THREE ESSAYS ON FINANCIAL POLICY OF A FIRM

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The first chapter of the dissertation analyzes how characteristics of a firm's brand affect financial decisions by using a proprietary database of consumer brand evaluation. It demonstrates that positive consumer attitude alleviates financial frictions by providing more net debt capacity, as measured by higher leverage and lower cash holdings. Brand perception reduces the overall riskiness of a firm, as strong consumer evaluations translate into lower future cash flow volatility, higher Z-scores, and better performance during recession. Creditors favor strong brands by demanding lower yields on corporate public bonds. The results are more pronounced among small firms and non-investment grade bonds, contradicting a number of reverse causality and omitted variables explanations.

The second chapter develops a framework that shows how exactly market timing and trade-off forces coexist. The idea is that market timing benefits dominate trade-off costs when firms are close to their target leverage, but become offset by the rebalancing considerations when firms are farther away. Two sets of empirical results support the validity of the framework. First, the sensitivity of equity issuances to past stock performance is the highest among firms close to the target leverage. Second, the long-run performance of equity issuers is also a function of their deviation from target leverage. The lower the leverage of issuing firms is relative to the target, the worse their after-issuance returns are, consistent with higher market timing incentives compared to other issuers.

The third chapter studies whether investors value dividend smoothing stocks differently by exploring the implications of dividend smoothing for firms' expected returns and their investor clientele. First, it demonstrates that dividend smoothing is

associated with lower average stock returns in both univariate and multivariate settings. Some of this return differential can be attributed to lower risk, captured by return co-movement among high (low) smoothing firms. Second, the chapter shows that institutional investors, and specifically, mutual funds, are more likely to hold dividend smoothing stocks. Last, firms that smooth their dividends issue equity more frequently. Together, these results are consistent with the role of dividend smoothing in mitigating the impact of agency conflicts on the cost of capital.

BIOGRAPHICAL SKETCH

Yelena Larkin joined the Finance program at the Johnson Graduate School of Management in 2006. During her PhD studies she developed an interest in empirical corporate finance, with particular focus on capital structure and payout policy, and conducted her research under the supervision of Professor Roni Michaely. Yelena's work was presented at various academic conferences, including the Financial Management Association and Western Financial Association annual meetings, the Conference on Corporate Finance at Washington University in St. Louis, and the Caesarea Centre Annual Academic Conference. During her studies at Cornell, Yelena also taught a course in Managerial Finance for non-Johnson students, and served as a teaching assistant for various MBA courses. Prior to joining the PhD program, Yelena gained extensive work experience in both government and financial sectors. Yelena worked as a research analyst at the Bank of Israel, and as an investment analyst at Emda Mutual Funds Management (Israel). Her last position prior to joining the PhD program was at the World Bank in Washington, DC, where she was responsible for hedge funds research. Yelena obtained her BA degree in psychology and economics from the Hebrew University of Jerusalem. She also holds an MA degree from an integrated program in financial economics and finance for outstanding students from the Hebrew University. Since 2011, Yelena Larkin is an Assistant Professor of Finance at Pennsylvania State University.

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CHAPTER 1:

BRAND PERCEPTION, CASH FLOW STABILITY, AND FINANCIAL POLICY

Abstract

This paper explores the determinants of asset pledgeability by examining the impact of intangibles on corporate financial policy. Specifically, we use a proprietary database of consumer brand evaluation to analyze how characteristics of a firm's brand affect financial decisions. We demonstrate that positive consumer attitude alleviates financial frictions by providing more net debt capacity, as measured by higher leverage and lower cash holdings. We also show that brand perception reduces the overall riskiness of a firm, as strong consumer evaluations translate into lower future cash flow volatility, higher Z-scores, and better performance during recession. Creditors consider favorable brand perception by demanding lower yields on corporate public bonds. The results are more pronounced among small firms and firms holding non-investment grade bonds, contradicting a number of reverse causality and omitted variables explanations.

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"If this business were split up, I would be glad to take the brands, trademarks and goodwill and you could have all the bricks and mortar—and I would fare better than you."

—John Stuart, the Chairman of Quaker, ca. 1900

Extensive theoretical and empirical literature has examined what asset characteristics determine optimal capital structure. Given incomplete contracting frictions, an important factor affecting creditors' willingness to lend is asset tangibility, which determines the final cash flow that debt holders receive after repossessing a firm's assets in liquidation (Titman and Wessels (1988)). Recent studies demonstrate that there is substantial variation within characteristics of tangible assets, and properties such as salability and redeployability (Benmelech (2009), Benmelech and Bergman (2009), Campello and Giambona (2010)) have an impact on capital structure and debt maturity, forcing a firm with a high proportion of tangible, but difficult to redeploy assets to hold less debt.

At the same time, little is known about the link between characteristics of a firm's intangible side and its financial policy. Capital structure literature has largely assumed that intangibles are not pledgeable, as their value is destroyed in liquidation. Yet, intangible assets, such as copyrights, patents, trademarks, and intellectual property account for a large proportion of a firm's market value, and play an important role in strategic management of a firm. Moreover, anecdotal evidence indicates that intangibles can also be sold separately from other assets. For example, the trademark and Web site of Linens 'n Things, a home furnishing retailer that filed for bankruptcy in May 2008, were acquired by a joint venture and since then the new entity has been successfully operated online, despite the liquidation of the brick-and-mortar stores.

This paper investigates what determines asset pledgeability by examining the impact of intangibles on financial decisions. Since there is substantial heterogeneity across their nature and characteristics, we focus our attention on brand, which is one of the largest components of a firm's intangible assets. According to the 2010 estimate, brand value accounts for over 100% of the book value of equity for the S&P 500 firms, and the numbers have been exponentially increasing over the past decade.[1] Therefore, analyzing brand characteristics is the first important step in understanding

[1] "The Brand Bubble" (pp. 9–11).

the role of intangibles in financial policy. We demonstrate that favorable perception of a firm's brand plays a role in corporate decisions by relaxing some of financial frictions and providing higher debt capacity. Our data comes from a novel database, Brand Asset Valuator (BAV), which is the world's largest study of consumer evaluation across different product brands.[2] Research in marketing demonstrates that positive consumer evaluations of a brand are associated with higher loyalty and quality perception, as well as larger purchase probabilities (Starr and Rubinson (1978), Rao and Monroe (1989), Dodds, Monroe, and Grewal (1991)). As a result, consumer favorable view of a firm's products can provide information about characteristics of its intangible assets, not reflected in the balance sheets.

We start by gauging a mechanism through which characteristics of a brand can be linked to financial decision. Which firm characteristics are shaped by consumer brand perception and how do they affect financial decisions? A critical assumption of perfect competition is that sellers provide homogeneous, or standard, goods. However, in practice, the majority of firms produces goods with somewhat different properties (or at least perceived differently by consumers). Product differentiation creates "monopolistic competition," in which a firm's market becomes separated from its competitors (Chamberlin (1933)), and clienteles of consumers with varying degrees of product loyalty evolve. Loyal consumers, in turn, create brand capital for the firm, as they are willing to stick with the product they like over time, and are less likely to switch to competitors. In two theoretical models, Gourio and Rudanko (2011) and Belo, Lin, and Vitorino (2011) demonstrate that brand capital affects investment and financial policy of a firm, and reduces the overall riskiness of its cash flow. As a result, although intangible, favorable consumer attitude affects asset pledgeability by

[2] Published academic studies in marketing, based on BAV data, include Mizik and Jacobson (2008, 2009), Bronnenberg, Dhar, and Dube (2007, 2009) and Romaniuk, Sharp, and Ehrenberg (2007).

reducing the cash flow riskiness, and improving the probability that a firm will meet its financial obligations to debt holders.

We examine the validity of the mechanism by empirically testing whether favorable brand perception reduces the riskiness of the firm. Our main proxy of consumer brand perception is brand *Stature*, which measures how familiar households are with the brand, and whether they have a positive regard towards it. We evaluate a firm's riskiness in a number of different ways, and find that our results are consistent with implications of the theoretical models by Gourio and Rudanko (2011) and Belo et al. (2011). Firms with higher brand *Stature* experience lower forward-looking volatility at both individual and industry-adjusted level, and have lower probability of getting into financial distress. We also demonstrate that credit ratings of non-investment grade bonds improve with high brand perception of a firm's products. All our results remain significant after adding commonly used historical measures of a firm's cash flow volatility. Finally, we examine whether firms with strong brand perception suffer more during recession, and find that this is not the case: Firm with high brand *Stature* experience better operating performance than their less valued by consumers peers.

After establishing the link through which brand relates to a firm's fundamental characteristics, we ask whether debt holders consider brand perception when determining the premium they require. We estimate credit spreads on public debt outstanding as a function of brand *Stature* and control variables, and find that higher brand *Stature* induces creditors to charge lower premium. The results are more pronounces among short-term maturity bonds, and not significant for long-term maturity, consistent with younger and riskier firms having access to short-term credit only.

Finally, we analyze the implications of a strong brand perception for financial policy. We estimate leverage and cash holding levels and find that firms with stronger brand perception hold more leverage: a one-standard deviation increase in brand *Stature* increases market leverage of a median firm in our sample by at least 1.7%. A firm with stronger brand perception also holds less cash, compared to firms with otherwise similar characteristics. The effects are more pronounced and about twice as strong in magnitude among small firms. A one standard deviation increase in Stature allows for over 4% of additional debt capacity, and reduces cash holdings by 4.5% for a firm in the 25th percentile.

The higher impact of brand on small firms, along with the findings that firms with low-grade rated bonds and bonds with relatively short maturities benefit more from the impact of *Stature*, is hard to reconcile with a number of alternative explanations, suggesting that a firm may actively attempt to alter consumer opinions about its brands by improving the quality of their products or through advertising. If this were the case, however, we would find that the effect is stronger among larger and more mature firms with good reputation in external capital markets, allowing them to allocate more resources to strategic brand management. A similar argument would hold for omitted variables explanation, which may affect both the brand stability and access to external capital markets. Our evidence indicates that firms with relatively limited access to external capital markets are the ones that obtain more financial flexibility when they have strong brand. Taken together, the results suggest that brand perception is important in explaining financial policy of a firm, and support the validity of the underlying mechanism.

Overall, this paper makes several contributions to the existing research. First, it adds to the literature on product market and financial decisions by identifying potential mechanism that link characteristics of consumer product demand to financial decisions of a firm and evaluates their impact. Also, while most of the existing studies focus on relationship between financial policy and industry variables, such as concentration ratio and competition (Chevalier (1995a, 1995b), Kovenock and Phillips (1995, 1997), Phillips (1995), Khanna and Tice (2000)), firm's relative technological position (MacKay and Phillips (2005)), and interdependence between operation of a firm and its rivals (Lyandres (2006)), this paper shows how characteristics of consumer demand at a firm level affect financial decisions.

Second, our paper complements research that examines the link between cash flow volatility and other firm characteristics. Brand *Stature* can be viewed as an alternative, forward-looking measure of cash flow volatility, which helps explain mixed empirical conclusions on the relations between commonly used historical cash flow volatility and capital structure.[3] In addition, this work investigates cross-sectional differences in cash flow volatility from the perspective of product market. Exploring this link is especially important given the recent findings by Irvine and Pontiff (2009) and Bates, Kahle, and Stulz (2009) that document an increasing trend in cash flow volatility over time, which they attribute to more intense economic competition.

Lastly, this study contributes to a small number of finance papers that map marketing concepts, such as advertising and brand perception, into financial theory. Most of those studies look at the link between firm characteristics and advertising (Grullon, Kanatas, and Weston (2004)), Chemmanur and Yan (2010a, 2010b)). Additional studies examine the relations between advertising and capital structure decisions (Chemmanur and Yan (2009), Grullon, Kanatas, and Kumar (2006)). Finally, Frieder and Subrahmanyam (2005) examine the impact of brand on a firm's ownership structure. Our study incorporates a new data set that captures consumer subjective evaluation of a firm's products and demonstrates that, in addition to

[3] Parsons and Titman (2008) provide an overview of existing literature on the topic (pp. 14–16).

visibility, marketing characteristics interact with firm's financial decisions through the channel of cash flow stability.

The rest of the paper is organized as follows: Section I develops the main hypotheses of the paper; Section II describes the data; and Section III explores the link between brand perception and different measures of a firm riskiness. In Section IV we test the implications of brand perception to financial policy; Section V discusses alternative explanations and verifies the robustness of our conclusions. Section VI concludes.

I. Hypotheses Development

In this section we develop the hypotheses of the paper. We start by explaining how consumer attitude towards a firm's products translates into intangible asset characteristics. We then generate hypotheses about how brand perception affects capital structure and cash holding policies.

Homogeneity in product characteristics and consumer preferences is a central assumption of perfect competition, allowing individuals to choose between different sellers based solely on price. However, in reality, consumers are surrounded by dozens, if not hundreds, of brands, which they value differently. Therefore, the actual heterogeneity in product and brand characteristics on one side, and consumer subjective preferences on the other, led Chamberlin (1933) to define a concept of "monopolistic competition": Whenever there is product differentiation (whether real or subjective), buyers will be paired with sellers according to their preferences, and the actual sales of the product will depend on the manner in which brands are differentiated from competitors. The more unique and appreciated the characteristics of the brand are, the more customers value the product, and the more loyal they become.

Empirical research has found support to this theory. Literature in industrial organization, using detailed data on household purchase behavior over time, shows that consumers do take into account specific characteristics of the product (such as color, styling, and quality) just as much as they consider prices of the brand and its competitors in their purchase decisions (Thomas (1989), Kwoka (1993), Landes and Rosenfield (1994)). Marketing studies, based on surveys and laboratory experiments, demonstrate that favorable consumer evaluations translate into the actual buying behavior. For example, using survey questions, Starr and Rubinson (1978) find that loyal consumers have higher repeat rates of purchase, lower probability of switching, and lower price elasticity of the demand function. Based on an experimental approach, Dodds et al. (1991) show that when brand perception is more favorable, the overall willingness to purchase the product is greater. To summarize, the two groups of studies provide evidence that within narrowly defined product markets strong brands with appealing to consumer characteristics enjoy higher purchase and lower switching probabilities, and increase the certainty of contemporaneous and future sales for the brand. It is possible then that these findings can be used to derive the effect of brands on the cash flows characteristics of the entire firm.

Two recent theoretical papers analyze the impact of brand on the value and riskiness of the overall cash flow of a firm. Gourio and Rudanko (2011) and Belo, Lin, and Vitorino (2011) study the role of brand capital on investment policy of a firm, its value, and the level and riskiness of the cash flow. In the first model brand impacts cash flows through consumer search costs for the product. Trying to minimize those costs, consumers become loyal to the product in the long-run, and turn into a firm's intangible capital, which the firm takes into account while making its investment decisions. The model predicts a negative relationship between the degree of search cost frictions and cash flow volatility of a firm. On the other side, Belo et al. (2011)

model brand capital as an accumulation of all the past advertising expenses, and assume that together with prices, brand capital defines demand function for the firm products. A firm maximizes its profits given an option to invest in brand capital through advertising, and makes the decision of whether to raise external capital or not. The model is solved numerically, and the results indicate that cash flow sensitivity of firms with higher level of both physical and brand capital to market risk is lower.

While theoretical implications of the two studies are consistent, and infer that brand reduces volatility of the firm riskiness, their empirical results are different. Although both studies use advertising expenses to proxy for brand capital, Gourio and Rudanko (2001) find that advertising increases firm volatility, while Belo et al. (2011) show a decrease in riskiness, as proxied by market beta. A number of industrial organization studies have also looked at how advertising intensity affects market share stability, and found mixed results.[4]

A possible reason for the mixed empirical pattern is that advertising is not a good proxy for brand capital and consumer loyalty. According to the informative view, developed in industrial organization literature, advertising may, in fact, facilitate competition and new entry, rather than creating barriers of entry, by creating visibility and providing consumers with information about new products (Bagwell (2007)). Therefore, using surveys of consumer attitude towards brands provides a better measure of brand capital. Moreover, advertising is just one of many inputs that a firm uses to affect consumer view of a product, together with promotions, public relations, events, and other tools of strategic brand management (Aaker (1996)). Therefore, brand perception measures the outcome of all the cumulative efforts of a firm to market the product, as well as exogenous factors, such as the fit between consumer preferences and product characteristics.

[4] See Bagwell (2007) for an overview of existing studies (pp. 1729–1731).

Given the conceptual differences between advertising expenses and brand perception, our first step is to test the implications of the theoretical model, described above, using survey data on consumer brand perception. If the predictions of the models are correct, and consumer loyalty indeed creates a buffer that reduces the volatility of a firm's profits over time, we should observe a negative relation between brand perception and cash flow volatility.

Hypothesis 1: Firms with stronger brand perception have lower cash flow volatility.

After confirming the validity of the mechanism through which brand perception affects firm characteristics, we ask whether the market participants take this into account in their investment decisions. Existing capital structure literature has long emphasized the importance of cash flow stability in contracting between equity and debt holders. In the world of uncertainty, the more stable the future cash flow of the firm is, the smaller is the probability of financial distress, which may lead to losses to creditors through reorganization, Chapter 11 settlements, and finally, firm liquidation. Thus, the overall pledgeability of a firm's assets is determined not only by the final cash flow that debt holders can obtain after selling the repossessed assets, but also by the probability of having to do so in the first place. Therefore, firms care both about the overall costs of financial distress and about the probability of getting into one. This discussion suggests that stronger brand perception that generates a loyal pool of satisfied consumers who value the brand more and therefore, securing the debt holders future payments of the debt contract. As a result, debt holders will be willing to charge lower rates on their debt. To summarize:

Hypothesis 2: Firms with stronger brand perception have lower cost of debt.

Finally, we establish the impact of this channel on financial policy of a firm. A firm with a strong brand perception will be able to enjoy the benefits of higher stability and lower costs of debt by taking on more credit. Therefore, incorporating consumer brand evaluation capital structure estimation can contribute to explaining the leverage, beyond commonly used controls. First, brand perception describes the quality of intangible assets in a firm's possession, so it should provide information which is not captured by the ratio of tangible to total assets. Existing literature has also used the historical measures of cash flow stability to estimate the probability of distress, but with mixed empirical findings. One possible explanation is that past-looking measure is not necessarily a good indicator of future performance, as the true cash flow stability comes to test during recession, entry of new competitors, and predatory behavior by competitors, events that may have not occurred in the past. As a result, brand perception should enhance debt capacity after controlling for historical cash flow volatility.

Hypothesis 3a: Firms with stronger brand perception have higher leverage.

In addition to affecting debt capacity, more secure, and less volatile cash flow also has implications on the cash holding decisions of the firm. Firms choose to insure against potential operating and financial losses associated with low cash flow realization by holding more liquid assets (Opler, Pinkowitz, Stulz, and Williamson (1999), Bates, Kahle, and Stulz (2009)). Since raising external capital is typically costly (either because of the direct fees to the intermediary or as an outcome of asymmetric information problems between the firm and outside investors), firms hold a certain proportion of their retained earnings in cash and other liquid assets as a cushion. When a firm has a secure stream of future cash flows, as well as a better access to external capital markets, the need to hold cash for precautionary reasons declines: Operating cash flow provides a ready source of liquidity and allows a firm to maintain lower levels of cash at any given point (Kim, Mauer, and Sherman (1998)). In addition, firms usually hoard cash as a means to fight peer predation. Brand capital in terms of a pool of loyal consumers increases the costs of predatory behavior for competitors, and as a result, a firm with strong brand perception can hold less cash.

Hypothesis 3b: Firms with stronger brand perception have lower cash holdings.

II. Data

1. Brand Asset Valuator

Brand Asset Valuator (BAV) is a proprietary brand metrics model, developed and managed by Brand Asset Consulting, a subsidiary of Young & Rubicam Brands. Brand Asset Consulting uses the model to help clients evaluate their brand and improve the strategic direction of its management by analyzing different aspects of brand image. The model is widely known among both marketing researchers and practitioners and is incorporated in major marketing textbooks (see, for example, Aaker (1996) and Keller (2008)).

The BAV model has several advantages over other marketing models that measure brand value. Most importantly, it relies on a customer-based approach. This is in contrast to a financial valuation approach, which uses accounting and financial data to estimate the brand value. For example, models by Interbrand and BrandFinance 2000 are based on cash flow forecasts. As a result, the BAV model is exogenous of accounting and market variables, such as stock prices, B/M ratios, and revenues. Second, the model has a wide base of respondents: It is a survey of nearly 16,000 US households who evaluate each brand with respect to a wide range of characteristics.[5] The sample of US households is constructed and managed to represent the US population, according to the following factors: gender, ethnicity, age and income groups, and geographic location. Households are offered a $5 compensation for their participation, and the response rates are more than 65%. The pilot surveys have been conducted in 1993, 1997 and 1999, and starting from 2001, the survey has been undertaken yearly.

The list of brands has expanded over time and as of 2010 included more than 4,500 US and international brands and sub-brands.[6] The survey is not limited to companies that are customers of Brand Asset Consulting and is continuously updated to include new brands and remove the brands that exit the market. Overall, the sample of firms is representative of all industries and is not biased towards the clients of Brand Asset Consulting, as the company tries to maintain a fair representation of all the major industry competitors. To make the questionnaires manageable, the overall sample of brands is split into 30 groups, so that the average number of brands to be evaluated per questionnaire does not exceed 120.[7] BAV metrics uses a randomization approach in organizing the brands in the questionnaires in order to not impose associations with a certain industry or firm competitors.

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[5] In addition to US studies, BAV also conducts international studies of consumers.

[6] Additional models, based on customer based approach, are Landor Associates, which covers around 300 brands, and EquiTrend, which covers more than 1,000. Landor Associates' ImagePower, which was the first model of consumer-based surveys, was expanded into BAV in the early 1990s.

[7] See Appendix 1.A for an example of a questionnaire page.

BAV questionnaire consists of two types of questions. The first type asks respondents to evaluate the following aspects of a brand on a 7-point scale: general knowledge of the brand, personal regard and relevance. The second type evaluates different aspects of brand image and asks participants to mark an "X" if a certain characteristic applies. The examples of the characteristics are: unique, innovative, traditional, good value. Additional questions ask respondents about the frequency of use of a certain brand, and also some demographic information.

The overall results are aggregated across respondents for any given brand-year, so that we observe the overall score on a certain brand's image characteristics but cannot identify individual respondents. Some of the brand-image results are aggregated into pillars that capture different aspects of brand value, and some are used for additional marketing analysis of brand characteristics. Brand *Knowledge* and *Esteem* constitute brand *Stature*, which we use as our main measure of brand loyalty and quality perception. The components of *Esteem* are (1) the proportions of respondents who consider the brand to be of "high quality," a "leader," and "reliable"; (2) brand score on *Regard* ("how highly you think and feel about the brand" on a 7-point scale). Bronnenberg, Dhar, and Dube (2007, 2009) use the percentage of responses to the "high quality" question, as well as the response rates to two additional questions, "good value" and "best brand," as their main measure of demand-related brand performance. We follow their approach, but use all the components of *Esteem*, as well as consumer's *Knowledge* of the brand ("how well are you familiar with the brand and its products?" on a 7-point scale). The reason for using a more general measure is twofold. First, the BAV model describes brand *Stature*, the combination of *Esteem* and *Knowledge*, as an indicator of the current perception of a brand by consumers (Gerzema and Lebar (2008), pp. 44–45), and we do not have a theoretical reason to exclude any of its components. Second, the knowledge of a brand is an essential part of capturing demand for a product, as consumers who are not familiar with the brand should be excluded. While we believe that brand *Stature* is a more general measure of consumer demand than the one that includes only selective components of *Esteem*, we address additional definitions in the robustness section.

Stature is computed as a product of *Esteem* and *Knowledge*. Since the two components are estimated on different scales its absolute value is meaningless. For convenient interpretation of the results, we transform the measure into a z-score.

The BAV questionnaire is constructed at a brand level, so in order to merge it with the commonly used financial data, which is reported at a firm level, we have manually created a bridge that links between BAV and Compustat. Specifically, we identify a representative brand for each firm by finding a brand with the most closely matching name, and use its scores. Appendix 1.B provides a detailed description of the algorithm we apply to construct the link, as well as alternative ways of aggregating the data across brands, which we use to verify robustness.

2. Financial Variables

The financial variables are selected based on the widely cited literature on capital structure and cash holdings.[8] We merge several different databases to construct them. First, we use Compustat data to obtain accounting and financial variables. *Sale* is the total net sales, expressed in millions of constant 1993 dollars. *Age* of the firm is calculated starting from the first year the firm appeared in the Compustat database. The two variables capture the size and relative positioning of the firm in the real and financial markets. Market to book ratio (*M/B*) is the market value of equity plus the

[8] See, among others, Hovakimian, Opler, Titman (2001), Fama and French (2002), Faulkender and Petersen (2006), Opler, Pinkowitz, Stulz, and Williamson (1999), and Kim, Mauer, and Sherman (1998).

book value of assets minus preferred stock[9] plus deferred taxes, all divided by the book value of assets. It captures the future prospects of the firm, as well as the total value of the firm assets, including the intangibles. Incorporating the measure in our analysis helps disentangling the implicit value that a brand has from its impact through cash flow stability. We also proxy for a firm's overall profitability with *EBITDA*, which is the ratio of earnings before depreciation to total assets. *Leverage* is the sum of short-term and long-term debt, scaled by book or market assets. We measure the tangibility of a firm's assets with two measures. First, we use *Tangibility*, defined as net property, plant, and equipment, divided by book assets. We employ *Depreciation*, scaled by assets, as an additional measure in our robustness tests.

We measure advertising and R&D expenses in two ways. For the sample description, we scale advertising expenses and R&D by assets. For multivariate analysis, we use the natural logarithm of the overall amount of advertising and R&D (in millions of constant 1993 dollars) (variables *log(advertising)* and *log(R&D)*, respectively).[10] Following Grullon et al. (2004), we do not scale advertising by assets or sales to capture its overall scope.[11] If advertising affects consumer tastes, it should be captured by the overall amount of advertising consumers were exposed to. An advertising campaign of a large firm can be effective even if it represents only a small proportion of a firm's revenues. For the same reason, we use *log(R&D)* rather than its ratio over assets or sales to capture a potential impact of a firm on consumer attitude

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[9] The book value of equity is the book value of total assets minus book liabilities minus preferred stock plus deferred taxes. Preferred stock equals to the liquidation value if not missing; otherwise I use redemption value if not missing; otherwise the carrying value.

[10] We add a value of 1 to advertising and R&D expenses, before converting them to logarithms, to capture the values of zero.

[11] Differently from Grullon et al. (2004), we assign values of zero for missing values of advertising expenditures. Since firms do not have to report advertising expenses (following the SEC's Financial Reporting Release No. 44 FRR44)), this is not entirely accurate. However, it preserves the number of observations. For robustness, we repeat the main analysis using only non-missing values of advertising expenses, and the results are almost the same.

through improving the quality of its products. Using the overall amount of advertising and R&D in our empirical estimations will better differentiate the effect of exogenous brand characteristics from the firm's attempts to alter consumer demand through advertising and R&D and make our tests more conservative. R&D also proxies for asset uniqueness, as technological innovations make capital and labor skills used by the firm, more specific, and potentially less re-adjustable to business and production model of competitors in case of liquidation.

We measure cash holdings in two ways. Our main measure is *Cash/Assets*, the ratio of cash and short-term investments to total assets. For robustness, we also scale cash by sales (*Cash/Sales*). Following Opler et al. (1999), we use working capital net of cash holdings (*Wcap*), scaled by assets, to capture additional liquid asset substitutes available to a firm. Since a firm with more projects to finance should hold more cash, we use a measure of capital expenditures (*Capex*) to proxy for required investments. *S&P500* is a dummy variable that equals one if a firm belongs to the S&P 500 index and zero otherwise. This dummy variable is another proxy for size and also a reflection of additional stock characteristics, such as visibility, liquidity, and the number of shareholders. *DivDummy* is an indicator variable to whether a firm pays out dividends to its shareholders.

A potential concern of a study that relies on brand data is that conceptually, the idea of a brand may be industry specific. To avoid capturing industry, rather than firm product characteristics, we control for industry characteristics by including industry fixed effects in all our specifications. Industries are defined using the SIC two-digit code. It is important to note, though, that brand perception is not another proxy for market concentration. While industry concentration is an important determinant of a firm's financial and operational decisions, there is still a potential variation in consumer demand characteristics among different firms for any degree of industry concentration. To support this claim, we create a Herfindahl index (*HHI*) by summing up squared market shares of all the publicly traded companies in each industry, defined by the SIC four-digit code, and include the measure in the descriptive statistics.

We obtain stock performance information from CRSP. We use average monthly stock returns (*Return*) over a year as an additional control variable used in our robustness tests. CRSP's PERMNO is also used to link the bond data (see Section III.4).

For the multivariate analysis, the variables *Size*, *Sales*, and *Age* are converted into natural logarithms. Before merging the Compustat data with BAV, we remove all observations with missing values for the following variables: *Size*, *Cash*, *EBITDA*, *Tangibilit*y, *M/B*. We also trim the top and bottom 1% of those variables to mitigate the effect of outliers. After merging BAV data with financial variables from Compustat, the final sample consists of 468 firms and 2,585 firm-year observations.

3. Sample Characteristics

Table 1.C.1 presents the descriptive statistics of the financial variables for BAV-matched sample. Overall, the firms in the sample are relatively large and profitable: an average BAV firm has an EBITDA of 14.8% and *log(Sales)* of 7.90, which is equivalent to about 7.3 billion of dollars. The sample firms also have a relatively high *M/B* ratio, consistent with the marketing view that brand is an intangible asset: branded products enjoy higher prices than the generic products, resulting in higher market valuation of firm assets, even if the production technology is somewhat similar. About half of the BAV firms belong to the S&P index. While the descriptive statistics raise some concerns about the representativeness of the sample, several things should be noted. First, the concept of brand is not applicable to some

industries. Industries based on business-to-business approach (such as mining, construction, and agricultural production) may not need to conceptually differentiate their products, as they either work based on contracts with customers or operate as suppliers to other industries. Therefore, the mere idea of product differentiation is potentially relevant only to a subset of firms. Second, even though the sample is relatively small in terms of the number of firms, its market capitalization represents 20% of the market capitalization of all Compustat firms.

The last column of the table reports correlation of the variables with *Stature*. Larger, more mature, and more profitable firms are associated with stronger demand, as measured by *Stature*. Tangibility is only weakly correlated with Stature, supporting the argument that consumer brand evaluations are not just another proxy for the amount of intangible assets within the firm. Advertising has almost no correlation with *Stature* when scaled by sales. However, when measured in logs, correlation increases to 0.32 (unreported). These results are consistent with the idea that from the consumers' perspective, it is the overall amount of advertising rather than its relative share of revenues, which increases their familiarity with the firm and affects their preferences. This provides additional evidence for using the overall advertising expenses, rather than the scaled version, in the multivariate regressions. *R&D/Sales* has a negative correlation because of the impact of *Sales* in the denominator, suggesting that consumers do not shape positive opinions about products based merely on their quality, and other factors, such as brand image and personal taste, are more influential in determining consumer loyalty and quality perception.[12]

[12] Experimental marketing studies provide additional evidence that consumer differential perception of brands is not based on objective differences between products. For example, Keller (2008, pp. 61–62) shows that consumers report different opinions regarding branded and unbranded versions of identical products.

We also examine the distribution of the BAV sample by industry. Table 1.C.2 summarizes the results. The first two columns present the distribution by the number of firms. BAV is more biased towards consumer nondurables and retail sectors, which is not surprising given the nature of the business: most of the firms in these sectors are business-to-consumer firms. Financial services and utilities are underrepresented, but these industries are typically excluded from the sample in most financial papers. The rest of the segments are quite comparable to the overall Compustat universe of firms. The results become more similar to the overall sample when the distribution is constructed based on market capitalization. The gap between the BAV sample and Compustat in the non-durables sector is less significant, and the rest of the segments have weights similar to the overall sample of firms.[13] The evidence in Table 1.C.2 suggests that even though the BAV sample is rather restricted by definition, the distribution of the market capitalization of the firms that it includes is representative of the overall industry.[14]

III. Brand Perception and Firm Risk

1. Future Cash Flow Stability

We start the empirical analysis by examining whether positive and strong perception by consumers translates into more stable operating and financial performance. Specifically, we look at how the overall riskiness of future cash flows depends on consumer perception of its brand.

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[13] In unreported results, we create a distribution of the number of firms in the BAV sample by the SIC two-digit code and find that none of the industries' weights exceeds 10%.

[14] To verify that our results are not driven by overrepresentation of firms in non-durables sector, we repeat the main results after removing non-durables from the sample. The results are very similar to the ones reported.

To analyze future cash stability, we construct two measures of future cash flow stability. The first measure is forward-looking cash flow volatility, defined as standard deviation of a firm's annual profitability (*EBITDA*) during period (*t+1*) through (*t+5*). It is possible, though, that cash flow volatility of a firm reflects specific characteristics of different industries, not captured by industry dummy variables. For example, industries that manufacture non-durable goods may be less volatile than industries producing durables, as the last ones are purchased less frequently. To account for that possibility, we construct the second measure, which is forward-looking relative cash flow volatility. It is computed by first averaging industry profitability across firms in a given industry (based on a SIC two-digit code), and then calculating standard deviation of the resulting average five years forward. Relative volatility is an individual firm's forward-looking volatility, scaled by the industry forward-looking volatility.

We estimate absolute and relative volatility of a firm's earnings as a function of brand stature and control variables, and report the results in Table 1.C.3. Panel A demonstrates that the effect of brand stature on future cash flow volatility is negative and significant in both specifications, and the magnitudes are not affected by adding advertising and R&D expenses. Interestingly, coefficients on those variables are positive, implying that investment in advertising and product development may be ex-ante risky, and only if they are absorbed in consumer attitude, the intangible asset is created. It is also interesting that adding historical volatility does not change the magnitude and significance of the *Stature* coefficient, and suggesting that *Stature* measures forward, rather than past-looking volatility, and captures certain firm characteristics that historical measure does not. The statistical significance *of Stature* is lower in Panel B, suggesting that some of the future variation may be driven by industry characteristics. Still, the effect the coefficient magnitude is persistent in both specifications, and suggests that a one standard deviation increase in brand perception reduces the volatility of an average (in its industry) firm by 8-9%. The one standard deviation in *Stature* can have several interpretations. Cross-sectionally, it is equivalent to the difference in brand perception between Tyson Foods and ConAgra Foods, or Campbell and General Mills. Firms can also increase/decrease their brand *Stature* by one standard deviation over time. Examples of firms that enhanced the consumer perception by one standard deviation over time are Canon and Starbucks. At the same time, the brand perception of Hilton and McDonalds eroded by one standard deviation over the sample period.[15]

To verify the robustness of the results, we calculate historical volatility of *EBITDA* based on the past 10, 5 and 3 year period, and forward-looking volatility based on future 3 and 5 years of data, and re-estimate the main results using each of the possible period length combinations.[16] We also create an alternative measure of volatility based on sales, rather than profitability (where we use total sales scaled by assets), and use it to estimate the impact of brand stature. The results using both absolute and industry-scaled forward-looking sales volatility remain similar to the ones presented.

2. Credit Riskiness

After demonstrating that brand stature is associated with more stable future cash flows, we ask whether market participants benefit from it. Specifically, we look at firm riskiness from the perspective of debt holders. The reason for focusing on debt holders is two-folds. First, the contract structure makes debt holders more sensitive to

[15] About 20% of the firms in the sample experience a change in *Stature* of at least one standard deviation during the sample period.

[16] Sample period limitations do not allow calculating volatility for a longer than 5-year period without a significant loss of observations.

volatility of the firm cash flow, as they do not benefit from positive shocks, but bear losses during cash flow drops. Second, it is not clear what the impact of lower cash flow volatility on stock holders should be. All else constant, equity volatility should decline as well. However, if brand policy has positive implications on leverage, the position of stock holders will become more levered, increasing both systematic and idiosyncratic volatility. As will be demonstrated in Section IV, higher *Stature* indeed has a positive effect on a firm leverage, and therefore, it is not clear a-priori which of the effects will dominate.[17]

To evaluate the impact of brand stature on a firm riskiness, we look at a firm's credit ratings, as well as its probability of distress, measured by Altman's (1968) Z-score. Data on credit ratings is obtained from Compustat. We use S&P domestic long-term issuer credit rating, the most populated field, as our main variable of credit rating. To estimate credit ratings in a linear regression setting, we convert the alphanumeric scale, employed by the S&P agency, into a numeric one. Thus, credit rating 'AAA' receives a score of 1, and credit rating of 'D' takes on a value of 23. To proxy for expected costs of financial distress, we use modified Z-score (see, for example, Mackie-Mason (1990) and Leary and Roberts (2005)). Since brand stature may affect capital structure, the component of market equity, scaled by book debt, is excluded from the score, so that the final ratio is defined as the sum of 3.3 times EBITDA plus sales, 1.4 times retained earnings, plus 1.2 times working capital, all scaled by total assets.

The results of credit rating estimation are presented in Table 1.C.4. While overall brand *Stature* improves credit ratings, as indicated by negative coefficients in Panel A, its statistical significance is marginal at best. However, after splitting the

[17] A number of marketing papers demonstrate that firms with higher customer satisfaction have lower stock market risk (see, for example, Fornell, Mithas and Morgenson (2006) and Tuli, Kapil and Bharadwaj (2009)).

sample into investment and non-investment grade bonds (credit ratings of ‘BBB-‘ and higher, and ‘BB+’ and lower, respectively), the effect of brand stature on bond rating differs substantially among investment and non-investment grade bonds. While the results for the investment grade bonds subsample remain insignificant, *Stature* significantly improves credit ratings of firms that issue non-investment grade bonds. The coefficients range from -0.34 to -0.37, suggesting that a one standard deviation increase in brand *Stature* helps closing about 1/3 of the distance between current and higher available rating. These results are important, as they challenge a number of alternative explanations, suggesting that brand *Stature* is related to the overall maturity and stability of the firm, and therefore, may indirectly proxy for its reputation in the external capital markets. At the same time, our findings are consistent with the main hypothesis of the paper, and indicate that brand stature captures intangible characteristics of a firm’s assets, which are more valuable for relatively risky and capital-constrained firms that cannot borrow cheaply. Similarly to the estimation of forward-looking volatility, adding control variables that have traditionally been used as a proxy for a firm’s riskiness and asset tangibility does not impact brand stature significance and magnitude in a material way.

Next, we estimate Z-score as a function of brand *Stature* and control variables. Since Z-score is a linear combination of commonly used control variables, using a standard set of independent variables, which include size and profitability, is impossible. Moreover, both variables are also highly persistent over time (for example, autocorrelation of sales is above 0.9), so that using lagged variables is also impossible. To overcome this problem, we look for another set of variables that are highly correlated with size and profitability, but do not come from sources, directly related to operating performance. To capture profitability, we use average stock returns and change in sales over the past period. We keep the M/B ratio, which indirectly captures the relative profitability of the firm as well. Finding alternatives for size is trickier, as the commonly used proxies such as sales, assets and market value of equity are highly correlated. Therefore, we use several alternative sets of variables. In specifications (1) and (2) we include the logarithm of the number of shareholders (*log(Sharehoders)*) holdings; in specifications (3)-(4) we use a dummy variable for access to external capital markets, as is proxied by availability of S&P credit rating (*Access*), and a dummy variable for belonging to the S&P500 index (*S&P500*). Finally, in the last set of specifications we proxy for size with the overall advertising expenses (we drop all the firms with zero and missing values). The results in Table 1.C.5 demonstrate that brand *Stature* has a positive impact on the probability of distress, as measured by Z-score. The coefficients are positive and statistically significant across all the specification, with the magnitudes ranging from 0.11 to 0.23, or about 10% of an average Z-score value. All the indirect size proxies have positive and significant coefficients, consistent with larger firms being more stable. Surprisingly, change in sales has a negative impact on Z-score. The coefficients may be driven by including M/B in the regression, which also captures profitability to a certain degree.

Taken together, the results in Tables 1.C.4 and 1.C.5 demonstrate that brand stature reduces the probability of distress and default, with the effect being especially pronounced for the subsample of firms with relatively poor credit rating. This suggests that firms the influence of strong brand is especially beneficial to improving stability of relatively risky firms.

3. Performance during Economic Downturns

The subsections above demonstrate that on average, strong brand perception is associated with lower forward looking stability of a firm's cash flow. It is possible, though, that the results are mainly driven by low-volatility performance of branded goods during periods of economic stability. While in good times consumers may consider their personal perception of brands in the purchase decisions, lower and less certain income following an economic slump may force them to switch to cheaper generic brands despite their actual preferences. Therefore, it is possible that during recession a firm with a loyal pool of consumers, who would normally secure its income, suffers more.

Theoretical literature on brand capital does not provide an answer to what happens to brands during recession. For example, the model by Belo et al. (2011) shows that systematic risk is decreasing in the level of brand capital stock. However, the brand capital evolution over time is determined solely by past brand level and advertising, and does not depend on economic conditions and wage rates. Therefore, it is not clear what would happen to the performance of firms if a negative wage shock reduces the impact of brand perception on sales. Moreover, the assumption itself is questionable. It is also possible that truly loyal customers, who believe there is no suitable alternative to the brand they value, continue buying brands they strongly prefer during economic downturns, while shifting to cheaper substitutes of brands that they do not value as much. Anecdotal evidence suggests that this, indeed, may be the case. For example, annual reports of Coca-Cola, which has one of the strongest *Stature* scores in our sample, indicate that the company’s sales volume (as measured by the number of unit cases) in North America declined only by 1% in 2008 and by 2% in 2009. At the same time, per capita GDP in US during the 2008-2009 periods remained almost unchanged, and unemployment rate doubled to 9.9%. Therefore, it is possible that consumer loyalty remains persistent despite income shocks.

Following the discussion above, we examine the performance of strong brand firms during recession relative to peers in a separate analysis. To test whether these firms suffer more during recession, we look at operating performance of firms with low versus high brand *Stature* during the two economic recessions that occurred within our sample period: the high-tech bubble crush of 2001, and the financial crisis of 2008-2009. We employ a matched sample methodology and in every year (*t-1*) allocate all the firms in our sample into quartiles of *Stature*. Firms in the lowest quartile are the *Low Stature* firms, and firms that belong to the top quartile are the *High Stature* ones. Next, for every firm in the *Low Stature* group we find the closest match from the *High Stature* group based on sales in period (*t-1*).[18] In Table 1.C.6 we compare changes in sales and profitability (*EBITDA*) of the two groups during the two recession periods. The first recession, as measured by NBER Business Cycle data, occurred between March and November 2001, so we look at the performance of firms during the fiscal year of 2001. The second recession officially started in December of 2007 and lasted till June 2009. Therefore, we use 2007-2009 as our second recession period.

The results demonstrate that the performance of firms with high brand *Stature* does not suffer more in recession. Thus, during the recent crisis the median profits and sales of *High Stature* firms increased by 2.19% and 2.80%, respectively, while the growth of *Low Stature* firms was only about half of that magnitude. The Z-score also remained stronger among *High Stature* versus the *Low Stature* firms. The differences are even more pronounced when comparing means,[19] and are similar when looking at the 2001 recession period. It is important to note, though, that focusing on a narrow

[18] To verify robustness of the results, we also match firms on size and profitability, and size, profitability, and industry. The results are similar to the ones based on size matching, but result in a significant loss of observations.

[19] To mitigate the impact of outliers, we winsorize the top and bottom 1% of changes in EBITDA and sales before performing the match. The differences among *Low* and *High Stature* firms for a non-winsorized sample have the same sign, and are more pronounced in terms of magnitude.

time period leads to a relatively small number of observations, so the results should be interpreted with caution.

Overall, however, the comparison of high and low brand perception firms during the two periods of economic downturn demonstrates that firms with high brand perception do not seem to suffer more, and in fact have a better performance than their competitors with lower consumer loyalty.

4. Cost of Debt

After documenting that strong brands have lower probability of financial distress, lower forward looking cash flow volatility, and better performance during crises we ask whether brand perception is incorporated in the cost of debt capital. A firm with strong brand perception may take advantage of lower borrowing costs by issuing more debt until the marginal costs equal the costs of debt for other firms. However, the *average* price it pays for the debt should still be lower.

To measure the cost of debt, we focus on public bond yields. The reason for that is twofold. First, the data on private loans does not exist in a time-series, as the loans are not traded over time, and the interest rate is available at origination date only. Second, private loans include a large number of covenants, which may affect the required yield, and make aggregation across contracts with different characteristics difficult. We obtain the yield data from two sources. Bond yields are extracted from FINRA's TRACE (Transaction Reporting and Compliance Engine) database. Trace was established in July 2002 to increase transparency in the secondary bond market, and it tracks intraday trading data in OTC markets. While initially the data has been reported only for a limited number of securities (investment-grade bonds with an initial size of $1 billion and higher), the reporting requirements expanded throughout 2003-2004 and starting from 2005 TRACE include almost all public transactions (although the par value is still truncated at $1 million and $5 million for non-investment and investment grade bonds, respectively). We identify the last available trade of each month and use the yields from this transaction.

TRACE reports the information on price, spreads, and yields, but does not include any characteristics of the bond issue, so to obtain this data we link it to the Mergent database, which maintains information on bond characteristics (for example, whether the bond is convertible, callable, etc.), the amount issued, and changes to the amount outstanding over time. We exclude convertible bonds, foreign and non-USD issues, as well as bonds with potentially difficult to evaluate characteristics, such as pass-through and pay-in kind. We obtain the average yield across all the bond tranches by weighting the yields by the amount outstanding. To aggregate data over time, we first calculate the value-weighted yields at a monthly frequency, and then average the results over a calendar year. After merging the bond yield data with our BAV sample, we end up with 739 observations for the period of 2002-2009. To obtain credit spreads, we subtract the yields of the Treasury notes and bonds with matching maturity from the corporate bond yields. If the exact maturity is unavailable, we use a linear extrapolation of two Treasury notes [bonds] with the closest maturities, so that the maturity of the corporate bonds falls in the range between the maturities of the two Treasury bonds.

We estimate credit spreads as a function of brand *Stature* and control variables and report our findings in Table 1.C.7. To analyze whether the results differ across bond characteristics, we split credit yields by bond maturities. To calculate short-term yields, every year we identify all the outstanding bond tranches with maturity less than median maturity (6 years), and value-weigh their yields. We compute long-term average yields in a similar way, using tranches with maturities equal to or longer than 6 years. Panel B reports the results of estimating short-term maturities, and in Panel C the dependent variable is the spread on long-term bonds. It is not surprising that *Credit Rating* is the most significant variable in all the estimations, incorporating the effects of size, age, and firm profitability. *M/B* and *Leverage* are the only additional controls that are significant. It is striking, though, that brand *Stature* has a negative and significant impact on credit ratings, reducing them by 37-47 basis points. The results have stronger magnitude among short-term maturity bonds, but are economically and statistically insignificant for long-term maturity. For robustness, we re-estimate our results starting from 2005, when TRACE reporting requirements included most of the public debt traded in the OTC market, and obtain similar results. Overall, this additional piece of evidence supports that hypothesis that brand perception affects firm's characteristics through the channel of lower riskiness, and the market takes that into account while pricing a firm's debt.[20] They also support the channel of cash flow volatility, as younger and riskier firms with access to short-term credit only benefit more from having a strong brand.

IV. Leverage and Cash Holdings

1. Leverage

We start with a univariate analysis of the relationships between consumer demand and capital structure. First, we examine the relationship pattern between demand characteristics and capital structure, controlling for size, which captures a significant part of cross-sectional differences among firms. Every year we partition the sample into five quintiles, based on *Sales*, and then form five brand *Stature* quintiles within each *Sales* group. Panel A of Table 1.C.8 presents average book and market leverage levels for each *Size-Stature* group. Consistent with previous studies, we find

[20] The results are consistent with the findings of marketing studies by Rego, Billett, and Neil (2009) and Anderson and Mansi (2009).

that size affects leverage levels: large firms in all *Stature* quintiles (except for the *High Stature* one) hold considerably more leverage than the firms in the lowest size quintile and the differences are even more pronounced for firms in the lowest *Stature* quintile. At the same time, there is a significant variation in the average leverage level across brand value groups. Even controlling for size, the leverage level increases for firms with higher *Stature* in all but the largest *Sale* groups, and the differences are statistically and economically significant. The differences in leverage across *Sale* quintiles are most pronounced among smallest firms, and equal 23% and 12% for book and market leverage, respectively.

We then turn to a multivariate analysis and estimate leverage as a function of customer perception of a firm's products and a variety of control variables drawn from a set of variables used in the previous capital structure research. We estimate each specification using Tobit model, which accounts for observations with zero leverage (about 10% of the sample). The results are presented in Table 1.C.9. Consistent with the univariate analysis, we find a positive and significant effect of *Stature* on *Leverage*. Its magnitude in Specification (1) ranges from 0.01 in market leverage estimation to 0.03. Smaller magnitude of the Stature coefficient in market leverage regression is not surprising: positive brand perception increases the overall value of the firm, and the market takes that into account. Interaction term between *Stature* and *Sale* has negative and significant coefficient in all the specifications, consistent with the univariate analysis, and suggesting that the impact of brand perception is more pronounced among small firms. Thus, a one standard deviation increase in *Stature* is associated with 1.7% increase in market leverage for a median-sized firm, and allows for over 4% of additional debt capacity for a firm in 25th percentile of our sample. Given that an average leverage is about 18%, this translates into more than 20% additional debt capital.

The rest of the control variables are in line with the previous studies. M/B and profitability has a negative impact on leverage, while firm size allows for more debt capacity, consistent with other capital structure findings. We also find that historical volatility of EBITDA does not have a negative impact on capital structure, confirming our previous discussion about fundamental differences between past and forward-looking cash flow volatility.

To verify the robustness of our results, we repeat the main analysis using additional definitions of leverage. First, we exclude the short-term debt component and define leverage as long-term debt, scaled by assets. Our results remain unchanged. Second, we re-estimate the main specifications using liabilities-to-assets. Welch (2011) points to fundamental flaws in using financial debt-to-assets as a leverage proxy and advocates the use of the ratio of total liabilities to assets as a more precise measure, capturing non-financial liabilities. We do not find any material differences in the coefficient of brand *Stature*, using total liabilities-to-assets. We also re-run the main specifications using additional control variables: *DivDummy*, sales growth in years *(t-1)* and *(t-2)*, *Depreciation, Return,* S&P credit rating of the firm's long-term debt, and *NYSE*. While some of the coefficients appear to be statistically significant, and have the predicted sign (for example, *Depreciation*, and *NYSE* dummy have a positive impact on leverage), they do not affect the magnitude and statistical significance of brand *Stature*.

Overall, the results of the capital structure estimation are consistent with the hypothesis that product demand characteristics have an economically and statistically significant impact on capital structure, even after controlling for other commonly used determinants of the capital structure. The positive impact of *Stature* on *Leverage* indicates that consumer brand perception reduces the bankruptcy risk and guaranteeing higher and more stable cash flows, as a result, providing a firm with more debt capacity.

2. Cash Holding

Following the methodology of the previous sub-section, we start with a univariate analysis of cash holdings scaled by assets and sales, across *Sales*-*Stature* groups. The results are presented in Panel B of Table 1.C.8. Consistent with previous studies, we find that size plays an important role in cash holding policy and larger firms hold significantly less cash than small firms, and the pattern linearly declines across size groups. Keeping size constant, cash holdings decrease across *Stature* groups, and the difference is the most pronounced for the smallest size quintile: while firms in the bottom of *Stature* quintile hold over 34% of their assets as cash and liquid securities (scaled by assets), firms in the top *Stature* group hold only 13%. The differences are even more pronounced when analyzing cash holding scaled by *Sales*.

We proceed with multivariate analysis and estimate cash holdings as a function of *Stature* and common control variables. The results are presented in Table 1.C.10. In Panel A cash holds are scaled by total assets, and in Panel B by *Sale*. Consistent with previous findings, we find that cash holdings decrease with size and net working capital, which can be considered a substitute for cash. More profitable and tangible firms hold less cash, as their probability and cost of financial distress are lower. At the same time, firms with more growth opportunities, as captured by M/B, accumulate more cash to be able to finance future projects. We alter the baseline specification by adding the interaction of Stature and Sale (Specification (2)), and also past cash flow volatility, as well as advertising and R&D expenses (Specification (3)). The coefficients of *log(Advertising)* and *log(R&D)* are positive and mostly significant, suggesting that both variables can be viewed as proxies for investment opportunities.

Similar to the leverage estimation, the *Stature*log(Sale)* interaction term is statistically significant, and indicates that the impact of Stature on cash holdings is more pronounced for smaller firms. In terms of magnitude, a median firm that experiences a one standard deviation increase in its brand perception, reduces its cash holdings by 2.5%, while a firm in the 25th percentile – by 4.5%.

To verify the robustness of our results for cash holding, in unreported regressions we include additional control variables (*log(Age)*, sales growth in years *(t-1)* and *(t-2), Depreciation, Return, NYSE*) and obtain results similar to the ones reported here.

The results for cash holding, together with the results on leverage, robustly demonstrate that firms with strong brand *Stature* hold significantly more net debt (debt minus cash holdings, all scaled by book assets). Net debt, commonly used by practitioners, shows how well a firm can manage its debt. Given a fixed debt level, a firm with more cash reserves is better able to handle financial troubles than an all equal firm with lower cash reserves. The higher levels of net debt among firms with high *Stature* provide evidence that firms with strong brand perception have lower expected costs of financial distress, which allows them to maintain a relatively high level of net debt.

3. Variance Decomposition

The results so far have established an economically and statistically significant relationship between consumer demand characteristics, as captured by brand *Stature*, and a firm leverage and cash holding policy. In this subsection we turn to a variance decomposition analysis and examine how much *Stature* contributes to explaining the overall variation in each of the dependent variables, compared to other control variables, commonly used in empirical research.

Following Lemmon et al. (2008), we perform an analysis of covariance (ANOVA). Specifically, we use Type III sum of squares, which is the increase in model sum of squares due to adding the variable of interest to a model that already contains all the other control variables. Type III sum of squares is more appropriate than Type I sum of squares for our analysis, since the former does not depend on the order in which the explanatory variables are entered into the model. To calculate the Type III sum of squares, we use the regression specifications identified in Tables 1.C.4 and 1.C.5. We first compute partial sum of squares and then normalize the vector obtained by dividing the partial sum for each variable by the total Type III partial sum of squares. The normalization procedure eases the interpretation of the results by demonstrating the relative contribution of each factor. It is important to note, though, that Type III partial sum of squares do not add up to the regression sum of squares but, rather, capture a marginal increase in explanatory power as a result of adding another variable.

The results of the variance decomposition are presented in Table 1.C.11. Panels A and B estimate book and market leverage, respectively, while Panels C and D present the results of cash holding as the dependent variable. Regression specifications (1) through (3) in each panel exclude industry fixed effect, which is added back in specifications (4) through (6). When *Stature* and industry fixed effect is not included, most of the variation in book and market leverage are explained by tangibility and Market-to-Book ratio. This is consistent with previous studies, suggesting that tangibility is one of the important factors determining debt capacity. Specifications (4) through (6) demonstrate that *Stature* and its interaction with size explain aver 50% of the variation of book leverage, significantly more than any other variable. In the regression of market leverage the contribution of these variables is lower, and is about 16%-20% of the overall sum of squares, but it is almost as substantial as the contribution of *Tangibility*. Incorporating industry fixed effects shifts most of the explanatory share from the control variables to the fixed effect components, which is responsible for 47% to 89% of the explained variation in leverage (specifications (4) through (6)). As industry fixed effect reduce the explanatory power of *Stature*, it still explains more of the variation than any of the control variables. The only variable that has more power in capturing the overall variation is M/B in the market leverage regression. It is important to note, though, that scaling leverage by market, rather than book, assets, creates a mechanical relation between the two variables. Overall, the sum of squares explained by brand *Stature* roughly equals the explained sum of squares of all the major explanatory variables: *log(Sale)*, *EBITDA*, tangibility, and most important, historical variance in a firm's profitability. Taken together, the results provide evidence that *Stature* accounts for a significant portion of explained variation in leverage, equivalent to the fraction, explained by the standard accounting characteristics of a firm.

A somewhat different picture emerges from Panel B, which decomposes the explained variance of cash holdings. Overall, M/B, tangibility, and net working capital are the important drivers of the explained sum of squares. Industry fixed effects, while still explaining a large portion of the variation, contribute 47% to 77%. Stature and its size interaction account for about 20% of the variation when fixed effects are excluded, and 10% in specifications that account for industry fixed effects. While this is a relatively small portion, it is still quite substantial compared to other control variables, such as size, profitability, historical volatility, and dividend payer indicator, suggesting once again that brand Stature bears information about cash flow characteristics, not captured by other variables.

V. Alternative Explanations and Robustness Tests

While this paper focuses cash flow stability as the main mechanism through which characteristics of intangible assets affect financial policies of a firm, it is possible that there exist alternative links between brand perception and corporate decisions. In this subsection we discuss other plausible explanations to the results above.

1. Agency Problems

The findings of the paper are potentially consistent with an agency explanation, as market competition is considered one of the managerial disciplining devices (see, among others, Alchian (1950), Stigler (1958), and Hart (1983)). A loyal pool of consumers may insulate the firm from the rest of the firms in the industry and reduce the impact of market competition. As a result, agency problems between managers and shareholders intensify. However, agency conflicts generate opposite predictions about the relations between demand function characteristics and a firm's financial decisions. Thus, firms with strong demand hoard cash and distribute less to the shareholders. Firms might also choose to hold less debt, as debt also restricts managerial discretion (Jensen (1986)).

It is still possible, though, that a firm decides to use higher debt and lower cash holdings as an alternative mechanism of mitigating the agency problems. Thus, managers may voluntarily restrict themselves from potential overuse of a firm's funds by choosing higher debt levels, lower cash reserves, and higher payouts to maintain a favorable reputation of operating in the best interests of the shareholders. To address this concern, we formally examine whether the substitution effect, associated with intensified agency problems, can be the actual driver of our results. To test the substitution model, we use the entrenchment index of the corporate governance provisions, suggested by Bebchuk, Cohen and Ferrell (2009).[21] The index is based on the most important components of the governance index by Gompers, Ishii, and Metrick (2003) and consists of six provisions: staggered boards, limits to shareholder bylaw amendments, poison pills, golden parachutes, and supermajority requirements for mergers and charter amendments. If the substitution hypothesis is correct, we should find that firms with stronger demand have lower entrenchment index.

We compute an average of the entrenchment index for each quintile of firms, constructed based on the *Stature* measure, and find no significant pattern between the entrenchment index and *Stature*. Moreover, the difference between the top and the bottom quintiles is negative, indicating that firms with stronger brand perception in fact have a better corporate governance. Next, we add the entrenchment index to our main regression specifications and find that it does not influence the main results (unreported).

2. Information Asymmetry

Higher brand perception may affect information asymmetry of the firm. For example, Chemmanur and Yan (2009, 2010b) demonstrate the link between information asymmetry and advertising. Grullon et al. (2004) show that advertising affects the overall visibility of a firm. While, as described in Section II, advertising and brand perception are quite different concepts, it is still plausible that strong brand perception of a firm's products leads to investor interest in a firm's financial performance, and results in more research on a firm and its operations. The empirical results for bond yields and cash holding are consistent with this explanation: firms with lower information asymmetry have lower cost of raising debt, and therefore, do

[21] The entrenchment index data were obtained from the Web site of Lucian Bebchuk at http://www.law.harvard.edu/faculty/bebchuk/data.shtml.

not need to hold cash to finance potential investment opportunities. However, information asymmetry does not explain the positive link between brand perception and leverage. If firms with stronger brand enjoy lower information asymmetry, the impact should be stronger for equity, rather than debt, because of the option-like structure of the equity payout. Therefore, according to this explanation, the leverage level of firms with strong brand perception should actually be higher.

3. Profitability

Higher brand perception may affect financial decisions of a firm through profitability, rather than cash flow volatility channel. If demand for a firm's product is more inelastic among loyal customers, who differentiate the product from other existing brands, they will not be willing to substitute the product for alternative brands, and the firm will exploit that by charging higher prices. As an outcome, brand stability will affect financial decisions through *level* of profitability, rather than through its future stability.

While theoretically plausible, the argument does not find support in the data. First, a simple correlation analysis in Table 1.C.2 demonstrates that the correlation between *Stature* and EBITDA is quite modest, and equals 0.17. To verify that this result is robust, in unreported results we calculate correlation between *Stature* in period *t* and *EBITDA* in periods (*t+1*) and (*t+2*) and find that the correlation does not change significantly. These results are consistent with brands such as McDonalds and Wal-Mart consistently scoring high on brand stature scale, and suggest that some brands appeal to consumers by positioning their products as being consistently cheap.

Finally, if the brand links to financial decisions through higher profit margins, which are not captured by EBITDA variable, one would expect to find negative, rather than positive impact on a firm's leverage, as past literature on capital structure has long documented the negative effect of profitability on leverage, consistent with the implications of pecking order theory (see, for example, Fama and French (2002)). Therefore, our results do not support this explanation.

4. Endogeneity and Reverse Causality

A large number of papers document the effect of financial frictions on the real policy of a firm, determining its behavior in the product market. Therefore, a reverse causality argument explaining the relationship between financial policy and consumer attitudes towards brand predicts that a firm with higher leverage competes more aggressively and, as result, may be willing to invest more resources in enhancing the value if its brand. While this explanation is plausible by itself, the negative relation between brand perception and cash holdings undermines it. Previous studies show that deep-pocketed firms increase their output and future market share gains at the expense of industry rivals (Telser (1966), Bolton and Scharfstein (1990), Fresard (2010)). We demonstrate that firms with stronger demand hold less cash, which is inconsistent with the reverse causality arguments that link strategic debt and cash holdings to product competition.

It is also plausible that relations between brand perception and financial decisions are driven by omitted variables. For example, more established and mature firms can have easy access to external capital markets, which will provide them with resources to advertise heavily, invest in enhancing the quality of their products, or use marketing strategies to alter consumer attitude towards the firm's products. However, this argument is not consistent with our findings that the impact of *Stature* is more pronounced among small firms with access to relatively short maturity debt and non-investment grade bonds. These firms are potentially more constrained in their access to the external capital market, and do not have a good reputation in the external capital markets. Therefore, it is unlikely that those rather than large and more mature firms, would spend more on enhancing their brand.

5. Robustness Tests

Finally, we perform additional robustness tests to verify that our main results hold across different subsamples and are robust to additional variable definitions.

To make sure that our results are not driven by large multi-national conglomerates, operating in a number of segments, we remove market leaders from the sample and repeat our analysis. We use several definitions to identify market leaders. Our first definition is based on a firm's age. Using the overall Compustat universe, we classify the oldest firm in each SIC four-digit industry as a market leader. Our second definition uses the market share of a firm. For each year we denote the firm with the largest sales in the industry as a market leader. Since the largest firm in the industry is most likely publicly traded, our definition is not likely to be biased by reliance on the sample of publicly traded firms in defining the market leader. Overall, only 6.8% of the firm-year observations fall into the category of market leaders using the definition of age and about 7.6%, using the definition of market share. We repeat the main estimations of leverage and cash holdings, removing market leaders, and obtain similar results. For additional robustness, we define both categories more broadly and assign the oldest/largest 1%, 5%, and 10% of firms to the category of market leaders. While we eliminate more firm-year observation by expanding the market leader criteria, the results of all estimations remain very similar to the ones presented here.

We also verify that our results are not sensitive to using *Stature* as our main measure of brand perception and loyalty. Since the *Knowledge* pillar may capture additional effects, such as elements of information asymmetry, rather than personal attitude as a consumer, it may introduce additional noise to the variable. We re-estimate our analysis using only the *Esteem* pillar and find very similar results. Next, we use the measure of brand performance, as suggested by Bronnenberg, Dhar, and Dube (2009). The authors use a simple average of positive response rates to the following brand characteristics: "high quality," "good value," and "best brand in the category" as a proxy for perceived quality. While "high quality" response is one of the components of "*Esteem*," the other two questions are not included in the brand *Stature* construct and may potentially affect our results. We re-estimate our specifications for leverage and cash holdings using the new index and find results similar to the ones obtained with the overall brand *Stature* measure.

Since the BAV surveys were not performed on a constant basis before 2001, our sample has gaps for the years 1994 to 1996, 1998, and 2000. As a robustness check, we correct the sample by imputing the missing BAV data. As most of the BAV survey components are extremely persistent, we use the linear function to obtain data between two data points to fill in missing data. As a result of the imputation, our sample increases to between 2,800 and 3,000 observations (depending on the specified regression). The main results remain very similar to the ones presented here. We also use a step function as an alternative imputation method and assign the values of the most available survey until we obtain new data. Again, we obtain results similar to the ones presented.

VI. Conclusion

This paper demonstrates that intangible assets characteristics have an impact on corporate financial policy. We focus on characteristics of a firm's brand, which accounts for a large portion of a firm's overall value, and is relevant to firms across various industries. To examine the role of intangible asset characteristics, we employ a novel data of consumer brand evaluation, Brand Asset Valuator, which summarizes individual attitudes towards different brands using US household surveys. Our main measure, brand *Stature*, captures the degree of familiarity and regards that consumers experience towards a certain brand. We use *Stature* measure to test whether positive perception of a brand affects a firm through cash flow stability channel. Previous evidence shows that strong brand results in a clientele of loyal consumers, who have high subjective value for the firm's products and are willing to stick with it over time. As a result, firms with favorable brand can enjoy a higher and more stable stream of future profits and lower riskiness.

To support the validity of the mechanism, we demonstrate that brand *Stature* reduces forward-looking volatility of a firm's profits and the probability of distress, as measured by Altman's (1968) modified Z-score. We also find that brand *Stature* improves credit ratings of non-investment grade corporate bonds. Next, we ask whether the lower cash flow riskiness, as proxied by brand *Stature*, is priced in the credit market. We estimate yields on publicly traded corporate bonds, and find that creditors require lower spreads on debt of firms with positive brand perception. The results are more pronounced among firms with short-term credit, and are small and insignificant for yields of bonds with maturity over six years.

After demonstrating that consumer attitude translates into lower riskiness and better prices of debt, we turn to the main question of the paper and investigate whether characteristics of intangible assets have implications on the financial policy of the firm. We find that brand *Stature* has a positive impact on leverage and a negative impact on cash flow, improving the net debt position of the firm. Our results hold after including historical cash flow volatility, the commonly used measure of a firm stability, in all of our regressions. The impact of *Stature* remains significant, suggesting that it captures certain information about the firm, not reflected in the past-looking accounting measures.

While it is possible that the relationship between financial policy and brand perception works in the opposite direction, and financially strong firms allocate more resources to an active management of its brand, our subsample results do not support these potential explanations. For the reverse causality explanation to hold, we would expect to find stronger results among larger, mature, and more established firms. We find the opposite. The impact of brand is more pronounces among small firms with low credit ratings and short debt maturity, or put differently, more financially constrained ones. These findings strengthen the validity of our main hypothesis by suggesting that financially constrained firms benefit from having a strong brand more, and receive better access to external capital market on more favorable terms.

Overall, our findings indicate that characteristics of intangible assets are just as significant in explaining financial policy of a firm, as the tangible assets are. The paper has important product market implications for investment policy, suggesting that a young firm may benefit from developing and enhancing its brand early in its business life, as it will improve not only relationships with its customers, but also with potential investors. From the creditors perspective, the results suggest that a due diligence process, accounting for soft information such as relative positioning of the firm among its competitors based on customers reviews may help in identifying potentially creditworthy borrowers. Finally, the paper shows the importance of the interaction between marketing and finance fields and suggests that marketing policy, such as brand management, and financial policy, such as capital and cash holding decisions, are interdependent.

APPENDIX 1.A: AN EXAMPLE OF A BAV QUESTIONNAIRE PAGE

Familiarity

By "familiarity" we mean your overall awareness of the brand as well as your understanding of what kind of product or service the brand represents.

Please put an "X" in the box next to each brand that best describes how familiar you are with it. All brands in the section must be rated. Remember, you do not have to have used or purchased the brand to rate it.

	Never Heard of					Extremely Familiar		Never Heard of					Extremely Familiar
	1	2	3	4	5	6	7		1	2	3	4	5	6	7
Herbal Essences	☐	☐	☐	☐	☐	☐	☐	Hungry Man	☐	☐	☐	☐	☐	☐	☐
Miller Lite	☐	☐	☐	☐	☐	☐	☐	Michelob	☐	☐	☐	☐	☐	☐	☐
Duracell	☐	☐	☐	☐	☐	☐	☐	Vijay Singh	☐	☐	☐	☐	☐	☐	☐
Alfa Romeo	☐	☐	☐	☐	☐	☐	☐	Marshalls	☐	☐	☐	☐	☐	☐	☐
Vidal Sassoon	☐	☐	☐	☐	☐	☐	☐	Chrysler	☐	☐	☐	☐	☐	☐	☐
World Cup (soccer)	☐	☐	☐	☐	☐	☐	☐	Heineken Lite	☐	☐	☐	☐	☐	☐	☐
Energizer	☐	☐	☐	☐	☐	☐	☐	Bergdorf Goodman	☐	☐	☐	☐	☐	☐	☐
Lance Armstrong	☐	☐	☐	☐	☐	☐	☐	Alex Rodriguez	☐	☐	☐	☐	☐	☐	☐
Mike's Hard Lemonade	☐	☐	☐	☐	☐	☐	☐	Kotex	☐	☐	☐	☐	☐	☐	☐
Wal-Mart	☐	☐	☐	☐	☐	☐	☐	Mercury	☐	☐	☐	☐	☐	☐	☐
	1	2	3	4	5	6	7		1	2	3	4	5	6	7
Saran Wrap	☐	☐	☐	☐	☐	☐	☐	Harp	☐	☐	☐	☐	☐	☐	☐
Radica	☐	☐	☐	☐	☐	☐	☐	Armour	☐	☐	☐	☐	☐	☐	☐
Barry Bonds	☐	☐	☐	☐	☐	☐	☐	Nice `N Easy	☐	☐	☐	☐	☐	☐	☐
Lord & Taylor	☐	☐	☐	☐	☐	☐	☐	Swanson	☐	☐	☐	☐	☐	☐	☐
Michelob Lite	☐	☐	☐	☐	☐	☐	☐	Foster`s	☐	☐	☐	☐	☐	☐	☐
Tampax	☐	☐	☐	☐	☐	☐	☐	Monopoly	☐	☐	☐	☐	☐	☐	☐
Beck`s	☐	☐	☐	☐	☐	☐	☐	Ford Taurus	☐	☐	☐	☐	☐	☐	☐

APPENDIX 1.B: MERGING BAV DATA WITH COMPUSTAT

Linking brands to firms is not trivial. The reason for that is that most companies have a quite complex brand hierarchy, through which firms manage different products across different brand groups.[22] There are four major types of branding strategies. In this appendix, we describe the merging rule that we apply for each type of brand portfolio.

The simplest, and actually the rarest, case is a "monobrand": firms in which one brand represents all or most of the firm's business (for example, Starbucks, Walmart, and Martha Stewart Living Omnimedia). In this case the identification of brand and company it belongs to is one to one.

The second case is a corporate brand, in which the corporate name is dominant (or is at least an element) in the product brand names (for example, General Electric, Logitech, and Hewlett-Packard). For this type of firm, the link to the company is also easy, since BAV typically asks about a brand either without mentioning the product type or using a separate entrance for the overall brand name (for example, Colgate, Colgate Total and Colgate mouthwash).

The third type of brand hierarchy is the house-of-brands strategy, in which the firm does not use its corporate name for branding its products. For example, Diageo, the world's largest beer, wine, and spirit company (whose brands include Guinness, Smirnoff, and Johnnie Walker), keeps the company name only at the background of its product labels. BAV typically asks about the overall brand name, as well as about each of the company brands, in a separate entry. The problem that arises in this case is that the combination of brands, composing the firm's operations, does not have to be similar to the overall company valuation. The reason for that is that consumers, while

[22] Rao, Agarwal, and Dahlhoff (2004) provide a comprehensive overview of different branding strategies.

being quite familiar with the brand, often do not know the company it belongs to, so when asked about the company name, they cannot relate it to the brands it owns. While this question can be quite interesting for further marketing research, our purpose in this paper is to get the best approximation at a company level. A weighted average of a firm's brands, while potentially providing a more precise brand value proxy, creates additional problems. The first problem is data availability: not all companies report the distribution of their balance of statement at a brand level. Second, it is not clear which weights are appropriate to use: revenues, gross profits, net profits, etc. The advantage of our data is that for most of the house-of-brand firms, BAV includes the company name, as well as the names of the brands it owns, as a separate entry. As a result, we use the BAV data for the company name rather than an aggregation of the individual brands it manages.

The final type of brand hierarchy is the mixed branding strategy, in which a firm uses its company name for some of its brands' products and employs a house-of-brand approach for the rest. The Gap Inc, which owns the Gap, Banana Republic, Old Navy, Piperlime, and Athleta brands, is a classic example of this strategy. The problem here is similar to the previous case: how to construct the best proxy for the company's overall BAV score. We use the brand with the same, or most similar, name to the company as a proxy to the firm's core business.[23] The reasoning for this is as follows: the choice of brand hierarchy is clearly an endogenous decision of a firm (for example, Rao, Agarwal, and Dahlhoff (2004) document the association of the branding strategy with firm's value), so if a firm chooses to identify itself with one of its brands, it must be part of the business strategy of the firm—this brand either

[23] Some firms have double names (for example, Molson-Coors). In this case we use a simple average of the BAV pillars and other variables (usage, brand image) as a proxy for the firm's overall brand value.

constitutes the core of the business or has been historically the main brand of the company, so that consumers associate it with the firm.

Since the data is a time-series, we identify all the changes in ownerships, such as mergers, acquisitions, and spin-offs, in the BAV-Compustat bridge and change the brand-firm links accordingly. For example, we create the link of Gillette brand to the Gillette Company, but discontinue it in 2005, when the company was acquired by Proctor & Gamble.

Overall, this approach of matching brands and firms is somewhat different from the one used in marketing. Marketing studies use the cases of monobrands only and do not consider more complex brand hierarchy structures (Mizik and Jacobson (2008, 2009)). We do not believe that our matching strategy introduces a systematic bias but are aware of the fact that it introduces additional noise. In the trade-off between precision and sample size, we prefer to sacrifice some degree of precision to obtain a larger sample of firms for our analysis. As a result, our final sample is almost twice as large as in the studies that use monobrands only.

We still address potential biases, resulting from implementing the approach described above, by applying three alternative matching algorithms for house of brands and mixed-strategy brand portfolios. First, we use a simple average of the *Stature* of all the brands that belong to a firm. As an alternative approach, we assume that the larger the segment of a certain brand in the overall portfolio of a firm's products, the better is consumer familiarity with it. Therefore, we weigh the *Stature* of each brand by the *Knowledge* of its brand, relative to the overall *Knowledge* of the firm (sum of *Knowledge* across all the brands of a firm). In the third approach we use the brand with the maximum *Stature* as the representative of the company strength. The idea behind this approach is that a firm typically starts with one brand, which becomes its core business, but as it grows, it starts introducing new brands. Since a firm can always go back to its core business in a case of unsuccessful development of a new brand, the *Stature* of the most valuable brand may be the important one. We repeat the main analysis using each of the alternative merging approaches and find that using alternative matching techniques does not change our conclusions in a material way.

APPENDIX 1.C: TABLES

Table 1.C.1. Descriptive Statistics

This table presents the distribution of main variables of interest with non-missing *Stature* values for the period 1993–2009. *log*(*Sale)* is the total sales, in millions of constant 1992 dollars, converted to logarithms. *M/B*, market to book ratio, is the market value of equity plus the book value of assets minus preferred stock plus deferred taxes. *EBITDA* is the ratio of operating income before depreciation to total assets. *Tangibility* is defined as net property, plant, and equipment divided by book assets. *S&P500* is a dummy variable that equals one if a firm belongs to the S&P 500 index, and zero otherwise. *Age* is calculated starting from the first year the firm appeared in the Compustat database. *Z-score* is the sum of 3.3 times *EBITDA* plus sales, 1.4 times retained earnings, plus 1.2 times working capital, all scaled by total assets. *Book Leverage* is the sum of short-term and long-term debt scaled by book assets. *Cash* is cash and short term investments, scales bo total assets (*Assets*). *Hist Volatility(EBITDA)* is the standard deviation of *EBITDA* in the previous 5 years. Herfindahl index is the summed squared market shares of all the publicly traded companies in an industry defined by the SIC four-digit code.

Variable	**Mean**	**Median**	**Std Dev**	**25th Pctl**	**75th Pctl**	**Correlation with Stature**
log(Sale)	7.90	8.15	1.45	6.91	9.06	0.30
M/B	2.15	1.72	1.37	1.23	2.58	0.08
EBITDA	14.8%	14.6%	11.4%	9.1%	20.8%	0.17
Tangibility	28.3%	23.9%	19.6%	13.1%	39.4%	0.04
S&P500	0.49	0.00	0.50	0.00	1.00	0.31
Age	26.42	17.00	23.39	8.00	38.00	0.35
Z-score	1.88	2.00	1.58	1.33	2.76	0.18
Advertising/Sales	3.9%	2.2%	6.7%	0.0%	4.8%	0.08
RD/Sales	3.0%	0.0%	6.5%	0.0%	2.5%	-0.17
Hist Volatility(EBITDA)	4.4%	2.7%	7.8%	1.6%	5.0%	-0.15
Book Leverage	23.9%	21.5%	24.5%	7.8%	33.5%	0.17
Cash/Assets	15.2%	10.4%	15.4%	3.6%	21.6%	-0.26
Herfindahl Index	0.07	0.05	0.07	0.04	0.08	0.19

Table 1.C.2. Industry Distribution

This table presents the distribution of BAV and Compustat samples (firm-year observations) by industry for the period 1993–2009. Industries are defined according to the Fama-French 12-industry classification. Panel A reports the ratio of the number of observations in each industry to the overall number of observations in the sample. Panel B reports the ratio of the market capitalization of each industry to the overall market capitalization of the sample.

Industry Number	Industry Name	Industry Description	Panel A Number of firms		Panel B Market Cap	
			BAV	Compustat	BAV	Compustat
1	Consumer Nondurables	Food, tobacco, textiles, apparel, leather, toys	0.223	0.054	0.164	0.078
2	Consumer Durables	Cars, TV's, Furniture, Household appliances	0.033	0.025	0.015	0.016
3	Manufacturing	Machinery, trucks, planes, off furn, paper, com printing	0.097	0.105	0.098	0.098
4	Energy	Oil, gas and coal extraction	0.007	0.039	0.005	0.054
5	Chemicals	Chemicals and allied products	0.030	0.022	0.027	0.029
6	Business Equipment	Computers, software, electronic equipment	0.156	0.188	0.234	0.169
7	Telecommunications	Telephone and television transmission	0.049	0.032	0.080	0.111
8	Utilities	Utilities	0.002	0.029	0.002	0.058
9	Shops	Wholesale, retail and some services	0.209	0.098	0.095	0.061
10	Healthcare	Healthcare, medical equipment and drugs	0.038	0.091	0.174	0.129
11	Money	Financial services	0.047	0.188	0.044	0.094
12	Other	Other	0.110	0.130	0.063	0.105

Table 1.C.3. The Effect of Brand Stature on Forward-Looking Cash Flow Volatility

This table reports the results of the OLS regression where the dependent variable is forward-looking absolute volatility of earnings in Panel A, and forward-looking relative volatility of earnings in Panel B. Forward-looking absolute cash flow volatility at time *t* is the standard deviation of a firm's annual profitability, scaled by total assets (*EBITDA*) during period (*t+1*) through (*t+5*). Forward-looking relative cash flow volatility is forward-looking absolute volatility, scaled by the industry forward-looking volatility, which is the volatility of the average industry profitability (based on a SIC two-digit code) five years forward. *Log(Sale)* is the logarithm of the total firm sales expressed in millions of constant 1992 dollars. *M/B*, market to book ratio, is the market value of equity plus the book value of assets minus preferred stock plus deferred taxes. *log(R&D)* and *log(Advertising)* are natural logarithms of the overall amount of R&D and advertising expenses, respectively, in millions of constant 1993 dollars. *Hist Volatility(EBITDA)* is the standard deviation of *EBITDA* in the previous 5 years. All explanatory variables are lagged by one period. All estimations models include year and industry fixed effects (at SIC two-digit level). Standard errors are reported in parentheses and are based on heteroskedastic consistent errors adjusted for clustering across firms. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	Panel A: Absolute Vol		*Panel B: Relative Vol*	
	(1)	(2)	(3)	(4)
Intercept	0.062***	0.049***	2.061***	1.572***
	(0.011)	*(0.012)*	*(0.435)*	*(0.402)*
Stature	-0.002**	-0.002**	-0.081*	-0.088*
	(0.001)	*(0.001)*	*(0.044)*	*(0.048)*
log(Sale)	-0.006***	-0.006***	-0.247***	-0.245***
	(0.001)	*(0.001)*	*(0.051)*	*(0.057)*
M/B	0.005***	0.004***	0.143***	0.105***
	(0.001)	*(0.001)*	*(0.039)*	*(0.035)*
EBITDA	-0.048***	-0.035*	-0.513	0.027
	(0.018)	*(0.019)*	*(0.742)*	*(0.708)*
log(Age)		-0.003*		-0.06
		(0.001)		*(0.057)*
log(advertising)		0.001***		0.045**
		(0.0005)		*(0.019)*
log(R&D)		0.0006		0.034
		(0.001)		*(0.025)*
Hist Volatility(EBITDA)		0.007**		0.045**
		(0.003)		*(0.022)*
Obs.	*2338*	*2304*	*2338*	*2337*
Number of firms	*452*	*446*	*452*	*452*
R-squared adj.	0.26	0.27	0.16	0.17

Table 1.C.4. The Effect of Brand Stature on Credit Rating

This table reports the results of the OLS regression where the dependent variable is S&P domestic long-term issuer credit rating. Panel A includes all the sample firms; Panel B includes firms with rating of 'BBB-' and higher; Panel C includes firms with rating of 'BB+' and lower. Credit ratings are converted into numeric scale, where credit rating 'AAA' receives a score of 1, and credit rating of 'D' receives a score of 23. *Log(Sale)* is the logarithm of the total firm sales expressed in millions of constant 1992 dollars. *M/B*, market to book ratio, is the market value of equity plus the book value of assets minus preferred stock plus deferred taxes. *EBITDA* is the ratio of operating income before depreciation to total assets. *Leverage* is the sum of short-term and long-term debt scaled by book assets. *Tangibility* is defined as net property, plant, and equipment divided by book assets. *Depreciation* is depreciation expenses scaled by assets. *Ret_mean* is the average monthly returns on equity over calendar year. *log(R&D)* and *log(Advertising)* are natural logarithms of the overall amount of R&D and advertising expenses, respectively, in millions of constant 1993 dollars. *Hist Volatility(EBITDA)* is the standard deviation of *EBITDA* in the previous 5 years. All explanatory variables are lagged by one period. All estimations models include year and industry fixed effects (at SIC two-digit level). Standard errors are reported in parentheses and are based on heteroskedastic consistent errors adjusted for clustering across firms. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	Panel A: All Ratings			*Panel B:Investment Ratings*			*Panel C: Non-Investment Ratings*		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Intercept	24.06***	23.52***	22.36***	20.26***	20.17***	18.76***	21.02***	21.3***	20.77***
	(1.31)	*(1.29)*	*(1.29)*	(1.77)	(1.68)	(1.69)	*(0.93)*	*(1.05)*	*(1.05)*
Stature	-0.11	-0.09	-0.17*	-0.06	-0.08	-0.1	-0.34***	-0.34***	-0.37***
	(0.1)	*(0.1)*	*(0.1)*	(0.11)	(0.11)	(0.11)	*(0.13)*	*(0.13)*	*(0.13)*
log(Sale)	-1.28***	-1.24***	-1.1***	-1.15***	-1.16***	-0.99***	-0.73***	-0.73***	-0.76***
	(0.13)	*(0.13)*	*(0.13)*	(0.17)	(0.16)	(0.17)	*(0.11)*	*(0.11)*	*(0.1)*
M/B	-0.19*	-0.21**	-0.19*	-0.05	-0.11	-0.13	-0.23**	-0.24**	-0.37***
	(0.1)	*(0.1)*	*(0.1)*	(0.1)	(0.09)	(0.08)	*(0.1)*	*(0.1)*	*(0.11)*
EBITDA	-14.9***	-15.2***	-15.04***	-7.21***	-5.65***	-5.03***	-11.64***	-12.02***	-10.39***
	(1.8)	*(1.75)*	*(1.72)*	(1.76)	(1.8)	(1.73)	*(1.56)*	*(1.56)*	*(1.56)*
Leverage	4.77***	4.53***	4.58***	3.66***	3.82***	3.49***	3.49***	3.38***	3.36***
	(0.66)	*(0.63)*	*(0.6)*	(1.03)	(1)	(0.95)	*(0.57)*	*(0.57)*	*(0.55)*
Tangibility		-3.33***	-3.05***		-4.12***	-3.68***		-1.16	-0.85
		(0.91)	*(0.91)*		(0.93)	(0.9)		*(0.86)*	*(0.81)*
Depreciation		18.46***	16.21***		7.36	5.61		11.39**	6.71*
		(5.54)	*(5.34)*		(6.43)	(6.26)		*(4.45)*	*(3.96)*
Ret_mean		-3.95*	-4.1**		-7.59	-8.16*		-3.16	-3.46
		(2.09)	*(2.03)*		(4.79)	(4.87)		*(2.19)*	*(2.13)*
log(Advertising)			0.07			-0.001			0.12**
			(0.05)			(0.04)			*(0.05)*
log(R&D)			-0.16**			-0.116*			0.02
			(0.07)			(0.06)			*(0.07)*
Hist Volatility(EBITDA)			8.08**			7.91***			11.66***
			(3.75)			(2.8)			*(3.26)*
Obs.	*1793*	*1793*	*1793*	*882*	*882*	*882*	*911*	*911*	*911*
Number of firms	*324*	*324*	*324*	*208*	*208*	*208*	*203*	*203*	*203*
R-squared adj.	0.67	0.68	0.69	0.51	0.54	0.56	0.58	0.59	0.61

Table 1.C.5. The Effect of Brand Stature on Z-Score

This table reports the results of the OLS regression where the dependent variable is Altman's (1968) Z-score, which is the sum of 3.3 times *EBITDA* plus sales, 1.4 times retained earnings, plus 1.2 times working capital, all scaled by total assets. *Log(Shareholders)* is the logarithm of the total number of stock shareholders. S&P is a dummy value that equals one if a firm belongs to the S&P500 index, and zero otherwise. Access is an indicator variable for having a credit rating. *M/B*, market to book ratio, is the market value of equity plus the book value of assets minus preferred stock plus deferred taxes. *log(R&D)* and *log(Advertising)* are natural logarithms of the overall amount of R&D and advertising expenses, respectively, in millions of constant 1993 dollars. Zero is assigned to missing variables. *log(Advertising) [if>0]* includes non-zero values only. Change in *Sales* is the percentage change in sales from previous year. *Tangibility* is defined as net property, plant, and equipment divided by book assets. *Ret_mean* is the average monthly returns on equity over calendar year. *Hist Volatility(EBITDA)* is the standard deviation of *EBITDA* in the previous 5 years. All explanatory variables are lagged by one period. All estimations models include year and industry fixed effects (at SIC two-digit level). Standard errors are reported in parentheses and are based on heteroskedastic consistent errors adjusted for clustering across firms. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	2.76***	2.97***	2.44***	2.82***	1.82***	2.37***
	(0.13)	*(0.27)*	*(0.21)*	*(0.24)*	(0.25)	(0.29)
Stature	0.23***	0.14**	0.19***	0.11**	0.17***	0.12**
	(0.06)	*(0.06)*	*(0.05)*	*(0.05)*	(0.06)	(0.06)
log(Shareholders)	0.03	0.02				
	(0.04)	*(0.04)*				
S&P500			0.23**	0.21**		
			(0.1)	*(0.09)*		
Access			0.33*	0.22		
			(0.17)	*(0.18)*		
log(Advertising) [if>0]					0.22***	0.2***
					(0.06)	(0.06)
Sales (change)	-0.24**	-0.25**	-0.21*	-0.23**	-0.18**	-0.18**
	(0.11)	*(0.1)*	*(0.11)*	*(0.1)*	(0.08)	(0.08)
Ret_mean	0.19	0.96	0.33	0.96	-0.21	0.5
	(0.93)	*(0.81)*	*(0.89)*	*(0.79)*	(0.99)	(0.86)
M/B	0.24***	0.276***	0.22***	0.26***	0.25***	0.28
	(0.04)	*(0.04)*	*(0.04)*	*(0.04)*	(0.05)	(0.05)
Tangibility	1.36***	1.16**	1.36***	1.18***	1.72***	1.48***
	(0.49)	*(0.46)*	*(0.47)*	*(0.43)*	(0.59)	(0.56)
log(Advertising)		0.05**		0.05*		
		(0.02)		*(0.02)*		
log(R&D)		-0.07*		-0.08**		-0.07
		(0.04)		*(0.04)*		(0.05)
Hist Volatility(EBITDA)		-5.09***		-4.91***		-4.53***
		(1.37)		*(1.31)*		(1.59)
Obs.	*2364*	*2364*	*2532*	*2532*	*1861*	*1861*
Number of firms	*438*	*438*	*464*	*464*	*357*	*357*
R-squared adj.	0.35	0.38	0.36	0.42	0.39	0.43

Table 1.C.6. Operating Performance of Low versus High Brand Stature Firms during Recession

This table presents sample statistics of selected variables for low and high brand *Stature* firms, matched on their sales as of (t-1). To assign firms into groups of *Low* and *High Stature*, every year all the firms are allocated into quartiles based on their Stature score. The bottom quartile includes *Low Stature* firms, and the top one includes *High Stature* firms. *Change in EBITDA* is the percentage change in firm operating performance, scaled by assets. *Change in Sale* in the percentage change in firm total sales, in millions of constant 1993 dollars. *Z-score* is the sum of 3.3 times *EBITDA* plus sales, 1.4 times retained earnings, plus 1.2 times working capital, all scaled by total assets. The periods of recession are based on NBER Business Cycle data. Tests on means and medians are t-test and Wilcoxon test, respectively. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively, and are based on two-tailed tests.

		Low Stature		High Stature		Low minus High Stature	
Variable	Number of observations	mean	median	mean	median	mean	median
	Panel A: Recession of 2001						
change in EBITDA	58	3.27%	1.58%	2.30%	2.46%	0.97%	-0.88%
change in Sale	58	-0.02%	0.05%	8.02%	5.25%	-8.04%***	-5.2%
Z-Score	58	0.55	1.21	1.93	2.04	-1.38***	-0.83***
	Panel B: Recession of 2007-2009						
change in EBITDA	152	1.23%	1.20%	5.90%	2.19%	-4.67%***	-0.99**
change in Sale	152	0.60%	1.30%	10.3%	2.80%	-9.7%***	-1.50%*
Z-Score	152	1.22	1.59	1.82	1.86	-0.60***	-0.27

Table 1.C.7. The Effect of Brand Stature on Credit Spreads

This table reports the results of the OLS regressions where the dependent variable is the spread on public bond, in percent terms. In Panel A spreads are aggregated across all bond maturities; in Panel B they are based on bonds with maturities of less or equal to 6 years; in Panel C spreads are based on bonds with maturities of longer than 6 years. *Credit Rating* corresponds to the appropriate maturity rating, and is converted into numeric scale. *Log(Sale)* is the logarithm of the total firm sales expressed in millions of constant 1992 dollars. *M/B*, market to book ratio, is the market value of equity plus the book value of assets minus preferred stock plus deferred taxes. *EBITDA* is the ratio of operating income before depreciation to total assets. *Tangibility* is defined as net property, plant, and equipment divided by book assets. *log(Age)* is calculated starting from the first year the firm appeared in the Compustat database. *log(R&D)* and *log(Advertising)* are natural logarithms of the overall amount of R&D and advertising expenses, respectively, in millions of constant 1993 dollars. *Hist Volatility(EBITDA)* is the standard deviation of *EBITDA* in the previous 5 years. All explanatory variables are lagged by one period. All estimations models include year and industry fixed effects (at SIC two-digit level). Standard errors are reported in parentheses and are based on heteroskedastic consistent errors adjusted for clustering across firms. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	Panel A: All Maturities		*Panel B: Short-Term Maturity*		*Panel C: Long-Term Maturity*	
	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	-3.02	-3.13	0.56	0.31	-8.25	-7.91
	(4.87)	*(4.86)*	(5.29)	(5.22)	*(5.83)*	*(5.57)*
Stature	-0.37**	-0.47***	-0.49**	-0.63***	-0.03	-0.01
	(0.15)	*(0.17)*	(0.21)	(0.21)	*(0.09)*	*(0.1)*
log(Sale)	0.32	0.29	0.04	0.02	0.56*	0.55*
	(0.29)	*(0.29)*	(0.31)	(0.31)	*(0.33)*	*(0.31)*
M/B	0.49**	0.48***	0.46**	0.47**	0.31	0.26
	(0.19)	*(0.18)*	(0.2)	(0.2)	*(0.22)*	*(0.2)*
EBITDA	-2.04	-2.82	0.89	0.24	1.4	0.42
	(1.92)	*(2.04)*	(2.48)	(2.84)	*(2.21)*	*(2.65)*
Tangibility	2.33*	2.388*	0.58	0.45	1.87*	1.74*
	(1.33)	*(1.32)*	(2.15)	(2.17)	*(0.99)*	*(1.03)*
log(Age)	0.54**	0.54**	0.12	0.17	0.41*	0.42*
	(0.25)	*(0.27)*	(0.32)	(0.33)	*(0.22)*	*(0.22)*
Credit Rating	0.64***	0.62***	0.57***	0.53***	0.63***	0.6***
	(0.11)	*(0.11)*	(0.13)	(0.13)	*(0.15)*	*(0.14)*
Leverage	4.28*	4.44*	5.92**	6.32***	-0.13	0.02
	(2.33)	*(2.33)*	(2.27)	(2.32)	*(0.99)*	*(1.04)*
log(Advertising)		0.12**		0.14*		-0.002
		(0.06)		(0.07)		*(0.04)*
log(R&D)		-0.014		-0.1		-0.04
		(0.07)		(0.1)		*(0.07)*
Hist Volatility(EBITDA)		0.22		5.02		11.26
		(5.35)		(7.39)		*(8.89)*
Obs.	*739*	*739*	*600*	*600*	*482*	*482*
Number of firms	*168*	*168*	*148*	*148*	*130*	*130*
R-squared adj.	0.54	0.54	0.49	0.49	0.54	0.55

Table 1.C.8. Brand Stature and Financial Policy: Univariate Analysis

This table presents a comparison of equally weighted group means for measures of leverage (Panel A), and cash holding (Panel B) The quintiles are formed by first partitioning the BAV sample by *Sales*, and then partitioning each quintile by *Stature* quintiles. Quintiles of Sale-Stature are re-formed every year. Reported averages are cross-sectional equally-weighted averages. *Leverage* is the sum of short-term and long-term debt; *Cash* is cash and short-term investments.

Table 1.C.8 (Continued)

Panel A: Leverage

	Small	2	3	4	Large	Small	2	3	4	Large
Stature/Sales quintile			*Book Leverage*					*Market Leverage*		
Low	0.06	0.14	0.18	0.23	0.25	0.04	0.09	0.13	0.16	0.17
2	0.16	0.15	0.21	0.27	0.26	0.12	0.10	0.15	0.19	0.18
3	0.20	0.21	0.25	0.30	0.26	0.14	0.15	0.18	0.22	0.19
4	0.14	0.30	0.24	0.21	0.28	0.10	0.17	0.15	0.14	0.20
High	0.29	0.32	0.33	0.32	0.22	0.16	0.20	0.17	0.17	0.13
Difference (High-Low)	0.23	0.17	0.15	0.09	-0.03	0.12	0.11	0.04	0.01	-0.04
t-stat (High-Low)	6.86	5.89	6.67	4.27	-1.33	6.20	5.86	2.48	0.51	-2.08

Panel B: Cash Holdings

	Small	2	3	4	Large	Small	2	3	4	Large
Stature/Sales quintile			*Cash/Assets*					*Cash/Sales*		
Low	0.34	0.25	0.23	0.15	0.14	0.40	0.41	0.37	0.21	0.23
2	0.22	0.20	0.12	0.13	0.13	0.19	0.19	0.11	0.19	0.20
3	0.22	0.13	0.14	0.13	0.12	0.16	0.15	0.13	0.14	0.19
4	0.21	0.13	0.13	0.13	0.13	0.16	0.10	0.12	0.14	0.18
High	0.13	0.10	0.07	0.07	0.13	0.11	0.07	0.07	0.08	0.19
Difference (High-Low)	-0.20	-0.16	-0.16	-0.07	-0.01	-0.29	-0.33	-0.30	-0.14	-0.04
t-stat (High-Low)	-7.65	-7.91	-7.60	-5.11	-0.76	-7.03	-8.00	-8.02	-5.95	-1.29

Table 1.C.9. Cross-Sectional Regression of Leverage on Brand Value Estimates

This table reports the results of the Tobit estimation of book and market leverage (Panel A and Panel B, respectively). *Leverage* is the sum of short-term and long-term debt scaled by book [market value of] assets. *log*(*Sale)* is the total sales, in millions of constant 1992 dollars, converted to logarithms. *M/B*, market to book ratio, is the market value of equity plus the book value of assets minus preferred stock plus deferred taxes. *EBITDA* is the ratio of operating income before depreciation to total assets. *S&P500* is a dummy variable that equals one if a firm belongs to the S&P 500 index, and zero otherwise. *Tangibility* is defined as net property, plant, and equipment divided by book assets. *log(Age)* is calculated starting from the first year the firm appeared in the Compustat database. *log(R&D)* and *log(Advertising)* are natural logarithms of the overall amount of R&D and advertising expenses, respectively, in millions of constant 1993 dollars. *Hist Volatility(EBITDA)* is the standard deviation of *EBITDA* in the previous 5 years. All estimation models include year and industry fixed effects (at SIC two-digit level). Standard errors are reported in parentheses and are based on heteroskedastic consistent errors adjusted for clustering across firms. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

Table 1.C.9 (Continued)

	Panel A: Book Leverage			*Panel B: Market Leverage*		
	(1)	(2)	(3)	(1)	(2)	(3)
Intercept	-0.02	0.05	0.02	-0.04	0.01	0.002
	(0.08)	*(0.08)*	*(0.08)*	*(0.05)*	*(0.05)*	*(0.05)*
Stature	0.03***	0.305***	0.31***	0.01*	0.18***	0.18***
	(0.01)	*(0.07)*	*(0.07)*	*(0.01)*	*(0.04)*	*(0.05)*
log(Sale)	0.01*	0.002	0.01	0.01***	0.01	0.01**
	(0.01)	*(0.01)*	*(0.01)*	*(0.005)*	*(0.01)*	*(0.01)*
*Stature*log(Sale)*		-0.03***	-0.03***		-0.02***	-0.02***
		(0.01)	*(0.01)*		*(0.01)*	*(0.01)*
M/B	-0.03***	-0.02***	-0.02***	-0.04***	-0.03***	-0.03***
	(0.01)	*(0.01)*	*(0.01)*	*(0.005)*	*(0.005)*	*(0.005)*
EBITDA	0	0	0.002	-0.02	-0.01	-0.01
	(0.02)	*(0.02)*	*(0.02)*	*(0.01)*	*(0.01)*	*(0.01)*
S&P500	-0.01	-0.01	-0.01	-0.004	-0.003	-0.001
	(0.01)	*(0.01)*	*(0.01)*	*(0.01)*	*(0.01)*	*(0.01)*
log(Age)	0.08	-0.01	-0.01	-0.002	-0.06	-0.09
	(0.1)	*(0.1)*	*(0.11)*	*(0.06)*	*(0.06)*	*(0.07)*
Tangibility	-0.01	0.004	0.002	-0.007	0.001	-0.0004
	(0.08)	*(0.07)*	*(0.07)*	*(0.05)*	*(0.05)*	*(0.05)*
log(Advertising)			0.003			0.001
			(0)			*(0.002)*
log(R&D)			-0.01*			-0.01***
			(0)			*(0.003)*
Hist Volatility(EBITDA)			0.1			-0.013
			(0.07)			*(0.05)*
Number of obs.	*2572*	*2572*	*2572*	*2569*	*2569*	*2569*
Number of clusters	*468*	*468*	*468*	*468*	*468*	*468*
Chi-squared	*843.17*	*947.14*	*967.56*	*1132.6*	*1211.8*	*1249.4*

Table 1.C.10. Cross-Sectional Regression of Cash Holding on Brand Value Estimates

This table reports the results of the OLS regression where the dependent variable is the ratio of cash to assets in Panel A, and the ratio of cash to sales in Panel B. *log*(*Sale)* is total sales, in millions of constant 1992 dollars, converted to logarithms. *S&P500* is a dummy variable that equals one if a firm belongs to the S&P500 index, and zero otherwise. *M/B*, market to book ratio, is the market value of equity plus the book value of assets minus preferred stock plus deferred taxes. *EBITDA* is the ratio of operating income before depreciation to total assets. *Tangibility* is defined as net property, plant, and equipment divided by book assets. *Wcap* is working capital net of cash, scaled by assets. *Capex* is the ratio of capital expenditures to total assets. *DivDummy* is a dummy variables that equals one if a firm pays out dividends, and zero otherwise. *log(R&D)* and *log(Advertising)* are natural logarithms of the overall amount of R&D and advertising expenses, respectively, in millions of constant 1993 dollars. *Hist Volatility(EBITDA)* is the standard deviation of *EBITDA* in the previous 5 years. All estimation models include year and industry fixed effects (at SIC two-digit level). Standard errors are reported in parentheses and are based on heteroskedastic consistent errors adjusted for clustering across firms. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

Table 1.C.10 (Continued)

	Panel A			Panel B		
	(1)	(2)	(3)	(1)	(2)	(3)
Intercept	0.45***	0.411***	0.373***	0.389***	0.335***	0.361***
	(0.047)	*(0.045)*	*(0.046)*	*(0.09)*	*(0.084)*	*(0.088)*
Stature	-0.017***	-0.1564***	-0.139***	-0.022***	-0.21***	-0.208***
	(0.005)	*(0.031)*	*(0.031)*	*(0.008)*	*(0.058)*	*(0.059)*
log(Sale)	-0.019***	-0.014***	-0.021***	-0.025***	-0.018**	-0.038***
	(0.005)	*(0.005)*	*(0.005)*	*(0.009)*	*(0.009)*	*(0.009)*
*Stature*log(Sale)*		0.016***	0.014***		0.022***	0.022***
		(0.004)	*(0.004)*		*(0.007)*	*(0.007)*
S&P500	-0.016	-0.018*	-0.018*	0.008	0.004	0.004
	(0.011)	*(0.011)*	*(0.01)*	*(0.02)*	*(0.02)*	*(0.018)*
M/B	0.03***	0.028***	0.023***	0.028***	0.025***	0.018***
	(0.004)	*(0.004)*	*(0.004)*	*(0.006)*	*(0.006)*	*(0.006)*
EBITDA	-0.117**	-0.076	-0.007	-0.287***	-0.231***	-0.169**
	(0.05)	*(0.051)*	*(0.047)*	*(0.071)*	*(0.07)*	*(0.071)*
Tangibility	-0.147***	-0.145***	-0.129***	-0.119**	-0.117**	-0.101*
	(0.036)	*(0.035)*	*(0.034)*	*(0.055)*	*(0.055)*	*(0.054)*
Wcap	-0.287***	-0.279***	-0.255***	-0.236***	-0.226***	-0.171***
	(0.043)	*(0.043)*	*(0.041)*	*(0.059)*	*(0.059)*	*(0.057)*
Capex	0.062	0.009	-0.041	0.037	-0.033	-0.08
	(0.092)	*(0.093)*	*(0.087)*	*(0.128)*	*(0.131)*	*(0.127)*
DivDummy	-0.013	-0.012	-0.01	0.002	0.003	0.009
	(0.01)	*(0.01)*	*(0.01)*	*(0.017)*	*(0.017)*	*(0.016)*
log(advertising)			0.006***			0.003
			(0.002)			*(0.003)*
log(R&D)			0.011***			0.03***
			(0.003)			*(0.005)*
Hist Volatility(EBITDA)			0.199***			-0.092
			(0.059)			*(0.15)*
Number of obs.	*2568*	*2568*	*2568*	*2568*	*2568*	*2568*
Number of clusters	*465*	*465*	*465*	*465*	*465*	*465*
R-squared adj.	0.52	0.53	0.56	0.420	0.43	0.46

Table 1.C.11. Variance Decomposition

This table presents the results of Type III variance decomposition analysis where the dependent variables are book leverage (Panel A) and cash holdings (Panel B). We first compute partial sum of squares, and then normalize the vector obtained by dividing the partial sum for each variable by the total Type III partial sum of squares. See Tables 1.C.5 and 1.C.6 for the description of the variables.

Table 1.C.11 (Continued)

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Stature		0.31	0.34		0.11	0.11		0.09	0.11		0.05	0.05
log(Sale)	0.00	0.04	0.03	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01
*Stature*log(Sale)*		0.23	0.26		0.08	0.08		0.07	0.09		0.04	0.04
M/B	0.13	0.03	0.02	0.06	0.03	0.03	0.62	0.46	0.40	0.32	0.26	0.21
EBITDA	0.11	0.00	0.00	0.02	0.00	0.00	0.00	0.02	0.04	0.00	0.00	0.01
S&P500	0.02	0.02	0.02	0.00	0.00	0.00	0.04	0.04	0.04	0.03	0.02	0.02
log(Age)	0.01	0.03	0.02	0.00	0.01	0.00	0.01	0.02	0.01	0.01	0.00	0.00
Tangibility	0.62	0.30	0.23	0.00	0.00	0.00	0.19	0.19	0.13	0.10	0.00	0.00
log(Advertising)			0.03			0.00			0.00			0.00
log(R&D)			0.01			0.00			0.04			0.02
Hist Volatility(EBITDA)			0.00			0.00			0.01			0.00
Year FE	0.11	0.04	0.04	0.02	0.02	0.02	0.14	0.11	0.12	0.07	0.08	0.08
Industry FE				0.89	0.75	0.74				0.47	0.55	0.56
R-squared adj.	0.04	0.10	0.10	0.22	0.26	0.26	0.2	0.23	0.23	0.32	0.33	0.34

	Panel C: Cash/Assets						Panel D: Cash/Sale					
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Stature		0.11	0.11		0.06	0.05		0.10	0.11		0.05	0.04
log(Sale)	0.05	0.01	0.02	0.05	0.02	0.05	0.12	0.04	0.10	0.04	0.02	0.06
*Stature*log(Sale)*		0.08	0.08		0.05	0.04		0.07	0.08		0.04	0.04
S&P500	0.00	0.00	0.00	0.01	0.01	0.01	0.03	0.04	0.03	0.00	0.00	0.00
M/B	0.15	0.14	0.08	0.14	0.13	0.08	0.07	0.06	0.02	0.05	0.05	0.02
EBITDA	0.04	0.01	0.00	0.02	0.01	0.00	0.10	0.06	0.02	0.04	0.02	0.01
Tangibility	0.35	0.32	0.22	0.03	0.03	0.03	0.29	0.27	0.11	0.01	0.01	0.01
Wcap	0.20	0.17	0.16	0.14	0.14	0.12	0.33	0.30	0.22	0.04	0.04	0.02
Capex	0.04	0.02	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
DivDummy	0.06	0.04	0.05	0.01	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00
log(advertising)			0.01			0.02			0.00			0.00
log(R&D)			0.08			0.04			0.25			0.12
Hist Volatility(EBITDA)			0.07	0.00	0.00	0.03			0.00			0.00
Year FE	0.11	0.10	0.10	0.09	0.08	0.07	0.06	0.06	0.05	0.05	0.05	0.04
Industry FE				0.52	0.47	0.46				0.77	0.74	0.63
R-squared adj.	0.37	0.41	0.44	0.51	0.53	0.56	0.25	0.28	0.32	0.42	0.43	0.46

REFERENCES

Aaker, David. A., 1996, *Building strong brands* (The Free Press, New York, NY).

Alchian, Armen, 1950, Uncertainty, evolution, and economic theory, *Journal of Political Economy 58*, 211–221.

Anderson, Eugene W., and Sattar A. Mansi, 2009, Does customer satisfaction matter to investors? Findings from the bond market, *Journal of Marketing Research* 46, 703–714.

Bagwell, Kyle, 2007, "The Economic Analysis of Advertising." In: Armstrong, M. and Porter, R. (Eds.) "*Handbook of Industrial Organization*," Volume 3, Elsevier B.V. Amsterdam, 1701–1844.

Bates, Thomas W., Kathleen M. Kahle, and René M. Stulz, 2009, Why do U.S. firms hold so much more cash than they used to? *Journal of Finance* 64, 1985–2021.

Bebchuk, Lucian, Alma Cohen, and Allen Ferrell, 2009, What matters in corporate governance? *Review of Financial Studies*, 22, 783–827.

Belo, Frederico, Xiaoji Lin, and Maria A. Vitorino, 2011, Brand capital, firm value and asset returns, *Working paper, University of Minnesota.*

Benmelech, Efraim, 2009, Asset salability and debt maturity: Evidence from nineteenth-century American railroads, *Review of Financial Studies* 22, 1545–1584.

Benmelech, Efraim, and Nittai K. Bergman, 2009, Collateral pricing, *Journal of Financial Economics* 91, 339–360.

Bolton, Patrick, and David S. Scharfstein, 1990, A theory of predation based on agency problems in financial contracting, *American Economic Review* 80, 93–106.

Bronnenber, Bart J, Sanjay K. Dhar, and Jean-Pierre H. Dube, 2007, Consumer packaged goods in the United States: National brands, local branding, *Journal of Marketing Research* 44, 4–13.

Bronnenber, Bart J, Sanjay K. Dhar, and Jean-Pierre H. Dube, 2009, Brand History, Geography, and the Persistence of Brand Shares, *American Economic Review* 117, 87–115.

Campello, Murillo, and Erasmo Giambona, 2010, Asset tangibility and capital structure, *Working paper, University of Illinois.*

Chamberlin, Edward, 1933, *The theory of monopolistic competition* (Harvard University Press, Cambridge, MA).

Chemmanur, Thomas, and An Yan, 2009, Product market advertising and new equity issues, *Journal of Financial Economics* 92, 40–65.

Chemmanur, Thomas, and An Yan, 2010a, Product market advertising, IPO valuation, and long-run stock returns, *Working paper*, *Boston College*.

Chemmanur, Thomas, and An Yan, 2010b, Advertising, attention, and stock returns, *Working paper, Boston College*.

Chevalier, Judith A., 1995a, Capital structure and product-market competition: Empirical evidence from the supermarket industry, *American Economic Review* 85, 415–435.

Chevalier, Judith A., 1995b, Do LBO supermarkets charge more? An empirical analysis of the effects of LBOs on supermarket pricing, *Journal of Finance* 50, 1095–1112.

Dodds, William B., Kent B. Monroe, and Dhruv Grewal, 1991, Effect of price, brand, and store information on buyers' product evaluations, *Journal of Marketing Research* 28, 307–319.

Fama, Eugene F., and Kenneth R. French, 2002, Testing trade-off and pecking order predictions about dividends and debt, *Review of Financial Studies* 15, 1–33.

Faulkender, Michael, and Mitchell A. Petersen, 2006, Does the source of capital affect capital structure? *Review of Financial Studies* 19, 45–79.

Fornell, Claes, Sunil Mithas, Forrest V. Morgeson III, and M.S. Krishnan, 2006, Customer satisfaction and stock prices: High returns, low risk, *Journal of Marketing* 70, 3–14.

Fresard, Laurent, 2010, Financial strength and product market behavior: The real effects of corporate cash holdings, *Journal of Finance* 65, 1097–1122.

Frieder, Laura, and Avanidhar Subrahmanyam, 2005, Brand perception and the market for common stock, *Journal of Financial and Quantitative Analysis* 40, 57–85.

Gerzema, John, and Ed Lebar, 2008, *The Brand Bubble* (Jossey-Bass, San Francisco, CA).

Gompers, Paul, Joy Ishii, and Andrew Metrick, 2003, Corporate governance and equity prices, *Quarterly Journal of Economics* 118, 107–155.

Gourio, Francois, and Leena Rudanko, 2011, Customer capital, *Working paper, Boston University*.

Grullon, Gustavo, George Kanatas, and Piyush Kumar, 2006, The impact of capital structure on advertising competition: An empirical study, *Journal of Business* 79, 3101–3124.

Grullon, Gustavo, George Kanatas, and James P. Weston, 2004, Advertising, breadth of ownership and liquidity, *Review of Financial Studies* 17, 439–461.

Hart, Oliver, 1983, The market mechanism as an incentive scheme, *Bell Journal of Economics* 14, 366–382.

Hovakimian, Armen, Tim Opler, and Sheridan Titman, 2001, The debt-equity choice, *Journal of Financial and Quantitative Analysis* 36, 1–24.

Jensen, Michael C., 1986, Agency costs of free cash flow, corporate finance, and takeovers, *American Economic Review* 76, 323–329.

Irvine, Paul J., and Jeffrey Pontiff, 2009, Idiosyncratic return volatility, cash flows, and product market competition, *Review of Financial Studies* 22, 1149–1177.

Keller, Kevin L., 2008, *Strategic brand management: Building, measuring and managing brand equity* (Pearson Education, Upper Saddle River, NJ).

Khanna, Naveen and Sheri Tice, 2000, Strategic responses of incumbents to the new entry: The effect of ownership structure, capital structure, and focus, *Review of Financial Studies* 13, 749–779.

Kim, Chang-Soo, David C. Mauer, and Ann E. Sherman, 1998, The determinants of corporate liquidity: Theory and evidence, *Journal of Financial and Quantitative Analysis* 33, 335–359.

Kovenock, Dan, and Gordon Phillips, 1995, Capital structure and product-market rivalry: How do we reconcile theory and evidence? *American Economic Review* 85, 403–408.

Kovenock, Dan, and Gordon Phillips, 1997, Capital structure and product market behavior: An examination of plant exit and investment decisions, *Review of Financial Studies* 10, 767–803.

Kwoka Jr., John E., 1993, “The Sales and Competitive Effects of Styling and Advertising Practices in the U.S. Auto Industry,” *Review of Economics and Statistics*, 75, 649–656.

Landes, Elisabeth M., and Andrew M. Rosenfield, 1994, “The Durability of Advertising Revisited,” *Journal of Industrial Economics*, 42, 263–274.

Leary, Mark T., and Michael R. Roberts, 2005, Do firms rebalance their capital structures?, *The Journal of Finance* 60, 2575–2619.

Lemmon, Michael L., Michael R. Roberts, and Jaime F. Zender, 2008, Back to the beginning: Persistence and the cross-section of corporate capital structure, *Journal of Finance* 63, 1575–1608.

Lyandres, Evgeny, 2006, Capital structure and interaction among firms in output markets: Theory and evidence, *Journal of Business* 79, 2381–2421.

MacKay, Peter, and Gordon M. Phillips, 2005, How does industry affect firm financial structure? *Review of Financial Studies* 18, 1433–1466.

MacKie-Mason, Jeffrey K., 1990, Do taxes affect financing decisions? *Journal of Finance* 45, 1471–1493.

Mizik, Natalie, and Robert Jacobson, 2008, The financial value impact of perceptual brand attributes, *Journal of Marketing Research* 45, 15–32.

Mizik, Natalie, and Robert Jacobson, 2009, Valuing branded businesses, *Journal of Marketing Research* 73, 137–153.

Opler, Tim C., and Sheridan Titman, 1994, Financial distress and corporate performance, *Journal of Finance* 49, 1015–1040.

Opler, Tim, Lee Pinkowitz, René Stulz, and Rohan Williamson, 1999, The determinants and implications of corporate cash holdings, *Journal of Financial Economics* 52, 3–46.

Parsons, Christopher, and Sheridan Titman, 2009, *Empirical capital structure* (Now Publishers Inc., Hanover, MA).

Phillips, Gordon, 1995, Increased debt and industry product markets: An empirical analysis, *Journal of Financial Economics* 37, 189–238.

Rego, Lopo L., Matthew T. Billett, and Neil A. Morgan, 2009, Consumer-based brand equity and firm risk, *Journal of Marketing* 73, 47–60.

Romaniuk, Jenni, Byron Sharp, and Andrew Ehrenberg, 2007, Evidence concerning the importance of perceived brand differentiation, *Australasian Marketing Journal* 15, 42–54.

Starr, Martin K., and Joel R. Rubinson, 1978, A loyalty group segmentation model for brand purchasing simulation, *Journal of Marketing Research* 15, 378–383.

Stigler, George, 1958, The economies of scale, *Journal of Law and Economics* 1, 54–71.

Telser, Lester G., 1966, Cutthroat competition and the long purse, *Journal of Law and Economics* 9, 259–277.

Thomas, Lacy G., 1989, "Advertising in Consumer Goods Industries: Durability, Economies of Scale, and Heterogeneity," *Journal of Law and Economics*, 32, 164–194.

Tuli, Kapil R., and Sundar G. Bharadwaj, 2009, Customer satisfaction and stock returns risk, *Journal of Marketing* 73, 184–197.

Welch, Ivo, 2011, Two common problems in capital structure research: The financial-debt-to-asset ratio, and issuing activity versus leverage changes, *International Review of Finance* 11, 1–17.

CHAPTER 2:

STRIKE WHILE THE IRON IS HOT: TIMING THE MARKET ON THE WAY TO THE OPTIMAL CAPITAL STRUCTURE

Abstract

The existing literature provides mixed evidence on the relative importance of market timing versus trade-off incentives in capital structure decisions. This paper shows how exactly these forces coexist and determines when one is more important than the other in affecting equity issuance decisions and long-run stock performance. The idea is that market timing benefits dominate trade-off costs when firms are close to their target leverage, but become offset by the rebalancing considerations when firms are farther away. Two sets of empirical results support the validity of the framework. First, the sensitivity of equity issuances to past stock performance is the highest among firms close to the target leverage. Second, the long-run performance of equity issuers is also a function of their deviation from target leverage. The lower the leverage of issuing firms is relative to the target, the worse their after-issuance returns are, consistent with higher market timing incentives compared to other issuers.

Introduction

Whether market timing or trade-off considerations are the main drivers of financial decisions has been an important debate in the capital structure literature (see, among others, Baker and Wurgler (2002), Welch (2004), and Leary and Roberts (2005)). Starting from early empirical evidence by Marsh (1982) and Jalilvand and Harris (1984), finance research has accumulated a body of evidence, indicating that firms may consider both market timing and trade-off incentives. Yet, it is unclear which of the two incentives is more important, and why studies find mixed results assessing the relative contribution of each force to capital structure decisions.

In this paper I develop a unified framework that demonstrates that firms proactively time the market, but at the same time consider target leverage when making their capital structure decisions. In addressing the mixed results about the relative importance of trade-off versus market timing forces, the framework demonstrates that incentives to time the market are determined not only by recent stock performance, but also by the relative distance of current leverage compared to the target one. Specifically, in every period firms weigh the benefits of market timing and the costs of deviation from the target, and make their capital structure decisions accordingly. All else equal, market timing impact on issuance decisions is most pronounced when firms are close to the target, and have low costs of deviation from the target. At the same time, the gap between current and optimal leverage becomes costlier than the benefits of raising cheap capital as firms' leverage moves farther away from the target. Overleveraged firms, facing an increased probability of getting into financial distress, higher borrowing rates and potential constraints on investments and future growth, place a higher priority on reducing their leverage rather than on waiting for market timing opportunities, and should issue equity regardless of the current market value of their equity. Similarly, the advantages of the tax shield and the role of debt as a manager disciplining device (Jensen (1986), Harris and Raviv (1990)) become more important for underleveraged firms, who will choose to forgo market timing opportunities and issue debt rather than equity to get back to the optimal leverage level. To summarize, market timing incentives are the dominant ones for firms that are close to the target leverage, while the trade-off considerations primarily determine capital structure decisions of underleveraged and overleveraged firms.

To test the validity of this unified framework, I empirically examine how the market timing impact on financial decisions of firms differs with the distance of their current leverage from the target. I study market timing behavior in two ways. In the first part of the empirical analysis I look at the sensitivity of issuances to the relative stock performance of firms and examine whether its magnitude differs with the distance of the firms' leverage from the target. In the second part I test whether the long-run performance of firms that issued equity differs depending on their relative leverage at the moment of issuance.

To measure the rebalancing motives, all firms in the sample are divided into three groups of relative leverage. I define relative leverage as deviation from the benchmark group leverage, which I use to proxy for the target leverage of a firm. It is calculated as the mean of industry-size peer group. Market timing incentives are measured by excess returns of a firm over the mean of the benchmark group (industry-size). To validate the robustness of the results, I consider additional specifications of the target leverage (including a parametric estimation of the target leverage), as well as different proxies of the market timing incentives.

The results of the empirical tests support the main idea of the paper. The first part of the analysis shows that firms' returns, as well as their relative leverage, have a significant impact on determining the amount of equity issued in the following period. The trade-off between the benefits of market timing and the costs of deviation from the optimal leverage level is non-linear, and depends on the firms' current level of leverage relative to their benchmark peers. The impact of stock returns on issuances is the highest in magnitude for those firms that are close to the target leverage, and small and insignificant for firms with high or low leverage relative to the peer group. I also find that the non-linear sensitivity of equity changes to market timing opportunities is more pronounced for equity issuances than for equity repurchases, and for stocks with extremely high returns. The results are robust to different specifications of relative leverage and market timing proxies.

The second part of the paper examines the long-run performance of issuing versus non-issuing firms as a function of their relative leverage. As previously documented, equity issues are characterized not only by stock price run-up before the equity issuance, but also by subsequent long-run deterioration of stock prices. Therefore, firms that had the most incentives to time the market should underperform their peers in the long-run, as the market corrects the price of the stock. Underleveraged firms that decide to issue equity are potentially the worst underperformers. Since these firms do not issue equity for rebalancing motives, their market timing opportunities at the time of issue should be the highest compared to their peers in other leverage groups. In general, long-run underperformance of issuers is expected to decrease across groups of relative leverage, as rebalancing considerations intensify.

I test this hypothesis using Buy-and-Hold Abnormal Returns (BHAR) and Fama-French calendar-time approach, and find that the portfolio of underleveraged firms that issued equity has the most negative abnormal performance. As the relative leverage increases, long-run excess returns of firms improve, indicating that firms issue more equity for rebalancing reasons. Taken together, the results of the tests suggest that relative leverage position of firms at the time of issue can reveal true motives behind the issue.

Overall, this paper has several contributions to the existing capital structure literature. First, it demonstrates that firms actively manage their capital structure to minimize the losses due to high deviation from the target by covering leverage gaps, but at the same time monitor their relative stock performance to rationally take advantages of temporary market inefficiencies. Second, it outlines a simple, but broad framework that determines how exactly the two forces interact under what conditions one incentive dominates the other. Third, the paper constructs two sets of econometric analyses, and provides an empirical support for the validity of the proposed framework. Finally, this framework helps identifying the purpose of the issue, and evaluating its long-run impact on investors' portfolio. More broadly, the paper adds to a large group of capital structure studies indicating that while equity issuances appear to be driven by stock price considerations, firms also have target leverage in mind (Graham and Harvey (2001), Hovakimian (2004, 2006), Leary and Roberts (2005), Kayhan and Titman (2007), Alti (2006), Elsas, Flannery, and Garfinkel (2006), Huang and Ritter (2009), Cook and Tang (2010)).

The remainder of the paper is organized as follows. I start with hypotheses development in Section I. Section II describes the data and methodology. Section III presents the results of estimating the issuance decisions. Section IV tests hypothesis about the long-run performance of the issuing firms, and Section V concludes.

I. Hypothesis Development

This section introduces the framework in which market timing and trade-off forces can be viewed as two elements of a broader set of capital structure considerations. The main idea of the framework is that in every period firms compare the benefits of timing the market with the costs of deviation from the target leverage. The strongest among the two forces will determine the capital structure decision.

Before outlining the framework in more details, it is important to note that two types of managerial actions can fall under the category of market timing behavior. The first one is issuing equity without an actual need for additional capital when the stock prices are high. The second is deferring a potential issuance until more favorable market conditions prevail. Both actions provide an opportunity for current shareholders to raise external capital with a discount, which is determined by the difference between the stock price at the time of equity issue and the price that prevails in the long run.[1]

Next, let's define the trade-off costs. These costs can be split into direct ones (proceeds that firms pay to intermediaries if they decide to issue or repurchase equity) and indirect, which are the costs of deviation from the optimal leverage level. How are the indirect costs established? The indirect costs of deviation from the target level are determined by several factors, which differ depending on whether firms are over- or underleveraged relative to the target. That is, firms with low leverage forego the benefits of the tax shield. In addition, debt plays a signaling role (Leland and Pyle (1977)), and mitigates agency costs by disciplining managers (Jensen (1986), Harris and Raviv (1990)). Overleveraged firms face an increased probability of getting into financial distress, higher borrowing rates and potential constraints on investment, which might impair future growth. In addition, agency problems between debt- and shareholders can intensify (Myers (1977), Jensen and Meckling (1976)). Overleveraged firms will thus prefer to issue equity regardless of the stock returns to close the gap between the actual and desired debt level.

To summarize, the costs of deviation from the optimal leverage will become higher than the benefits of market timing (which are determined by the temporary deviation of stock prices from the fundamental one) as firms move farther away from the target leverage. Therefore, market timing will be the driver of issuance decisions only for those firms that are close enough to the optimal leverage: their costs of deviation from the optimal target leverage are relatively low and are more than offset by the benefits of market timing.

[1] For simplicity, I ignore the time value of the money.

The intuition of this argument is illustrated in Figure 2.B.1. The marginal trade-off costs of deviating from the target leverage are presented by the line *F*(*Lev-Lev*),* which is a function of the difference between firms' current and target leverage (*Lev* and *Lev**, respectively*)*. I assume that the function is continuous, monotonically decreasing in the deviation from leverage (*Lev-Lev*)*, and convex.[2] The function achieves its maximum when (*Lev-Lev**=0), as firms at their target leverage do not incur any trade-off costs. Korteweg (2010) and van Bisbergen, Graham and Yang (2010) show that the costs of deviating from optimal leverage are asymmetric, and are higher for overleveraged, compared to underleveraged, firms. To incorporate their findings in the analysis of this paper, I allow for a steeper slope of the cost function *F*(*Lev-Lev*)* in the positive range of (*Lev-Lev*)* values. Without loss of generality, the analysis holds for symmetrical functional forms. The marginal profits from timing the market are represented by the function *M*=(*Ret-Ret**), which is parallel to the axis X.[3] *Ret* are the recent returns during the period *t*, and *Ret** is the cost of capital in the long run. The marginal profit from market timing, net of the trade-off costs, is determined by the difference (*F-M*), and represented by the function *G*(*Lev-Lev*)*. Firms will choose to time the market as long as *G*(*Lev-Lev*)* is positive. As a result, the decision to time the market becomes a function of firms' deviation from the target leverage. Firms in the range *LowLev* will choose to forgo market timing opportunities to issue debt or repurchase equity; firms in the *HighLev* range will issue equity independently of their actual stock performance; and firms in the *MidLev* group will time the market.

[2] The assumption of convexity is consistent with the model by Korteweg (2010). It is not critical to the main results of the framework, and can be substituted with a convex function of equity issuance costs, which is consistent with empirical evidence by Altinkilic and Hansen (2000).

[3] Without loss of generality it is possible to incorporate the direct costs of issuance by subtracting a constant.

After the general description of the framework, I now turn to developing the first hypothesis of the paper, which examines the sensitivity of the firm's issuances to the relative stock performance across leverage groups. First, we need to classify changes in firms' equity as market timing driven or not, since the mere decision to issue/repurchase does not necessarily indicate market timing motives. For example, according to the framework, a firm that is close to the target leverage will issue equity to time the market, while another firm in the *HighLev* range will issue equity for trade-off reasons. To empirically distinguish between the two cases, it is necessary to condition issues/repurchases on relative performance of the stock. In general, market timing behavior can be defined as:

$$(\Delta E > 0 | (Ret_t - Ret^*) > 0)$$

$$(\Delta E < 0 | (Ret_t - Ret^*) < 0)$$

where ΔE indicates changes in firm's equity between periods t and $(t+1)$. In words, an equity issue is motivated by market timing when it is preceded by positive relative performance of a firm. Similarly, a firm's decision to repurchase equity after a period of relatively low stock performance is also classified market timing.

Next, let's look at issuance and repurchase decisions of each of the three relative leverage groups as a function of their relative stock performance, and determine which of those are driven by market timing. The schematic analysis, illustrating the intuition behind each case, is presented in Figure 2.B.2. Each chart shows the amount of equity issued/repurchased in each relative leverage group as a function of the relative stock performance, while taking into account both market timing and trade-off motives. It also depicts an empirical linear approximation of measuring the sensitivity of stock issuances/repurchases to relative stock performance, while keeping the deviation from the target leverage constant.

Panel A shows the simplest case of firms that are close to the target leverage (*MedLev*). These firms do not need to issue or repurchase equity for rebalancing reasons, so if the market estimates the value of their equity correctly, firms will not take any action to rebalance their capital structure (the line passes through the origin). However, firms will decide to issue as the difference between the recent and long-run returns goes up. Similarly, those firms may choose to repurchase stocks if the market temporarily undervalues them. A linear approximation in this case (dotted line) will coincide with the theoretical prediction. Empirically, a positive and statistically significant coefficient of relative returns in predicting changes in equity will indicate market timing behavior.

A more complex theoretical relation between issuances and relative returns arises in the case of firms with high relative leverage (*HighLev*). Since these firms incur costs of deviation from the target leverage, their priority is to issue equity independently of the actual stock performance and close the leverage gap. Therefore, for a certain range of negative (*Ret*-*Ret**) (and possibly a range of positive, but low relative returns) the amount of issuances will be positive. Graphically, it is reflected by the parallel line AB, which crosses the Y axis at a positive level of ΔE and indicates zero sensitivity of issuances to relative stock performance in this range. As the relative returns increase, firms may still benefit from market timing by issuing a higher amount of equity than required by trade-off consideration, so that the slope can become positive within some range of positive (*Ret*-*Ret**). Similarly, when relative returns become considerably negative, firms may start taking market timing into account and decide to issue a lower amount of equity, or even switch to repurchasing, if the net benefits from doing so dominate the losses of deviation from target leverage. Empirically, measuring the sensitivity of issuances and repurchases to relative returns using a straight line will result in a flatter slope than in the case of *MedLev* firms (even if the actual sensitivity to relative returns the issuances above point *A* and below point *B* is the same as in Panel A).

Finally, the last possible case, depicted in Panel C, describes the relationship between issuances and returns for the *LowLev* group. The trade-off motives of underleveraged firms force them to repurchase equity to be able to return to the optimal leverage. Therefore, for the range of (*Ret-Ret**) up to the point *A* the amount of equity repurchases *ΔE* is negative, and independent of the actual returns. At a certain point, however, the market timing considerations start prevailing, and the firm eventually decides to issue equity to exploit the market timing opportunities. Therefore, beyond point *A´* the sensitivity of issuances to relative returns becomes positive. Likewise, when relative returns are substantially negative, a firm may decide to take advantage of the market timing opportunities and repurchase a higher amount of equity, so that the sensitivity of issuances to relative performance becomes positive again. Similarly to the case of overlevered firms, a linear empirical approximation of the relationships between issuances and returns will result in a lower slope.

The schematic analysis, described above, is informal. Still, it is pretty general and incorporates a range of possible cases. First, it includes both issuances and repurchases. Second, it allows incorporating other types of costs. For example, adding fixed issuance costs will shift the issuance line down, closer to the *X* axis, while preserving the main intuition (in the case of *MedLev* firms the straight line will transform into a step function with a period of issuance/repurchase inactivity around zero). Similarly, it is possible to incorporate varying issuing costs by changing the slopes of the issuance/repurchases line. Third, one can account for varying costs of deviation from target leverage. The higher the costs of deviation from target leverage are, the wider the *AB* range will be. Finally, the empirical test of the framework validity does not require that the functional form of the *G*(*Lev-Lev*),* which determines points A and B, be specified. To demonstrate the interaction between the trade-off and market timing forces, it is sufficient to show that the sensitivity of the issuance decisions has different magnitudes across the three groups of relative leverage.

The discussion above leads me to outlining the first hypothesis of the paper.

Hypothesis 1: The sensitivity of issuances to market timing opportunities is a non-linear function of the distance between current and target leverage of firms. Specifically:

H1a: The sensitivity of issuances/repurchases to the past stock performance for firms that are close to the target leverage (MedLev) is positive and significant.

H1b: The sensitivity of issuances/repurchases to the past stock performance for firms that are under- and overleveraged (LowLev and HighLev, respectively) is lower than the sensitivity of the MedLev firms.

Hypothesis 1 studies one aspect of market timing, which is the stock price run-up before the issuance. However, equity issues, as first documented by Stigler (1964) and Loughran and Ritter (1995), are also characterized by long-run price deterioration. Firms issue for a number of reasons, including a need to finance upcoming projects, change in capital structure, and opportunities to raise cheap capital (see, among others, DeAngelo, DeAngelo, and Stulz (2010), Leary and Roberts (2005), Baker and Wurgler (2002), and Welch (2004)). The true reason is usually unknown to shareholders, or can be masked by the firms' management.[4] The framework of this paper allows applying the idea of differences in market timing motives across relative leverage groups to the post-issuance period.

To examine the long-term stock performance of firms as a function of their relative leverage at the time of issue, let's go back to Figure 2.B.2 and look at firms that decided to issue equity (firms with positive ΔE). I start with Panel B first. The majority of overleveraged firms that issue equity do so for trade-off considerations (as characterized by the line AB). Therefore, there should be little price correction by the market in the long run, and little or no underperformance. As the deviation from target leverage decreases, though, more firms start issuing equity for market timing reasons. Thus, a group of *MedLev* firms (Panel A), which are close to the target leverage, can issue equity each time there is a positive deviation of their current stock price from the fundamental value. Those firms are also expected to perform worse than their peers in the *HighLev* group in the long-run, as the market learns about the true value of the firm. Finally, firms in the *LowLev* group should be the worst underperformers. Since their issuance decisions move them further away from the target, market timing considerations must be really strong to dominate potential trade-off costs. Panel C illustrates this intuition. The line of issuances obtains positive values beyond point A, when the relative returns are high. For comparison, *MedLev* firms start issuing equity in the positive range of (Ret-Ret*), and *HighLev* firms can issue equity almost independently of the actual stock performance. The lower is the relative leverage of firms, the more likely it is that the issues are motivated by market timing opportunities. Therefore, the long run underperformance should be the worst among

[4] Behavioral theories have also shown that individuals systematically bias available information. A number of studies, including Loughran and Ritter (1997) and Daniel, Hirshleifer, and Subrahmanyam (1998), demonstrate that investors exhibit biases by being overly optimistic and putting too much weight on past performance of a firm. These biases may explain long-run post-issue correction of the issuing firm's prices and the overall underperformance of the firm.

underleveraged firms and improve as the relative leverage of a firm at the time of issue increases. To summarize this hypothesis:

Hypothesis 2: Long-run performance of issuing firms improves in the relative leverage at the time of issuance.

II. Data and Methodology

1. Defining Issuances and Control Variables

I use annual data available on Compustat for the period 1970-2006 to obtain accounting variables. I exclude firms with assets under $1 million and firms that belong to utilities (SIC code 4900-4999) and financial sectors (SIC codes 6000-6999). Following the methodology, suggested by Fama and French (2005), changes in equity are identified from the balance sheet of firms. Net equity issuance (*EA*) is the change in book equity minus the change in retained earnings, as a percent of total assets. A positive value indicate that issuances were higher than repurchases during the fiscal year, while negative *EA* implies that in aggregate the firm repurchased shares during the period. Net debt issuance (*DA*) is the residual change in assets as a percent of total assets. Finally, net of net issuance (*Net_Iss*) is the difference between net equity and net debt issuance. Following Hovakimian, Opler and Titman (2001), I use a cutoff of 5% of the asset value for issuances, and 1% for repurchases. Specifically, I assign a value of zero to issuances that are smaller than 5% of the total assets. In addition, I trim the top and bottom 1% of observations for net debt and equity issuances.[5]

The independent variables, used in the multivariate analysis, are the commonly used ones in studies of issuance and leverage decisions of a firm (for the summary of

[5] As a robustness test, I repeat the analysis using symmetric cutoffs of 5% and 1% for both equity and debt issuances. The results remain unchanged.

the factors, determining capital structure decisions see, for example, Frank and Goyal (2009) and Lemmon, Roberts and Zender (2008)). *Leverage* is defined as the sum of long-term debt (data9) and debt in current liabilities (data34), scaled by total assets. I drop firm-year observations with leverage values above one. The size of the firm, *Log(Sales)*, is the total revenues of a firm, expressed in natural logarithms. Market-to-Book ratio *(M/B)* is defined as the ratio of assets and market equity minus book equity[6] to total assets, and reflects growth opportunities. *Profitability* is the ratio of the EBITDA (data12) to total assets. The tangibility of a firm's assets is captured by *PPE,* the ratio of total net property, plant and equipment (data8), to total assets. *R&D* is the ratio of a firm's research and development expenses (data46) to total sales (data12). The value of zero is assigned to missing variables. I use the first date on which the stock price is available in CRSP database to determine the IPO date. I merge CRSP and Compustat data and remove missing observations and observations recorded at dates earlier than the IPO. *Age* is the number of years since the first year of a firm's stock price appearance in CRSP database. I remove observations before the IPO year. To control for future investment opportunities, I use capital expenditures of the firm (data128), scaled by total assets, as of period *(t+1)* (*Capex(t+1)*).

Leary and Roberts (2005) emphasize the importance of accounting for adjustment costs in the estimation of the leverage and equity issuance decisions to avoid the mistake of falsely identifying adjustment costs as market timing opportunities. For example, a firm that does not close the gap between the current and target leverage by issuing equity might be waiting for a good opportunity to time the market, or trying to minimize the adjustment costs. Following Faulkender et al. (2010), I create a proxy for adjustment costs, by computing the free cash flow of the

[6] The book value of equity is the book value of total assets minus book liabilities minus preferred stock plus deferred taxes. Preferred stock equals to the liquidation value if not missing; otherwise I use redemption value if not missing; otherwise the carrying value.

firm (*FCF*) (operating income before depreciation (data13) minus taxes (data16) and capital expenditures[7] (data128), divided by book assets). I sort all the firm-years in the sample by FCF and use the cut-off of 15% to create a dummy variable *FCF_low* that gets a value of 1 if the firm's cash flow is in the bottom 15% of the sample, and zero otherwise. Similarly, *FCF_high* gets a value of 1 if a firm's cash flow is in the top 15% of the sample, and zero otherwise. Since firms with significantly negative free cash flow have to raise capital anyway, their marginal adjustment costs should be lower than for other firms, and they will have more incentive to issue debt or equity.

For the final sample I require that a firm has non-missing values for the following variables: *log(Sales)*, *Profitability*, *PPE*, *M/B*, *Age* and *Leverage*. These variables are trimmed at the top and bottom 1% to mitigate the effect of outliers. The final sample consists of 13,809 firms and 114,058 firm-year observations.

In addition, I create a variable for the external finance weighted average market-to-book ratio *(EFWA)*, as suggested by Baker and Wurgler (2002). Hovakimian (2006) finds that this measure proxies for growth opportunities of a firm rather than for market timing. Therefore, I include it in an alternative specification. I start by obtaining a continuous time-series of a firm's assets history and remove firms with at least one missing value of total assets variable (data 6) during the history of the firm's record on Compustat. The EFWA measure is a sum of all the past Market-to-Book ratios, weighted by the proportion of external finance in a given year out of the overall external finance raised in the firm's history of public trading. For a given firm-year it is defined as:

[7] We use capital expenditures at a firm, rather than industry, level to capture the idiosyncratic capital needs of a firm.

$$\text{(1) } EFWA_{t-1} = \sum_{s=0}^{t-1} \frac{e_s + d_s}{\sum_{r=0}^{t-1} e_r + d_r} \cdot (M/B)_s$$

where e_s and d_s are the dollar amounts of equity and debt issuances, respectively[8]. Since the construction of EFWA measure requires a more strict data filtering, the sample of firms with non-missing EFWA values includes only about 67,000 firm-year observations.

2. Defining Market Timing and Target Leverage

This paper defines target leverage ratio as the mean leverage ratio of the benchmark group it belongs to. I define a group of firms in the same industry and same size quartile as the benchmark group. In choosing this definition as our main proxy for target leverage, I rely on previous studies (see, for example, Bradley, Jarrell and Kim (1984) and MacKay and Phillips (2005)) that show that most of the variation in the financial structure among firms is captured by industry effects. In addition, Hovakimian (2006) uses industry-based proxy as his main definition of target leverage. To refine the industry proxy, I impose additional matching requirements of size groups, as size typically explains a large portion of cross-sectional variation in firm financial variables (Frank and Goyal (2009), Korteweg (2010)). Obviously, this is only one way to define target leverage. I elaborate on alternative measures of relative target leverage ratios that I use to verify the robustness of my results, in Section III.C.2.

To compute the benchmark leverage, in each year I sort all firms in the sample into industry groups based on Compustat 2-digit SIC code, and size quartiles based on

[8] Following Baker and Wurgler (2002) I set the minimum weight equal to zero by removing observations with negative sum of equity and debt issuances in a given year. I also drop firm-year observations where the resulting EFWA ratio is greater than 10.

Sales. Re-forming the benchmark groups every year serves two purposes. First, it allow for a time-series trends in target leverage. Second, it overcomes the problems of cold/hot markets (Alti (2006)), as well as incorporating changes in target leverage due to macroeconomic factors (Bhamra, Kuehn and Strebulaev (2010)). I then calculate an average book leverage of every industry-size benchmark group, requiring at least 10 observations in a given year. *Dev_Lev* is defined as the deviation of a firm's leverage from the mean leverage of the benchmark group in a given year. To classify firms into overleveraged, underleveraged and the ones close to the target, each year I sort all the firms into quartiles based on *Dev_Lev* variable. The bottom quartile consists of the most underleveraged firms, relative to their industry peers, the top quartile includes the most overleveraged firms, and quartiles 2 and 3 consist of firms that are close to the target leverage.

Following the market timing literature, I derive market timing proxy from a firm's stock returns. Stock returns are annual returns of a firm on a given fiscal year, as reported by Compustat. I use firm's excess returns over the benchmark group average (*Dev_Ret*) as the main proxy for firm's market timing incentives. Although this measure is somewhat simplistic, it is also the most direct one in measuring the firm's opportunities to raise capital with the lowest costs. In the survey of managers, Graham and Harvey (2001) find that CEOs issue equity in response to high raw stock performance of their firm. In addition, raw and excess past stock returns prior to the issuance are used as a proxy for market timing opportunities in previous studies (see, for example, Marsh (1982), Jalilvand and Harris (1984), Korajczyk, Lucas and McDonald (1991), Welch (2004), Elsas, Flannery and Garfinkel (2006), Alti and Sulaeman (2009), DeAngelo, DeAngelo and Stulz (2010), Hovakimian and Hutton (2010)). I perform robustness tests and describe alternative measures of market timing in Section III.C.1.

3. Summary Statistics

Table 2.A.1 presents the summary statistics of the main variables used in the sample. An average firm has leverage ratio of 0.23, similar to the median one. The average annual returns are 6%, somewhat smaller than the average of indices, but the results can be driven by the fact that the sample includes small firms with volatile returns and firms in distress. The profit of an average firm is about 10% a year, and M/B is 1.65. An average firm issues around 3.8% of equity a year (as a percentage of assets). This is a very small number, since it averages across years with no issuances as well as years with positive or negative net issuances. Consistently with previous studies, I find that only about 20% of the sample has positive equity issuances in a given year (75^{th} Pctl. Of *EA* is zero). Debt issues are more frequent, but the average issuance magnitude is smaller (the mean is 3%).

III. Results

1. Non-Parametric Analysis

1.1. Univariate Analysis

I first perform a univariate analysis of the issuances of debt, equity and the main control variables. The results are reported in Table 2.A.2. I sort the overall sample into quartiles by relative leverage (*Dev_Lev*) in Panel A and by relative stock performance (*Dev_Ret*) in Panel B (both as of (*t-1*) period).

Panel A shows that net debt issuances (*DA*) exhibit a declining pattern across leverage groups from 4.4% for the most underleveraged quartile to 0.8% for the highest leverage quartile. These results are consistent with a trade-off hypothesis: firms with low level of leverage are the ones that are the most likely to issue debt. There is no clear pattern, however, for the net equity issuances (*EA*), suggesting that there are other factors, besides leverage, that determine the decision of the firm to issue equity. The pattern of the net of net equity issuance (*Net_Iss*) monotonically increases across leverage quartiles from -0.7% for underleveraged firms to 3.1% for the overleveraged ones, also consistent with the trade-off hypothesis. Taken together, the results suggest that equity and debt serve different purposes: debt is issued/retired for rebalancing motives, while there seem to be additional reasons behind equity issuance. Some of the control variables also have a clear pattern. Profitability and Market-to-Book ratio (*M/B*) decrease with leverage, similar to the findings of other studies (for example, Hovakimian et al. (2001)). Overall, the results of the table suggest that these variables will be crucial to control for in the multivariate setting. There is no clear pattern, however, for age (*Age*), size (*log(Sales)*) and excess returns across relative leverage groups.

Panel B sorts the overall sample into quartiles based on relative performance (*Dev_Ret*). Not surprisingly, *Profitability* and *M/B* increase across return quartiles. Net issuances of equity (*EA*) have a U-shaped pattern, and net issuances of debt (*DA*) increase linearly, which can be interpreted as a sign of market timing, or of a need to raise capital in response to increasing growth opportunities, since *M/B* and *Profitability* also increase across return groups.

1.2. Double Sorting Analysis

In Table 2.A.3 I sort all the observations by deviation of the firm's leverage from the peer book leverage (*Dev_Lev*) and independently by deviation of the firm's returns from the benchmark group average returns (*Dev_Ret*). Fixing return group and following the issuances across leverage groups should approximately capture the rebalancing impact, when highly leveraged firms issue less debt and more equity than low–leveraged firms that should prefer debt. Holding leverage constant and following issuances across return quartiles captures the potential market timing effect: firms with higher returns should be more willing to issue equity.

The pattern of net equity issuances (*EA*) across leverage groups is inconclusive, consistent with the univariate results, and implying that other factors, besides rebalancing motives, affect firms' issuing decisions. Net debt issuances (*DA*), however, clearly decline with leverage. For example, net debt issuances decrease from 3.5% to -1.9% for the firms in the low returns quartile, and from 5% to 3.7% for those in the best performing quartile. All the differences are statistically significant. The overall net of net issuance pattern (*Net_Iss*) is significantly higher for more leveraged firms across all return quartiles. The different issuance patterns between debt and equity suggest that these instruments serve different purposes: firms use debt to rebalance their capital structure, and equity to time the market or finance potential projects.

The net issuance pattern across return groups (*EA*) is more complicated and forms a U-shape. High issuances in the high return groups compared to the median quartiles are consistent with market timing behavior. High equity issuances in the lowest return quartile are somewhat surprising. For example, the worst performing firms (the ones that belong to the low return quartile) issue 4.1% equity as percent of their total assets in the second leverage quartile, and only 2.6% and 2.4%, when their performance falls in the second or third return quartile, respectively. However, it is possible that the lowest return quartile contains firms in distress (column of low returns for *Profitability*, *Age* and *FCF0* variables supports this idea – the variables have lower magnitude than for other return quartiles), with no internal capital, so the only channel to raise external capital available for them is through equity issuance. One way to deal with the problem is to identify the distressed firms and eliminate them from the overall sample. However, that can create a potential selection bias.

Performing a multivariate analysis, while controlling for the other factors, should minimize this problem. Besides, I use additional proxies for market timing, which I describe below, that eliminate the impact of distressed firms' issuances.

2. Parametric Analysis

2.1 Main Specification

To examine the differences in the impact of market timing across different groups of relative leverage, I interact the market timing proxy (*Dev_Ret*) with three dummies, derived from *Dev_Lev* variable. *LowLev* takes value of 1 if a firm belongs to the bottom *Dev_Lev* quartile, and zero otherwise. *HighLev* takes value of 1 if a firm belongs to the top *Dev_Lev* quartile, and zero otherwise. Finally, *MedLev* takes value of 1 if a firm belongs to one of the medium *Dev_Lev* quartiles, and zero otherwise. The final estimation takes the following form:

$$(2)\quad Issuance_{i,t} = \alpha + \beta_1 \cdot Dev\_Ret_{i,t-1} \cdot LowLev + \beta_2 \cdot Dev\_Ret_{i,t-1} \cdot MediumLev + \beta_3 \cdot Dev\_Ret_{i,t-1} \cdot HighLev + X'_{i,t-1}\delta + \varepsilon_{i,t}$$

where *X* is a vector of control variables, and δ is a vector of their coefficients.

To obtain empirical support for Hypothesis 1, two conditions have to hold. First, β_2 has to be positive and significant to demonstrate the effect of market timing on equity issuance decisions. Second, β_2 has to be significantly higher than the coefficients of *Dev_Ret*, interacted with other groups of relative leverage. To test whether the second condition has statistical support, I conduct the following F test for OLS estimations (Chi-squared test for the Logit estimations):

$$(3)\quad \beta_2 = \frac{\beta_1 + \beta_3}{2}$$

If market timing effect is homogeneous across relative leverage groups, then all the coefficients of *Dev_Ret* will have similar magnitudes, and each β should not be different from the average of the other two (H0). On the other side, if β_2 is significantly higher than the other coefficients, the F-test will reject the null hypothesis (H1).

Table 2.A.4 presents the results of estimating equity issuances in period *t* as a function of excess returns over the benchmark group (*Dev_Ret*), relative book leverage and a set of control variables as of (*t-1*). Panel A uses *EA,* the percentage of issuance as a fraction of a firm's assets, as the independent variable. Panel B is a logit regression where the dependent variable receives a value of 1 if *EA*>0, and zero otherwise. Logit specification helps addressing issues of non-linear impact of size and growth opportunities, when larger firms with higher investment opportunities may issue higher proportion of equity. Following Petersen (2009), the method of heteroskedasticity consistent clustered standard errors is used to control for possible autocorrelations of residuals in time-series data of each firm.

Table 2.A.4 includes several specifications. Specifications (1) and (5) are the baseline ones and include the vector of commonly used firm characteristics. Specifications (2) and (6) control for adjustment costs by adding *FCF_low* and *FCF_high* dummies, and future growth opportunities by including future capital expenditures (*Capex (t+1)*). Specifications (3) and (7) allow for non-linear interaction of leverage with relative leverage groups. Finally, Specifications (4) and (8) are estimated using the subsample of firms for which the EFWA measure is available.

Table 2.A.4 demonstrates that the main variable of interest, *Dev_Ret*MedLev*, has a positive and significant coefficient in all specifications. A 10% increase in excess returns leads to additional 0.5% of equity issuances. Given that an average firm issues about 3.8% of its assets as equity, this is a substantial number. At the same time, the coefficients of *Dev_Ret*HighLev* and *Dev_Ret*LowLev* are small in magnitude and statistically insignificant. The F-test that compares the magnitude of

*Dev_Ret*MedLev* coefficient to the average of the other two interactions of excess returns with relative leverage, is highly significant, further supporting the hypothesis that market timing is pronounced mainly for the group of firms close to their target leverage. The coefficients of *Leverage* are also statistically significant, implying the existence of rebalancing motives: firms issue more equity when leverage is high, and vice versa. Interestingly, the coefficient of *Leverage*HighLev* is smaller than the coefficient of *Leverage *MedLev*, contrary to what a trade-off theory would predict. Although this finding may seem counterintuitive, it follows from the tendency of highly leveraged firms to retire debt rather than issue equity in order to return to the optimal leverage level.

Most of the control variables are statistically significant and have the expected signs, consistent with previous studies. *Profitability* and *Log(Sales)* have a negative effect on equity issuance, as more profitable and large firms use internal resources and have better access to debt capital. The impact of *Age* is negative, since mature firms gradually increase their leverage. Tangibility (*PPE*) reduces the costs of bankruptcy and allows for higher levels of debt, resulting in mostly negative impact on equity issuances. Proxies of adjustment costs (*FCF_high* and *FCF_low*) are also significant, suggesting that raising external capital is costly and firms have to take that into account when deciding whether to issue equity. Finally, *M/B* has a positive impact on issuances, consistent with the idea that firms with growth opportunities need more access to external capital market. Interestingly, *EFWA* has statistically significant coefficient only in Panel B. *EFWA* has positive and significant coefficient in the specification that omits the capital expenditure variables (not reported). These results are in line with Hovakimian (2006), who finds that *EFWA* captures future investment opportunities rather than past market timing attempts of the firm.

One problem of the analysis in Table 2.A.4 is that excess returns can proxy for growth opportunities as well. An issuance, preceded by a stock run-up can be interpreted both as driven by market timing incentives, and by information about future investment opportunities, which rational agents immediately incorporate into the stock prices. To overcome this concern, I use net of net issuances as the dependent variable. Using *Net_Iss* instead of *EA* is more precise for a number of reasons. First, if a firm raises capital to finance future growth opportunities, it may decide to finance it with debt. Therefore, using the net of net issuances should mitigate this effect. Second, *Net_Iss* captures the overall net change in leverage of the firm, and therefore, reflects the trade-off forces more precisely. I re-estimate the analysis of Table 2.A.4 using net of net issues (*Net_Iss*) as a dependent variable. The results are presented in Panel A of Table 2.A.5. Panel B estimates a set of logit regressions of equity versus debt choice for a subsample of firms that raised external capital in a given year. The dependent variable, *Net_dummy*, takes a value of 1 if a firm issues equity, and 0 if it issues debt.

The convex pattern of the interaction between excess returns and relative leverage is still present, though the magnitude of the coefficients for *Dev_Ret*MedLev* is somewhat smaller: 0.19 in Table 2.A.5 compared to 0.542 in Table 2.A.4. The coefficient of *Dev_Ret*LowLev* is much smaller and insignificant, while the coefficient of *Dev_Ret*HighLev* is even negative, although the magnitude is very small. F-test is significant at 10% confidence level. Similar pattern emerges from Panel B, which shows that high returns increase the probability that a firm with leverage close to the target one will choose to issue equity rather than debt.

Specifications (3) and (4) indicate that trade-off concerns become more important as the firm deviates further away from target leverage: the coefficient of *Leverage *MedLev* is 0.04, the coefficient of *Leverage *HighLev* is 0.076, and the coefficient of *Leverage *LowLev* is negative, although insignificant. Taken together, these results suggest that firms will try to reduce the leverage when their leverage level is too high, and will issue less net equity when it is low. Combined with findings from Table 2.A.4, the results provide indirect support to previous studies that find that debt reductions are initiated to offset the deviation from the target leverage.

To summarize, the results of Tables 2.A.4 and 2.A.5 support the main hypothesis of the paper. Both coefficients of trade-off and market timing are positive and significant, suggesting that firms rebalance towards the target leverage, but also have market timing incentives. The interaction of the market timing proxy with the leverage group dummies confirms the idea that firms are more willing to time the market when they are closer to the target leverage, while for firms in the extreme leverage quartiles market timing considerations matter less.

2.2. Equity Issuances versus Repurchases

In the next step of the analysis I re-estimate the main specification separately for equity issuing (*EA*>0) and equity repurchasing firms (*EA*<0). Since repurchases are defined as negative issuances, the coefficients should have opposite signs if one anticipates the same impact of a variable on both issuances and repurchases. The results, presented in Table 2.A.6, indicate that equity repurchases are not simply a mirror image of issuances, and most of the factors that lead a firm to issue more equity, also cause it to repurchase more. Thus, larger, more profitable and tangible firms issue and repurchase less, as indicated by negative coefficients of *log(Sales)*, *Profitability* and *PPE* in Panel A, and positive coefficients in Panel B.

Equity issues are consistent with both market timing and rebalancing incentives. The coefficients of Leverage are in the range of 0.022-0.025 and statistically significant, indicating that firms issue higher amounts of equity as their leverage increase. The magnitude of the leverage coefficients in Specification (3) increases across relative leverage groups, also supporting the trade-off considerations. The interaction of *Dev_Ret* with relative leverage groups produces similar pattern to the one described in the previous subsection: firms are more sensitive to market timing when their leverage is close to the target one.

At the same time, both market timing and trade-off considerations have a somewhat mixed impact on a firm's decisions to repurchase. While the coefficient of Leverage is 0.007 and significant, indicating that firms repurchase less when their leverage is high, the interaction of leverage with relative leverage dummies produces conflicting results. The magnitude of the coefficients decreases across the groups, opposite from the predictions of the trade-off theory: firms repurchase smaller amounts of equity when they are underleveraged. The results of *Dev_Ret* coefficients are also inconclusive. The positive sign is consistent with market timing motives: firms repurchase equity when the relative performance of their stock is poor. At the same time the magnitude of *Dev_Ret* across leverage groups is inconsistent with trade-off considerations, and I do not find that firms time the market by repurchasing shares in the medium group of relative leverage. The overall inconsistency of results for equity repurchases can be explained by the fact that aside from being a channel to modify a firm's capital structure, share repurchases are a way to distribute cash to shareholders, and serve as a substitute to dividend payouts (Grullon and Michaely (2002)). As a result, repurchases may be determined by additional factors, such as cash holdings, investor composition etc. that do not make it a main tool to rebalance. Similar findings were also documented by Hovakimian (2006), who concludes that target leverage does not play a major role in equity repurchases.

3. Robustness Tests

3.1. Alternative Definitions of Market Timing

This sub-section refines the definition of market timing by concentrating on highly positive returns. Univariate results, as well as previous studies, indicate that a poorly performing firm may issue equity in an attempt to exit from distress and survive, rather than for rebalancing reasons (see, for example, Park (2010)). Therefore, excess returns can be an imprecise proxy for market timing, since very low performance captures additional factors, unrelated to market timing. In addition, the analysis above reveals that repurchases follow a somewhat different pattern from equity issuances, so eliminating low returns from the analysis will not eliminate the market timing effect from the share repurchasing perspective.

To capture the market timing effect more precisely, I construct a new market timing proxy, *Ex_Ret*, which equals excess returns over the benchmark group if it falls in the top quartile of excess return distribution, and zero otherwise. I use the new proxy to re-estimate the original specifications, and summarize the results in Table 2.A.7. Clearly, the pattern of market timing is similar to the one obtained in Table 2.A.4: the interaction of *Ex_Ret* with leverage is of the highest magnitude in the specifications of net and net of net equity issuances, and the coefficients decline in magnitude across leverage groups in the logit specification of equity versus debt. However, the coefficients are significantly larger than the ones in Table 2.A.4 and provide additional evidence that firms time the market mainly by issuing equity when stocks are overvalued. The results are consistent across different specifications, and estimation methods (OLS versus logit).

Second, I use raw past stock returns, rather than excess returns over the benchmark group, as an alternative measure of market timing. I interact raw returns with the groups of relative leverage and repeat the main estimations. The results remain very similar to the ones, reported above, and are not presented.

3.2. Alternative Definitions of Target Leverage

I also test the robustness of results to alternative definitions of target leverage. First, to refine the definition of peer group, I use a larger number of size groups (5 and 6) and find similar results. Second, I further split the sample into M/B groups, and use industry-size-M/B peer group to determine target leverage. The results remain unchanged.

As an alternative method to calculate target leverage, I use a parametric approach to estimate target leverage (see, among others, Hovakimian et al. (2001), Hovakimian (2006) and Flannery and Rangan (2006)). Specifically, using a Fama-MacBeth (1973) methodology, every year I estimate leverage as a function of leverage in the previous year and a set of control variables (size, profitability, M/B, tangibility, NOLC and R&D dummy). The estimated specification takes the following form:

$$(4)\quad Leverage_{i,t+1} = (\lambda\beta)X_{i,t} + (1-\lambda)Leverage_{i,t} + \varepsilon_{i,t}$$

where *X* is a vector of control variables and λ is a speed of adjustment coefficient.

Using the obtained coefficients, I compute the speed of adjustment for each firm in a given year:

$$(5)\quad Target_{i,t} = \beta X_{i,t}$$

I use the obtained target leverage to calculate the deviation of a firm from its target leverage in a given year, and then sort all firms in the sample into four quartiles based on their relative leverage. Finally, I re-estimate the main specification using the new proxy for relative leverage, and obtain similar results (not reported).

3.3. Book versus Market Leverage

The literature does not have a clear agreement on whether book or market leverage is a better one to use in research. In one of the first empirical studies of capital structure Marsh (1982) argues that although theoretically market leverage is correct, in practice managers look at book leverage. Following him, book leverage is used by Jalilvand and Harris (1984), Frank and Goyal (2003), Fama and French (2005), Leary and Roberts (2005), Alti (2006), Hovakimian (2006). On the other side, Welch (2004) argues that market leverage better reflects problems between debt and equity holders and therefore, views market leverage as a better measure of leverage. Additional studies that base their analysis on market leverage include Strebulaev (2007), Hertzel and Li (2010), and Fama and French (2002). Finally, the majority of the papers use both market and book leverage in their analysis, and usually conclude that the results are robust to either specification.

While book and market leverage indeed behave in a similar way in many studies, it does not have to be true for any research question, especially the one focusing on interaction of equity value and leverage. The reason for that is the mechanical effect of Market-to-Book and past returns on the level of market leverage and changes in it over time. For example, a firm that experienced a run-up in stock prices during the last year will automatically end up with lower market leverage at the end of the year, even if it has not had actual issuances or repurchases during the same period. Similarly, the definition of market leverage incorporates the implicit effect of Market-to-Book as well. As a result, assigning firms into leverage groups based on market leverage will be systematically biased. The group of underleveraged firms will actually include firms with higher market timing opportunities. Similarly, the high leverage group will consist of poorly performing firms, who can time the market by repurchasing shares. Adding M/B as a control variable in the estimation will not solve the problem, since I hypothesize non-linear relationship between the variables of interest. As a result, the coefficients of market timing will be biased in the low and high leveraged group, compared to the results based on book leverage.

IV. Long-Term Stock Performance

The results so far indicate that a firm exploits market timing opportunities when costs of doing so are low, and issues equity when its actual leverage is close to the target one. This section examines the post-issuance performance of firms and tests whether it is consistent with the general framework. Specifically, I test whether the long-run underperformance of equity issuing firms is correlated with their relative leverage during the issue.

1. Data Description

To perform the analysis of this section, I use SDC database of public issuances. The reason for using SDC, as opposed to Compustat, is the ability to precisely identify the issuance date, which is important for computing long-run returns of a firm. Compustat-based measures are more appropriate for the first part of the analysis, as they capture both equity and debt issuances, as well as issues of private instruments, while SDC is more suitable for the long-term analysis, as it provides the exact issuance date. A potential disadvantage of using different datasets is the discrepancies between the Compustat-based and SDC-based measures of issuance. However, studies by Hovakimian et al. (2001) and Korajczyk and Levy (2003) document that calculating issuances from Compustat, using a 5% cut-off, produce results similar to those obtained using SDC.

I start by obtaining all the US public issues for the period of 1970-2006. The sample includes all public equity issues by US firms with non-missing issuance date and CUSIP number. I merge the data with the Compustat sample, described in the previous section, by using CUSIP, if available, and ticker, if not. I also merge the data with CRSP monthly file to obtain raw returns of each firm. To verify the validity of the merges, I re-estimate the summary statistics of the number of issues and the long-run performance after the issuances from Loughran and Ritter (1995) and Ritter (2003) and get similar results. The final sample consists of 12,863 issuances.

To test Hypothesis II, I apply two commonly used methodologies: the Buy-and-Hold approach and Fama-French factor regression analysis. For robustness, I use both equally and value weighted portfolios, and different event window periods. Below I describe the results for each method separately.

2. BHAR Approach

The first approach I use is Buy-and-Hold (BHAR). The idea of BHAR is to compare the cumulative post-issuance performance of issuing firms to the performance of similar firms that did not issue. Several ways have been suggested to compute the performance of matching firms. While some papers use matching-methodology approach, other studies argue that matching SEOs to individual firms may create a bias towards finding underperformance (Brav, Geczy, and Gompers (2000)). Following Brav et al. (2000), I compare the long-run performance portfolios of issuing firms with portfolio of non-issuing firms with similar characteristics.

To create a subsample of non-issuing, or benchmark firms, at any given month I require that a firm that did not issue equity (whether in a form of SEO or IPO) in the previous five years. This filtering step eliminates benchmark bias, discussed by Loughran and Ritter (2000). I form size, B/M and *Dev_Lev* portfolios as follows. First, I use Fama-French (1993) size and B/M breakpoints to assign all issuing and matching firms into 5 size and 5 B/M groups. The size quintile breakpoints are based on NYSE traded firms. The size measure is a firm's market capitalization as of December *(t-1)*, and is obtained from CRSP monthly files. The B/M breakpoints are computed based on NYSE, AMEX and NASDAQ firms[9]. Following Fama and French (1993), B/M is defined as the book equity of a firm for the fiscal year ending in calendar year *(t -1)*, divided by market equity at the end of December of *(t -1)*. To mitigate the effect of outliers, I trim top and bottom 1% of size and B/M observations to mitigate the effect of outliers. Independently, I create the *Dev_Lev* quartiles, as described in Section II.B. The bottom quartile represents underleveraged firms, the top quartile – overleveraged firms, and the medium two quartiles include firms close to their target leverage. The firms are then aggregated into 5 x 5 x 4 portfolios of issuers and non-issuers, and their long-run 3 and 5 year performance is computed, using equally-weighted and value-weighted returns. To construct long-run returns, I cumulate the monthly returns of issuing and non-issuing firms starting one month after the issue date and for the following 36 (60) months, or the delisting or new equity issuing month, whichever comes first. Finally, I average the returns across size-B/M groups and present the results for each *Dev_Lev* group in Table 2.A.8.

The pattern of prior returns is the first indication of different market timing incentives across *Dev_Lev* groups. The portfolio of underleveraged firm has a 65% stock price increase in the pre-issuance year, compared to 44% and 50% for firms in third and fourth quartile, respectively. This suggests that ex-post, firms that issued while being underleveraged, had higher incentives to do so. The three and five-year long-term returns also indicate that firms, issuing at the bottom *Dev_Lev* quartile, did so to time the market. The performance of those firms is significantly different from the performance of firms in other quartiles. Interestingly, the long-run returns of the

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[9] The breakpoints for size and B/M are obtained from Kenneth French data library at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

highest *Dev_Lev* group are somewhat lower than those in the medium quartile, although their market timing incentives are low. The difference can be explained by differences in growth opportunities among different leverage groups. The main hypothesis focuses on the interaction of market timing and trade-off forces, keeping all else equal. However, it is possible that there are additional factors that change across leverage group, and weaken the main findings. As a result, it is important to compare the performance of issuers net of the performance of the benchmark group with the same relative leverage. The return pattern across control groups is not homogeneous, and firms in the high leverage group are also characterized by relative low long-run performance. Those results are consistent with the findings by Gomes and Schmid (2010), which show that leverage and investments are correlated, and firms with high leverage typically have lower investment opportunities.

The abnormal performance of issuing firms, net of benchmark returns, is increasing across *Dev_Lev* quartiles, consistent with Hypothesis 2. Underleveraged firms underperform their overleveraged peers by about 24-27% during the three years after the SEO, and by about 30%-40% during the five year period, following the issuance. The results suggest that underleveraged firms issuing equity are the ones with high market timing incentives to do so, and hence, they also suffer from the worst underperformance in the long-run. The results are robust to using different time-windows (three versus five years) and different weighting methodologies (equally versus value-weighted).

3. Calendar-Time Approach

While the results above are consistent with the general predictions, a number of critics challenge the BHAR-based analysis. First, it is possible that there are some risk factors, determining the risk premium of issuing versus non-issuing firms and driving the main results. Second, cross-sectional dependence in returns could result in understated standard errors and inflated *t*-statistics. To overcome these problems and verify the robustness of the results to different methodologies, I next use a factor-based calendar-time approach.

The calendar-time approach is performed as follows. First, I identify all firms that had at least one SEO in the previous three/five years, and create a subsample of equity issuers. The subsample of control firms includes firms that did not have an IPO or SEO event during three/five years, preceding the date of portfolio formation. I trim the top and bottom 1% of returns, B/M and size to mitigate the effect of outliers, which can be especially acute in the regression setting. I then assign all the firms in each subgroup into size-B/M-*Dev_Lev* groups, following the methodology, described in the previous subsection. The portfolios are re-formed every calendar month. I calculate time-series returns (equally and value weighted) of each of the 100 portfolios for issuers and non-issuers. I then estimate the returns of each portfolio, net of risk-free return, as function of Fama and French (1993) three factors[10], and average the coefficients across size-B/M group to obtain a coefficient pattern across each *Dev_Lev* quartile. I do not use the momentum factor in the specification, since I want to capture the overall trend of stock underperformance after the equity issuance, rather than separating it into excess returns and momentum factors.

The results are presented in Table 2.A.9. Panel A defines as issuers all the firms that issued equity in the past three years, while Panel B extends the event long-run period to five years. Each panel presents results for equally and value-weighted portfolios. The main coefficient of interest is the intercept. If firms in the bottom relative leverage group time the market more, their excess return, as measured by the

[10] The factors used in the analysis are obtained from Kenneth French website at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html. See Fama and French (1993) for a description of factor construction.

intercept of the regression, should be smaller in magnitude than the intercept of the other leverage groups. Table 2.A.9 shows that issuing firms indeed have low excess returns compared to the medium groups. However, the excess returns of the highly leveraged group are also significantly negative. This, again, might result from leverage-investment correlation, discussed in the previous sub-section. The pattern of excess returns across relative leverage groups for non-issuing firms confirms the pattern[11]. The excess returns of non-issuers decrease along the *Dev_Lev* quartiles, suggesting that other factors determine the pattern as well. As a result, the correct comparison is of the differences between the issuers and non-issuers across the quartiles. The differences of excess returns between issuers and non-issuers exhibit an increasing pattern. It ranges from -57% to 35% for firms in the bottom quartile, and is statistically significant. The difference in the top *Dev_Lev* quartile is positive, although insignificant. Finally, the difference in differences between the top and bottom quartiles is positive and also significant, indicating that the relative excess returns of underleveraged issuers is negative, even after controlling for risk factors. The results support Hypothesis II and indicate that firms with more market timing incentives underperform their peers in the long run.

V. Conclusion

Although market timing may not have a permanent impact on a firm's capital structure, firm still have incentive to time the market, while keeping the target leverage in mind. This paper shows under what conditions firms are more likely to be motivated by market timing versus trade-off considerations in their issuance decisions. Thus, market timing can be viewed as one of the trade-off forces, which has its

[11] The results for non-issuing firms are identical for non-issuing firms across both panels, as I require a 5-year non-issuance window to assign a firm into a group of non-issuers.

benefits (the opportunity to raise cheap capital) and costs (the costs of deviating from the target leverage/not closing the gap).

The framework of the paper, verified by an empirical analysis, shows that there is a non-linear relationship between the two incentives: market timing effect is more pronounced for firms that are close to their target leverage, and less pronounced for over- and underleveraged firms. The results are robust to different definitions of issuances. The empirical analysis also suggests that firms time the market mainly through equity issuances, while trade-off forces do not determine equity repurchases. I also find that market timing is more pronounced for firms with extremely high past stock performance.

The second part of the paper addresses the long-run stock underperformance, which usually follows equity issues, and constitutes another aspect of market-timing phenomenon. Firms that issue capital while being underleveraged, have more market timing incentives, compared to other firms. As a result, they are expected to underperform their peers in the long-run. Using BHAR and calendar-time approach, I find empirical support to this idea. Firms at the bottom *Dev_Lev* quartile have the lowest long-run performance, compared to their peers that did not issue equity. The relative performance of equity issuers improves as the deviation from the target leverage becomes more positive.

This study can be extended in several ways. First, it is possible to examine debt, and not just equity, timing. The problem, though, is identifying a proxy for debt market timing that will still create cross-sectional variation (for this reason, looking at the average spreads in the market may not be a good idea). Another way to extend the results of this paper is by conditioning the speed of adjustment on the size of the remaining gap between the current and optimal debt level. As this study suggests, the speed of adjustment may slow down as a firm gradually covers the leverage gap and other considerations, such as market timing, start playing a role. I leave these questions for future research.

APPENDIX 2.A: TABLES

Table 2.A.1. Descriptive Statistics

Table 2.A.1 presents the summary statistics of the sample. *Leverage* is the ratio of book debt to total assets. *Return* is the annual return of a firm during a fiscal year. *Log(Sales)* is total revenues of a firm, in logarithms. Profitability is the ratio of EBITDA to total assets; Market-to-Book ratio *(M/B)* is defined as the ratio of assets and market equity minus book equity to total assets. *Age* is the number of years since the first year of a firm's stock price appearance in CRSP database. *PPE is* the ratio of total net property, plant and equipment to total assets. *R&D* is the ratio of a firm's research and development expenses (data46) to total assets. The value of zero is assigned to missing variables. *Cape*x is the capital expenditures of the firm, scaled by total assets. EFWA is the external finance weighted average, as suggested by Baker and Wurgler (2002). Equity issuance (*EA*) is defined as the change in book equity minus the change in retained earnings as a percent of total assets. Debt Issuance (*DA*) is the residual change in assets as a percent of total assets. Net_iss is the difference between *EA* and *DA*. I use a cutoff of 5% of the asset value to determine an issuance, and 1% to determine a repurchase.

Variable	N	Mean	Median	Std Dev	25th Pctl	75th Pctl
Leverage	114,058	0.23	0.22	0.18	0.08	0.35
Return	114,058	0.06	-0.02	0.72	-0.36	0.33
log(Sales)	114,058	4.86	4.78	2.17	3.44	6.26
Profitability	114,058	0.10	0.13	0.17	0.06	0.18
M/B	114,058	1.65	1.22	1.30	0.93	1.82
Age	114,058	13.64	9.00	14.10	4.00	18.00
PPE	114,058	31.22	26.71	21.24	14.58	43.73
R&D	114,058	0.01	0.00	0.06	0.00	0.00
Capex	114,058	0.06	0.04	0.07	0.02	0.08
EFWA	66,834	1.59	1.24	1.15	0.97	1.81
EA	114,058	0.038	0.00	0.13	0.00	0.00
DA	114,058	0.030	0.00	0.14	0.00	0.09
Net_Iss	114,058	0.007	0.00	0.19	(0.08)	0.06

Table 2.A.2. Issuances and Control Variables by Quartiles of Dev_lev and Dev_ret

Table 2.A.2 presents the summary statistics of the sample, sorted by *Dev_Lev* (Panel A) and *Dev_Ret* (Panel B) quartiles. *Leverage* is the ratio of book debt to total assets, and *Dev_Lev* is the deviation of leverage from the benchmark group. *Dev_Ret* is the annual excess return of a firm over its benchmark group. *Profitability* is the ratio of EBITDA to total assets; *Age* is the number of years since the first year of a firm's stock price appearance in CRSP database. *Log(Sales)* is total revenues of a firm, in logarithms. Market-to-Book ratio *(M/B)* is defined as the ratio of assets and market equity minus book equity to total assets. Equity issuance (*EA*) is defined as the change in book equity minus the change in retained earnings as a percent of total assets. Debt Issuance (*DA*) is the residual change in assets as a percent of total assets. Net_iss is the difference between *EA* and *DA*. I use a cutoff of 5% of the asset value to determine an issuance, and 1% to determine a repurchase.

Panel A: by *Dev_Lev* Quartiles

Rank for Dev_Lev	Leverage	Dev_Ret	Profitability	Age	log(Sales)	M/B	EA	DA	Net_Iss
Low	0.05	4.94%	0.13	12.24	4.58	2.02	0.037	0.044	-0.007
1	0.14	1.75%	0.09	14.20	4.81	1.77	0.043	0.040	0.003
2	0.27	-1.55%	0.10	15.59	5.28	1.45	0.032	0.030	0.002
High	0.46	1.00%	0.08	12.42	4.76	1.38	0.039	0.008	0.031

Panel B: by *Dev_Ret* Quartiles

Rank for Dev_Ret	Leverage	Dev_Ret	Profitability	Age	log(Sales)	M/B	EA	DA	Net_Iss
Low	0.23	-67.02%	0.04	10.80	4.23	1.41	0.042	0.012	0.030
1	0.24	-21.54%	0.10	15.36	5.16	1.47	0.026	0.028	-0.002
2	0.24	4.38%	0.13	16.16	5.36	1.61	0.026	0.035	-0.010
High	0.23	89.49%	0.13	12.19	4.69	2.11	0.057	0.046	0.011

Table 2.A.3. Issuances and Control Variables by Quartiles of Dev_lev and Dev_ret

Table 2.A.3 presents the summary statistics of the sample by *Dev_Lev* - *Dev_Ret* quartiles. Dev*_Lev* is the deviation of book leverage from the benchmark leverage group. *Dev_ret* is the annual excess return of a firm over its benchmark group. *Profitability* is the ratio of EBITDA to total assets; *Log(Sales)* is total revenues of a firm, in logarithms. *Age* is the number of years since the first year of a firm's stock price appearance in CRSP database. Market-to-Book ratio *(M/B)* is defined as the ratio of assets and market equity minus book equity to total assets. *FCF is* operating income before depreciation minus taxes and capital expenditures, divided by book assets. Equity issuance (*EA*) is defined as the change in book equity minus the change in retained earnings as a percent of total assets. Debt Issuance (*DA*) is the residual change in assets as a percent of total assets. Net_iss is the difference between *EA* and *DA*. I use a cutoff of 5% of the asset value to determine an issuance, and 1% to determine a repurchase.

Panel A: Profitability

	Dev_Ret-Low	2	3	Dev_Ret-High	Diff. (High - Low)	t-stat (High-Low)
Dev_Lev-Low	5.9%	12.4%	15.2%	16.2%	**10.3%**	11.8
2	0.7%	10.0%	12.6%	12.9%	**12.2%**	14.5
3	4.8%	10.7%	12.4%	13.1%	**8.4%**	10.4
Dev_Lev-High	3.8%	8.5%	10.5%	11.1%	**7.3%**	10.4
Diff. (High-Low)	**-2.0%**	**-3.9%**	**-4.7%**	**-5.1%**		
t-stat (High-Low)	-2.2	-3.7	-5.4	-8.2		

Panel B: Log(Sales)

Dev_Ret-Low	2	3	Dev_Ret-High	Diff. (High - Low)	t-stat (High-Low)
3.99	4.76	5.03	4.46	**0.46**	6.2
3.93	5.15	5.49	4.60	**0.67**	10.5
4.52	5.63	5.76	5.05	**0.53**	7.2
4.30	5.09	5.20	4.63	**0.34**	5.2
0.30	**0.32**	**0.16**	**0.18**		
4.1	3.5	1.8	2.7		

Panel C: Age

	Dev_Ret-Low	2	3	Dev_Ret-High	Diff. (High - Low)	t-stat (High-Low)
Dev_Lev-Low	9.6	13.4	14.6	11.2	**1.60**	6.6
2	10.2	16.2	17.7	12.4	**2.25**	8.9
3	12.1	17.5	18.3	13.6	**1.48**	4.5
Dev_Lev-High	10.6	14.0	14.3	11.6	**1.00**	3.8
Diff. (High-Low)	**1.01**	**0.57**	**(0.23)**	**0.41**		
t-stat (High-Low)	4.7	1.4	-0.5	1.4		

Panel D: FCF

Dev_Ret-Low	2	3	Dev_Ret-High	Diff. (High - Low)	t-stat (High-Low)
-4.5%	1.1%	3.0%	3.4%	**7.9%**	8.8
-7.8%	-0.1%	1.7%	1.9%	**9.7%**	11.4
-3.8%	1.1%	2.0%	2.5%	**6.2%**	7.4
-3.5%	0.0%	1.1%	1.2%	**4.8%**	6.4
0.9%	**-1.0%**	**-1.8%**	**-2.2%**		
0.9	-1.0	-2.1	-3.7		

Panel E: M/B

	Dev_Ret-Low	2	3	Dev_Ret-High	Diff. (High - Low)	t-stat (High-Low)
Dev_Lev-Low	1.64	1.76	1.94	2.63	**0.98**	13.5
2	1.55	1.51	1.65	2.31	**0.77**	10.9
3	1.27	1.30	1.44	1.79	**0.51**	8.7
Dev_Lev-High	1.21	1.28	1.39	1.72	**0.51**	10.0
Diff. (High-Low)	**-0.43**	**-0.48**	**-0.55**	**-0.91**		
t-stat (High-Low)	-6.9	-7.9	-8.0	-14.3		

Panel F: EA

Dev_Ret-Low	2	3	Dev_Ret-High	Diff. (High - Low)	t-stat (High-Low)
4.1%	2.6%	2.4%	5.5%	**1.35%**	2.0
5.5%	2.7%	2.7%	6.3%	**0.82%**	1.2
3.8%	2.0%	2.3%	5.0%	**1.27%**	1.9
3.7%	2.8%	3.2%	6.2%	**2.42%**	3.8
-0.4%	**0.2%**	**0.8%**	**0.7%**		
-0.5	0.3	1.2	1.2		

Panel G:DA

	Dev_Ret-Low	2	3	Dev_Ret-High	Diff. (High - Low)	t-stat (High-Low)
Dev_Lev-Low	3.5%	4.2%	4.6%	5.0%	**1.5%**	3.1
2	2.4%	3.9%	4.2%	5.1%	**2.6%**	5.5
3	1.0%	2.6%	3.5%	4.9%	**3.9%**	6.4
Dev_Lev-High	-1.9%	0.7%	2.0%	3.7%	**5.7%**	8.2
Diff. (High-Low)	**-5.5%**	**-3.6%**	**-2.6%**	**-1.3%**		
t-stat (High-Low)	-8.3	-4.8	-3.7	-2.5		

Panel H: Net_Iss

Dev_Ret-Low	2	3	Dev_Ret-High	Diff. (High - Low)	t-stat (High-Low)
0.6%	-1.7%	-2.2%	0.4%	**-0.2%**	-0.2
3.0%	-1.2%	-1.6%	1.2%	**-1.8%**	-2.1
2.8%	-0.6%	-1.2%	0.2%	**-2.6%**	-2.8
5.7%	2.1%	1.2%	2.4%	**-3.2%**	-3.2
5.1%	**3.8%**	**3.4%**	**2.0%**		
5.0	3.4	3.3	2.4		

Table 2.A.4. Multivariate Regressions of Net Equity Issuance as a Function of Market Timing and Relative Leverage

The table reports the results of estimating net equity issuances as a function of leverage, market timing and control variables for the period 1970-2006. The dependent variable is *EA* in Panel A, and *EA_dummy* in Panel B (takes a value of 1 if EA>0 and 0 otherwise). *LowLev* is a dummy variable that takes a value of 1 if the firm belongs to the bottom *Dev_Lev* quartile, and 0 otherwise. *MedLev* is a dummy variable that takes a value of 1 if the firm belongs to the 2-nd and 3-rd *Dev_Lev* quartile, and 0 otherwise. *HighLev* is a dummy variable that takes a value of 1 if the firm belongs to the top *Dev_Lev* quartile; and 0 otherwise. See Table 2.A.1 for description of the rest of the variables. All the explanatory variables are lagged by one period. The standard errors are reported in parentheses and are clustered at a firm level (Petersen (2009)). ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively.

Table 2.A.4 (Continued)

	Panel A: OLS				Panel B: Logit			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.025***	0.018***	0.018***	0.027***	-1.721***	-1.891***	-1.738***	-1.86***
	(0.002)	*(0.002)*	*(0.002)*	*(0.002)*	*(0.04)*	*(0.041)*	*(0.041)*	*(0.062)*
log(Sales)	-0.005***	-0.0043***	-0.004***	-0.005***	-0.074***	-0.055***	-0.054***	-0.05***
	(0)	*(0)*	*(0)*	*(0)*	*(0.007)*	*(0.007)*	*(0.007)*	*(0.011)*
Profitability	-0.229***	-0.226***	-0.226***	-0.2***	-2.289***	-191.92***	-1.842***	-2.125***
	(0.006)	*(0.008)*	*(0.008)*	*(0.011)*	*(0.075)*	*(9.17)*	*(0.09)*	*(0.153)*
PPE	0.021***	-0.001	-0.002	-0.001	0.239***	-0.003***	-0.254***	-0.251***
	(0.002)	*(0.003)*	*(0.003)*	*(0.003)*	*(0.059)*	*(0.001)*	*(0.063)*	*(0.088)*
M/B	0.032***	0.03***	0.03***	0.026***	0.484***	0.455***	0.46***	0.421***
	(0.001)	*(0.001)*	*(0.001)*	*(0.001)*	*(0.011)*	*(0.011)*	*(0.011)*	*(0.02)*
Age	-0.0003***	-0.0002***	-0.0002***	-0.0002***	-0.017***	-0.016***	-0.016***	-0.014***
	(0)	*(0)*	*(0)*	*(0)*	*(0.001)*	*(0.001)*	*(0.001)*	*(0.002)*
R&D/Assets	0.175***	0.175***	0.174***	0.315***	0.042	0.082	0.098	1***
	(0.018)	*(0.018)*	*(0.018)*	*(0.031)*	*(0.172)*	*(0.168)*	*(0.167)*	*(0.382)*
Leverage	0.017***	0.02***			0.489***	0.571***		
	(0.003)	*(0.003)*			*(0.059)*	*(0.059)*		
*Leverage*LowLev*			0.022***	-0.0002			1.516***	1.217***
			(0.008)	*(0.009)*			*(0.139)*	*(0.188)*
*Leverage*MedLev*			0.029***	0.016***			1.161***	1.211***
			(0.004)	*(0.004)*			*(0.195)*	*(0.265)*
*Leverage*HighLev*			0.019***	0.009***			0.552***	0.441***
			(0.003)	*(0.003)*			*(0.089)*	*(0.127)*
FCF_low		0.015***	0.015***	0.019***		0.421***	0.423***	0.422***
			(0.002)	*(0.002)*		*(0.032)*	*(0.032)*	*(0.046)*
FCF_high		0.006***	0.007***	-0.001		0.065**	0.065**	-0.046
			(0.008)	*(0.001)*		*(0.03)*	*(0.03)*	*(0.042)*
Capex (t+1)		0.127***	0.127***	0.11***		2.287***	2.351***	2.788***
		(0.008)	*(0.008)*	*(0.009)*		*(0.151)*	*(0.151)*	*(0.222)*
EFWA				0.001				0.084***
				(0.001)				*(0.016)*
*Dev_Ret*LowLev*	0.039	0.038	0.038	0.03	0.008	0.007	0.008	0.006
	(0.038)	*(0.038)*	*(0.038)*	*(0.03)*	*(0.008)*	*(0.008)*	*(0.009)*	*(0.005)*
*Dev_Ret*MedLev*	0.542***	0.543***	0.54***	0.965***	0.143***	0.145***	0.14***	0.268***
	(0.085)	*(0.084)*	*(0.084)*	*(0.196)*	*(0.021)*	*(0.021)*	*(0.021)*	*(0.045)*
*Dev_Ret*HighLev*	0.003	0.003	0.003	-0.001	0.001	0.001	0.001	0
	(0.008)	*(0.008)*	*(0.008)*	*(0.004)*	*(0.001)*	*(0.001)*	*(0.001)*	*(0.001)*
Obs.	*114,058*	*114,058*	*114,058*	*66,834*	*114,058*	*114,058*	*114,058*	*66,834*
R-squared adj.	0.28	0.28	0.28	0.28				
F test	35.87	36.62	36.44	23.51				
Prob. (F test)	<0.01	<0.01	<0.01	<0.01				
Likelihood Ratio					14,457	15,092	15,343	6,738
Chi-squared					22.01	23.52	20.84	14.53
Prob. (Chi-squared)					<0.01	<0.01	<0.01	<0.01

Table 2.A.5. Multivariate Regressions of Net of Net Equity Issuance as a Function of Market Timing and Relative Leverage

The table reports the results of estimating net of net issuances (Panel A) and equity versus debt choice (Panel B) as a function of leverage, market timing and control variables for the period 1970-2006. The dependent variable is *Net_Iss* in Panel A (*EA-DA*), and *Net_dummy* in Panel B (takes a value of 1 if *Net_Iss*>0 and 0 if *Net_Iss*<0). *LowLev* is a dummy variable that takes a value of 1 if the firm belongs to the bottom *Dev_Lev* quartile, and 0 otherwise. *MedLev* is a dummy variable that takes a value of 1 if the firm belongs to the 2-nd and 3-rd *Dev_Lev* quartile, and 0 otherwise. *HighLev* is a dummy variable that takes a value of 1 if the firm belongs to the top *Dev_Lev* quartile; and 0 otherwise. See Table 2.A.1 for description of the rest of the variables. All the explanatory variables are lagged by one period. The standard errors are reported in parentheses and are clustered at a firm level (Petersen (2009)). ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively.

Table 2.A.5 (Continued)

	Panel A: OLS				Panel B: Logit			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.01***	0.008***	0.011***	0.018	-0.094***	0.173***	0.144**	-1.86***
	(0.002)	*(0.002)*	*(0.002)*	*(0.003)*	*(0.03)*	*(0.037)*	*(0.057)*	*(0.062)*
log(Sales)	-0.0065***	-0.0062***	-0.006***	-0.007	-0.111***	-0.099***	-0.112***	-0.05***
	(0)	*(0)*	*(0)*	*(0)*	*(0.005)*	*(0.005)*	*(0.008)*	*(0.011)*
Profitability	-0.277***	-0.295***	-0.294***	-0.294	-2.019***	-2.129***	-2.79***	-2.125***
	(0.007)	*(0.009)*	*(0.009)*	*(0.013)*	*(0.07)*	*(0.094)*	*(0.169)*	*(0.153)*
PPE	-0.018***	-0.008**	-0.004	0.002	-0.541***	-0.192***	-0.197***	-0.251***
	(0.003)	*(0.004)*	*(0.004)*	*(0.004)*	*(0.045)*	*(0.05)*	*(0.071)*	*(0.088)*
M/B	0.024***	0.023***	0.022***	0.017	0.173***	0.148***	0.103***	0.421***
	(0.001)	*(0.001)*	*(0.001)*	*(0.001)*	*(0.007)*	*(0.008)*	*(0.016)*	*(0.02)*
Age	0.0002***	0.0002***	0.0002***	0.0002	-0.001	-0.002**	-0.001	-0.014***
	(0)	*(0)*	*(0)*	*(0)*	*(0.001)*	*(0.001)*	*(0.001)*	*(0.002)*
R&D/Assets	0.134***	0.126***	0.129***	0.243	-0.493***	-0.548***	-0.126	1***
	(0.021)	*(0.021)*	*(0.021)*	*(0.034)*	*(0.167)*	*(0.165)*	*(0.407)*	*(0.382)*
Leverage	0.08***	0.078***			1.405***	0***		
	(0.004)	*(0.004)*			*(0.051)*	*(0)*		
*Leverage*LowLev*			-0.02	-0.0249*			1.503***	1.217***
			(0.013)	*(0.015)*			*(0.202)*	*(0.188)*
*Leverage*MedLev*			0.04***	0.028			1.939***	1.211***
			(0.005)	*(0.006)*			*(0.294)*	*(0.265)*
*Leverage*HighLev*			0.076***	0.063			1.564***	0.441***
			(0.004)	*(0.005)*			*(0.191)*	*(0.127)*
FCF_low		0.003	0.003	-0.006*		0.05*	-0.018	0.422***
			(0.003)	*(0.003)*		*(0.03)*	*(0.044)*	*(0.046)*
FCF_high		0.025***	0.025***	0.018		0.332***	0.319***	-0.046
			(0.004)	*(0.002)*		*(0.025)*	*(0.036)*	*(0.042)*
Capex (t+1)		-0.026**	-0.025**	-0.043***		-0.95***	-1.067***	2.788***
		(0.012)	*(0.012)*	*(0.014)*		*(0.138)*	*(0.218)*	*(0.222)*
EFWA				0.005				0.084***
				(0.001)				*(0.016)*
*Dev_Ret*LowLev*	0.044	0.043	0.045	0.041	0.003	0.005	0.002	0.006
	(0.036)	*(0.038)*	*(0.04)*	*(0.035)*	*(0.006)*	*(0.008)*	*(0.005)*	*(0.005)*
*Dev_Ret*MedLev*	0.19*	0.199*	0.21*	0.473***	0.021**	0.026**	0.071***	0.268***
	(0.108)	*(0.108)*	*(0.108)*	*(0.155)*	*(0.01)*	*(0.01)*	*(0.02)*	*(0.045)*
*Dev_Ret*HighLev*	-0.021***	-0.02***	-0.021***	-0.018	-0.043**	-0.037**	-0.014	0
	(0.004)	*(0.004)*	*(0.004)*	*(0.001)*	*(0.021)*	*(0.019)*	*(0.027)*	*(0.001)*
Obs.	*114,058*	*114,058*	*114,058*	*66,834*	*80,626*	*80,626*	*80,626*	*45,620*
R-squared adj.	0.13	0.13	0.13	0.10				
F test	2.66	2.96	3.32	8.86				
Prob. (F test)	0.10	0.08	0.07	<0.01				
Likelihood Ratio					6,459	6,768	7,054	3,569
Chi-squared test					5.38	5.45	4.69	10.18
Prob. (Chi-squared)					0.02	0.02	0.03	<0.01

Table 2.A.6. Multivariate Regressions of Equity Issuances and Repurchases as a Function of Market Timing and Relative Leverage

The table reports the results of estimating equity issuances (*EA*>0) and repurchases (*EA*<0) as a function of leverage, market timing and control variables for the period 1970-2006. *LowLev* is a dummy variable that takes a value of 1 if the firm belongs to the bottom *Dev_Lev* quartile, and 0 otherwise. *MedLev* is a dummy variable that takes a value of 1 if the firm belongs to the 2-nd and 3-rd *Dev_Lev* quartile, and 0 otherwise. *HighLev* is a dummy variable that takes a value of 1 if the firm belongs to the top *Dev_Lev* quartile; and 0 otherwise. See Table 2.A.1 for description of the rest of the variables. All the explanatory variables are lagged by one period. The standard errors are reported in parentheses and are clustered at a firm level (Petersen (2009)). ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively.

Table 2.A.6 (Continued)

	Panel A: Issues				Panel B: Repurchases			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.221***	0.211***	0.212***	0.216***	-0.044***	-0.043***	-0.044***	-0.042***
	(0.004)	*(0.005)*	*(0.005)*	*(0.007)*	*(0.001)*	*(0.001)*	*(0.001)*	*(0.002)*
log(Sales)	-0.012***	-0.0111***	-0.011***	-0.013***	0.0005**	0.0003*	0.0002	0.0003
	(0.001)	*(0.001)*	*(0.001)*	*(0.001)*	*(0)*	*(0)*	*(0)*	*(0)*
Profitability	-0.263***	-0.273***	-0.273***	-0.268***	0.008**	0.012***	0.012***	-0.003
	(0.008)	*(0.01)*	*(0.01)*	*(0.017)*	*(0.003)*	*(0.004)*	*(0.004)*	*(0.005)*
PPE	-0.008	-0.024***	-0.023***	-0.007	0.006***	0.004**	0.003*	0.006**
	(0.005)	*(0.006)*	*(0.006)*	*(0.008)*	*(0.002)*	*(0.002)*	*(0.002)*	*(0.002)*
M/B	0.024***	0.023***	0.023***	0.025***	-0.006***	-0.005***	-0.005***	-0.004***
	(0.001)	*(0.001)*	*(0.001)*	*(0.002)*	*(0)*	*(0)*	*(0)*	*(0.001)*
Age	-0.0005***	-0.0005***	-0.0005***	-0.0004***	0	0	0	0
	(0)	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*	*(0)*
R&D/Assets	0.05***	0.05***	0.05***	0.102***	0.013	0.017	0.016	0.011
	(0.018)	*(0.018)*	*(0.018)*	*(0.028)*	*(0.018)*	*(0.018)*	*(0.018)*	*(0.043)*
Leverage	0.022***	0.025***			0.007***	0.007***		
	(0.007)	*(0.007)*			*(0.002)*	*(0.002)*		
*Leverage*LowLev*			0.01	0.0337			0.018**	0.012
			(0.027)	*(0.032)*			*(0.008)*	*(0.01)*
*Leverage*MedLev*			0.018*	0.017			0.015***	0.007*
			(0.011)	*(0.013)*			*(0.003)*	*(0.004)*
*Leverage*HighLev*			0.025***	0.025***			0.007***	0.006**
			(0.007)	*(0.009)*			*(0.002)*	*(0.003)*
FCF_low		0.009**	0.008**	0.011**		-0.005***	-0.005***	-0.007***
			(0.004)	*(0.005)*		*(0.001)*	*(0.001)*	*(0.002)*
FCF_high		0.022***	0.022***	0.016***		-0.008***	-0.008***	-0.008***
			(0.1)	*(0.004)*		*(0.001)*	*(0.001)*	*(0.001)*
Capex (t+1)		0.108***	0.109***	0.057***		0.012**	0.012**	0.02**
		(0.018)	*(0.018)*	*(0.02)*		*(0.006)*	*(0.006)*	*(0.008)*
EFWA				-0.001				-0.001
				(0.002)				*(0.001)*
*Dev_Ret*LowLev*	-0.022	-0.045	-0.044	0.154	0.006***	0.007***	0.007***	0.006***
	(0.188)	*(0.187)*	*(0.187)*	*(0.382)*	*(0.002)*	*(0.002)*	*(0.002)*	*(0.001)*
*Dev_Ret*MedLev*	0.36**	0.356**	0.362**	0.73***	0.076	0.07	0.077	0.03
	(0.149)	*(0.148)*	*(0.149)*	*(0.211)*	*(0.064)*	*(0.064)*	*(0.064)*	*(0.124)*
*Dev_Ret*HighLev*	0.024	0.016	0.015	0.716*	0.172**	0.157**	0.13	0.2433*
	(0.106)	*(0.101)*	*(0.1)*	*(0.37)*	*(0.081)*	*(0.08)*	*(0.08)*	*(0.126)*
Obs.	*22,496*	*22,496*	*22,496*	*11,186*	*17,008*	*17,008*	*17,008*	*17,008*
R-squared	0.31	0.32	0.32	0.30	0.03	0.03	0.01	0.04
F test	3.93	4.24	4.35	0.79	0.030	0.03	0.01	0.47
Prob. (F test)	0.05	0.04	0.04	0.37	0.860	0.86	0.91	0.49

Table 2.A.7. Multivariate Regressions of Net Equity Issuance as a Function of Market Timing (Extreme Returns Only) and Relative Leverage

The table reports the results of estimating net equity issuances as a function of leverage, market timing and control variables for the period 1970-2006. The dependent variable is *EA* in Panel A, and *EA_dummy* in Panel B (takes a value of 1 if EA>0 and 0 otherwise). *LowLev* is a dummy variable that takes a value of 1 if the firm belongs to the bottom *Dev_Lev* quartile, and 0 otherwise. *MedLev* is a dummy variable that takes a value of 1 if the firm belongs to the 2-nd and 3-rd *Dev_Lev* quartile, and 0 otherwise. *HighLev* is a dummy variable that takes a value of 1 if the firm belongs to the top *Dev_Lev* quartile; and 0 otherwise. *Ex_Ret* equals *Dev_Ret* if in the top quartile, and zero otherwise. See Table 2.A.1 for description of the rest of the variables. All the explanatory variables are lagged by one period. The standard errors are reported in parentheses and are clustered at a firm level (Petersen (2009)). ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively.

Table 2.A.7 (Continued)

	Panel A: OLS				Panel B: Logit			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.024***	0.017***	0.017***	0.025***	-1.721***	-1.938***	-1.786***	-1.792***
	(0.002)	*(0.002)*	*(0.002)*	*(0.002)*	*(0.04)*	*(-0.042)*	*(0.042)*	*(0.062)*
log(Sales)	-0.005***	-0.0042***	-0.004***	-0.005***	-0.073***	-0.045***	-0.044***	-0.052***
	(0)	*(0)*	*(0)*	*(0)*	*(0.007)*	*(-0.006)*	*(0.006)*	*(0.01)*
Profitability	-0.228***	-0.225***	-0.225***	-0.197***	-2.289***	-1.885***	-1.803***	-2.054***
	(0.006)	*(0.008)*	*(0.008)*	*(0.011)*	*(0.075)*	*(-0.082)*	*(0.081)*	*(0.136)*
PPE	0.021***	-0.001	-0.001	-0.001	0.239***	-0.268***	-0.253***	-0.302***
	(0.002)	*(0.003)*	*(0.003)*	*(0.003)*	*(0.059)*	*(-0.06)*	*(0.059)*	*(0.082)*
M/B	0.032***	0.03***	0.03***	0.026***	0.484***	0.439***	0.444***	0.459***
	(0.001)	*(0.001)*	*(0.001)*	*(0.001)*	*(0.011)*	*(-0.009)*	*(0.009)*	*(0.014)*
Age	-0.0003***	-0.0002***	-0.0002***	-0.0002***	-0.017***	-0.016***	-0.017***	-0.016***
	(0)	*(0)*	*(0)*	*(0)*	*(0.001)*	*(-0.001)*	*(0.001)*	*(0.002)*
R&D/Assets	0.177***	0.176***	0.176***	0.318***	0.043	-0.046	-0.024	0.824**
	(0.018)	*(0.018)*	*(0.018)*	*(0.031)*	*(0.172)*	*(-0.138)*	*(0.137)*	*(0.322)*
Leverage	0.018***	0.021***			0.489***	0.568***		
	(0.003)	*(0.003)*			*(0.059)*	*(-0.056)*		
*Leverage*LowLev*			0.027***	0.0054			1.515***	1.22***
			(0.008)	*(0.009)*			*(0.129)*	*(0.175)*
*Leverage*MedLev*			0.026***	0.013***			0.953***	1.094***
			(0.004)	*(0.004)*			*(0.184)*	*(0.25)*
*Leverage*HighLev*			0.021***	0.011***			0.578***	0.412***
			(0.003)	*(0.003)*			*(0.084)*	*(0.119)*
FCF_low		0.015***	0.015***	0.018***		0.377***	0.381***	0.39***
			(0.002)	*(0.002)*		*(-0.029)*	*(0.029)*	*(0.042)*
FCF_high		0.006***	0.006***	-0.001		0.071**	0.071**	-0.04
			(0.007)	*(0.001)*		*(-0.028)*	*(0.028)*	*(0.039)*
Capex (t+1)		0.127***	0.126***	0.111***		2.125***	2.2***	2.705***
		(0.008)	*(0.008)*	*(0.009)*		*(-0.136)*	*(0.136)*	*(0.197)*
EFWA				0.001				0.034***
				(0.001)				*(0.011)*
*Ex_ret*Low*	0.04	0.037	0.038	0.02	0.008	0.004	0.003	0.001
	(0.038)	*(0.037)*	*(0.037)*	*(0.021)*	*(0.008)*	*(-0.004)*	*(0.003)*	*(0.003)*
*Ex_ret*Medium*	0.916***	0.915***	0.897***	1.164***	0.143***	0.052**	0.051**	0.038
	(0.156)	*(0.154)*	*(0.156)*	*(0.311)*	*(0.021)*	*(-0.021)*	*(0.021)*	*(0.026)*
*Ex_ret*High*	0.002	0.002	0.002	-0.002	0.001	-0.0004	-0.0004	-0.0017**
	(0.007)	*(0.007)*	*(0.007)*	*(0.003)*	*(0.001)*	*(-0.001)*	*(0.001)*	*(0.001)*
Obs.	*114,058*	*114,058*	*114,058*	*66,834*	*114,058*	*114,058*	*114,058*	*66,834*
R-squared adj.	0.28	0.28	0.28	0.23				
F test	32.78	33.39	31.42	13.78				
Prob. (F test)	<0.01	<0.01	<0.01	<0.01				
Likelihood Ratio					16,464.0	17,119.0	17,408.0	8,051.0
Chi-squared					27.2	29	16.94	11.4
Prob. (Chi-squared)					<0.01	<0.01	<0.01	<0.01

Table 2.A.8. The Long-Run Performance of SEOs – BHAR

The table reports three and five year buy-and-hold returns of SEO issuers, compared to benchmark portfolios. Benchmark portfolios are based on a subsample of firms that did not issue equity (as SEO or IPO) in the preceding 5 years. To mitigate the effect of outliers in eh benchmark group, I trim top and bottom 1% of size and B/M observations. The portfolios of size-B/M-*Dev_Lev* are formed by splitting the sample into quintiles of size and B/M (using Fama and French (1993) breakpoints), and independently sorting the sample into quartiles of *Dev_Lev*. The portfolio formation is repeated monthly. I calculate equally and value weighted returns of the resulting 100 portfolios of issuers and non-issuers. I use 36 obs starting from the month after the issuance for three-year BHAR, and 60 obs for the five-year BHAR. If an issuing firm delists before the 36-th (60-th) month, I use the available return data until the delisting month. The final results are averaged across size-B/M portfolios. Prior returns are the 12-month returns of the issuing firms before the SEO date. The abnormal return is an arithmetic difference between SEO and Control groups for each given *Dev_Lev* quartile.

Panel A: Equally - Weighted

		SEO		Control		Difference (SEO - Conrol)	
Dev_Lev Group	Prior return	3 Years	5 Years	3 Years	5 Years	3 Years	5 Years
Low	0.65	0.22	0.53	0.47	0.90	-0.26	-0.37
2	0.55	0.37	0.73	0.55	1.00	-0.18	-0.27
3	0.44	0.39	0.71	0.52	0.97	-0.13	-0.26
High	0.50	0.35	0.60	0.34	0.57	0.01	0.03
Diff. (High-Low)	-0.15	0.13	0.07	-0.13	-0.33	0.27	0.40
t-stat (High - Low)						3.42	2.15

Panel B: Value - Weighted

		SEO		Control		Difference (SEO - Conrol)	
Dev_Lev Group	Prior return	3 Years	5 Years	3 Years	5 Years	3 Years	5 Years
Low	0.60	0.17	0.43	0.37	0.65	-0.20	-0.22
2	0.52	0.31	0.51	0.47	0.76	-0.15	-0.25
3	0.46	0.36	0.57	0.43	0.70	-0.07	-0.13
High	0.45	0.31	0.47	0.28	0.39	0.04	0.08
Diff. (High-Low)	-0.14	0.15	0.04	-0.10	-0.26	0.24	0.30
t-stat (High - Low)						3.21	1.87

Table 2.A.9. The Long-Run Performance of SEOs – Calendar Approach

The table reports the results of Fama and French (1993) three-factor analysis of portfolios of issuers and non-issuers. Every month issuers are defined as firms that had SEO at least once in the previous three years (Panel A), or five years (Panel B). Non-issuers are defined as firms that did not have an equity issuance (in terms of IPO or SEO) in the previous five years. Both issuers and non-issuers are assigned into portfolios of size-B/M-*Dev_Lev*, which are re-formed monthly. I compute equally and value weighted (based on market capitalization) portfolios and create a time-series of returns. I regress excess returns of each portfolio over the 3-month T-bill rate as function of market returns, SMB and HML factors, as constructed using Fama and French (1993) methodology. The estimation takes the following form:

$$R_{p,t} - R_{f,t} \;=\; a + b\left[R_{m,t} - R_{f,t}\right] + cSMB_t + dHML_t + \varepsilon_t$$

Each regression has 444 monthly observations. The table presents the intercepts of the regression (*a*), averaged across size_B/M groups for issuers and non-issuers for each *Dev_Lev* group, and the differences between them.

Table 2.A.9 (Continued)

Panel A: 3-year window

	Equally-Weghted Portfolios					Value-Weghted Portfolios				
	a					***a***				
	Low *Dev_Lev*	2	3	High *Dev_Lev*	Diff. (High - Low)	Low *Dev_Lev*	2	3	High *Dev_Lev*	Diff. (High - Low)
Issuers	-0.41	-0.15	-0.30	-0.37	0.04	-0.25	-0.09	-0.24	-0.37	-0.12
Non-issuers	0.16	0.10	-0.03	-0.43	-0.59	0.12	0.07	-0.07	-0.44	-0.56
Diff. (Issuers - Non-issuers)	-0.57	-0.25	-0.27	0.06	0.63	-0.37	-0.16	-0.17	0.07	0.44
t-stat	-3.79	-2.75	-3.43	0.47	3.13	-2.33	-2.17	-2.45	0.62	2.19

Panel B: 5-year window

	Equally-Weghted Portfolios					Value-Weghted Portfolios				
	a					***a***				
	Low *Dev_Lev*	2	3	High *Dev_Lev*	Diff. (High - Low)	Low *Dev_Lev*	2	3	High *Dev_Lev*	Diff. (High - Low)
Issuers	-0.30	-0.12	-0.27	-0.40	-0.10	-0.23	-0.07	-0.28	-0.35	-0.12
Non-issuers	0.16	0.10	-0.03	-0.43	-0.59	0.12	0.07	-0.07	-0.44	-0.56
Diff. (Issuers - Non-issuers)	-0.47	-0.22	-0.24	0.03	0.49	-0.35	-0.14	-0.21	0.08	0.44
t-stat	-2.95	-2.77	-3.83	0.25	2.40	-2.21	-1.82	-2.41	0.76	2.36

APPENDIX 2.B: FIGURES

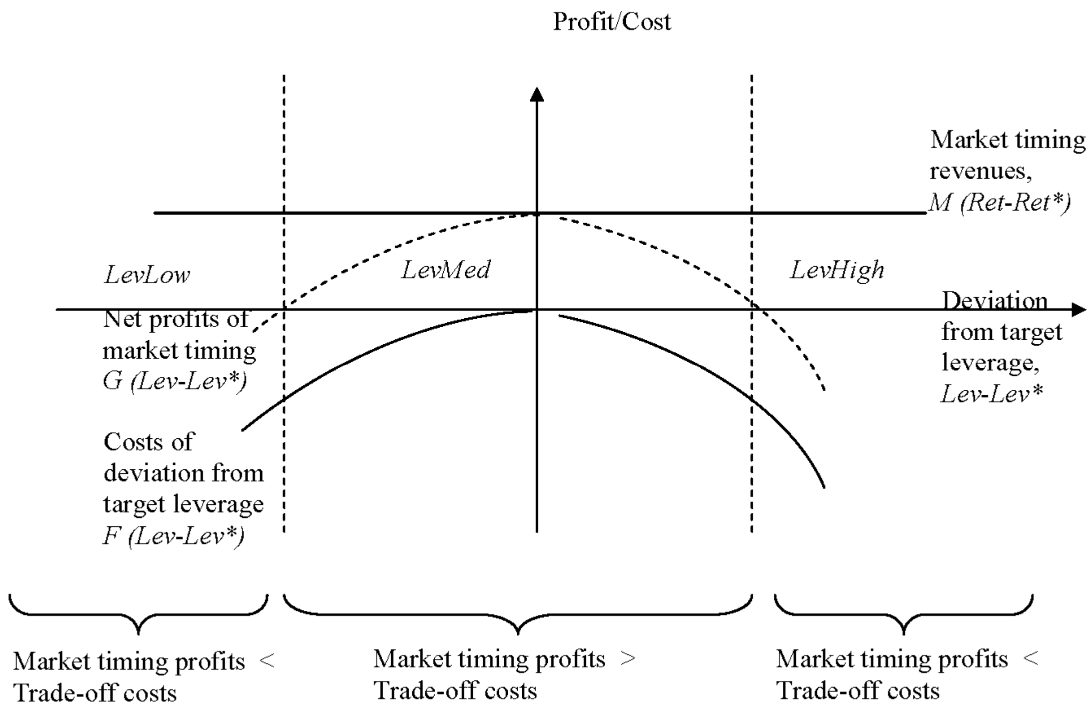

Figure 2.B.1. The interaction of market timing benefits with trade-off costs.

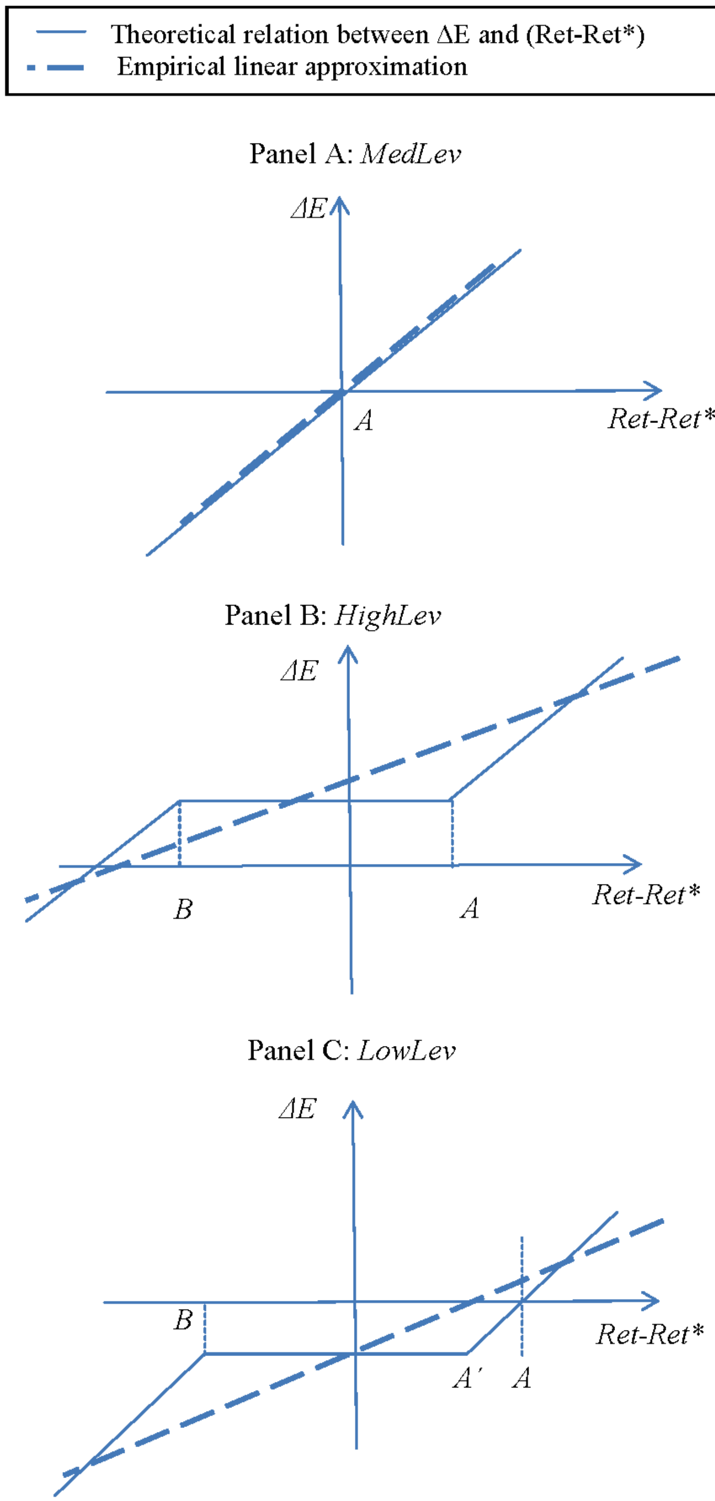

Figure 2.B.2. Sensitivity of issuances to relative returns.

REFERENCES

Alti, Aydogan, 2006, How persistent is the impact of market timing on capital structure?, *The Journal of Finance* 61, 1681–1710.

Alti, Aydogan, and Johan Sulaeman, 2009, When do high stock returns trigger equity issues?, *Working Paper*, *University of Texas at Austin*.

Altinkiliç, Oya, and Robert S. Hansen, 2000, Are there economies of scale in underwriting fees? Evidence of rising external financing costs, *The Review of Financial Studies* 13, 191–218.

Baker, Malcolm, and Jeffrey Wurgler, 2000, The equity share in new issues and aggregate stock returns, *The Journal of Finance* 57, 1–32.

Baker, Malcolm, and Jeffrey Wurgler, 2002, Market timing and capital structure, *The Journal of Finance* 55, 2219–2257.

Bhamra, Harjoat H., Lars-Alexander Kuehn, and Ilya A. Strebulaev, 2010, The aggregate dynamics of capital structure and macroeconomic risk, *The Review of Financial Studies* 23, 4187–4241.

Van Binsbergen, Jules H., John R. Graham, and Jie Yang, 2010, The costs of debt, *The Journal of Finance* 65, 2089–2136.

Bradley, Michael, Gregg A. Jarrell, and E. Han Kim, 1984, On the existence of an optimal capital structure: Theory and evidence, *The Journal of Finance* 39, 857–878.

Brav, Alon, Christopher Geczy, and Paul A. Gompers, 2000, Is the abnormal return following equity issuances anomalous?, *The Journal of Financial Economics* 56, 209–249.

Cook, Douglas O., and Tian Tang, 2010, Macroeconomic conditions and capital structure adjustment speed, *Journal of Corporate Finance* 16, 73–87.

Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam, 1998, Investor psychology and security market under- and overreactions, *The Journal of Finance* 53, 1839–1885.

DeAngelo, Harry, Linda DeAngelo, and Rene M. Stulz, 2010, Seasoned equity offerings, market timing and the corporate lifecycle, *The Journal of Financial Economics* 95, 275–295.

Eckbo, B. Espen, Ronald W. Masulis, and Oyvind Norli, 2008, Securities offerings, in Eckbo, B. Espen, ed., *Handbook of corporate finance: empirical corporate finance*, Vol. A, Ch. 6.

Elsas, Ralf, Mark J. Flannery, and Jon A. Garfinkel, 2006, Major investment, firm financing decisions, and long-run performance, *Working Paper, Institute for Finance and Banking, LMU Munchen*.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *The Journal of Financial Economics,* 33, 3–56.

Fama, Eugene F., and Kenneth R. French, 2002, Testing trade-off and pecking order predictions about dividends and debt, *The Review of Financial Studies* 15, 1–33.

Fama, Eugene F., and Kenneth R. French, 2005, Financing decisions: Who issues stock?, *The Journal of Financial Economics,* 76, 549–582.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, Return, and Equilibrium: Empirical Tests, *Journal of Political Economy* 81(3), 607–636.

Faulkender, Michael, Mark J. Flannery, Kristine Watson Hankins, and Jason M. Smith, 2010, Cash flows and leverage adjustments, *Working Paper, University of Maryland*.

Flannery, Mark J., and Kasturi P. Rangan, 2006, Partial adjustment toward target capital structures, *The Journal of Financial Economics* 79, 469–506.

Frank, Murray Z., and Vidhan K. Goyal, 2003, Testing the pecking order theory of capital structure, *The Journal of Financial Economics* 67, 217–248.

Frank, Murray Z., and Vidhan K. Goyal, 2009, Capital structure decisions: Which factors are reliably important?, *Financial Management* 38, 1–37.

Gomes, Joao F., and Lukas Schmid, 2010, Levered returns, *Journal of Finance* 65, 467–494 (28).

Graham, John R., and Campbell R. Harvey, 2001, "The theory and practice of corporate finance: Evidence from the field," *Journal of Financial Economics* 60, 186–243.

Grullon, G., and R. Michaely, 2002, Dividends, share repurchases, and the substitution hypothesis, *The Journal of Finance* 57, 1649–1684.

Harris, Milton, and Artur Raviv, 1990, Capital structure and the informational role of debt, *The Journal of Finance* 46, 321–349.

Hertzel, Michael G., and Zhi Li, 2010, Behavioral and rational explanations of stock price performance around SEOs: Evidence from a decomposition of Market-to-Book ratios, *Journal of Financial and Quantitative Analysis, forthcoming* 45,935–958.

Hovakimian, Armen, 2004, The role of target leverage in security issues and repurchases, *Journal of Business* 77, 1041–1071.

Hovakimian, Armen, 2006, Are observed capital structures determined by equity market timing?, *Journal of Financial and Quantitative Analysis* 41, 221–243.

Hovakimian, Armen, and Irena Hutton, 2010, Market feedback and equity issuance: Evidence from repeat equity issuance, *Journal of Financial and Quantitative Analysis* 45, 739–762.

Hovakimian, Armen, Tim Opler, and Sheridan Titman, 2001, The debt-equity choice, *Journal of Financial and Quantitative Analysis* 36, 1–24.

Huang, Rongbing, and Jay R. Ritter, 2009, Testing theories of capital structure and estimating the speed of adjustment, *Journal of Financial and Quantitative Analysis* 44, 237–271.

Jalilvand, Abolhassan, and Robert S. Harris, 1984, Corporate behavior in adjusting to capital structure and dividend targets: An econometric study, *The Journal of Finance* 39, 127–145.

Jensen, Michael C., 1986, Agency costs of free cash flow, corporate finance, and takeovers, *The American Economic Review* 76, 323–329.

Jensen, Michael C., and William H. Meckling, 1976, Theory of the firm: Managerial behavior, agency costs and ownership structure, *The Journal of Financial Economics* 3, 305–360.

Kayhan, Ayla, and Sheridan Titman, 2007, Firms' histories and their capital structures, *The Journal of Financial Economics* 83, 1–32.

Korajczyk, Robert A., and Amnon Levy, 2003, "Capital structure choice: Macroeconomic conditions and financial constraints," *The Journal of Financial Economics* 68, 75–109.

Korajczyk, Robert A., Deborah J. Lucas, and Robert L. McDonald, 1991, The effect of information releases on the pricing and timing of equity issues, *Review of Financial Studies* 4, 685–708.

Korteweg, Arthur, 2010, The net benefits to leverage, *The Journal of Finance* 65, 2137–2170.

Leary, Mark T., and Michael R. Roberts, 2005, Do firms rebalance their capital structures?, *The Journal of Finance* 60, 2575–2619.

Leland, Hayne E., and David H. Pyle, 1977, Informational asymmetries, financial structure, and financial intermediation, *The Journal of Finance* 32, 371–387.

Lemmon, Michael L., Michael R. Roberts, and Jaime F. Zender, 2008, Back to the beginning: Persistence and the cross-section of corporate capital structure, *Journal of Finance* 63, 1575–1608.

Loughran, Tim, and Jay R. Ritter, 1995, The new issues puzzle, *The Journal of Finance* 50, 23–51.

Loughran, Tim, and Jay R. Ritter, 1997, The operating performance of firms conducting seasoned equity offering, *The Journal of Finance* 52, 1823–1850.

Loughran, Tim, and Jay R. Ritter, 2000, Uniformly least powerful tests of market efficiency, *The Journal of Financial Economics* 55, 361–389.

MacKay, Peter, and Gordon M. Phillips, 2005, How does industry affect firm financial structure?, *The Review of Financial Studies* 18, 1433–1466.

Marsh, Paul, 1982, The choice between equity and debt: An empirical study, *The Journal of Finance* 37, 121–144.

Myers, Stewart, 1977, Determinants of corporate borrowing, *The Journal of Financial Economics* 5, 147–175.

Park, James, 2010, Equity issuance and returns to distressed firms, *Working Paper, University of Pennsylvania*.

Petersen, Mitchell A., 2009, Estimating standard errors in finance panel data sets: Comparing approaches, *The Review of Financial Studies* 22, 435–480.

Ritter, Jay R., 2003, Investment banking and securities issuance, in Constantinides, G.M, Milton R. Harris, and Rene Stulz, ed., *Handbook of the economics and finance*, Ch. 5.

Stigler, George J., 1964, Public regulation of the securities markets, *Journal of Business* 37, 117–142.

Strebulaev, Ilya A., 2007, Do tests of capital structure theory mean what they say?, *The Journal of Finance* 62, 1747–1787.

Welch, Ivo, 2004, Capital structure and stock returns, *Journal of Political Economy* 112, 106–131.

CHAPTER 3:
DO INVESTORS VALUE DIVIDEND SMOOTHING STOCKS DIFFERENTLY?*

Abstract

It is almost an article of faith that managers have a preference for smooth dividends. Yet, it is not clear whether managers' preferences reflect investors' preferences. In this paper, we study whether investors indeed value dividend smoothing stocks differently by exploring the implications of dividend smoothing for firms' expected returns and their investor clientele. We first document that dividend smoothing is associated with lower average stock returns both in a univariate setting and after controlling for firm characteristics and commonly used risk factors. We also find that some of this return differential can be attributed to lower risk, captured by return comovement among high (low) smoothing firms. Second, we find that retail investors are less likely to hold dividend smoothing stocks, while institutional investors are more likely. Among institutional investors, though, mutual funds are the only type that robustly favors dividend smoothing stocks. Last, we document that firms that smooth their dividends issue equity more frequently. Together, these results offer little support for behavioral explanations for why stable dividends are valued at a premium, but are consistent with the role of dividend smoothing in mitigating the impact of agency conflicts on the cost of capital.

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I. Introduction

Since the pivotal study by Lintner (1956), the phenomenon of dividend smoothing has been documented in a number of empirical studies (e.g., Fama and Babiak (1968), Brav, Graham, Harvey and Michaely (2005)). Dividend changes respond only slowly to earnings changes and managers are willing to bear significant costs to avoid dividend cuts. Survey evidence suggests that managers bear these costs because they believe investors value a smooth dividend stream. Lintner (1956, p. 104) found that one of the most important factors driving dividend policy is "management's views of its stockholders' preference between reasonably stable or fluctuating dividend rates, and its judgment of the size and importance of any premium the market might put on stability or stable growth in the dividend rate." Brav et al. (2005) find that even today "managers perceive a substantial asymmetry between dividend increases and decreases: there is not much reward in increasing dividends but there is perceived to be a large penalty for reducing dividends." Yet, as noted by Berk and DeMarzo (2007), more than fifty years after Lintner's study, "there is no clear reason why firms *should* smooth their dividends, nor convincing evidence that investors prefer this practice."

We address this gap by studying whether investors value dividend smoothing stocks differently. If an investor has a preference for smooth dividends, she would be willing to pay more for the equity of a firm that smoothes its dividends than for an equivalent firm that does not. The associated pricing impact should lead to lower (abnormal) expected returns for dividend smoothing firms.

Consistent with this prediction, our main finding is that portfolios of firms with smoother dividend streams earn lower abnormal returns than firms that smooth less. This result is robust to the empirical specification and asset pricing models used. The findings suggest that investors place a higher value on stocks that distribute smooth dividends, and are willing to sacrifice a portion of the stock's expected returns for holding those stocks. While these findings immediately raise additional questions as to why investors are willing to pay more for dividend smoothing firms, they are important in their own right, as they serve as a starting point to understanding why managers care about dividend smoothing.

We also attempt to address the question of why investors might value dividend smoothing stocks differently. The first explanation is that these stocks are associated with lower risk, and hence their returns are different. In this case, the returns differential may not be driven by the smoothing behavior itself. Rather, smoothing may proxy for some omitted risk factor not captured by commonly used firm characteristics or risk factors.

However, there are also several non-risk based explanations for why firms that smooth dividends enjoy a lower cost of capital. First, investors may have a behavioral preference for smooth dividends, based either on prospect theory type of utility (Baker and Wurgler (2010)) or a desire to smooth consumption (Shefrin and Statman (1984), Baker, Nagel and Wurgler (2007)). Second, dividend smoothing may itself lower the costs of external finance created by agency conflicts and asymmetric information. For example, several models demonstrate that with incomplete contracting, external equity financing is only sustainable if dividends above a given threshold are consistently maintained (e.g. Myers (2000), Fluck (1999)). Related, other authors (e.g., Shleifer and Vishny (1997), Gomes (2000), DeAngelo and DeAngelo (2007)) argue that firms avoid dividend cuts in order to establish a reputation in the equity markets for fair treatment of dispersed shareholders, facilitating future access to equity capital. Additionally, Allen, Bernardo and Welch (2000) suggest that a high and stable dividend stream serves to attract and retain institutional investors, which provide valuable monitoring and information production.

Our results show that differences in risk can account for at least part of the return premium associated with low dividend smoothing stocks. We construct a dividend smoothing factor, generated similarly to Fama and French (1993) Size and Book-to-Market factors, and show that sensitivity to this smoothing factor helps explain the cross-section of returns. Low-smoothing firms exhibit greater sensitivity to this factor, indicating that they are systematically riskier, and command higher returns. However, abnormal returns for dividend smoothing firms are still present even after controlling for the smoothing factor, suggesting that risk alone is not sufficient to explain our findings.

We next examine non-risk based explanations for the value differential between high and low dividend smoothing stocks. First, we explore which investor types, if any, exhibit a preference for dividend smoothing. We document that institutional investors favor dividend smoothing firms, while retail investors choose stocks with a low degree of smoothing. This is particularly surprising in light of the fact that institutions shy away from high dividend stocks (Grinstein and Michaely (2005)), and dividend smoothing is associated with high dividend yields. Moreover, managerial surveys, summarized in Brav et al. (2005), show that "executives believed that if there was any class of investors that preferred dividends as the form of payout, it was retail investors."

This evidence is difficult to reconcile with the behavioral preference explanations, which suggest that individual investors would be the ones attracted to stocks paying smoothed dividends. However, it is consistent with reduced agency costs, given the monitoring provided by institutional investors. This explanation is further supported by the finding that the preference for dividend smoothing is not shared among all types of institutions. Only mutual funds exhibit a significant tendency to hold shares of firms that smooth. Indeed, previous studies document the monitoring ability of large mutual funds. Brickley, Lease and Smith (1988) show that mutual funds and independent investment advisors are more likely to vote their proxies against management. Almazan, Hartzell and Starks (2005) present empirical evidence that more active institutional investors (such as independent advisors and investment company managers) provide more intense monitoring of corporate management; and Chen, Harford and Li (2007) find that independent institutional investors (that maintained stake in a company for at least a year) will specialize in monitoring activities. Hence the preference for dividend smoothing stocks is primarily present with institutions that tend to monitor more heavily, consistent with the role of dividend smoothing in reducing agency costs (Leary and Michaely (2011)).

Finally, if firms maintain a consistent dividend stream (and avoid cuts) in order to facilitate low-cost access to equity capital (as in Shleifer and Vishny (1997) or Myers (2000)), we would expect the firms implementing a dividend smoothing policy to take advantage of this access by subsequently issuing equity. Consistent with this prediction, we find that dividend smoothing firms indeed have more frequent seasoned equity offerings, providing empirical support to the agency and reputation based explanations.

To summarize, we show that dividend smoothing is priced, and firms that smooth their dividends more enjoy a lower cost of capital. We then provide evidence supporting two classes of explanations for this phenomenon. First, the returns differentials are partly attributable to differences in risk between firms that smooth dividends heavily and those that do not. This systematic co-variation between the smoothing factor and equity returns is not captured by other factors such as momentum, HML, SMB or dividend yield factor. Second, the institutional investor clientele and more frequent equity issuance of dividend smoothing firms suggest that dividend smoothing helps minimize external finance costs associated with agency conflicts, leading to a lower cost of capital. Taken together, our results offer possible explanations for why managers may be willing to bear the cost of dividend smoothing.

The reminder of the paper is organized as follows. Section II explains the methodology of measuring dividend smoothing, and describes the sample and its properties. Section III examines whether dividend smoothing is priced in stock returns. Section IV explores the risk explanation and tests whether smoothing is priced as a factor. Section V investigates the non-risk based explanations and presents evidence on the preferences for smooth dividends by different classes of investors as well as the equity issuance activity of dividend smoothing firms. Section VI concludes.

II. Data and Summary Statistics

1. Measures of Dividend Smoothing

For the estimation of smoothing, we use Compustat data for the period 1976-2008, excluding financial firms (SIC codes 6000-6999). We construct our measures of smoothing, as suggested by Leary and Michaely (2011).

The first measure of dividend smoothing, the speed of adjustment (*SOA*), is derived from a modified partial adjustment model of Lintner (1956). We use a two-step procedure to compute it. First, we estimate a firm's target payout ratio (TPR_i) as the median payout over a 10-year period. Next, we obtain the deviation from the target payout (dev_i) using the following formula:

$$(1)\ dev_{i,t} = TRP_i * E_{i,t} - D_{i,t-1}$$

where $E_{i,t}$ is the earning per share, and D_i is the level of dividends per share (DPS).

Finally, to estimate the speed of adjustment, we regress the changes in dividends on the deviation from the target payout (dev_i):

$$(2)\ \Delta D_{i,t} = \alpha + \beta_i * dev_{i,t} + \epsilon_{i,t}$$

SOA is the coefficient of the deviation variable (*β*). The higher its magnitude, the more the firm changes its dividend level to adjust for changes in earnings, and the less it smoothes.

Our second measure of dividend smoothing is relative volatility *(RelVol)*, and it captures the ratio of dividend volatility to earnings volatility. To obtain it, for every stock during a 10-year period we fit a quadratic trend to both the split-adjusted dividend and the scaled, split-adjusted earnings series:

$$(3)\ AdjDPS_{i,t} = \alpha_1 + \beta_1 * t + \beta_2 * t^2 + \epsilon_{i,t}$$

$$(4)\ TPR_i * AdjEPS_{i,t} = \alpha_2 + \gamma_1 * t + \gamma_2 * t^2 + \eta_{i,t}$$

The final measure *RelVol* is computed by dividing the root mean square errors from the regression of adjusted dividends per share by the root mean square errors from the regression of the split-adjusted earnings series. High *RelVol* implies that the volatility of dividends is high relative to the volatility of earnings, and the firm's dividend smoothing is low.

Both measures are estimated by firm for each 10-year rolling window period. As a result, we obtain a time-series of speed of adjustment (*SOA)* and relative volatility (*RelVol*) for each firm for the period of 1985-2008. For each rolling time period we require at least 8 non-missing observations and one positive dividend observation for the *SOA* estimation, and 6 consecutive observations for the estimate of *RelVol*. We also remove observations before each firm's first positive value for DPS and after each firm's last positive DPS. To mitigate the effect of outliers, we trim the top and bottom 2.5% of the resulting distribution of *SOA* and *RelVol*, as well as observations with negative values of *SOA*.

2. Control Variables

For our control variables we use Compustat, CRSP, and 13F databases at the annual frequency. Variable definitions are described in Appendix 3.A. We lag all the Compustat variables by one year to avoid the problem of reports being released during the following year. To be included in the sample, we require that a firm have non-missing values for the following variables: *SOA* or *RelVol*, *Assets*, *Age*, *Tangibility*, *M/B*, share price, leverage and annual standard deviation of monthly return (from CRSP). The final sample consists of about 29,000 firm-year observations for the *SOA* measure and about 26,000 for *RelVol*. The number of firms each year ranges between 923 and 1,941.

Since the methodology of computing the speed of adjustment is applicable only to dividend paying firms, our final sample is a subgroup of Compustat universe.[2] However, in terms of market capitalization the final sample captures a substantial proportion of the overall Compustat firms, and represents almost 47% of the overall equity traded.

3. Summary Statistics

Table 3.B.1 shows the distribution of the main control variables across smoothing quintiles. Panel A presents the results based on the speed of adjustment as a proxy for smoothing, and Panel B is based on relative volatility. The distribution of control variables across smoothing quintiles is very similar for both measures. High dividend smoothing firms are larger, older, more tangible and less risky in terms of

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[2] A potential concern arises as a result of limiting our sample to dividend paying firms only. However, while in a study of dividend *levels* it is important to examine firms that pay zero dividends, this is not the case in the research of dividend *smoothing* behavior. Firms that do not pay dividends have a constant dividend stream of zero, which mechanically assigns them to the top smoothing group. The behavior of those firms is fundamentally different from the behavior of firms that pay constant and positive dividends. We therefore, exclude firms that do not pay dividends from our analysis.

return volatility and beta than the low-smoothing firms. Firms that smooth more also tend to pay higher dividends: the dividend yield is 3.3% for the lowest *SOA* quintile, and only 2.0% for the highest quintile. Finally, institutional ownership is significantly higher for the high-smoothing firms (35.9%) than for the low-smoothing ones (29.7%). The trends in the control variables across smoothing quintiles are similar when using *RelVol* smoothing measure (Panel B).

Panel A of Table 3.B.2 reports descriptive statistics for the smoothing measures across all year-firm observations. The mean (median) SOA is 0.18 (0.13), suggesting that the median firm takes roughly 6 years to close half the gap between actual and target dividends. Overall, the averages and distributions of both measures are similar to those reported in other studies of dividend smoothing (e.g., Leary and Michaely (2011)).

Panels B and C show the stability of our smoothing measures over time. In every year *t* we allocate all the firms in the sample into deciles based on their smoothing measure (*SOA* in Panel A, and *RelVol* in Panel B). The bottom *SOA* [*RelVol*] decile consists of firms with the highest degree of dividend smoothing, while the top *SOA* [*RelVol*] decile includes firms with the lowest dividend smoothing policy. We then calculate the percentage of firms that remained in the same decile in year (t+1) [(t+2), (t+5)], as well as the percentage of firms that changed their ranking. The results of Panel A show that 57.62% of the firms remain in the same *SOA* decile in the following year, while roughly 85% of the firms remain within +/-1 decile. After 5 years, about 50% of the firms still remain in the range of +/-1 deciles of the smoothing ranking. Similar results hold when using *RelVol* (Panel C). Taken together, the time-series distribution of our measures of dividend smoothing are relatively stable from year to year, consistent with the evidence that some firms put significant effort into maintaining their payout policy at a certain level over time.

III. Is Smoothing Priced?

1. Univariate Analysis

In this section, we ask to what degree variation in dividend smoothing policies is associated with differences in expected stock returns. We start by a simple univariate analysis of firm equity returns as a function of smoothing. We divide all the firms in the sample into smoothing deciles and calculate the average/median monthly returns of all firms within the smoothing decile portfolio. The results are presented in Table 3.B.3.

Both the average and median returns increase across smoothing deciles. The differences between the top and the bottom deciles are statistically and economically significant. For example, firms that smooth their dividends the most (bottom *SOA* decile), have average monthly returns of 0.95%, compared to 1.35% for firms in the high *SOA* decile. This difference, which is statistically significant, is equivalent to an annualized return differential of 4.91%. The increase in returns over smoothing deciles is robust when we use medians instead of means, and also when we use *RelVol* as an alternative measure of dividend smoothing (Panel B). To verify that the pattern is consistent over time, we split the sample into two subperiods of equal length (1985-1996 and 1997-2008) and repeat the analysis. The difference in returns of low versus high dividend smoothing firms remains economically and statistically significant (not tabulated).

2. Factor Regressions

While the results presented in Table 3.B.3 tentatively suggest that smoothing is priced, the returns differential might be caused by differences in exposure of firms to risk factors. To this end, we use multivariate analysis to determine whether the returns differential documented above can be attributed to one of the commonly used risk factors. Specifically, we examine whether the excess return on firms with low-smoothing can be explained by different loadings on the market return, Size, Book-to-Market, and momentum factors.

Every year, we sort all the firms in our sample into smoothing deciles. The smoothing measure in year *t* is obtained from the estimation of *SOA*/*RelVol* from the stream of dividends and earnings during the period (*t-9*) through *t*. We use the three bottom deciles of the speed of adjustment variable to construct the portfolio of high-smoothing firms, and the top three to construct the portfolio of the low-smoothing firms. We then create equal- and value-weighted portfolios of firms in the top smoothing, bottom smoothing and medium smoothing groups. We also use the difference between the top and the bottom smoothing groups to create a strategy that is long low-smoothing firms and short high-smoothing firms. We regress the time-series of monthly returns of each portfolio on the Fama-French three factors plus the momentum factor (Carhart (1997)):

$$(5)\ R_{p,t} = \alpha + \beta^{Mkt}(R_{m,t} - R_{f,t}) + \beta^{SMB} SMB_t + \beta^{HML} HML_t + \beta^{MOM} MOM_t + \varepsilon_t$$

Table 3.B.4 presents the intercept estimates of regressing each one of the portfolios on four factors. Panel A summarizes the results based on *SOA* as a proxy for smoothing, and Panel B reports the estimation using *RelVol*. The results indicate that after controlling for these four factors, the portfolio of low-smoothing firms generates higher abnormal returns than the portfolio of high-smoothing firms. The estimated alphas decline monotonically with SOA and RelVol, with the largest differences between the high and medium groups. The abnormal alpha of the high *SOA* minus low *SOA* portfolio is positive and significant for both equally and value weighted estimations, and robust for both proxies of dividend smoothing. Buying low-

smoothing firms and selling high-smoothing firms generates monthly returns of at least 20 basis points, which is equivalent to 2.4% annually.[3]

To verify that the results above are robust to alternative model specifications, we first exclude the momentum factor and re-estimate our regressions using Fama-French three factors only. The results are quite similar to the ones presented here. Second, following a strand of literature that demonstrates that liquidity factor is another source of risk, incorporated into stock returns (see, among others, Chordia, Roll and Subrahmanyam (2000) and Amihud (2002)), we add the Pastor and Stambaugh (2003) liquidity factor to Specification (5). We find that the pattern in excess alpha across smoothing portfolios is insensitive to the addition of the liquidity factor.

3. Characteristic Regressions

The results in the previous section demonstrate that the returns differentials between low and high-smoothing portfolios are not explained by different sensitivities to standard risk factors. However, Daniel and Titman (2007) argue that returns differentials based on size and book-to-market are better explained by firm characteristics themselves than by their associated risk factors. Therefore, in this section we examine the relation between smoothing and returns in a specification that controls for firm characteristics associated with returns differentials.

We first estimate Fama-MacBeth (1973) cross-sectional regressions of returns as a function of standard firm characteristics, such as size, Book-to-Market, and beta, and ask whether dividend smoothing explains returns beyond those variables.

[3] Since our objective is to show economic differences is return and valuations, (and not in arbitrage profits), we do not account for the transaction costs associated with these trades.

To construct the explanatory variables, we closely follow the methodology of Fama and French (1992) in matching the timing of variable measurement. Thus, we measure the size of the firm with the log of market value of the firm (*ln(ME)*), as of June, *t*. We also use log of Book-to-Market equity (*ln(BE/ME)*), rather than Book-to-Market assets (*M/B*), as common in corporate research, and compute it as of December, *t-1*.

Post-ranking beta is computed in two steps. First, we estimate "pre-ranking beta" for each stock based on contemporaneous and one-month lagged market returns for CRSP value-weighted index. The sampling window is 60 months, when we require at least 24 months of non-missing return observations. The estimates are updated every June of year *t*, so that in June of every year we estimate beta over the past 5 years.

To estimate post-ranking beta, we first sort stocks into size deciles each month using NYSE breakpoints, as in Fama and French (1993).[4] We further divide each size decile into 10 deciles based on pre-ranking beta. For each of the resulting 100 size-beta portfolios we calculate equally-weighted monthly returns over the sample period. Finally, we regress the obtained monthly returns of each portfolio on the contemporaneous and lagged returns of the CRSP value-weighted index. The sum of the coefficients is the post-ranking beta, which is assigned to each stock in the specific size- beta group for use in the analysis.

In addition to post-ranking beta, size and Book-to-Market ratio, in an alternative specification we also include dividend yield (common dividend scaled by market value, as of *(t-1)*) as an additional characteristic variable, since it is important for us to separate the impact of smoothing on returns from the impact of dividend *level*

[4] Obtained from Kenneth French's website at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

on returns. Using these variables, every month we estimate the following specification:

$$(6)\ r_{i,t} = \alpha + \gamma_1\beta_{i,t} + \gamma_2 ln(ME)_{i,t} + \gamma_3 ln(BE/ME)_{i,t} + \gamma_4 DivYield_{i,t} + \gamma_5 Smooth_{i,t} + \varepsilon_t$$

Table 3.B.5 presents the results of the monthly cross-sectional estimation of stock returns as a function of the risk-proxying variables and smoothing (Columns (1) and (3) for SOA and $RelVol$, respectively). The estimates of the alternative specification that includes dividend yield are reported in columns (2) and (5). In columns (3) and (6), we replace dividend yield with total payout yield (sum of dividends and share repurchases), which Boudoukh, Michaely, Richardson and Roberts (2007) find better predicts stock returns. [5]

The results of the multivariate regression are consistent with the univariate findings. Both proxies for smoothing have positive and statistically significant coefficients. The coefficient of *SOA* ranges from 0.48 to 0.53, and the coefficients of *RelVol* are between 0.13 and 0.17, depending on the regression specification. The results suggest that firms that smooth their dividends (and therefore, have low speed of adjustment), require a lower risk premium, leading to lower expected returns. From an economic perspective, a one-standard deviation increase in *SOA*, which is about 0.16 (see Panel C of Table 3.B.2), adds on average 8 basis points to the monthly stock returns. Compounding the difference over 12 months translates into 1.0% additional risk premium at an annual basis.

The sign of the coefficients on control variables are in line with previous studies. Market beta does not have a material effect on stock returns when risk

[5] Following Grullon and Michaely (2002) we define total payout as common dividends plus total expenditure on the purchase of common and preferred stocks, plus any reduction in the value of the net number of preferred stocks outstanding.

characteristics are added to the model. The impact of size is negative (although statistically insignificant), consistent with larger firms being more stable and less risky. It is possible that some of the impact of the size variable disappears because our sample of smoothing firms is already based on relatively large firms. The effect of Book-to-Market ratio is positive and significant in most specifications. The only control variables that have unexpected coefficients are the dividend and total payout yields. While Boudoukh, et al. (2007) report a positive and insignificant coefficient of dividend yield in return regressions and a positive and significant coefficient of total yield, their coefficients in our estimation are negative and mostly insignificant. As higher dividend yield is associated with more smoothing, regressing returns on just the dividend yield includes the direct effect of dividend level and the indirect effect of dividend smoothing.

For robustness, we verify that the results of Table 3.B.5 are not influenced by the methodology we use to estimate our smoothing measures. We use a constant, rather than rolling, measure of dividend smoothing and obtain similar results (not tabulated).

IV. Dividend Smoothing and Risk

The results of the previous section show that smoothing is an important characteristic in determining the cross-section of returns and that dividend smoothing firms have lower cost of capital. The pattern cannot be explained by the standard risk factor models or by firm characteristics commonly associated with returns. These findings are consistent with managers' views, expressed in Lintner (1956) that investors exhibit a preference for stable dividends and are willing to pay for this stability. However, a question that still remains is why high dividend smoothing firms are traded at a premium compared to low dividend smoothing firms. There are at least two potential (and not mutually exclusive) reasons.

First, the difference in returns between low- and high-smoothing firms can reflect differences in risk not captured by the standard risk factors. For example, Allen, Bernardo, and Welch (2000) suggest that dividend smoothing may attract informed institutional investors, which in turn reduces a firm's opacity, asymmetric information and agency problems. Therefore, smoothing may result in lower risk and lower cost of capital. It is also possible that dividend smoothing does not lower the risk of the firm directly, but is correlated with other underlying firm characteristics associated with lower risk. As long as dividend smoothing explains some portion of the firm's risk premium, not captured by other established risk factors, this may provide a risk-based explanation for the differences in returns.

Second, as will be discussed in Section V, smoothing may be a priced characteristic for reasons unrelated to risk (see, for example, Lakonishok, Shleifer and Vishny (1994)). For example, the returns differential may be an outcome of some investors' preferences (e.g. Baker and Wurgler (2010)) that result in higher valuation (that is, in lower alpha). This section explores the risk explanation in further detail.

To investigate whether dividend smoothing is a possible risk factor, we use the Fama and French (1993) framework, and examine whether a low- minus high-smoothing portfolio can be a factor-mimicking portfolio as well, explaining return variation across stock portfolios that is not captured by the commonly used asset pricing factors.

To construct the smoothing risk factor, in the beginning of every year *t* we assign our sample firms into deciles of smoothing. We also (independently) create deciles of total payout yield. For each variable, we aggregate the results into three groups: high, which consists of the top three deciles, low, which includes the bottom three deciles, and middle, which includes deciles 4 through 7. The intersection of the two variables results in nine *TotYield*-smoothing portfolios, and for each portfolio we compute monthly returns, weighted by the market capitalization of each stock. We obtain the time-series of returns of the *SOA* risk factor by subtracting the average of the three low *SOA* portfolios from the average of the high *SOA* portfolios. We then repeat the procedure for *RelVol* instead of SOA as a measure of smoothing. The approach mirrors Fama and French (1993) construction of factor-mimicking portfolios and should help in examining whether smoothing captures some common variation of returns within high- and low-smoothing portfolios, which is unexplained by market, SMB and HML factors.

Boudoukh et al. (2007) create a factor-mimicking portfolio based on dividend and total payout yields, and show that this portfolio successfully captures some cross-sectional variation of time-series portfolio returns. Since dividend smoothing is correlated with dividend yield, we need to orthogonalize the impact of dividend smoothing from the impact of the dividend yield factor. Therefore, we construct the dividend-yield risk factor and include it in our regression as well. Following the methodology of Boudoukh et al., we sort all dividend paying firms into deciles of dividend yield, and (independently) into deciles of total payout yield. The dividend risk factor is the average of three high dividend yield portfolios minus the average of low dividend yield portfolios. We weight returns in each portfolio by market capitalization to mirror the construction of SMB and HML factors by Fama and French (1993).

The dependent variables are 15 *DivYield*-smoothing portfolios of stock returns. To construct these portfolios, we start by sorting the sample into deciles of dividend yield and allocating firms into three groups of Low (deciles 1-3), Medium (deciles 4-7), and High (deciles 8-10) dividend yields. We then assign firms in each dividend yield group to five equal-sized portfolios of dividend smoothing. The dividend yield-smoothing groups are re-formed every year. We compute the weighted average returns of each of the resulting 15 portfolios, as well as returns on the High SOA minus Low SOA portfolio within each dividend yield group. Finally, we regress each series, net of risk-free rate, on an intercept, market risk premium, SMB, HML, momentum, dividend yield, and dividend smoothing factors. Table 3.B.6 presents the results of the estimated intercepts, and the coefficients on the dividend yield and dividend smoothing factors, as well as their t-statistics. Panel A shows the results using *SOA*, and Panel B using *RelVol*, as the measure of dividend smoothing.

The results in Table 3.B.6 provide evidence that dividend smoothing may be a priced factor. The coefficient on the LMH dividend smoothing factor is significant at least at a 5% level for 11 out of 18 portfolios in Panel A, and 10 portfolios in Panel B. The pattern of dividend smoothing factor coefficients across groups of smoothing is consistent with the idea that it captures some common variation in portfolios of high- versus low-smoothing stocks. Specifically, the smoothing factor loading is -0.30 for low *SOA* stocks in the smallest dividend yield quintile, but it increases to 1.03 for the high *SOA* portfolio, and both coefficients are statistically significant. In fact, five out of six coefficients in the top two SOA quintiles are positive and significant. These results suggest that some of the excess returns of the high *SOA* portfolio can be attributed to the higher volatility of this portfolio due to its exposure to a risk source, captured by *SOA*. The differences remain significant as we move across dividend yield quintiles. The *SOA* coefficient is -0.08 for stocks with high dividend yield that smooth dividends (low *SOA* quintile), but is 0.55 for stocks in the top *SOA* quintile, suggesting that the smoothing factor plays a more important role for firms that pay out less to the shareholders.

The coefficient on the dividend yield factor is consistent with previous findings, and suggests that it bears some useful information for estimating stock returns, beyond commonly used asset pricing factors. Almost all of the coefficients are significant, implying that dividend smoothing and dividend yield factors capture different sources of risk and are not mutually exclusive.

Results are similar when we use *RelVol* as a measure of smoothing. Statistical significance of the coefficients is high, and the difference in factor loadings between high- and low-smoothing portfolios remains quite substantial, supporting the conclusions above. For example, the smoothing factor loading is -0.68 for stocks with low dividend yield that smooth dividends, as measured by the lowest *RelVol* quintile, but is 0.59 for stocks in the highest *RelVol* quintile in the same *DivYield* group.

Alpha, the intercept of the regression, is positive for all and significant for at least half of the portfolios. These results are consistent with Table 3.B.4 (that summarizes the results of regressing three *SOA* portfolios as a function of Fama and French factors plus the momentum factor), in which we find that all portfolios in our sample have positive and significant alpha across smoothing groups. Given our sample selection, our findings are in line with previous studies that demonstrate that relatively stable and successful firms have better performance in terms of excess returns. Thus, to analyze the impact of the dividend smoothing policy on stock returns within the sample, we focus on the relative magnitude of alphas across different groups, rather than their absolute values. The pattern in alphas of High minus Low smoothing portfolios across the dividend yield quintiles is somewhat mixed. While incorporating the dividend smoothing factor seems to capture at least some of the excess returns differential, among the Medium dividend yield portfolios (which comprise 40% of our sample firms) alphas increase across smoothing quintiles in both panels. The alpha of the High-Low portfolio in this dividend yield group is 0.31 in Panel A, which uses

SOA as a smoothing measure, and 0.38 in Panel B, which measures the degree of dividend smoothing with *RelVol* variable. Both differences are statistically significant at a 5% confidence level. The differences between high and low dividend smoothing portfolios in other dividend yield groups are small in magnitude, and statistically insignificant. Overall, the results indicate that while the new dividend smoothing factor absorbs some of the differences in alphas, there is still a component of the return premium that cannot be fully attributed to risk.

To ensure the robustness of our results, we repeat our asset pricing analysis of whether a smoothing factor captures an additional source of risk for portfolios of smoothing-dividend yield, portfolios of smoothing-size, and portfolios of smoothing-Book-to-Market. We obtain results consistent with the ones presented here. We also re-estimate the main specification using a dividend yield factor, rather than total yield factor. The results remain very similar to the ones presented. Finally, we verify that the results above hold when we estimate the standard three-factor model plus the dividend smoothing factor (i.e. excluding the dividend yield and momentum factors from the regression). We find that using alternative specifications does not change the main conclusions in a material way.

V. Non-Risk Based Explanations

The results of the previous section demonstrate that differences in risk provide a partial, but incomplete, explanation for the returns differential between the low and high dividend smoothing firms. In this section, we consider why, apart from risk, investors may be willing to pay a premium for stocks with smooth dividends. Recent literature has suggested two classes of reasons.

First, investors may have a behavioral bias toward smooth dividends. Baker and Wurgler (2010) discuss how prospect theory preferences can lead to such a bias. If investors display both reference dependence (measuring losses and gains relative to a reference point) and loss aversion, they lose more utility from a dividend cut than they gain from an equivalent increase. A smooth dividend stream then maximizes utility over time. Alternatively, Shefrin and Statman (1984) and Baker, Nagel and Wurgler (2008) argue that investors consume out of dividends rather than capital gains. To the extent that they prefer a smooth consumption stream, they will also value smooth dividends.

Second, dividend smoothing may lower the cost of capital by reducing agency and adverse selection costs. Several theoretical models show that consistent dividends above a given threshold enable firms to access equity capital on favorable terms by establishing favorable reputation in rational markets. For example, Myers (2000) demonstrates that in incomplete contracts setting, outside equity financing is only feasible if the manager makes sufficient regular dividend payments, which generate investors' expectations of obtaining a similar stream of dividends in the future. Dividend cuts are therefore avoided in order to maintain access to equity capital.[6] Building on the model of Gomes (2000), LaPorta, Lopez-de-Silanes, Shleifer and Vishny (2000) and DeAngelo and DeAngelo (2007) argue that firms anticipating future external capital needs maintain consistent dividends (and avoid cuts) in order to establish a reputation in the equity markets for fair treatment of dispersed shareholders. High and stable dividends can also reduce agency (or information) costs by attracting strong monitors. Allen, Bernardo and Welch (2000) suggest that a high and smooth dividend stream is a means of attracting and maintaining institutional investors, who minimize financing costs through their monitoring and information gathering roles. Somewhat similarly, Easterbrook (1984) and John and Knyazeva (2008) argue that a high and stable dividend provides a substitute governance

[6] See Fluck (1999), Zwiebel (1996) and Warther (1994) for models with similar implications.

mechanism by reducing free cash flow and forcing firms to access external capital markets, which discipline managers through external monitoring.

We provide evidence on the potential relevance of these explanations by examining two issues. First, we ask which investors are attracted to stocks that pay a smooth dividend. The behavioral explanations based on prospect theory or consumption smoothing imply that individual investors should be the primary clientele for dividend smoothing stocks. On the other hand, if smooth dividends lower agency costs by attracting strong monitors, we would expect these shares to be held predominantly by institutional investors. The models in which consistent dividends enable access to outside equity (e.g. Myers (2000)), as well as the model of Allen, Bernardo and Welch (2000), postulate that investors have the power to discipline managers if dividends are reduced. This is more likely in the case of large institutional investors rather than in the case of dispersed individual investors.

Briefly, we find that shares of dividend smoothing stocks are held more by institutional investors, primarily mutual funds, consistent with the second set of predictions, in which dividend smoothing reduces external finance costs. We then examine the predictions of the second class of models further. If firms pay a consistent dividend in order to raise equity in the future at attractive prices, we anticipate these firms to be more likely to subsequently issue equity. Again we find supporting evidence.

1. Which Investors Prefer Smooth Dividends?

While prior studies (e.g. Grinstein and Michaely (2005), Graham and Kumar (2006)) have shown that individual investors exhibit a preference for dividend paying stocks, less is known about which investors are attracted to stocks that smooth their dividends. Theoretical models generate mixed predictions about who the target clientele for dividend smoothing behavior would be. Baker and Wurgler (2010) show that by evaluating dividend increases and cuts relatively to a reference point, loss averse individuals will prefer to receive a smooth stream of dividends over time. Survey evidence by Brav et al. (2005) also suggests that individual investors exhibit preference for dividend smoothing – perhaps for income smoothing considerations. At the same time, the models by Allen, Bernardo and Welch (2000) and Myers (2000) show that managers use dividend smoothing as an instrument to retain institutional investors, who prefer dividend payouts for tax purposes.

To determine whether there is a dividend smoothing clientele, we start by examining whether the propensity to hold dividend smoothing stocks varies across investor types. We first perform a simple non-parametric analysis to distinguish between two broad groups of investors: institutional versus retail. For each firm in the sample we calculate the overall number of common shareholders (*#Invest*), in thousands. The size of the investor base proxies for the number of retail investors holding the stock.[7] We also obtain the overall number of institutions (*InstNum*), and the percentage of institutional holdings (*InstHold*) out of the overall investor holding, from Thomson Financial's 13F filings. We use both the number and the percentage of institutional holding to account for potential differences in stock holdings of large versus small institutions. Every year we independently sort all the stocks in the sample into quintiles of smoothing and quintiles of dividend yield. We then average the investor and institutional holdings across each of the resulting 25 dividend yield-smoothing portfolios and report our results in Table 3.B.7.

[7] While the overall number of investors includes both the retail and the institutional investors, the number of institutions constitutes a very small portion of the overall shareholder base. The ratio of the number of institutions to the number of overall investors for a given stock has a median of 1.3% and does not exceed 6.3% for 90% of our sample firms.

Two clear trends emerge from the table. First, both the number and the weight of institutional ownership decrease with dividend yield, consistent with Grinstein and Michaely (2005). While institutional investors tend to hold firms that pay dividends as opposed to those that do not, within the dividend paying sample institutions seem to avoid high levels of dividends. For example, institutions hold 50% of the overall market value of firms that have low dividend yield and low speed of adjustment, but only 26% of outstanding shares of firms that are in the top dividend yield quintile. As a complement to institutional behavior, retail investors do like firms that pay high dividends. Their holdings (proxied by the number of shareholders) increase dramatically across the yield groups. Firms in the bottom *SOA* quintile that pay the lowest dividend yield have about 13,300 investors, while firms with a similar smoothing behavior but high dividend yield have three times as many investors (around 41,700 in the top dividend yield quintile).

Second, within each dividend yield group, institutions exhibit a clear preference for dividend smoothing firms. Among the firms in the low yield quintile institutions hold only 34% of the shares of low dividend smoothing firms (as measured by *SOA*), but they own half of the equity of high-smoothing firms (Panel C). The pattern remains robust when we look at the overall number of institutions, rather than their relative weight, and suggests that the preference for dividend smoothing firms is not driven by institutions of a particular size. At the same time, we do not observe a clear preference of retail investors toward dividend smoothing firms. While the number of shareholders is higher for high- smoothing versus low-smoothing firms within the top dividend yield quintile, there is no pattern for the rest of the sample. As also reported in the table, using relative volatility instead of *SOA* yields very similar results.

Overall, the findings that institutions prefer smoothed dividends are consistent with the univariate analysis of the relations between smoothing and institutions, as documented by Leary and Michaely (2011). However, this relationship may still be an artifact of correlation between dividend smoothing and other variables, such as age, and turnover that are also correlated with institutional holding. Therefore, in Table 3.B.8 we turn to multivariate analysis and estimate the number of the overall investors, the number of institutions and the percentage of institutional holding for each firm as a function of dividend smoothing and control variables.

We employ a set of commonly used firm characteristics that were found to be correlated with institutional holding (Gompers and Metrick (2001), Grullon, Kanatas, Weston (2004)) as our control variables. We use a firm's size, age, and price reciprocal to control for the size and maturity of the firm. Since some institutions, such as pension and mutual funds, have a number of restrictions on the type of firms they can invest in, they usually prefer bigger and more stable firms. We use stock returns and returns on assets (*ROA*) as the performance measures of the firm. Asset tangibility, the ratio of Market-to-Book assets (*M/B*), and leverage control for additional factors that are correlated with smoothing and may affect investor composition as well. We also include advertising and R&D expenses to account for investment of a firm in intangible assets, such as technology and brand. Finally, we use turnover to capture the liquidity of a firm's stock and the standard deviation of stock returns to proxy for its risk. To distinguish the effect of dividend *smoothing* from the impact of dividend *level*, we include dividend yield. All the clientele variables are converted into natural logarithms (the dependent variables become *ln(#Invest)*, *ln(InstNum), and ln(InstHold)*) to mitigate the impact of positive skewness in the distribution of individual and institutional holding on the estimation parameters.[8]

The results in Table 3.B.8 summarize the estimations with the overall number of shareholders, number of institutions and institutional holdings as the dependent variables. Similar to the previous findings, institutions prefer holding profitable and liquid (in terms of turnover) firms with large market capitalization and low proportion of tangible assets. Consistent with the non-parametric analysis above, institutions do not like high dividend payouts. However, they do like dividend smoothing firms. The coefficient on *SOA* is negative and significant for both the number of institutions and the proportion of institutional holding. Similar results are obtained for *RelVol* (Panel B), confirming that the findings are robust to using different measures of smoothing. The implications remain similar whether we use the number or the proportion of institutional holding, suggesting that the results are not driven by a few large institutions, but rather hold for the overall universe of institutional investors. The relation between the number of shareholders (*ln(#Invest))* and firms' characteristics are quite different from the institutional picks. Overall, retail investors prefer firms with tangible assets that pay high dividends. Another striking difference is their negative attitude towards dividend smoothing: as opposed to institutions, retail investors not only do not like dividend smoothing, but also exhibit a certain preference towards a volatile stream of dividends, as suggested by positive coefficients on *SOA* and *RelVol*.

To confirm the robustness of our results, we consider alternative specifications, which include *log(ME)*, *log(Sales)*, *Payout* and *TotYield* as control variables. The main conclusions are unchanged. The significance of the results also holds when we

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[8] To incorporate values of zero into our analysis, we add 1 to the number and percentage of institutional holdings, before converting it to logarithms.

re-estimate the results for the subsample of firms with positive institutional holding only.

We next investigate the link between institutions and smoothing further by breaking the overall institutional holding into groups by investment types, as defined in Thomson Financial's 13F database. There are five major types of institutions. Type 1 is bank trusts, Type 2 is insurance companies, Type 3 consists of investment companies (primarily mutual funds), Type 4 is investment advisors (mostly large brokerage firms), and all the other institutions are classified as Type 5, which is mainly pension funds and endowments. The classification of institutions has changed at the end of 1998 as a result of Thomson database integration. While the aggregate institutional holding remains the same, the decomposition of holdings by type has a structural break, impossible to correct. As a result of this mapping error, starting from 1999 some portion of institutions classified as Types 1 through 4 are wrongly labeled as Type 5. To rely on the accurate classification, for the next part of our analysis we use the period of 1985-1998 as our main time period, but we still address the full time period in the robustness test.

We start by re-running the estimation of the overall number of shareholders, the number of institutions and their relative weight in the overall stock holding for the sub-sample of 1985-1998. The results are very similar to the ones reported in Table 3.B.8 and are not presented here. We then estimate the specification of Table 3.B.8 separately for each institution type and report the results in Table 3.B.9.

There is a substantial variation in firm characteristics that different types of institutions are attracted to. Panel A shows that Types 1 (bank trusts) and 5 (others) prefer to invest in large and mature firms (coefficients of *log(Age)* are 0.006 for both types), while Type 4 institutions (large brokerage firms) prefer smaller firms (coefficient of *Size* is -0.002). All institutional groups avoid high dividends, and prefer stocks with higher turnover and low return volatility. Similar patterns emerge when relative volatility is used as the smoothing measure (Panel B).

Interestingly, only mutual funds robustly hold a greater concentration in dividend smoothing firms. The coefficient on *SOA* is -0.014, the only one that is statistically significant in both panels. It also has the highest (absolute) value among all the types, with the exception of Type 4 in Panel A. The heterogeneity of institutional preferences for dividend smoothing stocks is especially noteworthy given that all types of institutions are similar in their avoidance of high dividend levels. It suggests that dividend level and the degree of dividend smoothing are dissimilar characteristics in their impacts on the investor decision whether or not to hold the stock.

For robustness, we re-estimate the equations using sales and market value as alternative measures of size, and obtain similar results. We also replace *DivYield* with *TotYield* and *Payout* as alternative measures of a firm's distribution of cash, and find that the results are close to the ones reported in Table 3.B.9. Finally, we rerun all the regressions above using the overall sample of 1985-2008, keeping in mind that the results should be interpreted with caution due to the mapping error in institutional types.[9] Including year dummy variables accounts for the time-series break in the proportion of institutions at the end of 1998 as a result of misclassification. Despite type coding inaccuracy, we still find that the dividend smoothing impact on institutional holding is pronounced mainly for Type 3 (mutual funds) investors. The results for Type 5 (others) are also significant, which is consistent with inclusion some of the mutual funds in the Type 5 category starting from 1999. For the sake of brevity,

[9] Brian Bushee (http://acct3.wharton.upenn.edu/faculty/bushee/IIclass.html) overcomes the problem of institutional misclassification by carrying the reliable type codes forward in time after 1998 and manually assigning types to new institutions, emerged after 1998. Unfortunately, his classification is not applicable in our study as it does not distinguish between types 3 and 4.

the results of the robustness tests are not presented here and are available upon request.

The finding that share holdings of stocks with smooth dividends are concentrated among mutual funds is particularly supportive of an agency cost explanation. Several authors document the monitoring ability of mutual funds. For example, Almazan, Hartzell and Starks (2005) present empirical evidence that independent advisors and investment company managers, who have skilled employees and low costs of information gathering, have advantages in monitoring of corporate management. Brickley, Lease and Smith (1988) show that mutual funds and independent investment advisors are more likely to vote their proxies against management. Kisin (2010) and Cella (2010) demonstrate that mutual funds influence corporate investments of a firm, including capital expenditures, R&D, and acquisitions. Further, this evidence is consistent with Leary and Michaely (2011) who find that dividend smoothing is most pronounced among firms most exposed to potential agency conflicts. On the other hand, the fact that individual investors do not display a preference for smooth dividends is less supportive of the behavioral explanations.

2. Dividend Smoothing and Equity Issuance

Another implication of the agency-based explanations for a dividend smoothing premium is that firms maintain a consistent dividend and avoid dividend cuts in order to ensure future low-cost access to external equity. To the extent that maintaining a smooth dividend is costly – either to the manager in terms of limiting private benefits or to the firm in terms of limiting investment – we would expect this behavior to be most prevalent among firms anticipating future equity issuance. In this section, we provide evidence for this motivation by examining the relationship between dividend smoothing and equity issuance decisions.

We obtain data on seasoned equity issues from the SDC Platinum database for the period 1985-2008. The sample includes all public equity issues by US firms with non-missing issuance date and CUSIP number. We merge the data with our main sample by using CUSIP, if available, and ticker, if not. To verify the validity of the merge, we calculate the summary statistics of the number of issues and obtain results similar to the previous studies (see, among others, Loughran and Ritter (1995) and Ritter (2003)).

We estimate issuance decisions using a logit regression where the dependent dummy variable takes a value of 1 if a firm issues in a given year, and zero otherwise. Our control variables include the main firm characteristics, such as size, M/B and profitability (*ROA*). We also use firm leverage to capture the trade-off forces that determine a firm's issuance decisions, and past stock returns (*Ret_mean*) to control for potential growth and market timing opportunities, which can provide firms with additional incentives to issue equity. Similarly to our previous estimations, we want to distinguish between the impact of dividend smoothing and dividend level, and therefore, include dividend yield in an alternative specification. All the specifications are estimated using *SOA* and *RelVol* to verify that the coefficients are robust to using different measures of dividend smoothing. The results are presented in Table 3.B.10.

The results in Panels A and B indicate that both smoothing measures have a negative and statistically significant impact on the issuance decisions of the firm, implying that firms that smooth their dividends, access external equity markets more often. Including additional variables, such as firm leverage, past returns and dividend yield does not change the magnitude of dividend smoothing coefficients in a material way. Overall, the results provide evidence that dividend smoothing is indeed associated with lower costs of access to external equity, and firms take advantage of it through more frequent issuances.

In a robustness test, we address a possible alternative explanation for our results, namely that firms committed to a smooth dividend policy are forced to access external equity markets if they do not have enough internal capital to maintain their dividend. In this case, the firm may issue equity and pay out the proceeds. However, if the alternative explanation is correct, our results are driven either by firms with relatively poor pre-issuance performance or by financially constrained firms. To address the first concern, we drop all the observations with negative ROA in period (*t-1*) and re-estimate our regression. Our results remain very close to the ones reported. To make sure that the results are not driven by financially constrained firms that do not have enough internal capital, we remove all firms that fall into the bottom quartile of *Cash* distribution (cash and short-term investments, scaled by total assets), and repeat the estimation. We find that re-estimating the results for firms that do not have problems with cash reserves also does not change our conclusions in a material way.

VI. Conclusion

This paper explores why managers care about dividend smoothing. First of all, it documents that investors place a higher value on stocks that distribute smooth dividends, and are willing to sacrifice a portion of the expected returns for holding those stocks. We show that portfolios of low dividend smoothing firms generate higher abnormal returns compared to high dividend smoothing firms in both a univariate setting and a four-factor Fama-French model. The level of dividend smoothing is also significant in explaining the cross-section of returns after controlling for risk-related characteristics, such as size, Book-to-Market, and momentum.

We then identify two potential channels (which are not mutually exclusive) through which dividend smoothing firms enjoy lower cost of capital. First, we ask whether dividend smoothing captures additional risk factors, which are not incorporated in the standard Fama-French three factor model. To test this hypothesis, we construct a dividend smoothing factor, using the methodology of Fama and French (1993), and find that the additional premium on firms that do not smooth their dividends can be at least partially attributed to risk differences. These results suggest that to the extent that firm characteristics proxy for firm risk, firms that do not smooth dividends are riskier, and require additional premium. We find evidence that the new smoothing risk factor, constructed as the difference between low and high smoothing firms, is significant in pricing the time-series of stock portfolios. Taken together, the results provide strong evidence that firms that do not smooth dividends bear additional risk, which is priced in the returns of their stocks. A by-product of our analysis is to show that a dividend smoothing factor helps explain the cross-section of stock returns. While beyond the scope of our current study, understanding the sources of these risk differentials is a question for future research.

Still, some of the return differential between smoothing and non-smoothing firms remains significant, so we turn to the non-risk based reasons that dividend smoothing firms may enjoy a lower cost of capital. We first document that institutional investors favor dividend smoothing firms, while retail investors do not have a pronounced preference for dividend smoothing policy. This runs counter to the predictions of the behavioral explanations, which suggest that retail investors will prefer smooth dividends.

We then present two pieces of evidence consistent with the role of dividend smoothing in mitigating the impact of agency conflicts on the cost of capital. First, we find that the preference for dividend smoothing is not shared among all types of institutions. In particular, only mutual funds exhibit a significant tendency to hold shares of firms that smooth. Previous literature has documented a wide range of advantages that a firm can gain by attracting mutual funds, including monitoring of corporate management and impact on a firm's investment policy. Second, we find that firms that smooth their dividends issue equity more frequently, suggesting that a demonstrated commitment to dividends facilitates access to external capital markets. Taken together, the results of this study provide the first evidence on why managers find dividend smoothing policy important.

APPENDIX 3.A: VARIABLE DEFINITIONS

Size: the natural log of book assets (AT) in constant 1993 dollars.

Age: the number of years since the firm first appeared in the CRSP database

M/B: the market value of equity, plus the book value of assets (AT) minus the book value of equity, all divided by the book value of assets.

Book value of equity: book assets minus book liabilities (LT) minus preferred stock plus deferred taxes (TXDITC).

Preferred stock: equals the liquidation value (PSTKL) if not missing; otherwise we use the redemption value (PSTKRV) if not missing; otherwise the carrying value (PSTK).

ln(ME): the log of market value of the firm as of June, *t*.

ln(BE/ME): the log of the ratio of book equity to market equity, as of December, *t-1*;

Invest: total number of common shareholders (CSHR), in thousands.

InstHold: we pick the holdings as they are reported in 13F at December of each year. It is defined as the sum of shares held by all the institutions, divided by the overall number of shares outstanding. If the data for institutional holdings is missing, we use the last available quarter of the year as a proxy for the end-of the year holdings. For firms that have no institutional reporting for the period we assign the value of zero. The variable is defined as the sum of shares held by all the institutions, divided by the overall number of shares outstanding.

InstNum: the overall number of institutions that hold shares of a firm, as reported in 13F.

Tangibility: the ratio of net property, plant and equipment (PPENT) to total assets.

Leverage: the sum of short-term (DLC) and long-term (DLTT) debt divided by total assets.

Adver: advertising expenses (XAD), scaled by book assets. Values of zero are assigned to missing observations.

R&D: expenses on research and development (XRD), scaled by book assets. Values of zero are assigned to missing observations.

Cash: cash and short-term investments (CHE), scaled by book assets.

Turnover: the annual average ratio of monthly traded volume of shares to total shares.

ROA: operating income before depreciation (OIBDP), scaled by total assets.

DPS: dividend per share (DVPSP_C).

EPS: earning per share (EPSPX).

DivYield: common dividends (DVC), scaled by the contemporaneous year-end market capitalization

TotYield: common dividends (DVC) plus repurchases, scaled by the contemporaneous year-end market capitalization

Repurchases: total expenditure on the purchase of common and preferred stocks (PRSTKC) plus any reduction in the value of the net number of preferred stocks outstanding (PSTKRV).

Payout: common dividends (DVC) divided by net income (IB).

RetVol: standard deviation of a firm's daily stock returns over a calendar year.

Beta: is computed in two steps. First, we estimate "pre-ranking beta" for each stock based on contemporaneous and market returns for CRSP value-weighted index. The sampling window is 60 month, when we require at least 24 month of non-missing return observations. The estimates are updated every June of year t, so that in June of every year we estimate beta over the past 5 years. To estimate post-ranking beta, we first sort stocks into size deciles each month using Fama and French (1993) size breakpoints[10]. Size breakpoints are based on allocating all the CRSP-Compustat data into deciles based on NYSE breakpoints. We further divide each size decile into 10 deciles, based on pre-ranking beta. For each of the resulting 100 size-beta portfolios we calculate equally-weighted monthly returns over the sample period. Finally, we regress the obtained monthly returns of each portfolio on the contemporaneous and lagged returns of the CRSP value-weighted index. The sum of the coefficient is the post-ranking beta used in the analysis, which is assigned to each stock in the specific size-postbeta group.

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[10] Obtained from Kenneth French website at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

APPENDIX 3.B: TABLES

Table 3.B.1. Cross-sectional Distribution of Smoothing Measures

The sample consists of Compustat firms for the period 1976-2008, excluding financial firms (SIC codes 6000-6999). The speed of adjustment SOA is estimates as $\tilde{\beta}$ from a modified partial adjustment model of Lintner (1956): $\Delta DPS_{i,t} = \alpha + \beta * dev_{i,t-1} + \epsilon_{i,t}$, where $dev_{i,t} = TPR_i * EPS_{i,t} - DPS_{i,t-1}$ and TPR_i is defined as the firm-median payout ratio (common dividends divided by net earnings) over the sample period. *DPS* and *EPS* are common dividends and earnings per share, respectively. *RelVol* is defined as the ratio of root mean square errors from the following two regressions: $AdjDPS_{i,t} = \alpha_1 + \beta_1 * t + \beta_2 * t^2 + +\epsilon_{i,t}$ and $TPR_i * AdjEPS_{i,t} = \alpha_2 + \gamma_1 * t + \gamma_2 * t^2 + +\eta_{i,t}$ where $AdjDPS_{i,t}$ and $AdjEPS_{i,t}$ are split-adjusted DPS and EPS series, and $TPR_i$is as defined previously. The split adjusted *DPS* (*EPS*) series is constructed by first calculating the split-adjusted change in *DPS* (*EPS*) each year. The split adjusted series for year *t* is then defined as $AdjDPS_{i,t} = DPS_{i,1} + \sum_{i=2}^{t} \Delta\, DPS_{i,t}$. Both measures are estimated for each of the 10-year rolling widow periods. As a result, we obtain a time-series of speed of adjustment (*SOA)* and relative volatility (*RelVol*) for the period of 1985-2008. For each rolling time period we require at least 8 non-missing observations and one positive dividend observation for the *SOA* estimation, and 6 consecutive observations for the estimate of *RelVol*. We also remove observations before each firm's first positive value for dividend per share and after each firm's last positive *DPS*. To mitigate the effect of outliers, we trim the top and bottom 2.5% of the resulting distribution of *SOA* and *RelVol*, and remove negative *SOA* values. We start by obtaining the median of the time-series variable for each firm. Then firms are sorted into quintiles based on their median *SOA* (Panel A) and *RelVol* (Panel B) and the means of the firm median characteristics are reported. *Size* is the log of total book assets in constant 1993 dollars; *Age* is the number of years since the firm first appeared in the CRSP database; *Tangibility* is the ratio of net property, plant and equipment to total assets; *M/B*: the market value of equity, plus the book value of assets minus the book value of equity, all divided by the book value of assets; *RetVol* is the deviation of a firm's daily stock returns over a calendar year; *Beta* is the firm's post-ranking beta, following the Fama and French (1992) methodology. *InstHold* are obtained from 13F reports, as of December of each year. It is defined as the sum of shares held by all the institutions, divided by the overall number of shares outstanding. To aggregate institutional holdings across firms and years we use the mean, rather than median institutional holding of a firm. *Turnover* is the annual average ratio of monthly traded volume of shares to total shares; *Payout* ratio is defined as common dividends scaled by net income. *DivYield* is *DPS* divided by the year-end share price; *Leverage* is the sum of short-term and long-term debt divided by total assets. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively.

Table 3.B.1 (Continued)

Panel A: Speed of Adjustment

Characteristic	**1**	**2**	**3**	**4**	**5**	**t-stat (5-1)**
SOA	0.034	0.091	0.150	0.235	0.440	***
Size	6.996	6.856	6.681	6.415	6.155	***
Age	26.51	26.19	23.29	20.26	18.03	***
Tangibility	0.377	0.330	0.293	0.269	0.256	***
M/B	1.273	1.318	1.290	1.396	1.457	***
RetVol	0.020	0.022	0.023	0.023	0.025	***
Beta	0.883	0.963	1.016	1.015	1.089	***
InstHold	0.359	0.353	0.333	0.332	0.297	***
Turnover	0.627	0.622	0.619	0.619	0.634	**
Payout	0.528	0.491	0.319	0.301	0.239	***
DivYield	0.033	0.038	0.032	0.030	0.020	***
Leverage	0.281	0.253	0.243	0.229	0.222	***

Panel B: Relative Volatility

Characteristic	**1**	**2**	**3**	**4**	**5**	**t-stat (5-1)**
RelVol	0.094	0.202	0.323	0.500	0.997	***
Size	6.907	6.940	6.685	6.532	6.332	***
Age	27.16	25.84	24.28	20.18	19.38	***
Tangibility	0.395	0.320	0.292	0.256	0.260	***
M/B	1.272	1.297	1.320	1.409	1.489	***
RetVol	0.020	0.022	0.022	0.023	0.024	***
Beta	0.856	0.944	0.995	1.026	1.013	***
InstHold	0.354	0.354	0.342	0.328	0.327	*
Turnover	0.557	0.658	0.588	0.657	0.701	***
Payout	0.450	0.369	0.520	0.285	0.325	***
DivYield	0.036	0.029	0.037	0.027	0.022	***
Leverage	0.268	0.265	0.243	0.214	0.217	***

Table 3.B.2. Time-series Distribution of the Dividend Smoothing Measures

Table 3.B.2 presents the distribution of the smoothing measures (Panel A), and their stability over time (*SOA* in Panel B and *RelVol* in Panel C). The sample consists of Compustat firms for the period 1985-2008, excluding financial firms (SIC codes 6000-6999). See Table 3.B.1 for description of the estimation methodology of *SOA* and *RelVol*. To calculate stability of the smoothing measures, very year the overall sample is divided into deciles based on *SOA* [*RelVol*]. The bottom *SOA* [*RelVol*] decile consists of firms with the highest degree of dividend smoothing, while the top *SOA* [*RelVol*] decile includes firms with the lowest dividend smoothing policy. In each year *t* we calculate the difference between the firm's future ranking (as of years *(t+1)* and *(t+5),* respectively) and the firm's current smoothing ranking and present the percentage of firms that experienced changes in their smoothing ranking of that magnitude. Thus, "0" refers to the percentage of firms which dividend smoothing ranking between year *t* and year *(t+1)* [*(t+5)*] remained unchanged. Negative changes indicate an increase in the degree of dividend smoothing of a firm, when it moves to a lower decile of *SOA*[*RelVol*] over time. Positive changes indicate transition to less dividend smoothing policy over time. By construction, the maximal possible change in ranking is +/-9, when a firm moves from the top to the bottom smoothing decile, or vice versa.

Table 3.B.2 (Continued)

Panel A: Distribution of the Dividend Smoothing Measures

Smoothing measure	Mean	Std Dev	25th Pctl	Median	75th Pctl
SOA	0.18	0.16	0.06	0.13	0.26
RelVol	0.41	0.38	0.14	0.29	0.55

Difference between the rank of the smoothing decile in year (t+1) [(t+2)] and the rank of the smoothing decile in year t	Panel B: SOA		Panel C: RelVol	
	Percentage of firms after one year	Percentage of firms after five years	Percentage of firms after one year	Percentage of firms after five years
9	0.06	0.18	0.00	0.15
8	0.10	0.5	0.05	0.34
7	0.21	0.84	0.12	0.78
6	0.43	1.23	0.14	1.04
5	0.60	1.95	0.44	1.92
4	0.92	3.07	0.80	2.95
3	1.80	5.7	2.25	5.34
2	3.96	9.21	5.54	9.05
1 (Rank increase of one decile)	12.79	14.08	15.76	14.07
0 (No change in ranking)	57.62	20.01	51.35	21.03
-1 (Rank decrease of one decile)	14.87	14.36	16.05	14.58
-2	3.73	10.08	4.46	10.19
-3	1.39	6.57	1.70	7.00
-4	0.71	4.63	0.70	4.97
-5	0.37	3.2	0.31	2.8
-6	0.24	1.97	0.13	1.92
-7	0.08	1.18	0.13	1.07
-8	0.06	0.79	0.05	0.60
-9	0.04	0.46	0.02	0.20

Table 3.B.3. Smoothing and Returns – Univariate Analysis

Table 3.B.3 presents the distribution of stock returns across deciles of dividend smoothing measures (*SOA* in Panel A and *RelVol* in Panel B) over time. The sample consists of firms that appear both in Compustat and CRSP during the period 1985-2008, excluding financial firms (SIC codes 6000-6999). See Table 3.B.1 for description of the estimation methodology of *SOA* and *RelVol*. We first divide the sample into deciles based on the smoothing measure and then calculate average and median monthly returns across firms and years in each smoothing decile. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively.

Panel A			**Panel B**		
Rank for SOA	**Mean**	**Median**	**Rank for RelVol**	**Mean**	**Median**
low SOA	0.95%	1.09%	low RelVol	0.94%	1.05%
1	1.10%	1.20%	1	1.03%	1.16%
2	1.05%	1.16%	2	1.07%	1.16%
3	1.13%	1.13%	3	1.12%	1.17%
4	1.05%	1.10%	4	1.02%	1.06%
5	1.10%	1.25%	5	1.11%	1.22%
6	1.18%	1.21%	6	1.16%	1.15%
7	1.17%	1.21%	7	1.20%	1.24%
8	1.34%	1.28%	8	1.23%	1.26%
High SOA	1.35%	1.31%	High RelVol	1.20%	1.22%
t-stat (High-Low)	**5.29*****		**t-stat (High-Low)**	**3.55*****	

Table 3.B.4. Factor Regressions on Portfolios of Smoothing

Table 3.B.4 presents the intercepts of factor regressions of monthly returns of portfolios, formed based on the degree of a firm's dividend smoothing, as a function of Fama and French (1993) three risk factors plus the momentum factor. The sample consists of firms that appear both in Compustat and CRSP during the period 1985-2008, excluding financial firms (SIC codes 6000-6999). The dependent variable is monthly stock returns of portfolios of different levels of dividend smoothing. Every year we assign the sample firms into deciles based on *SOA* [RelVol] and form three portfolios: High *SOA* [*RelVol*] portfolio consists of all the firms that belong to the top three *SOA* [*RelVol*] deciles; Low *SOA* [*RelVol*] portfolio consists of all the firms that belong to the bottom three *SOA* [*RelVol*] deciles; Medium *SOA* [*RelVol*] portfolio consists of all the firms that belong to deciles 4 through 7 of *SOA* [*RelVol*]. See Table 3.B.1 for the description of the estimation methodology of *SOA* and *RelVol*. We then compute equally or value weighted (by *ME*) returns on the portfolio for the following year. The sample is re-sorted into portfolios of smoothing every year. The time-series returns of each portfolio ($R_{p,t}$) is then regressed on four risk factors. The equation is

$$R_{p,t} - R_{f,t} = \alpha + \beta_1\left[R_{m,t} - R_{f,t}\right] + \beta_2 * SMB_t + \beta_3 * HML_t + \beta_4 * MOM_t + \varepsilon_t,$$

where ($R_{f,t}$) is the risk-free rate; ($R_{m,t}$) is the market portfolio, based on all NYSE, AMEX and NASDAQ stocks; SMB_t is the small minus big factor return; HML_t is the high minus low factor return; and MOM_t is the momentum factor. The table presents the values, standard errors and t Value of the intercept (α) of each regression.

Panel A: SOA

	Value-Weighted			Equally-Weighted		
Portfolios	**Parameter Estimate**	**Standard Error**	**t Value**	**Parameter Estimate**	**Standard Error**	**t Value**
High SOA	0.69	0.11	6.19	0.69	0.09	7.79
Medium SOA	0.56	0.10	5.78	0.49	0.08	6.30
Low SOA	0.46	0.09	5.38	0.49	0.07	6.61
High minus Low	0.23	0.09	2.54	0.20	0.07	2.95

Panel B: RelVol

	Value-Weighted			Equally-Weighted		
Portfolios	**Parameter Estimate**	**Standard Error**	**t Value**	**Parameter Estimate**	**Standard Error**	**t Value**
High RelVol	0.70	0.12	6.08	0.70	0.09	7.70
Medium RelVol	0.55	0.09	5.94	0.50	0.08	6.17
Low RelVol	0.49	0.10	4.68	0.48	0.08	6.30
High minus Low	0.21	0.09	2.27	0.22	0.07	3.19

Table 3.B.5. Smoothing and Returns – Characteristics Regression

Table 3.B.5 presents the results of a Fama-MacBeth (1973) estimation of monthly stock returns as a function of firm characteristics and dividend smoothing variables (*SOA* and *RelVol* in Panels A and B, respectively). See Table 3.B.1 for the description of the estimation methodology of *SOA* and *RelVol*. The sample consists of firms that appear in both Compustat and CRSP during the period 1985-2008, excluding financial firms (SIC codes 6000-6999). Cross-sectional regressions of raw monthly stock returns are estimated every month (total of 278 estimations), and the distribution of the coefficients (mean and standard deviation) is reported in the table. *ln(ME)* is the log of market value of the firm as of June, *t*. *ln(BE/ME)* is the ratio of book equity to market equity, as of December, *t-1*; Beta is the post-ranking beta, as estimated in Fama and French (1992); *ln(DivYield)* is the logarithm of 0.01 plus *DivYield*, where *DivYield* is common dividend divided by market value, *ME*, as of year *t-1*; *ln(TotYield)* is the logarithm of 0.01 plus *TotYield*, where *TotYield* is common dividend divided plus common share repurchases, divided by market value, *ME*, as of year *t-1*. Time-series standard deviation is reported in parenthesis. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively.

Panel A				Panel B			
	(1)	(2)	(3)		(4)	(5)	(6)
Intercept	1.241***	1.526***	1.331***	*Intercept*	1.198***	1.411***	1.21***
	(6.603)	*(6.527)*	*(6.732)*		*(6.726)*	*(6.718)*	*(7.021)*
Beta	0.054	-0.046	0.04	*Beta*	0.091	0.024	0.115
	(5.337)	*(5.071)*	*(5.173)*		*(5.336)*	*(5.051)*	*(5.215)*
ln(ME)	-0.016	-0.007	-0.012	*ln(ME)*	-0.014	-0.005	-0.004
	(0.685)	*(0.678)*	*(0.685)*		*(0.697)*	*(0.689)*	*(0.7)*
ln(BE/ME)	0.079	0.17**	0.149**	*ln(BE/ME)*	0.066	0.137**	0.13*
	(0.843)	*(1.102)*	*(1.113)*		*(0.891)*	*(1.132)*	*(1.129)*
ln(DivYield)		-0.151**		*ln(DivYield)*		-0.125	
		(1.11)				*(1.305)*	
ln(TotYield)			-0.058	*ln(TotYield)*			-0.059
			(0.945)				*(1.008)*
SOA	0.524***	0.481**	0.532***	*RelVol*	0.165**	0.134*	0.157**
	(3.068)	*(3.129)*	*(3.242)*		*(1.25)*	*(1.256)*	*(1.275)*

Table 3.B.6. Dividend Smoothing as a Factor

This table presents the results of estimating excess returns of stock portfolios as a function of Fama and French three factor model, dividend yield and dividend smoothing factors. The sample consists of Compustat firms for the period 1985-2008, excluding financial firms (SIC codes 6000-6999). The dependent variables are excess returns on the 15 Dividend payout yield - Smoothing portfolios. To construct them, we first sort the sample into deciles of dividend yield and allocate firms into groups of Low (deciles 1-3), Medium (deciles 4-7), and High (deciles 8-10) dividend yields. Next, we allocate firms in each dividend yield group into quintiles of dividend smoothing. Every year we compute the weighted average returns of each of the resulting 15 portfolios. The regression equation is:

$$R_{p,t} - R_{f,t} = \alpha + \beta_1\left[R_{m,t} - R_{f,t}\right] + \beta_2 * SMB_t + \beta_3 * HML_t + \beta_4 * MOM_t + \beta_5 * DivYieldHML_t + \beta_6 * SmoothLMH_t + \varepsilon_t$$

where $(R_{f,t})$ is the risk-free rate; $(R_{m,t})$ is the market portfolio, based on all NYSE, AMEX and NASDAQ stocks; SMB_t is the small minus big factor return; HML_t is the high minus low factor return; MOM_t is the momentum factor; $DivYieldHML_t$ is the dividend yield factor, and $SmoothLMH_t$ is the dividend smoothing factor. *DivYield* is common dividend divided by market value. The table presents the values and t-stat of the intercept (α) and coefficients on dividend yield and dividend smoothing factors (β_5 and β_6, respectively) of each regression. In Panel A dividend smoothing portfolios and dividend smoothing factor is constructed based on *SOA* measure, and Panel B repeats the same analysis using *RelVol*. See Table 3.B.1 for the description of the estimation methodology of *SOA* and *RelVol*.

Table 3.B.6 (Continued)

Panel A: SOA

Dividend Yield	**Low SOA**	**2**	**3**	**4**	**High SOA**	**High-Low**	**Low SOA**	**2**	**3**	**4**	**High SOA**	**High-Low**
			α						**t-stat (α)**			
Low	0.36	0.50	0.46	0.13	0.23	**-0.12**	2.68	3.04	2.69	0.84	1.39	**-0.74**
Medium	0.40	0.31	0.43	0.48	0.71	**0.31**	2.98	2.30	3.12	3.48	5.38	**2.39**
High	0.41	0.51	0.40	0.51	0.40	**-0.01**	0.41	0.51	0.40	0.51	0.40	**-0.01**

Dividend Yield	**Low SOA**	**2**	**3**	**4**	**High SOA**	**High-Low**	**Low SOA**	**2**	**3**	**4**	**High SOA**	**High-Low**
			β_5(*DivYield* HML)						**t-stat (β_5)**			
Low	-0.41	-0.37	-0.36	-0.51	-0.28	**0.13**	-7.25	-5.26	-5.00	-7.78	-3.87	**1.89**
Medium	-0.11	-0.16	-0.30	-0.15	-0.18	**-0.07**	-1.91	-2.77	-5.01	-2.51	-3.21	**-1.29**
High	0.51	0.41	0.50	0.45	0.36	**-0.15**	9.07	7.34	7.97	7.08	5.69	**-1.93**

Dividend Yield	**Low SOA**	**2**	**3**	**4**	**High SOA**	**High-Low**	**Low SOA**	**2**	**3**	**4**	**High SOA**	**High-Low**
			β_6(*Smooth* LMH)						**t-stat (β_6)**			
Low	-0.30	-0.30	0.15	0.43	1.03	**1.33**	-3.53	-2.80	1.39	4.27	9.52	**12.38**
Medium	-0.03	0.01	0.17	0.27	0.54	**0.57**	-0.40	0.06	1.91	3.07	6.36	**6.87**
High	-0.08	-0.23	0.07	0.11	0.55	**0.63**	-0.94	-2.66	0.71	1.20	5.70	**5.32**

Table 3.B.6 (Continued)

Panel B: RelVol

Dividend Yield	Low RelVol	2	3	4	High RelVol	High-Low	Low RelVol	2	3	4	High RelVol	High-Low
	alpha						t-stat (alpha)					
Low	0.37	0.63	0.26	0.30	0.36	**-0.01**	2.28	3.63	1.63	1.77	2.18	**-0.06**
Medium	0.33	0.55	0.53	0.42	0.70	**0.38**	2.39	3.57	3.90	3.15	4.69	**2.77**
High	0.56	0.63	0.49	0.09	0.45	**-0.12**	3.90	4.18	3.21	0.48	2.59	**-0.57**

Dividend Yield	Low RelVol	2	3	4	High RelVol	High-Low	Low RelVol	2	3	4	High RelVol	High-Low
	β_5(*DivYield* HML)						t-stat (β_5)					
Low	-0.47	-0.54	-0.20	-0.31	-0.21	**0.26**	-6.55	-7.16	-2.94	-4.25	-2.88	**3.39**
Medium	-0.22	-0.26	-0.15	-0.05	-0.12	**0.10**	-3.73	-3.89	-2.63	-0.92	-1.78	**1.79**
High	0.41	0.62	0.49	0.43	0.37	**-0.04**	6.63	9.60	7.44	5.35	5.02	**-0.45**

Dividend Yield	Low RelVol	2	3	4	High RelVol	High-Low	Low RelVol	2	3	4	High RelVol	High-Low
	β_6(*Smooth* LMH)						t-stat (β_6)					
Low	-0.68	-0.37	0.15	0.48	0.59	**1.26**	-6.65	-3.40	1.46	4.59	5.68	**11.56**
Medium	-0.15	-0.32	0.15	0.02	0.42	**0.57**	-1.76	-3.34	1.85	0.27	4.50	**6.73**
High	-0.10	0.02	-0.12	-0.03	0.33	**0.43**	-1.10	0.17	-1.31	-0.24	3.12	**3.33**

Table 3.B.7. Institutional Holdings by Dividend Yield and Smoothing

This table presents the overall number of common shareholders, in thousands *(# Invest*), the overall number of institutions (*InstNum*) and the proportion of institutional holdings (*InstHold*) out of the overall investor holdings by quintiles of dividend smoothing and *Div yield*. The sample consists of Compustat firms for the period 1985-2008, excluding financial firms (SIC codes 6000-6999). The groups are formed by independently partitioning the sample by *SOA* in the left column [*RelVol* in the right column] and also partitioning the sample by *Div yield* quintiles. Reported averages are cross-sectional averages for firm-year observation in each of the resulting 25 smoothing-*Div yield* groups. See Table 3.B.1 for the description of the estimation methodology of *SOA* and *RelVol*. *Div yield* is common dividend divided by market value, *ME*; *InstNum* and *InstHold* are obtained from 13F reports, as of December of each year. *InstHold* is defined as the sum of shares held by all the institutions, divided by the overall number of shares outstanding.

Panel A: *#Invest*

	Low	2	3	4	High
SOA			***DivYield***		
Low	13.3	15.7	18.8	28.2	41.7
2	17.7	16.1	19.7	24.3	39.7
3	15.5	21.0	17.6	60.0	35.7
4	12.6	14.1	12.7	21.0	24.3
High	13.3	17.2	16.0	21.8	27.7
t-stat(High-Low)					***

	Low	2	3	4	High
RelVol			***DivYield***		
Low	16.9	20.2	22.6	27.4	37.2
2	22.0	20.9	19.5	27.9	38.4
3	14.4	15.0	14.6	56.7	33.6
4	13.4	14.1	13.2	17.1	26.4
High	21.0	24.8	23.6	30.9	23.5
t-stat(High-Low)					***

Panel B: *InstNum*

	Low	2	3	4	High
SOA			***DivYield***		
Low	153.4	164.3	167.6	148.6	108.4
2	137.1	156.4	150.5	130.6	96.9
3	138.9	145.0	141.4	104.9	79.2
4	111.3	133.7	111.7	96.2	69.0
High	99.2	130.9	111.9	85.3	59.4
t-stat(High-Low)	***	***	***	***	***

	Low	2	3	4	High
RelVol			***DivYield***		
Low	206.8	179.3	192.7	147.2	100.2
2	167.4	162.4	160.4	129.6	97.3
3	138.2	151.4	130.4	109.5	86.1
4	127.7	132.5	107.0	96.8	69.9
High	127.0	142.8	119.8	106.4	63.6
t-stat(High-Low)	***	***	***	***	***

Panel C: *InstHold*

	Low	2	3	4	High
SOA			***DivYield***		
Low	0.50	0.49	0.49	0.41	0.26
2	0.41	0.46	0.42	0.37	0.24
3	0.40	0.43	0.41	0.36	0.22
4	0.39	0.42	0.37	0.33	0.21
High	0.34	0.39	0.34	0.29	0.20
t-stat(High-Low)	***	***	***	***	***

	Low	2	3	4	High
RelVol			***DivYield***		
Low	0.56	0.51	0.49	0.41	0.24
2	0.45	0.45	0.43	0.38	0.22
3	0.43	0.43	0.40	0.34	0.23
4	0.42	0.42	0.37	0.33	0.21
High	0.40	0.39	0.36	0.33	0.22
t-stat(High-Low)	***	***	***	***	**

Table 3.B.8. Multivariate Regression of Individual and Institutional Holding

This table reports the results of estimating OLS regressions, where the dependent variables are the logarithm of shareholder base (*ln(# Invest)*), and the logarithms of 1 plus the number and the proportion of institutions, invested in a stock (variables *ln(InstNum)* and *ln(InstHold)*, respectively. The sample consists of Compustat firms for the period 1985-2008, excluding financial firms (SIC codes 6000-6999). See Table 3.B.1 and Appendix 3.A for the description of the independent variables. All estimation models include year fixed effects. Standard errors are reported in parenthesis and are based on heteroskedastic consistent errors adjusted for clustering across firms (Rogers (1993)). ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively.

	Panel A			Panel B		
Independent\Dependent variable	*ln(# Invest)*	*ln(InstNum)*	*ln(InstHold)*	*ln(# Invest)*	*ln(InstNum)*	*ln(InstHold)*
Intercept	-5***	-2.851***	-0.085***	-5.078***	-2.774***	-0.052*
	(0.17)	*(0.263)*	*(0.026)*	*(0.185)*	*(0.29)*	*(0.028)*
SOA	0.225**	-0.466***	-0.069***			
	(0.098)	*(0.128)*	*(0.014)*			
RelVol				0.066	-0.231***	-0.023***
				(0.044)	*(0.055)*	*(0.006)*
Size	0.567***	0.272***	0.012***	0.576***	0.275***	0.012***
	(0.013)	*(0.018)*	*(0.002)*	*(0.014)*	*(0.02)*	*(0.002)*
log(Age)	0.345***	0.225***	0.009*	0.334***	0.223***	0.006
	(0.033)	*(0.044)*	*(0.005)*	*(0.037)*	*(0.051)*	*(0.005)*
Return	-1.277***	-1.556***	-0.224***	-1.157***	-1.592***	-0.236***
	(0.271)	*(0.353)*	*(0.04)*	*(0.295)*	*(0.393)*	*(0.045)*
ROA	-0.118	2.244***	0.297***	-0.089	2.658***	0.376***
	(0.199)	*(0.337)*	*(0.043)*	*(0.241)*	*(0.357)*	*(0.04)*
Adver	1.265***	1.464**	0.113*	1.486***	1.289*	0.098
	(0.342)	*(0.667)*	*(0.061)*	*(0.368)*	*(0.696)*	*(0.063)*
R&D	3.195***	1.045	0.299**	2.75***	0.244	0.262**
	(0.59)	*(1.213)*	*(0.125)*	*(0.649)*	*(1.19)*	*(0.124)*
1/Price	0.083***	-0.061**	-0.008**	0.156**	-0.095	-0.013
	(0.031)	*(0.028)*	*(0.004)*	*(0.063)*	*(0.061)*	*(0.008)*
log(Turnover)	0.089***	0.257***	0.073***	0.095***	0.257***	0.073***
	(0.024)	*(0.028)*	*(0.003)*	*(0.026)*	*(0.03)*	*(0.003)*
log(RetVol)	-0.105**	-0.11*	-0.039***	-0.133***	-0.075	-0.029***
	(0.041)	*(0.061)*	*(0.006)*	*(0.045)*	*(0.066)*	*(0.007)*
M/B	0.242***	0.233***	-0.0003	0.235***	0.247***	-0.002
	(0.024)	*(0.036)*	*(0.004)*	*(0.026)*	*(0.033)*	*(0.004)*
Leverage	-0.091	-0.597***	-0.006	-0.16	-0.582***	-0.007
	(0.123)	*(0.159)*	*(0.017)*	*(0.135)*	*(0.179)*	*(0.019)*
DivYield	2.831***	-2.169***	-0.392***	3.107***	-2.57***	-0.483***
	(0.3)	*(0.352)*	*(0.044)*	*(0.454)*	*(0.51)*	*(0.064)*
Tangibility	1.355***	-0.232*	-0.064***	1.461***	-0.278**	-0.074***
	(0.089)	*(0.131)*	*(0.009)*	*(0.092)*	*(0.139)*	*(0.014)*
Obs.	*26023*	*29100*	*29100*	*24099*	*26667*	*26667*
# of firms/clusters	*2648*	*3081*	*3081*	*2445*	*2845*	*2845*
R-squared adj.	0.623	0.346	0.356	0.644	0.368	0.377

Table 3.B.9. Multivariate Regression of Institutional Holding by Institutional Type

This table reports the results of estimating OLS regressions, where the dependent variable is the logarithms of 1 plus the weight of the institutional holding of each type out of the overall holdings of a stock. Only observations with positive holdings are included. *Type1* is bank trusts, *Type2* is insurance companies, *Type3* consists of investment companies (primarily mutual funds), *Type4* is investment advisors, and *Type5* is all the other institutions. The sample consists of Compustat firms for the period 1985-1998, excluding financial firms (SIC codes 6000-6999). See Table 3.B.1 and Appendix 3.A for the description of the independent variables. All estimation models include year fixed effects. Standard errors are reported in parenthesis and are based on heteroskedastic consistent errors adjusted for clustering across firms (Rogers (1993)). ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively.

Table 3.B.9 (Continued)

Panel A: SOA

Independent\Dependent variable	*Type1*	*Type2*	*Type3*	*Type4*	*Type5*
Intercept	-0.083***	0.014	0.227***	0.241***	0.081***
	(0.013)	*(0.009)*	*(0.011)*	*(0.016)*	*(0.008)*
SOA	0.0018	-0.0087**	-0.014***	-0.018*	-0.006
	(0.008)	*(0.004)*	*(0.005)*	*(0.009)*	*(0.005)*
Size	0.013***	0.001*	0.001	-0.002*	0.006***
	(0.001)	*(0.001)*	*(0.001)*	*(0.001)*	*(0.0005)*
log(Age)	0.006***	0.003	-0.001	0.003	0.006***
	(0.002)	*(0.002)*	*(0.002)*	*(0.003)*	*(0.001)*
Return	-0.048**	-0.05***	0.03*	-0.032	-0.123***
	(0.022)	*(0.016)*	*(0.018)*	*(0.031)*	*(0.015)*
ROA	0.077***	0.009	0	0.1***	0.041***
	(0.024)	*(0.01)*	*(0.01)*	*(0.023)*	*(0.01)*
Adver	0.039	-0.046***	-0.041***	0.008	-0.005
	(0.041)	*(0.011)*	*(0.015)*	*(0.03)*	*(0.009)*
R&D	0.134***	0.043*	0.056*	0.171***	0.121***
	(0.051)	*(0.025)*	*(0.03)*	*(0.056)*	*(0.03)*
1/Price	-0.001	0.001	-0.028***	-0.008*	-0.001
	(0.001)	*(0.006)*	*(0.009)*	*(0.005)*	*(0.0004)*
log(Turnover)	0.011***	0.01***	0.018***	0.054***	0.013***
	(0.002)	*(0.001)*	*(0.002)*	*(0.002)*	*(0.001)*
log(RetVol)	-0.02***	-0.01***	-0.006*	-0.039***	-0.008***
	(0.003)	*(0.003)*	*(0.004)*	*(0.004)*	*(0.002)*
M/B	0.003*	0.002*	0	-0.009***	0.003***
	(0.002)	*(0.001)*	*(0.001)*	*(0.002)*	*(0.001)*
Leverage	-0.041***	0.006	0.012**	0.033***	0
	(0.008)	*(0.007)*	*(0.006)*	*(0.011)*	*(0.004)*
DivYield	-0.023	-0.039**	-0.068***	-0.185***	-0.043***
	(0.015)	*(0.017)*	*(0.011)*	*(0.026)*	*(0.009)*
Tangibility	-0.006	-0.003	-0.001	-0.046***	-0.003
	(0.006)	*(0.004)*	*(0.01)*	*(0.008)*	*(0.003)*
Obs.	*14052*	*11932*	*10827*	*14092*	*12616*
# of firms/clusters	*2049*	*1811*	*1759*	*2036*	*1897*
R-squared adj.	0.240	0.069	0.312	0.294	0.424

Table 3.B.9 (Continued)

Panel B: RelVol

Independent\Dependent variable	*Type1*	*Type2*	*Type3*	*Type4*	*Type5*
Intercept	-0.064***	0.017**	0.22***	0.285***	0.08***
	(0.015)	*(0.008)*	*(0.014)*	*(0.02)*	*(0.008)*
RelVol	-0.0045	-0.0002	-0.008***	0.0001	-0.001
	(0.003)	*(0.002)*	*(0.002)*	*(0.004)*	*(0.002)*
Size	0.015***	0.002***	0.0003	-0.002**	0.007***
	(0.001)	*(0.001)*	*(0.001)*	*(0.001)*	*(0.001)*
log(Age)	0.005*	0.002	-0.0001	0.004	0.006***
	(0.003)	*(0.002)*	*(0.002)*	*(0.003)*	*(0.001)*
Return	-0.054**	-0.061***	0.018	-0.1***	-0.129***
	(0.025)	*(0.019)*	*(0.022)*	*(0.038)*	*(0.016)*
ROA	0.109***	0.032***	-0.004	0.12***	0.055***
	(0.025)	*(0.011)*	*(0.02)*	*(0.023)*	*(0.01)*
Adver	0.047	-0.051***	-0.06***	0.005	-0.008
	(0.046)	*(0.013)*	*(0.017)*	*(0.033)*	*(0.009)*
R&D	0.105*	0.049*	0.037	0.167***	0.127***
	(0.054)	*(0.027)*	*(0.032)*	*(0.059)*	*(0.031)*
1/Price	0.002*	0.008	-0.038*	-0.053**	-0.003
	(0.001)	*(0.008)*	*(0.022)*	*(0.022)*	*(0.005)*
log(Turnover)	0.01***	0.011***	0.014***	0.053***	0.013***
	(0.002)	*(0.001)*	*(0.004)*	*(0.002)*	*(0.001)*
log(RetVol)	-0.014***	-0.008***	-0.002	-0.026***	-0.006***
	(0.003)	*(0.002)*	*(0.006)*	*(0.005)*	*(0.002)*
M/B	0.003	0.001	0.002	-0.011***	0.003**
	(0.002)	*(0.001)*	*(0.003)*	*(0.002)*	*(0.001)*
Leverage	-0.051***	0.006	0.016*	0.035***	0.003
	(0.009)	*(0.007)*	*(0.008)*	*(0.013)*	*(0.004)*
DivYield	-0.046***	-0.058***	-0.082***	-0.223***	-0.052***
	(0.015)	*(0.013)*	*(0.016)*	*(0.039)*	*(0.019)*
Tangibility	-0.007	-0.007	-0.004	-0.051***	-0.005
	(0.007)	*(0.004)*	*(0.016)*	*(0.008)*	*(0.003)*
Obs.	*12974*	*11084*	*10087*	*12965*	*11728*
# of firms/clusters	*1887*	*1853*	*1613*	*1873*	*1745*
R-squared adj.	0.250	0.087	0.281	0.292	0.446

Table 3.B.10. Logit Regression of SEOs and Dividend Smoothing

This table reports the results of estimating logit regressions, where the dependent variables takes a value of one if a firm raises public equity (Seasoned Equity Offering) in year *t*, and zero otherwise. The sample consists of Compustat firms for the period 1985-2008, excluding financial firms (SIC codes 6000-6999). Equity issues are obtained from SDC Platinum and include all public equity issues by US firms. See Table 3.B.1 for the description of the independent variables. All estimation models include year fixed effects. Standard errors are reported in parenthesis and are based on heteroskedastic consistent errors adjusted for clustering across firms (Rogers (1993)). ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively.

	Panel A			Panel B		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-4.385***	-4.591***	-4.611***	-4.183***	-4.413***	-4.457***
	(0.253)	*(0.265)*	*(0.265)*	*(0.267)*	*(0.274)*	*(0.273)*
SOA	-0.592**	-0.433*	-0.421*			
	(0.261)	*(0.253)*	*(0.253)*			
RelVol				-0.554***	-0.494***	-0.481***
				(0.137)	*(0.131)*	*(0.131)*
log(sale)	0.176***	0.169***	0.17***	0.156***	0.146***	0.146***
	(0.022)	*(0.022)*	*(0.022)*	*(0.024)*	*(0.023)*	*(0.023)*
M/B	-0.051	-0.028	-0.026	-0.057	0.019	0.025
	(0.071)	*(0.08)*	*(0.08)*	*(0.072)*	*(0.068)*	*(0.068)*
ROA	-1.858***	-2.512***	-2.519***	-2.464***	-3.429***	-3.445***
	(0.543)	*(0.802)*	*(0.813)*	*(0.482)*	*(0.502)*	*(0.503)*
Lev		2.28***	2.254***		2.488***	2.44***
		(0.192)	*(0.192)*		*(0.204)*	*(0.203)*
Ret_mean		11.218***	11.269***		10.874***	10.983***
		(1.087)	*(1.084)*		*(1.213)*	*(1.214)*
DivYield			0.531			1.068**
			(0.439)			*(0.489)*
Obs.	*29,144*	*29,084*	*29,077*	*26,713*	*26,674*	*26,668*
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Likelihood Ratio	372.17	615.75	616.71	342.86	561.28	564.21
P(Chi-squared)	0	0	0	0	0	0

REFERENCES

Allen, Franklin, Antonio E. Bernardo, and Ivo Welch, 2000, A Theory of Dividends Based on Tax Clienteles, *Journal of Finance*, 55, 2499–2536.

Almazan, Andres, Jay C. Hartzell and Laura T. Starks, 2005, Active Institutional Shareholders and Costs of Monitoring: Evidence from Executive Compensation, *Financial Management*, 34, 5–34.

Amihud, Yakov, 2002, Illiquidity and Stock Returns: Cross-Section and Time-Series Effects, *Financial Markets*, 5, 31–56.

Baker, M., S. Nagel, and J. Wurgler. 2007. The Effect of Dividends on Consumption. *Brookings Papers on Economic Activity* 1:231–91.

Baker, Malcolm, and Jeffrey Wurgler, 2010, Signaling with Reference Points: Behavioral Foundations for the Lintner Model of Dividends, *Working Paper*, Harvard University.

Berk, Jonathan and Peter DeMarzo, 2007, *Corporate Finance*, Boston, MA: Pearson-Addison Wesley.

Boudoukh, Jacob, Roni Michaely, Matthew Richardson, and Michael M. Roberts, 2007, On the Importance of Measuring Payout Yield: Implications for Empirical Asset Pricing, *Journal of Finance*, 62, 877–915.

Brav, Alon, John Graham, Campbell Harvey, and Roni Michaely, 2005, Payout Policy in the 21st Century, *Journal of Financial Economics*, 77, 483–527.

Brickley, James A., Ronald C. Lease and Clifford W. Smith Jr., 1988, Ownership Structure and Voting on Antitakeover Amendments, *Journal of Financial Economics*, 20, 267–291.

Carhart, M., 1997, On Persistence of Mutual Fund Performance, *Journal of Finance*, 52, 57–82.

Cella, Cristina, 2010, Institutional Investors and Corporate Investors, *Working paper*, *Stockholm School of Economics*.

Chen, Xia, Jarrad Harford, and Kai Li, 2007, Monitoring: Which Institutions Matter?, *Journal of Financial Economics*, 86, 279–305.

Chordia, Tarun, Richard Roll, and Avanidar Subrahmanyam, 2000, Commonality in liquidity, *Journal of Financial Economics*, 56, 3–28.

Daniel, Kent and Sheridan Titman, 1997, Evidence on the Characteristics of Cross Sectional Variation in Stock Returns, *Journal of Finance* 52, 1–33.

DeAngelo, H., and L. DeAngelo. 2007. Capital Structure, Payout Policy, and Financial Flexibility. Working paper, University of Southern California.

Easterbrook, Frank H., 1984, Two Agency-Cost Explanations of Dividends, *American Economic Review*, 74, 650–659.

Fama, Eugene F. and Harvey Babiak, 1968, Dividend Policy: An Empirical Analysis, *Journal of the American Statistical Association* 63, 1132–1161.

Fama, Eugene F., and Kenneth R. French, 1992, The Cross-Section of Expected Stock Returns, *Journal of Finance* 47(2), 427–465.

Fama, Eugene F., and Kenneth R. French, 1993, Common Risk Factors in the Returns of Stocks and Bonds, *Journal of Financial Economics* 33, 3–56.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, Return, and Equilibrium: Empirical Tests, *Journal of Political Economy* 81(3), 607–636.

Fluck, Zsuzsanna, 1999, The Dynamics of the Management-Shareholder Conflict, *Review of Financial Studies* 12, 379–404.

Gomes, Armando, 2000, Going Public without Governance: Managerial Reputation Effects, *Journal of Finance* 55: 615—646.

Gompers, Paul A. and Andrew Metrick, 2001, Institutional Investors and Equity Prices, *Quarterly Journal of Economics* 116, 229–259.

Graham, John R., and Alok Kumar, 2006, Do Dividend Clienteles Exist? Evidence on Dividend Preferences of Retail Investors, *Journal of Finance* 59, 1125–1165.

Grinstein, Yaniv and Roni Michaely, 2005, Institutional Holdings and Payout Policy, *Journal of Finance* 60, 1389–1426.

Grullon, Gustavo, George Kanatas and James P. Weston, 2004, Advertising, Breadth of Ownership and Liquidity, *Review of Financial Studies* 17, 439–461.

John, K., and A. Knyazeva. 2008. Corporate Governance and Payout Commitments. Working paper, New York University.

Kisin, Roni, 2010, The Impact of Shareholders on Corporate Investments: Evidence from Mutual Funds Holdings, *Working paper*, *Washington University in St. Louis*.

Lakonishok, Josef, Andrei Shleifer, and Robert W. Vishny, 1994, Contrarian Investment, Extrapolation, and Risk, *Journal of Finance* 49, 1541–1578.

La Porta, R., F. López-de-Silanes, A. Shleifer and R. Vishny. 2000. Agency Problems and Dividend Policies around the World. *Journal of Finance* 55:1–33.

Leary, Mark T. and Roni Michaely, 2011, Determinants of Dividend Smoothing: Empirical Evidence, *Review of Financial Studies,* 24: 3197–3249.

Lintner, John, 1956, Distribution of Incomes of Corporations among Dividends, Retained Earnings, and Taxes, *American Economic Review*, 46(2), 97–113.

Loughran, Tim, and Jay R. Ritter, 1995, The New Issues Puzzle, *The Journal of Finance* 50, 23–51.

Myers, Stuart, 2000, Outside Equity, Journal of Finance, 55: 1005–1037.

Pastor, Lubos, and Robert F. Stambaugh, 2003, Liquidity Risk and Expected Stock Returns, *Journal of Political Economy*, 111, 642–685.

Ritter, Jay R., 2003, Investment Banking and Securities Issuance, in Constantinides, G.M, Harris M., and R. Schulz, ed., *Handbook of the economics and finance*, Ch. 5.

Rogers, Willard L., 1993, Regression Standard Errors in Clustered Samples. *Stata Technical Bulletin,* 13, 19–23.

Shefrin, Hersh M., and Meir Statman, 1984, Explaining Investor Preference for Cash Dividends, *Journal of Financial Economics* 13(2), 253–282.

Shleifer, Andrei and Robert Vishny, 1997, A survey of corporate governance, *Journal of Finance* 52: 737–783.

Warther, Vincent A., 1994, Dividend Smoothing: A Sleeping Dog Explanation, *Unpublished Working Paper*.

Zwiebel, Jeffrey, 1996, Dynamic Capital Structure under Managerial Entrenchment, *American Economic Review*, 86(5), 1197–1215.