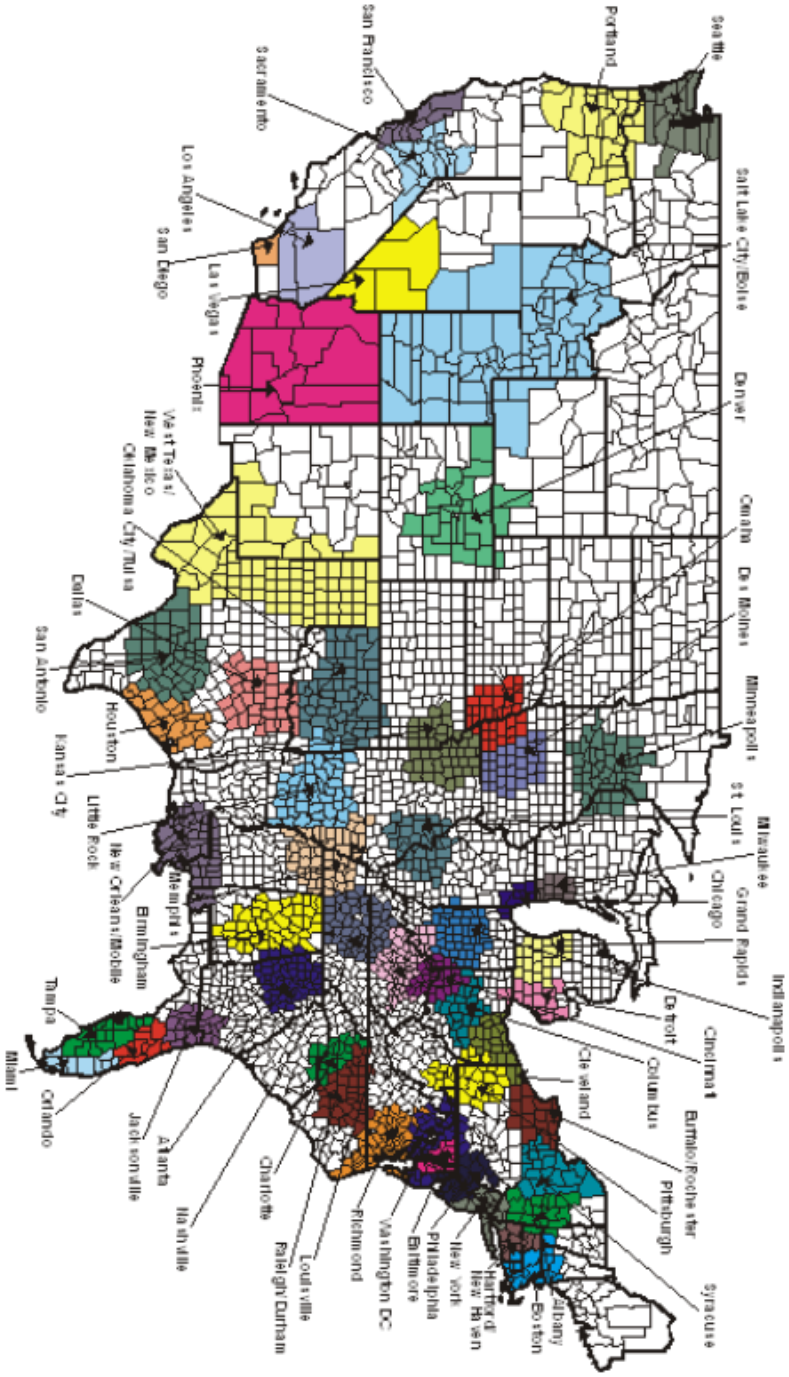


Figure 2: This figure plots the daily consumption growth from 2004 to 2015.

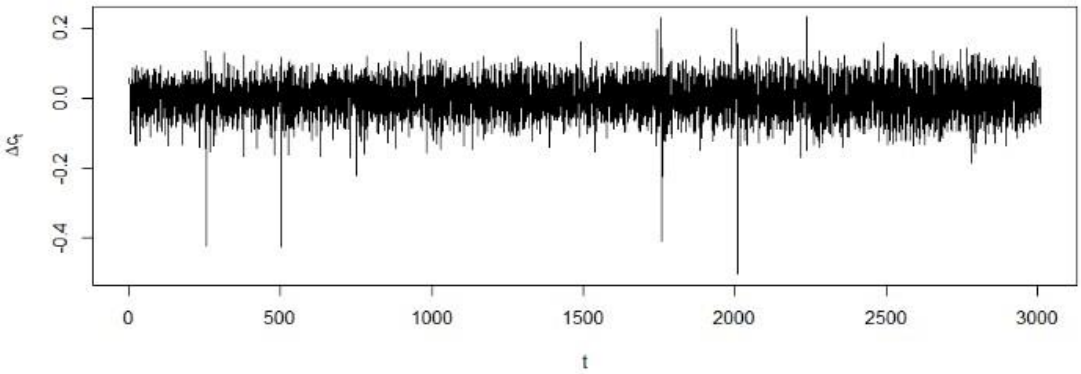


Figure 3: Autocorrelation and Partial Autocorrelation

This figure plots the autocorrelation and partial autocorrelation for daily consumption growth.

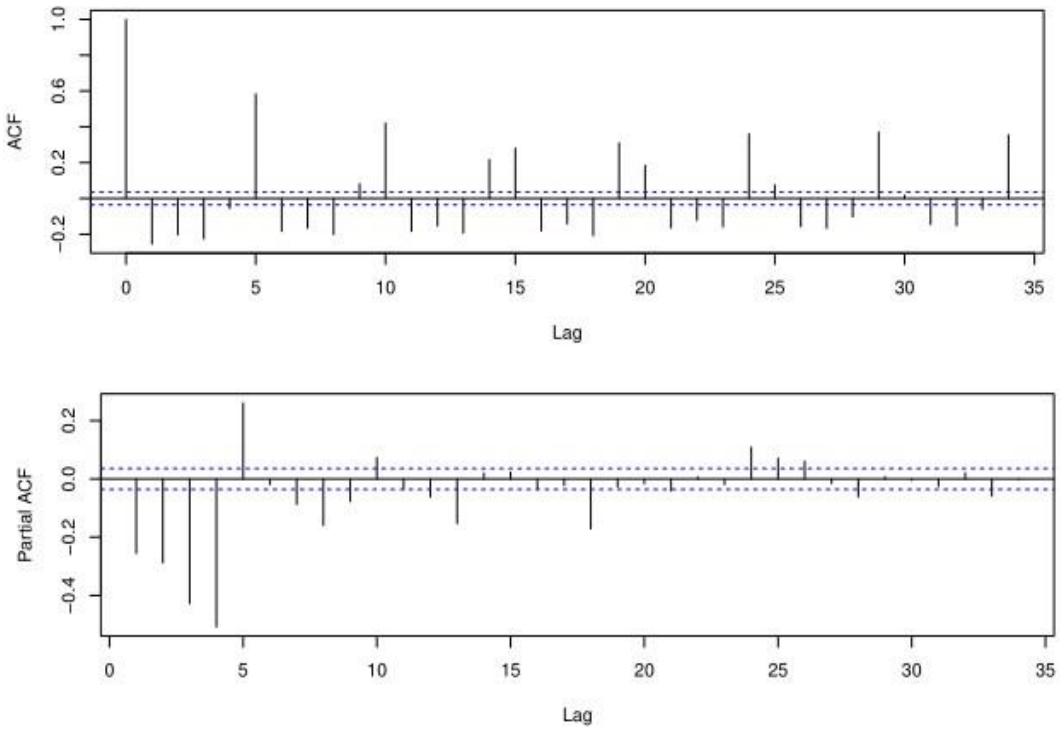


Figure 4: Fit of the Model: Low-frequency Variance with only $f_1(t)$

This figure shows the fitted value of low-frequency variance (τ_t), which has a strong rise-fall pattern and suggests a cyclical smoother ($f_2(d)$) is required.

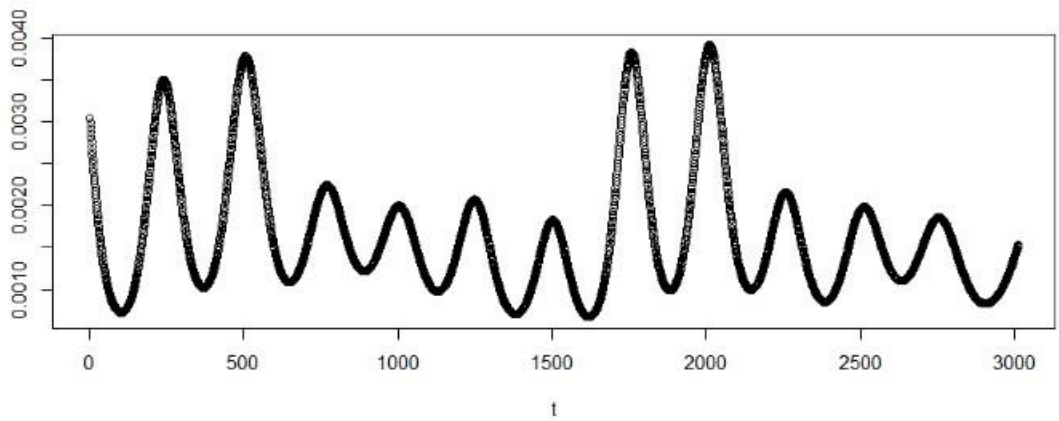


Figure 5: Fit of the Model: Low-frequency Variance with $f_1(t)$ and $f_2(d)$

This figure plots the fitted value of two smooth functions ($f_1(t)$ and $f_2(d)$) and low-frequency variance (τ_t).

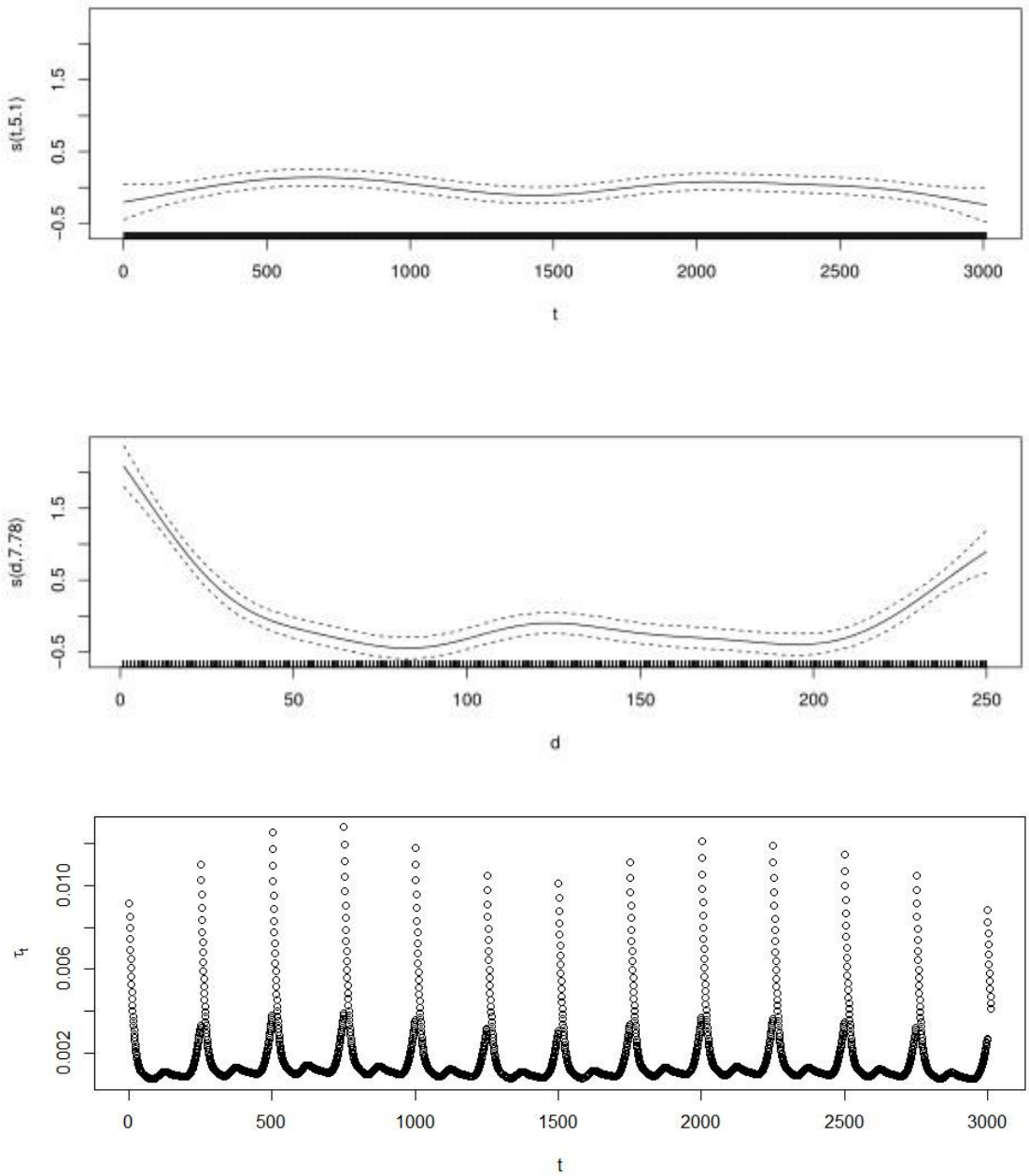


Figure 6: Fit of the Model: Low- and High-frequency Variance

This figure shows the fitted value of low-frequency variance (τ_t) and high-frequency variance (h_t), where we find strong intra-annual fluctuations in the low-frequency variance and strong short-run dynamics in the high-frequency variance.

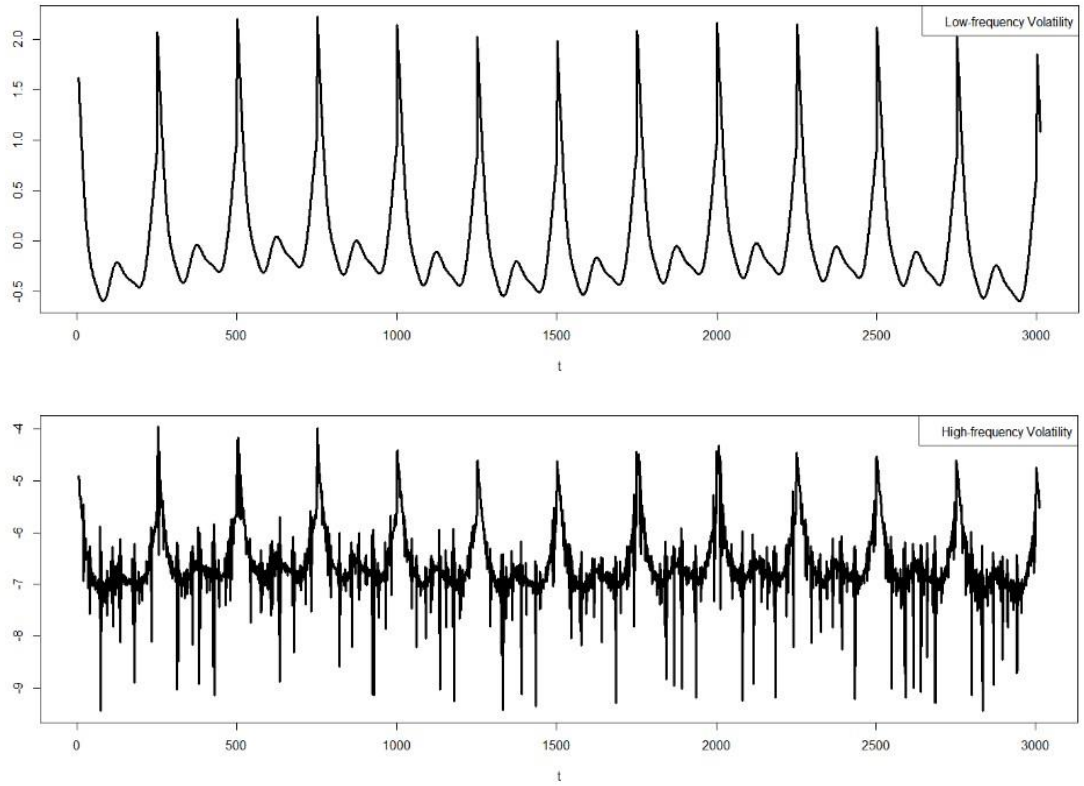


Table 1: Summary Statistics

In this table, panel A presents the summary statistics of daily consumption. We report mean, standard deviation, variance. In addition, we include the auto-correlation and the correlation with the market return. We calculate the statistics of other consumption measures in the same sample period as our daily measure. In panel B, we report other consumption measures in full sample period.

	Panel A. Sample Period (2004-2015)					*Panel B. Sample Period (1960-2007)*			
	Daily Consumption	Daily Consumption at Annual Level	Unfiltered NIPA	P-J Dec-Dec	Q4-Q4	Garbage	Unfiltered NIPA	P-J Dec-Dec	Q4-Q4
Mean (%)	0.170	6.226	1.054	2.723	0.93	1.472	1.513	2.118	1.51
Standard Deviation (%)	6.164	18.160	2.199	2.810	1.25	2.973	2.618	1.385	1.98
Var (%)	0.380	3.298	0.048	0.079	0.01	0.088	0.069	0.019	0.03
Autocorr (1) (%)	-19.410	-18.820	31.210	66.950	50.2	-14.51	-8.310	80.180	21.7
Corr with Rm (%)	2.640	10.222	73.509	59.384	69.5	19.70	33.432	39.569	39.6
Corv with Rm	0.185	0.342	0.292	0.301	0.15	0.095	0.139	0.087	0.12

Table 2: GMM Test and Risk Aversion Estimates

Panel A shows the GMM test on estimating the relative risk aversion coefficient. It uses the exactly identified model. The moment restriction is as follows:

$$E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma}R^e_{t+1}] = 0$$

Panel B shows the GMM test on estimating the relative risk aversion coefficient. In addition to the equity premium, this panel reports a risk-free rate. The moment restrictions are as follows:

$$E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma}R^e_{t+1}] = 0 \qquad E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma}R^f_{t+1}] = 1$$

and Panel C shows the GMM test on estimating the relative risk aversion coefficient with instruments. The instrument set Z_t contains a constant, lagged consumption growth, one plus the lagged excess market return and the detrended logged log price to dividend ratio. The moment restrictions are as follows:

$$E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma}R^e_{t+1} \otimes Z_t] = 0$$

We fix β to be 0.95. R^e_{t+1} is the value weighted CRSP index return in excess of daily risk free rate. γ is the relative risk aversion (RRA). We also report RRA's standard error and mean absolute pricing error (MAPE). The implied risk-free rate is derived from RRA.

	Panel A. Equity Premium (Exactly Identified)				
	Daily Consumption	Garbage (Annual from 1960-2007)	Unfiltered NIPA (1960-2014)	P-J Dec-Dec (1960-2014)	Q4-Q4 (1960-2014)
RRA (γ) (Gamma)	9.219	15.630	22.530	42.350	64.050
(s.e.)	3.028	8.380	11.980	22.870	39.610
t stat	3.045	1.865	1.881	1.852	1.617
MAE	0.445	0.000	0.000	0.000	0.000
Implied risk free rate	1.255	17.250	30.090	158.190	82.600
Observations	3023				
	Panel B. Equity Premium and Risk-free Rate (One-stage GMM)				
	Daily Consumption	Garbage (Annual from 1960-2007)	Unfiltered NIPA (1960-2014)	P-J Dec-Dec (1960-2014)	Q4-Q4 (1960-2014)
RRA (γ) (Gamma)	11.477	28.720	50.840	171.840	215.160
(s.e.)	2.215	9.390	12.990	48.060	58.140
t stat	5.182	3.059	3.914	3.576	3.701
MAE	0.433	4.570	7.270	0.120	0.120
Observations	3023				
	Panel C. Equity Premium and Instruments (One-stage GMM)				
	Daily Consumption	Garbage (Annual from 1960-2007)	Unfiltered NIPA (1960-2014)	P-J Dec-Dec (1960-2014)	Q4-Q4 (1960-2014)
RRA (γ) (Gamma)	5.464	16.960	15.380	60.000	74.000
(s.e.)	2.450	8.150	11.040	70.000	9.000
t stat	2.231	2.081	1.393	0.857	8.222
MAE	0.537	1.250	2.790	0.250	0.240
Implied risk free rate	1.114	17.750	22.884	367.000	250.000
Observation	3022				

Table 3: Fama-MacBeth Cross-Sectional Regressions – Portfolios as Testing Asset

This table reports the Fama-MacBeth regressions using portfolios as testing assets. Panel A uses 10 portfolios separately sorted by size, book to market and investment, in addition to a market portfolio. Panel B uses 25 Fama-French (1993) 25 portfolios sorted by size and book to market and 10 industry portfolios. On the top half of table, we report first stage betas from time-series regressions, and then we document risk premiums in the bottom half of table. For all models, we use three lag Newey-West t-statistics. We also report mean absolute pricing error as MAPE. *p <0.1; **p <0.05; ***p <0.01.

	Betas in the First Stage							
	Panel A. 31 Portfolio				*Panel B. 35 Portfolio*			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Daily Consumption Measure	0.372***	0.050***	0.039***	-0.012***	0.519***	0.043***	0.039***	-0.017***
	(0.021)	(0.001)	(0.001)	(0.001)	(0.022)	(0.001)	(0.001)	(0.001)
MRF (q-MKT in model 4)		1.012***	1.007***	1.017***		1.002***	0.999***	0.998***
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
SMB (q-ME in model 4)		0.201***	0.193***	0.194***		0.380***	0.376***	0.357***
		(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)
HML (q-IA in model 4)		0.095***	0.082***	0.106***		0.110***	0.103***	0.095***
		(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)
CMA (q-ROA in model 4)			-0.051***	-0.091***			-0.025***	-0.126***
			(0.001)	(0.001)			(0.001)	(0.001)
RMW (q-EG in model 4)			0.007***	0.038***			0.007***	0.026***
			(0.001)	(0.001)			(0.001)	(0.001)
UMD			-0.005***				-0.003***	
			(0.000)				(0.000)	
	Risk Premia							
	Panel A. 31 Portfolio				*Panel B. 35 Portfolio*			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Daily Consumption Measure	0.012**	0.009**	0.009**	0.010**	0.012**	0.009**	0.006*	0.008*
	(0.006)	(0.004)	(0.004)	(0.005)	(0.006)	(0.004)	(0.003)	(0.005)
MRF (q-MKT in model 4)		0.015	0.012	0.010		-0.005	0.001	-0.016
		(0.027)	(0.026)	(0.025)		(0.021)	(0.020)	(0.025)
SMB (q-ME in model 4)		0.005	0.007	0.005		-0.003	-0.001	0.001
		(0.010)	(0.010)	(0.010)		(0.008)	(0.007)	(0.010)
HML (q-IA in model 4)		-0.003	0.001	-0.002		-0.006	-0.007	-0.007
		(0.012)	(0.012)	(0.007)		(0.007)	(0.006)	(0.009)
CMA (q-ROA in model 4)			0.011	0.001			0.004	0.010
			(0.012)	(0.014)			(0.008)	(0.010)
RMW (q-EG in model 4)			-0.003	0.009			-0.001	0.003
			(0.006)	(0.012)			(0.007)	(0.011)
UMD			-0.032				-0.005	
			(0.030)				(0.020)	
Constant	0.035*	0.018	0.021	-0.049*	0.035*	0.042**	0.043**	0.053**
	(0.021)	(0.019)	(0.018)	(0.027)	(0.020)	(0.019)	(0.019)	(0.021)
Observations	93,713	93,713	93,713	93,713	105,805	105,805	105,805	105,805
R Squared	0.129	0.475	0.606	0.560	0.118	0.431	0.555	0.547
MAPE	0.033	0.026	0.023	0.048	0.034	0.056	0.050	0.0385

Table 4: Fama-MacBeth Cross-Sectional Regressions - Individual Stocks as Testing Assets

This table reports the Fama-MacBeth regressions using individual stocks as testing assets. On the top half of table, we report first stage betas from time-series regressions, and then we document risk premiums in the bottom half of table. To control for individual stocks' characteristics and size differences, we include log-transformed market value of equity and book to market ratio in each model. We use twelve lag Newey-West t-statistics (Boguth and Kuehn 2013). We also report mean pricing error as MAPE. *p <0.1; **p <0.05; ***p <0.01.

	Betas in the First Stage			
	(1)	(2)	(3)	(4)
Daily Consumption Measure	0.647***	0.328***	0.253***	0.184***
	(0.011)	(0.004)	(0.005)	(0.005)
MRF (q-MKT in model 4)		0.772***	0.769***	0.764***
		(0.000)	(0.000)	(0.000)
SMB (q-ME in model 4)		0.617***	0.597***	0.573***
		(0.001)	(0.001)	(0.002)
HML (q-IA in model 4)		0.080***	0.021***	0.011***
		(0.001)	(0.001)	(0.002)
CMA (q-ROA in model 4)			-0.188***	-0.258***
			(0.002)	(0.002)
RMW (q-EG in model 4)			-0.032***	-0.042***
			(0.002)	(0.001)
UMD			-0.058***	
			(0.001)	
	Risk Premia			
	(1)	(2)	(3)	(4)
Daily Consumption Measure	0.002***	0.001*	0.001**	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
MRF (q-MKT in model 4)		-0.019***	-0.016***	-0.019***
		(0.006)	(0.004)	(0.006)
SMB (q-ME in model 4)		0.006*	0.001	-0.001
		(0.003)	(0.003)	(0.003)
HML (q-IA in model 4)		-0.002	-0.004*	-0.001
		(0.003)	(0.002)	(0.002)
CMA (q-ROA in model 4)			-0.000	-0.002
			(0.001)	(0.003)
RMW (q-EG in model 4)			-0.003**	0.001
			(0.001)	(0.002)
UMD			-0.000	
			(0.004)	
Log(Market Value of Equity)	-0.001***	-0.001**	-0.001**	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Book to Market Ratio	-0.000***	-0.016***	-0.010***	-0.000***
	(0.000)	(0.002)	(0.001)	(0.000)
Constant	0.012	0.047***	0.048***	0.047***
	(0.021)	(0.016)	(0.017)	(0.014)
Observations	11,111,427	11,096,566	11,059,822	11,055,939
R Squared	0.017	0.047	0.065	0.061
MAPE	0.065	0.065	0.066	0.029

Table 5: Kleibergen and Zhan (2020) Tests

This table reports KZ tests. Panel A shows the risk premium of daily consumption measure using 31 portfolios used in KZ (2020), and Panel B shows the results with 31 portfolios to be consistent with that in Savov (2011). We provide p-value of KZ's first rank test, which is based on a F-test of a null hypothesis that first passes betas are jointly zero. A 95% confidence interval for price of consumption risk is also shown. This interval is constructed by the critical value from the F distribution in a GRS-FAR test.

	2004-2015 Daily Consumption Measure	1960-2014			
		Garbage	Unfiltered NIPA	PJ Dec-Dec	Q4-Q4
		Panel A. 31 Portfolios			
Estimate of Lambda	0.061	2.090	2.440	10.140	2.270
t lambda with Shanken correction	2.262	2.510	2.590	1.469	2.389
t lambda with Shanken and NW corrections	2.184	2.750	2.367	1.346	2.172
MAE	0.009	1.330	0.870	0.013	0.010
KZ Test I: Rank Test P Value	0.088	0.006	0.211	0.531	0.273
KZ Test II: 95% C.S. of Lambda GRS-FAR	(-1.034, 0.957)	(-0.8,7.8)	(-∞, -5.8) & (-0.6, ∞)	(-∞, ∞)	(-∞, ∞)
		Panel B. 35 Portfolios			
Estimate of Lambda	0.055	13.346	4.641	7.838	3.493
t lambda with Shanken correction	2.134	5.964	1.751	2.029	2.151
t lambda with Shanken and NW corrections	2.177	6.106	1.891	2.172	2.142
MAE	0.011	0.021	0.114	0.035	0.020
KZ Test I: Rank Test P Value	0.004	0.520	0.923	0.651	0.791
KZ Test II: 95% C.S. of Lambda GRS-FAR	(0.029, 0.112)	(-4.474,0.868)	(-2.019, 2.131)	(-5.696, 5.314)	(-2.579, 2.340)

Table 6: Estimation Results for the Daily Consumption Measure

This table reports the estimation results for the daily consumption measure. Estimation is based on a model with Gaussian innovations. See model specification in Equations (9), (10), (11) and (12).

Variables	Coefficient	s.e.
α_1	−0.5376	0.0176
α_2	−0.4758	0.0192
α_3	−0.4895	0.0191
α_4	−0.3334	0.0192
α_5	0.2611	0.0176
ω_1	0.1070	0.0197
ω_2	−0.0796	0.0204
ω_3	−0.0801	0.0204
ω_4	0.0526	0.0197

Table 7: GMM Tests with Alternative Low-frequency Consumption Measures

This table shows the risk averse coefficients with different consumption frequencies of weekly, monthly and annual levels. We use the exactly identified model. The moment restriction is as follows:

$$E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma}R^e_{t+1}] = 0$$

We fix β to be 0.95. R^e_{t+1} is the value weighted CRSP index return in excess of daily risk free rate. γ is the relative risk aversion (RRA). We also report RRA's standard error and mean absolute pricing error (MAPE). The implied risk-free rate is derived from RRA.

	Weekly Consumption Growth	Monthly Consumption Growth	Annual Consumption Growth
RRA (γ)	17.962	1.738	-72.846
(s.e.)	3.858	71.148	22.876
t stat	4.655	0.024	-3.184
Implied r_f	1.174	1.055	0.000
Observations	604	144	11

Table 8: Magnet Products

This table shows the summary statistics and risk averse coefficients for Magnet products that proxy for the instant consumption, such as fruits, vegetables and in-store backed goods. For durables, it includes detergent, computer and motor-vehiclem among others. For summary statistics, we report mean, standard deviation, correlation and covariance with the excess market return in percentage format. For GMM estimation, We use the exactly identified model. The moment restriction is as follows:

$$E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma}R^e_{t+1}] = 0$$

We fix β to be 0.95. R^e_{t+1} is the value weighted CRSP index return in excess of daily risk free rate. γ is the relative risk aversion (RRA). We also report RRA's standard error and mean absolute pricing error (MAPE). The implied risk-free rate is derived from RRA.

	Magnet Product (2007-2015)
% of Magnet Consumption to Total Consumption	18.57%
Mean	0.27%
Stdev	8.51%
Corr with Market	-0.95%
Cov with Excess Market Return	-0.11%
RRA (γ)	7.960
(s.e.)	4.274
t stat	1.862
Implied RF	1.309
Number of Observations	2258

Table 9: Daily Consumption Measure and Long-horizon Returns

This table tests our main consumption measure's ability in explaining the long-run variation in average returns. We run GMM estimating by using future consumption growth up to 26 weeks. γ is the relative risk aversion (RRA). We also report RRA's standard error and mean absolute pricing error (MAPE). The implied risk-free rate is derived from RRA.

Horizon (Weeks)	*RRA (γ)*	(s.e.)	z stat
1 Week Ahead Growth	16.84	11.83	1.42
4 Week Ahead Growth	7.61	5.68	1.34
8 Week Ahead Growth	4.99	1.74	2.87
16 Week Ahead Growth	-10.50	5.54	-1.90
24 Week Ahead Growth	-11.60	3.60	-3.22
26 Week Ahead Growth	7.49	3.49	2.15

Table 10: Partisanship and Risk Aversion Estimates

This table shows the GMM test on estimating the relative risk aversion coefficient by three kinds of politically controlled states. The partisanship is determined through the data provided by the National Conference of State Legislatures. We sort households into three portfolios, including Democratic Party controlled states, Republican Party controlled states and divided states. This table only uses the exactly identified model. The moment restriction is as follows:

$$E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma}R^e_{t+1}] = 0$$

We fix β to be 0.95. R^e_{t+1} is the value weighted CRSP index return in excess of daily risk free rate. γ is the relative risk aversion (RRA). We also report RRA's standard error.

	Democrat Controlled States	Republican Controlled States	Split Controlled States
RRA (γ)	9.179	-7.524	9.371
s.e.	3.085	2.560	3.136
z stat	2.975	-2.939	2.988
Implied Rf	1.246	3.013	1.376

Table 11: Partisanship and Cross Section of Stock Returns

This table reports the Fama-MacBeth regressions by three kinds of politically controlled areas. Panel A uses 31 portfolios with three lag Newey-West t-statistics; Panel B uses 25 Fama-French (1993) portfolios sorted by size and book to market and 10 industry portfolios with three lag Newey-West tstatistics; Panel C uses individual stocks as testing assets with twelve lag Newey-West t-statistics. We also report mean pricing error as MAPE. *p <0.1; **p <0.05; ***p <0.01.

	Panel A: 31 Portfolios	*Panel B: 35 Portfolios*	*Panel C: Individual Stocks*
	(1)	(2)	(3)
Democrat Controlled States	0.013**	0.017**	0.004*
	(0.006)	(0.007)	(0.002)
Republican Controlled States	-0.023	0.007	-0.009
	(0.019)	(0.021)	(0.007)
Split Controlled States	0.009	0.007	0.010***
	(0.008)	(0.007)	(0.003)
Ln(Market Value of Equity)			-0.000***
			(0.000)
Book to Market Ratio			0.001
			(0.002)
Constant	0.040**	0.049***	0.137
	(0.020)	(0.019)	(0.107)
Observations	93,713	105,805	12,516,917
R Squared	0.290	0.282	0.042
MAPE	0.024	0.015	0.334

Table 12: Partisanship, Income and Risk Aversion Estimates

This table shows the GMM test on estimating the relative risk aversion coefficient by two sets of double-sorted portfolios. The first set is first sorted on politically controlled states and then on income level above or below median. The second set is first sorted on politically controlled states and then on income level of top and bottom decile. The partisanship is determined through the data provided by the National Conference of State Legislatures. This table only uses the exactly identified model. The moment restriction is as follows:

$$E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma}R^e_{t+1}] = 0$$

We fix β to be 0.95. R^e_{t+1} is the value weighted CRSP index return in excess of daily risk free rate. γ is the relative risk aversion (RRA). We also report RRA's standard error.

	RRA γ	s.e.	z-stat
Democrat wealth top10	6.234	2.455	2.539
Democrat wealth bottomp10	5.524	3.431	1.610
Democrat wealth above median	6.869	2.645	2.597
Democrat wealth below median	4.465	2.583	1.729
Republican wealth top10	-38.871	21.475	-1.810
Republican wealth bottomp10	-2.826	2.044	-1.383
Republican wealth above median	3.458	2.405	1.438
Republican wealth below median	-6.356	4.059	-1.566
Divided wealth top10	5.463	1.370	3.987
Divided wealth bottomp10	9.381	6.078	1.543
Divided wealth above median	9.204	2.202	4.179
Divided wealth below median	8.230	3.356	2.452

Table 13: Partisanship, Income and Cross Section of Stock Returns

This table reports the Fama-MacBeth regressions by two sets of double-sorted portfolios. The first set is first sorted on politically controlled states and then on income level above or below median. The second set is first sorted on politically controlled states and then on income level of top and bottom decile. Panel A uses 25 Fama-French (1993) portfolios sorted by size and book to market and 10 industry portfolios with three lag Newey-West t-statistics; Panel B uses 31 portfolios with three lag Newey-West t-statistics; Panel C uses individual stocks as testing assets with twelve lag Newey-West t-statistics. We also report mean pricing error as MAPE. *p <0.1; **p <0.05; ***p <0.01.

	Panel A. 31 Portfolios		*Panel B. 35 Portfolios*		*Panel C. Individual Stocks*	
	(1)	(2)	(1)	(2)	(1)	(2)
Democrat Wealth Top 10	0.019**		0.006*		0.002***	
	(0.009)		(0.003)		(0.001)	
Republican Wealth Top 10	-0.301		-0.006		-0.008**	
	(0.232)		(0.188)		(0.004)	
Divided Wealth Top 10	0.008		0.005		0.002***	
	(0.013)		(0.013)		(0.001)	
Democrat Wealth Bottom 10	0.005		0.006		-0.005***	
	(0.007)		(0.008)		(0.000)	
Republican Wealth Bottom 10	-0.015		0.003		-0.004**	
	(0.030)		(0.011)		(0.002)	
Divided Wealth Bottom 10	0.012		0.004		-0.004***	
	(0.008)		(0.009)		(0.001)	
Democrat Wealth Above Median		0.004*		0.013*		0.002***
		(0.002)		(0.007)		(0.000)
Republican Wealth Above Median		-0.001		-0.048		-0.003
		(0.010)		(0.033)		(0.002)
Divided Wealth Above Median		0.004		0.008		0.003***
		(0.003)		(0.008)		(0.001)
Democrat Wealth Below Median		0.000		0.014		-0.002***
		(0.002)		(0.009)		(0.000)
Republican Wealth Below Median		-0.000		0.012		-0.001
		(0.006)		(0.022)		(0.001)
Divided Wealth Below Median		0.004*		0.002		-0.002***
		(0.002)		(0.006)		(0.000)
Ln(Market Value of Equity)					-0.001***	-0.001***
					(0.000)	(0.000)
Book to Market Ratio					-0.000***	-0.000***
					(0.000)	(0.000)
Constant	0.021	0.054***	0.033*	0.037**	0.032**	0.029*
	(0.019)	(0.015)	(0.019)	(0.017)	(0.015)	(0.015)
MAPE	0.043	0.010	0.049	0.010	0.065	0.024

Table 14:Partisanship and Industry Characteristics

This table reports the relation between the betas of daily consumption measure and industry mean returns with 10 industry portfolios. The betas are obtained from time-series regressions of industry returns on daily consumption growth by three household groups defined by partisan controls:

$$R^e_{i,t+1} = \alpha_i + \beta_{i,c,political}\frac{C_{t+1}}{C_t} + \epsilon_{i,t} \tag{22}$$

We also provide the correlation between industry mean returns and consumption betas. *p <0.1; **p <0.05; ***p <0.01.

	Mean	Democratic Beta	Republican Beta	Divided Beta
			10 Industries	
NoDur	0.041	0.395*	-0.162	-0.126
t-statistic		1.709	-0.749	-0.579
Durbl	0.026	0.359	-0.436	-0.276
t-statistic		0.831	-1.076	-0.677
Manuf	0.038	0.486	-0.146	-0.125
t-statistic		1.475	-0.475	-0.402
Enrgy	0.041	0.408	-0.471	-0.418
t-statistic		0.920	-1.135	-1.001
HiTec	0.035	0.067	-0.533*	-0.304
t-statistic		0.204	-1.717	-0.976
Telcm	0.036	0.647**	-0.152	-0.037
t-statistic		2.057	-0.517	-0.123
Shops	0.041	0.098	-0.496*	-0.247
t-statistic		0.345	-1.860	-0.922
Hlth	0.038	0.09	-0.356	-0.335
t-statistic		0.346	-1.457	-1.361
Utils	0.037	0.333	-0.216	-0.303
t-statistic		1.164	-0.807	-1.124
Other	0.025	0.708*	-0.382	-0.116
t-statistic		1.771	-1.021	-0.308
Corr Return and Beta		-0.421	0.166	-0.227

Table 15: Out-of-Sample Test: GMM Test and Risk Aversion Estimates

Panel A shows the GMM test on estimating the relative risk aversion coefficient. It uses the exactly identified model. The moment restriction is as follows:

$$E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma} R^e_{t+1}] = 0$$

Panel B shows the GMM test on estimating the relative risk aversion coefficient. In addition to the equity premium, this panel reports a risk-free rate. The moment restrictions are as follows:

$$E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma} R^e_{t+1}] = 0 \qquad E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma} R^f_{t+1}] = 1$$

and Panel C shows the GMM test on estimating the relative risk aversion coefficient with instruments. The instrument set Z_t contains a constant, lagged consumption growth, one plus the lagged excess market return and the detrended logged log price to dividend ratio. The moment restrictions are as follows:

$$E_t[\beta(\frac{C_{t+1}}{C_t})^{-\gamma} R^e_{t+1} \otimes Z_t] = 0$$

We fix β to be 0.95. R^e_{t+1} is the value weighted CRSP index return in excess of daily risk free rate. γ is the relative risk aversion (RRA). We also report RRA's standard error and mean absolute pricing error (MAPE). The implied risk-free rate is derived from RRA. The p-value to J test of overidentifying restrictions is also reported.

	Daily Spending Measure from 2016 to 2018
	Panel A. Equity Premium (Exactly Identified)
RRA (γ)	17.954
(s.e.)	6.808
t stat	2.637
MAE	0.562
Implied risk free rate	1.626
Observations	753
	Panel B. Equity Premium and Risk-free Rate (One-stage GMM)
RRA (γ)	13.600
(s.e.)	6.123
t stat	2.221
MAE	0.566
Observations	753
	Panel C. Equity Premium and Instruments (One-stage GMM)
RRA (γ)	11.957
(s.e.)	7.121
t stat	1.679
MAE	0.562
Implied risk free rate	1.280
Observations	752

Table 16: Out-of-Sample Test: Fama-MacBeth Cross-Sectional Regressions

This table reports the Fama-MacBeth regressions for out of sample tests using data from 2016 to 2018. Panel A uses 31 portfolios with three lag Newey-West t-statistics; Panel B uses 25 Fama-French (1993) portfolios sorted by size and book to market and 10 industry portfolios with three lag Newey-West tstatistics; Panel C uses individual stocks as testing assets with twelve lag Newey-West t-statistics. We also report mean pricing error as MAPE. *p <0.1; **p <0.05; ***p <0.01.

	Panel A: 31 Portfolios	*Panel B: 35 Portfolios*	*Panel C: Individual Stocks*
	(1)	(1)	(1)
Daily Consumption Measure	0.007*	0.008**	0.002***
	(0.004)	(0.004)	(0.000)
Ln(Market Value of Equity)			-0.001***
			(0.000)
Book to Market Ratio			-0.000***
			(0.000)
Observations	23,343	26,355	2,568,650
R Squared	0.696	0.694	0.012
MAPE	0.088	0.072	0.026

Table 17: Factor Mimicking Portfolio and Out-of-Sample Test

This table reports the first approach to construct a factor mimicking portfolio that hedges future consumption risk. Panel A shows the projection of consumption growth from 2004-2015 on a set of assets, including Fama-French three factors and ten industry portfolios; Panel B uses coefficient estimated in Panel A to construct an out of sample fitted value of consumption growth from 2016-2018 and report its correlation with the real time consumption growth from 2016-2018. *p <0.1; **p <0.05; ***p <0.01.

Panel A. In-sample Projection of Consumption Growth on FF3 and 10 Industry Portfolios 04-15	
	Consumption Growth 2004-2015
MKT	0.236***
	(0.069)
SMB	0.006
	(0.005)
HML	-0.002
	(0.007)
NODUR	-0.015**
	(0.007)
DURBL	-0.006*
	(0.004)
MANUF	-0.013
	(0.011)
ENRGY	-0.020***
	(0.006)
HITEC	-0.054***
	(0.013)
TELCM	-0.010*
	(0.006)
SHOPS	-0.031***
	(0.008)
HLTH	-0.028***
	(0.008)
UTILS	-0.018***
	(0.005)
OTHER	-0.046**
	(0.019)
Panel B. Correlation with Consumption Growth Out of Sample	10%***
Observation	3,024
R-squared	0.013
F statistics	3.060

Table 18: Factor Mimicking Portfolio and Asset Pricing Tests

This table reports the second approach to construct a factor mimicking portfolio that enables further tests of asset pricing implications on consumption growth as a traded factor. Panel A reports the projection results of consumption growth in the full sample on Fama-French three factors and ten industry portfolios. Panel B presents risk premiums and average alphas whose significance level is based on GRS F test for traded consumption factor and other traditional asset pricing factors. Panel B.a and b respectively use 35 and 31 portfolios to represent the cross-section of stocks. *p <0.1; **p <0.05; ***p <0.01.

Panel A. Projecting Consumption Growth on the Cross Section		*Panel B. Use FMP to run TS and CS tests*			
Variables	Consumption Growth	*Panel B.a. Price of Risk Using 31 Portfolios as Cross-Section*			
MKT_RF	-0.002	FMPConsumption	0.101**		
	(0.027)		(0.048)		
SMB	0.004*	MKT		0.038***	0.038***
	(0.002)			(0.013)	(0.013)
HML	-0.003	SMB		-0.003	-0.003
	(0.003)			(0.008)	(0.008)
NODUR	0.002	HML		-0.007	-0.005
	(0.003)			(0.007)	(0.008)
DURBL	-0.004**	MOM			0.047
	(0.002)				(0.030)
MANUF	0.010**				
	(0.004)	Observations	117,087	117,087	117,087
ENRGY	-0.002	R Squared	0.346	0.687	0.708
	(0.002)	F statistics	4.365	3.425	3.974
		Average GRS			
HITEC	-0.006	Alpha	0.034***	0.012**	0.040
	(0.005)	*Panel B.b. Price of Risk Using 35 Portfolios as Cross-Section*			
TELCM	0.004*	FMPConsumption	0.080**		
	(0.002)		(0.037)		
SHOPS	-0.006*	MKT		0.038***	0.039***
	(0.003)			(0.014)	(0.014)
HLTH	-0.001	SMB		-0.003	-0.003
	(0.003)			(0.008)	(0.008)
UTILS	-0.001	HML		-0.007	-0.007
	(0.002)			(0.007)	(0.007)
OTHER	0.005	MOM			0.023
	(0.008)				(0.022)
		Observations	132,195	132,195	132,195
Observations	3,776	R Squared	0.289	0.767	0.777
R-squared	0.010	F statistics	4.640	3.078	2.806
		Average GRS			
F statistics	2.986	Alpha	0.033***	0.012*	0.004*

VITA

Ruixiang Wang was born in Bengbu of Anhui Province located in central China. He is grateful to Bengbu for giving him a joyful childhood. Ruixiang is still reminiscent of all the memorable times growing up along the Huai River that passes through this city.

Ruixiang's parents moved to Shanghai when he was 11. After graduating from a Shanghai-based college, he worked many different jobs in various industries including sales representative in a medical device company, department assistant in a nutrition multinational, news brief writer in a leading pharmaceutical consultancy and financial news editor in a domestically listed company. Ruixiang appreciates Shanghai for its inclusiveness, vastness and diversity that shaped his mind and broadened his horizon. It is because of those experiences that sparkles his decision to seek further education in the U.S.

He applied for Master of Business Administration (MBA) program in the U.S. and was admitted by the University of San Diego in 2016. He spent two years obtaining his MBA degree. He loves San Diego for its beaches, beautiful trails and all the water sports that gave him countless good times. After working for a fund company and a local startup, he decided to pursue a Ph.D degree that led him to the University of Missouri Columbia (Mizzou). He spent five years completing his Ph.D program in Mizzou and now is prepared to start his academic career.