Two Essays on Corporate Finance

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(ABSTRACT)

This Dissertation consists of two essays. The first essay examines how corporate financial policies depend on the properties of future cash flows. In contrast to prior literature, we investigate the role of asymmetries in the distributionof cash flows. We document the relevance of such asymmetries for firms' payout, liquidity, and capital structure policies. Policies are more sensitive to downside volatility and the directional effect of upside variation is often opposite that of downside. Controlling for cash flow volatility,policies significantly relate to measures of skewness. Firms adopt more conservative policies (lower propensity to pay, more cash, less leverage) when cash flow news is more negatively skewed.

The second essay addresses a mythical relationship between corporate payout and short-termism. Over the past 30 years, aggregate investment by US public corporations has declined, and corporate payout has increased. These facts are interpreted as evidence that public firms are plagued by short-termism and are foregoing valuable investment opportunities to support the large payouts. We find that large increases in corporate payout do not impact firm investment or innovative activities in the short run. In the long run, firms which increase their payout invest more in physical capital than control firms and that their R&D spending is comparable. Firms which increase their payout do not experience a decline in operating profitability or valuation in the long run. These conclusions hold when we restrict our attention to firms who persist in making large payouts and for those high payout firms that rely on internal funds. Our results are inconsistent with the view that unusually high payout harms the long-term viability of US firms. The evidence in the paper suggests that the high payers are from industries with declining growth opportunities but the firms themselves are expecting their high profitability and cash flow to persist.

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(GENERAL AUDIENCE ABSTRACT)

Large increases or decreases in a company's earnings or stock returns are breathcatching. Do such large changes contain information about the company's future performance? If so, what information do they carry? My first essay answers these questions by looking into the data. We find that extreme stock returns do carry information about firms' long-run performance, and this information effectively predicts firms' financial decisions including payout, cash balance, and leverage.

U.S. public firms have been decreasing their capital investment and increasing their cash payout to shareholders in the past 30 years. This create a concern because these firms are supposed to support economy growth and create jobs. Some commenters would conclude that if public firms payout so much money to shareholders, they would not have enough resource to support economy growth and create jobs. We try to find evidence from the data to support or refute this argument. The data shows that firms that payout a large amount of cash to shareholders do not reduce investment relative to their otherwise similar peers, neither in the short run nor in the long run. We also find that the firms that payout high amount are from industries with declining growth opportunities but the firms themselves are expecting their high profitability and cash flow to persist.

Dedication

To Nan Shao.

To Anna and Albert.

To my parents, family and friends.

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Chapter 1

Cash Flow News and Corporate Policies: The Role of Asymmetries

1.1 Introduction

A large literature hypothesizes that corporate financial policies are influenced by the nature of uncertainty surrounding future performance. Broadly, this body of work suggests that a firm with risky future prospects will adopt more conservative policies relative to a firm with less risky prospects, all else equal. Previous empirical studies testing this hypothesis focus on measures of cash flow variance or volatility.[1] However, theoretical explanations for corporate policy choices highlight the role of downside outcomes. For example, trade-off theories of capital structure emphasize the role of costs incurred upon default, and standard models of corporate liquidity focus on the precautionary motive for holding cash.[2] Although features of uncertain future performance beyond variance are presumably relevant, there is little empirical evidence on this point.

This paper provides new evidence concerning the relation between firms' cash flow distributions and key corporate policies. We construct a set of novel measures capturing different aspects of future performance. In contrast to prior literature, which we review in Section 2,

[1]Examples of such studies include Bradley et al. [18], Opler et al. [81], and Hoberg and Prabhala [54].

[2]The possibility of large positive innovations to cash flow and value might also reasonably be expected to impact corporate policy decisions (Jagannathan et al. [58]; Guay and Harford [51]).

our paper focuses on the role of asymmetries in the distribution of future cash flows. We document the relevance of such asymmetries for firms' payout, liquidity, and capital structure policies. To do so, we decompose measures of total cash flow variation into downside and upside components and test the hypothesis that total variation fully captures future cash flow risk as it relates to these policies. We find that it does not. Policies are more sensitive to downside volatility, and often the *directional* effect of upside variation is opposite that of downside variation. We also show that, controlling for cash flow volatility, firm policies significantly relate to measures of cash flow skewness. Firms adopt more conservative policies (less leverage, more cash, and a lower propensity to pay) when cash flows news is more negatively skewed.

The distributional properties of future firm performance are challenging to measure.[3] We construct proxies from firm-level stock returns. The rationale supporting this approach stems from return-decomposition results developed in the asset pricing literature (Campbell and Shiller [21], Campbell [20]). These results establish that stock return innovations are composed of news about fundamentals ('cash flow news') and news about expected returns. Stock return innovations therefore contain rich information concerning future firm performance. Previous studies implicitly exploit this idea in constructing stock return-based measures of firm volatility (e.g., Hoberg and Prabhala [54] and Chay and Suh [23]). We extend this rationale to construct return-based measures capturing more nuanced aspects of cash flow news. Specifically, we decompose volatility into upside and downside components, and compute related measures of skewness. An obvious concern is that return innovations

[3] There is wide variation in how prior studies construct proxies for cash flow volatility, with some studies basing measures on accounting data and others constructing measures from firm stock returns. Although evidence concerning the role of cash flow volatility is fairly consistent for some policies (e.g., the propensity to pay dividends and cash holdings), mixed results obtain for other policies such as capital structure. Researchers examining the relation between firm risk and capital structure in some cases obtain significant coefficients of the expected sign, insignificant coefficients, or even significant coefficients of the unexpected sign.

are potentially contaminated (from our perspective) with news about time-varying expected returns. To account for this possibility, we follow Vuolteenaho [91] from the asset pricing literature and Michaely et al. [76] from the corporate finance literature and decompose firm-level return surprises into discount rate and cash flow components. We then construct alternative measures using only the cash-flow component of return shocks. We consider numerous variations on these measures, including measures based on unlevered stock returns, market-adjusted returns, and returns at alternative sampling frequencies.

We first examine corporate payout decisions using the familiar propensity to pay a dividend (Fama and French [34]) and propensity to repurchase shares where the dependent variable takes a value of 1 if the firm pays out in a given fiscal year and 0 otherwise. For both dividends and repurchases, panel logistic regressions indicate that the propensity to pay is negatively related to the volatility of cash flow news when it is used as the only cash flow uncertainty variable, confirming results initially reported by Hoberg and Prabhala [54] and consistent with recent risk-signaling evidence for payout decisions in Michaely et al. [76]. We then show that, conditional on volatility, the propensity to pay depends negatively on the skewness of cash flow news, i.e., firms with more negatively skewed cash flow news are less likely to pay. To further investigate the role of asymmetries, we separate total volatility into downside and upside components. The marginal effect of downside variation is several times greater than that of upside variation across several alternative model specifications. We obtain qualitatively similar results when we examine firms' propensity to increase or decrease payout. We find that downside and upside volatility not only have different marginal effects, they also have different directional effects for changes in the quantity of payout. Greater downside volatility is associated with a lower propensity to increase dividends, whereas greater upside volatility is associated with a higher propensity to increase payout.

We then examine models for liquidity (using cash holdings) and capital structure (using the market-based leverage ratio). Our results for these policies again highlight the importance of asymmetries in cash flow news. We find that skewness is significantly negatively (positively) related to cash (leverage), controlling for the level of cash flow volatility and other firm characteristics. After splitting volatility into components, the coefficient on downside uncertainty has the expected sign and is significant for both cash and leverage policies. In contrast, the coefficient on upside volatility is relatively smaller and often takes the opposite sign to that for downside volatility. Jointly including multiple measures of cash flow news clarifies the role of particular aspects of this news. Measures of cash flow volatility often take an unexpected sign when included alone (more precisely, along with standard firm controls) in cash and leverage models. However, after jointly including a measure of the degree of asymmetry in cash flow news, cash flow volatility then takes the theoretically expected sign and is generally significant.

The novel relations we document between corporate policies and asymmetries in cash flow news are economically, as well as statistically, significant. Panel logit estimates imply that the odds of paying a dividend increase from approximately 30% to 43% upon increasing our measure of cash flow skewness from the 10th to the 90th percentile for a typical firm-year, controlling for cash flow volatility and other characteristics linked to the propensity to pay in prior studies. The effects of asymmetries in cash flow news are also economically significant for cash and leverage policies. Estimates from a dynamic panel data model for cash holdings imply that a one standard deviation increase in the skewness of cash flow news is associated with a long-run decrease in cash of approximately 1.8%, which is approximately 18% of the median cash level. With respect to leverage policy, estimates imply that a one standard deviation increase in skewness is associated with a long-run increase in leverage of approximately 1.6%, which is roughly 13% of median leverage. The effects of increases in downside volatility are economically different and often directionally different from equivalent increases in upside volatility across all policies we examine.

Our main findings survive a battery of robustness checks. Key results continue to obtain under a variety of alternative methods for constructing return-based measures, including measures constructed after applying a vector autoregression (VAR) to purge return shocks of expected return news, and measures constructed using unlevered returns. Indeed, our examination of alternative approaches to constructing measures constitutes an ancillary contribution of the paper. For example, we demonstrate that the choice of sampling frequency and the use of log versus simple returns impacts measures as much or more than filtering for expected return news. We also contrast the behavior of skewness measures based on stock returns with alternatives constructed from past accounting data. We present evidence indicating that return-based measures better capture firm attributes likely to be associated with similarly skewed future cash flow outcomes.

The relations we document between cash flow uncertainty measures and corporate policies obtain under a wide range of panel data specifications that control for various potential sources of endogeneity. We estimate standard static pooled panel and fixed effects models, as well as a variety of dynamic panel data approaches. The latter accommodate unobserved time-invariant heterogeneity that is potentially correlated with explanatory variables, as well as bona fide policy dynamics consistent with, e.g., models of partial adjustment in firm capital structure. It is challenging to obtain consistent estimates in such models, and we apply several approaches, including a simulation-based biased-corrected estimator and the dynamic panel data estimator recently proposed by (Elsas and Florysiak [32]) that accounts for the inherently fractional nature of many financial ratios. Finally, we apply an alternative estimator that relaxes the *strict exogeneity* assumption required for consistent parameter estimates under many standard panel data approaches. This approach explicitly permits feedback effects or ‘reverse causality’ from corporate policy shocks to future values of explanatory variables.[4] The nature of the econometric method proves most important for leverage. For this policy decision, we find intuitive results under dynamic panel data methods, whereas simpler approaches generate mixed and sometimes counterintuitive results.

The portfolio choice and asset pricing literatures have long recognized the theoretical and empirical importance of asymmetries in asset payoffs and returns. Theoretical analyses of corporate policies such as payout, cash holdings, and capital structure also acknowledge, at least implicitly, potential differences in the relevance of upside versus downside variation in firm performance. To our knowledge, this paper is the first to provide explicit empirical evidence establishing the role of asymmetries in future cash flow uncertainty as statistically and economically significant determinants of key corporate policy decisions.

1.2 Theoretical Motivation and Related Literature

We study how expectations of future firm performance influence corporate policy. A large body of theoretical work provides guidance concerning this relation, and an even larger body of empirical literature analyzes the determinants of corporate policies such as leverage and payout, including various proxies for future firm performance. Below we highlight theoretical literature that motivates our analysis, and briefly review empirical work connected to our contribution.

1.2.1 Theoretical motivation

Consider first the static trade-off theory of optimal firm leverage. Under this theory, the firm's leverage choice optimizes the trade-off between the value of interest tax shields gener-

[4] Grieser and Hadlock [49] emphasize the importance of this issue in panel data applications in corporate finance and point out that few published studies apply methods that permit feedback effects.

ated by debt with bankruptcy costs associated with potential default. Standard explications of the theory (Leland [69], Leland and Toft [71]) build upon Merton [74]'s structural analysis of the valuation of corporate debt, which assumes that firm value follows a geometric Brownian motion.[5] Despite its convenience, the geometric Brownian motion process makes certain restrictive assumptions. In particular, a single volatility parameter σ fully describes firm risk. Innovations in firm value are likely to be more leptokurtotic and skewed than implied under the log-normal distribution.[6] More realistic models incorporate the possibility of jumps in firm value. Intuitively, jumps impact optimal capital structure because jump behavior alters the expected bankruptcy cost component that managers trade-off against interest tax shields. Chen and Kou [25] analyze the implications of incorporating occasional jumps in firm value for optimal capital structure. They find that jump risk reduces the optimal leverage ratio significantly.[7]

The logic of recent thinking in the payout literature (e.g., Jagannathan et al. [58], Brav et al. [19], and Skinner [86]) is that managers find reducing dividend payments to be difficult and associated with a substantial price penalty, and endeavor to maintain dividends at sustainable levels. This view implicitly emphasizes the critical role of potential adverse cash flow realizations and associated downside uncertainty. Michaely et al. [76] revisit the classic signaling paradigm for dividends (Miller and Rock [78]) with an explicit focus on risk. In their model, payout decisions signal future changes in cash flow risk, rather than the level of cash

[5] A continuous time setting is not critical. For example, Kraus and Litzenberger [65] develop the trade-off theory in a discrete state setting. Nevertheless, potential downside outcomes with respect to firm performance play a crucial role, as it is precisely under these circumstances that assumed costs associated with bankruptcy are incurred.

[6] A pharmaceutical firm might, with some probability, discover a revolutionary treatment. Innovations in firm value for such a firm will be positively skewed and fat-tailed. Other firms face risks of technological shifts or market disruptions causing large, rapid deterioration in firm value. Empirically, structural models of capital structure in which firm values evolve according to a Geometric Brownian Motion underestimate credit spreads and short-horizon default probabilities (Jones et al. [60] and other related studies).

[7] See also related contributions by Hilberink and Rogers [53], Leland [70], and Le Courtois and Quittard-Pinon [67]. These papers differ with respect to the particular specification of the jump process.

flow. Specifically, Michaely et al. [76] find both theoretically and empirically that an increase in dividends predicts a decrease in future volatility. For tractability, the model of Michaely et al. [76] associates risk with variance/volatility. However, a broader interpretation of their analysis suggests that firms' dividend policy specifically signals the *downside component* of future cash flow variation. Indeed, the cost of signaling via dividends in Michaely et al. [76] is foregone investment opportunities driven by imperfect access to capital markets. This cost is specifically borne upon insufficient (downside) realizations in terms of internal cash generation. The relevance of upside variation in cash flow is less clear from extant theory.

Early theories of firms' cash holdings policy assumed that fluctuations in cash balances are deterministic (see, e.g., Baumol [12]). Miller and Orr [77] introduced risk and focused attention on the precautionary motive for holding cash. Subsequent papers typically assume stylized cash flow distributions for analytical tractability. For example, Almeida et al. [1] and Han and Qiu [52] assume that cash inflows from existing assets follow a Bernoulli distribution with potential 'high' or 'low' outcomes. Although these models do not explicitly disentangle effects from different aspects of cash flow uncertainty, their intuition suggests that cash holdings will be sensitive to asymmetries.[8] Higher moments of firm cash inflows may influence cash holdings via channels other than pure precautionary motives. Under the pecking order theory of Myers and Majluf [79], internal financing is less costly than external financing, providing firms with an incentive to hold cash to meet future financing needs. Negatively skewed cash inflow distributions increase the likelihood of the firm being caught in a 'financing trap' of the sort studied by Myers and Majluf [79]. This motivates firms to hold greater financial slack (cash and liquid assets).

[8] To be more explicit, Han and Qiu [52] show that, when firms cannot perfectly hedge cash flow risk, optimal cash holdings increase under a mean-preserving spread in the distribution of cash inflows. This result is driven by the assumed convexity of the marginal return on investment. Given this convexity, it is reasonable to conjecture that more negatively skewed firm cash inflows will lead to an increase in optimal cash holdings via a similar mechanism.

Broadly, the theoretical literature suggests that asymmetries in the uncertainty surrounding future firm performance are relevant for corporate policies, and motivates a more nuanced empirical analysis of the relation between policies and aspects of the uncertainty surrounding performance.

1.2.2 Related empirical literature

Existing empirical work analyzing the relationship between corporate policies and cash flow risk is abundant. Castanias [22], Bradley et al. [18], Faulkender and Petersen [36], Xu [95], and Levine and Wu [73] find a negative relationship between leverage ratio and cash flow volatility, while Friend and Lang [43] find a positive relationship. Leary and Roberts [68], Lemmon et al. [72], Frank and Goyal [41], and Antoniou et al. [4] do not find that volatility exerts a consistent impact on leverage. D'Acunto et al. [28] highlight the degree of output price flexibility as a determinant of leverage and show that the part of cash flow volatility predicted by price stickiness is consistently negatively associated with leverage, contrary to the unconditional association. With regard to cash holdings, Opler et al. [81] find a positive relationship between cash and their proxy for cash flow risk in most of their empirical models, but they find a negative and significant relationship when they switch to a firm fixed effects model. Bates et al. [11], Foley et al. [40], and Gao et al. [44] find a positive and significant relationship. A number of previous studies find a negative relation between cash flow volatility and the propensity to pay and/or quantity of payout, including Hoberg and Prabhala [54], Chay and Suh [23], Hoberg et al. [55], Walkup [92], and Michaely et al. [76]. None of these studies explicitly study the role of asymmetries in the distribution of future performance in shaping firm policy decisions.

Risk is measured in different ways across studies. The payout literature (e.g., Hoberg and

Prabhala [54] and Chay and Suh [23] typically constructs measures from stock returns. Hoberg and Prabhala [54] split risk into systematic and idiosyncratic components while Chay and Suh [23] use the standard deviation of returns. Frank and Goyal [41] use unlevered stock returns to explain leverage. Frank and Goyal include a measure of prior return along with the volatility of unlevered returns. Many other leverage studies use accounting-based measures of the volatility of earnings or cash flows to measure risk. Many of these measures are based on an operating ROA measure using EBIT, operating income, or a cash flow measure scaled by assets or sales. Rountree et al. [85] consider a range of alternative cash flow volatility measures in the context of analyzing the relation between firm value and cash flow smoothness. Michaely et al. [76] apply empirical decompositions of returns into cash flow and expected return news in a corporate finance context, as we do in this paper. We focus on asymmetric aspects of return news and analyze cash and leverage policies in addition to payout. Our results concerning payout are complementary to Michaely et al. [76], who highlight the risk content associated with payout policy, but focus on total volatility as the relevant risk measure.

Avramov et al. [9] apply textual analysis methods to construct a measure of negative or downside risk from firm annual reports. Their measure is based on the proportion of downside-oriented words to total word usage in a report. Avramov et al. [9] find that increases in this text-based measure are associated with more conservative policies. These results complement several of ours: using novel measures constructed from rather different sources (stock returns versus annual report text), both studies link greater downside risk in future firm performance with more conservative corporate policies. In contrast to the text-based measures studied in Avramov et al. [9], the measures we construct carry clear interpretations as capturing particular aspects of cash flow uncertainty (e.g., skewness versus volatility). This allows us to explicitly test for the relevance of asymmetric cash flow outcomes in corporate policy decisions. We also evaluate the role of *upside* variation in cash flow news in contrast to downside shocks.

1.3 Stock Returns and Future Cash Flows

We consider a variety of alternative proxies designed to capture features of future firm cash flows. Most proxies are constructed from firm-level stock returns, rather than from accounting data. Return-based proxies enjoy several advantages relative to measures based on accounting data. First, stock returns contain *forward-looking* information regarding firm cash flows (see discussion below on this point), in contrast to historical accounting information. Second, stock returns are less subject to non-stationarity biases associated with accounting measures such as realized earnings or cash flows. Third, reported earnings reflect both discretionary earnings management through the use of accruals and real earnings management. If discretionary earnings management has income smoothing as its purpose, reported earnings will understate the volatility and asymmetries in future earnings. Real earnings management might cause past earnings-based measures to be poor predictors of future operating performance. Fourth, standard accounting information is available only at quarterly or lower (annual) frequencies. In contrast, stock returns are available at monthly or even daily frequencies. This affords greater statistical precision associated with estimates of higher order moments. Finally, a number of different earnings and cash flow measures have been utilized in empirical studies, and results can be sensitive to the choice of measure. Although we focus on measures constructed from stock returns, we also construct a benchmark accounting-based measure for comparison. Section 1.7 of the paper further considers the distinction between return-based and accounting-based measures.

The rationale for constructing measures using firm-level stock returns stems from the asset pricing literature. Consider the following decomposition of firm-level stock return innovations, due to Vuolteenaho [91]:

$$r_{i,t} - \mathrm{E}_{t-1}(r_{i,t}) \approx \Delta E_t \sum_{j=0}^{\infty} \rho^j (roe_{t+j} - f_{t+j}) - \Delta E_t \sum_{j=1}^{\infty} \rho^j r_{t+j} \tag{1.1}$$

where $r_{i,t}$ denotes the log excess return for the i-th firm in period t, roe is the log return on equity, f_t is the log of one plus the interest rate, ρ is a discount factor less than one, and E_{t-1} (ΔE_t) denotes the expectation at time $t-1$ (revision in expectation from time $t-1$ to t).[9] Eq. (1.1) states that a positive return shock comes from either an upward revision to cash flow expectations or a downward revision to future expected returns. We write the decomposition as

$$\epsilon_{i,t} \equiv r_{i,t} - \mathrm{E}_{t-1}(r_{i,t}) = \epsilon_{i,t}^{CF} - \epsilon_{i,t}^{ER}, \tag{1.2}$$

where $\epsilon_{i,t}$ is the return surprise for firm i in period t, $\epsilon_{i,t}^{CF}$ and $\epsilon_{i,t}^{ER}$ are defined as the first and second terms in Eq. (1.1), respectively, and can be interpreted as the cash-flow and expected return components of the return surprise. It is worth emphasizing that the cash flow news component of stock returns $\epsilon_{i,t}^{CF}$ reflects revisions in expectations of the discounted value of *all* future cash flows. This contrasts starkly with single-period cash flow shocks computed from accounting data.

The decomposition of Eq. (1.2) shows that return innovations contain information concerning future firm performance, *however*, they are in general not a clean measure due to

[9] The log return on equity is defined as $roe_t = \log(1 + X_t/B_{t-1})$, where X_t and B_t denote earnings and book value, respectively. The parameter $\rho \approx 0.98$ is a discount factor. The decomposition of Vuolteenaho [91] relies on several assumptions. Earnings, dividends, and book equity are assumed to satisfy the clean-surplus accounting identity. In addition, it is assumed that log book equity and log market equity are cointegrated and log dividends and log book equity are also cointegrated.

contamination from expected return news.[10] As a benchmark case, suppose there is no variation in discount rates and the expected return $\mathrm{E}(r_{i,t})$ is known so that return surprises are observed without error. Under these assumptions, return shocks are directly observable and (only) reflect news about future cash flows, i.e., $\epsilon_{i,t} \equiv \epsilon_{i,t}^{CF}$. Return shock moments therefore measure aspects of uncertain future firm performance. For example, the variance of cash flow news, denoted $\mathrm{Var}(\epsilon_i^{CF})$, constitutes one potential measure of cash flow risk. The skewness of return shocks, denoted $\mathrm{Skew}(\epsilon_i^{CF})$ represents a measure of asymmetry in cash flow news. It is of course unrealistic to expect that that there is no variation in firm-level expected returns. However, Vuolteenaho [91] finds that return variation attributable to expected return news is relatively small compared with variation attributable to cash flow news. This suggests that return-based moments should be useful proxies for the corresponding moments of cash flow news.

Researchers can obtain a clean measure of cash flow news by imposing sufficient structure on time-varying expected returns and cash flow expectations. Vuolteenaho [91] models conditional expectations of returns and state variables in the context of a first-order vector autoregression (VAR) model.[11] It is then possible to back out shocks to cash flow news (ϵ^{CF}) given VAR slope estimates (see the Appendix for details). Applying the VAR-based decomposition involves important implementation choices and entails certain limitations. First, it is necessary to specify the set of state variables. There are many plausible candidate

[10]With potential discount rate variation, the variance of stock returns can be written as:

$$\mathrm{Var}(\epsilon_i) = \mathrm{Var}(\epsilon_i^{CF}) + \underbrace{\mathrm{Var}(\epsilon_i^{ER}) - 2\,\mathrm{Cov}(\epsilon_i^{CF}, \epsilon_i^{ER})}_{\text{Contamination from expected returns}} \quad . \tag{1.3}$$

Other moments of return shocks, e.g., skewness or partial (downside or upside) variances are similarly contaminated.

[11]Vuolteenaho [91] builds on earlier, related contributions at the aggregate level using dividend-based firm decompositions (e.g., Campbell and Shiller [21] and Campbell [20]). Few papers in the empirical corporate literature exploit the decomposition. An exception is a recent study by Michaely et al. [76], who apply the approach to study the variance of cash flow news before and after dividend initiations, omissions, and changes.

variables. Second, one must determine how to estimate the VAR parameters. Vuolteenaho [91] primarily relies on a pooled estimation; however, appropriate VAR parameters may differ materially in the cross-section of firms and other estimation approaches are possible. Third, the VAR-decomposition approach limits the researcher to quarterly data, because common state variables are constructed using accounting data (e.g., the return on equity). This produces noisier estimates of variances and related moments relative to, say, monthly or even daily stock return innovations. In light of these remarks, is is unclear whether isolating cash flow shocks via a VAR decomposition approach delivers superior measures of cash flow news in practice relative to measures constructed from 'raw' return shocks. For this reason, we consider measures based on the VAR decomposition, but do not solely rely on such measures.

1.4 Data, Empirical Measures, and Descriptive Statistics

We construct our sample from the WRDS merged CRSP/Compustat files for the period 1983 to 2017. We use balance sheet data from the annual or quarterly Compustat file and stock-return data from the monthly or daily CRSP file. We start with all firm-year observations in the Compustat dataset with the following exceptions: (1) We exclude the utility (SIC 4900 - 4949) and financial (SIC 6000 - 6999) firms; (2) we only include firms traded on NYSE, AMEX, and NASDAQ with CRSP share codes of 10 or 11; and (3) we exclude firm-year observations with less than $5 million of total assets and less than $2.5 million of book equity. The Appendix provides explicit definitions of book equity and other control variables. We winsorize all variables at the 1st and 99th percentiles.

1.4.1 Corporate policies

We identify a firm as a dividend payer in a fiscal year if its common dividends are greater than zero. We define a firm as a share repurchaser in a fiscal year if it repurchases in that year. To identify repurchases, we use the purchase of common and preferred stock (PRSTKC) minus the purchase of preferred stock (PRSTKPC). Banyi et al. [10] find high error rates in commonly used repurchase estimators. In their analysis, even the most accurate measure deviates from the actual number of shares repurchased by a substantial amount in about 15% of firm-years. In untabulated tests, we use the measures discussed by Banyi et al. [10] to identify repurchasers and obtain similar results. We define payout changes similar to Hoberg et al. [55]. A firm is defined as a dividend increaser (decreaser) in year t if it pays a dividend in $t-1$ and increases (decreases) the amount in year t or if it initiated a divided in year t. To economize on our presentation of results we pool initiations with increases. Results are similar if increases and initiations are analyzed separately. Similarly, we pool omissions of dividends with decreases in dividends.

We also examine firms' liquidity and capital structure policies. We use a market value-based leverage ratio to assess the firm's use of debt financing. Specifically, we use book value of debt divided by market value of total assets to measure leverage. Book value of debt is the sum of total long-term debt and debt in current liabilities. Market value of total assets equals market value of equity plus book value of assets minus book value of equity (BE). Book value of equity (BE) is defined following Hoberg and Prabhala [54]. To describe liquidity policies, we follow Bates et al. [11] and use cash and short-term investment (CHE) standardized by beginning period total assets (TA) as our liquidity measure.

1.4.2 Empirical measures of firm uncertainty

This section describes our empirical return-based measures of future firm performance. As discussed in Section 1.3, there is not a single, clearly superior approach to obtaining cash flow shocks from returns. We therefore consider a range of methods. We first define the various proxies we compute conditional on a particular method for obtaining cash flow shocks. We then enumerate the alternative methods we apply to obtain these shocks.

We construct measures at the firm-year level based on firm fiscal years. It is convenient to introduce the notation $\mathcal{S}_{i,t}$, which denotes, for each firm fiscal year, the set of cash flow shocks $\hat{\epsilon}_{i,j}$ that occur within a specified backward-looking time window from the end of (fiscal) year t. We set the backward-looking window to three years when the underlying cash flow shocks are monthly or daily, and five years for quarterly shocks. As an example, for measures constructed from monthly cash flow shocks, the set $\mathcal{S}_{i,t}$ includes the available monthly cash flow shocks for the i-th firm over the past three years (including year t). The notation $\#\mathcal{S}_{i,t}$ denotes the number of cash flow shocks in $\mathcal{S}_{i,t}$. We define the following empirical measure of the variance of cash flow news:

$$\mathrm{VAR}_{i,t} = \frac{1}{\#\mathcal{S}_{i,t}} \sum_{\mathcal{S}_{i,t}} (\hat{\epsilon}_{i,j}^{CF})^2, \tag{1.4}$$

where the summation notation indicates the sum over all shocks in $\mathcal{S}_{i,t}$. We then decompose the total variance of cash flow news into downside and upside components as follows:

$$\mathrm{DSVAR}_{i,t} = \frac{1}{\#\mathcal{S}_{i,t}} \sum_{\mathcal{S}_{i,t}} \left(\min(\hat{\epsilon}_{i,j}^{CF} - B, 0)\right)^2, \tag{1.5}$$

where B is a specified benchmark return around which the downside variation is computed.

The (sample) upside variation is defined similarly:

$$\text{USVAR}_{i,t} = \frac{1}{\#\mathcal{S}_{i,t}} \sum_{\mathcal{S}_{i,t}} \left(\max(\hat{\epsilon}^{CF}_{i,j} - B, 0)\right)^2, \tag{1.6}$$

We compute volatility measures by taking square roots of the corresponding variance measures. For example, $\text{VOL}_{i,t} \equiv \sqrt{\text{VAR}}_{i,t}$. DSVOL and USVOL are defined similarly.[12]

In addition to downside and upside components of cash flow variation, we construct several measures of asymmetry in firm-level cash flow news. The first such measure is based on the traditional sample skewness, computed as

$$\text{SKEW}_{i,t} = \frac{(1/\#\mathcal{S}_{i,t}) \sum_{\mathcal{S}_{i,t}} (\hat{\epsilon}^{CF}_{i,j})^3}{(VOL_{i,t})^{3/2}}. \tag{1.7}$$

As an alternative, we follow Chen et al. [24] and compute an asymmetry measure as the log ratio of upside to downside volatility $\text{U/DVOL}_{i,t} \equiv \ln(\text{USVOL}_{i,t}/\text{DSVOL}_{i,t})$. Chen et al. [24] argue that, relative to the traditional skewness statistic, their measure is less likely to be influenced by extreme observations because it does not involve third moments.

We require at least 12 observations of estimated cash flow shocks (over a five-year window) in order to construct measures for quarterly data, 24 observations (over a three-year window) for monthly data, and 250 observations (over a three-year window) for daily data. We set the split-point for downside versus upside volatility B to zero. We rescale all volatility measures to a monthly basis for comparability.

[12] We prefer to focus on volatility measures rather than variances in our empirical work to facilitate interpretation of slope estimates. This introduces a Jensen's inequality effect that breaks the direct additive relation between total variance and up/down side components. We obtain qualitatively similar results in panel regressions that include variances rather than volatilities.

1.4.3 Cash flow shocks

As a first approach, we construct cash flow shocks as monthly stock return deviations from the pooled time series mean. The approach makes no explicit attempt to purge returns of potential expected return news, and assumes a time- and firm-invariant expected return $E_{t-1}(R_{i,t})$ used to construct innovations. We reference this procedure as the **baseline method**. The assumption of a firm- and time-invariant expected return is restrictive and therefore we consider several variations. One variation (**firm-specific mean method**) estimates firm-level expected returns as the historical mean over a 2–3 year window (e.g., Chay and Suh [23], Hoberg and Prabhala [54]). A second **market-adjusted return method** defines the cash flow shock as the monthly stock return for each firm minus the cross-sectional average return for that month. A third variation is identical to the baseline method except that cash flow shocks are computed using (demeaned) unlevered returns (**unlevered firm return method**), calculated as the weighted average of levered stock and debt returns with weights based on the proportions of equity and debt for the corresponding firm-year.[13] As descriptive statistics reported below reveal, these variations produce measures highly correlated with those obtained using the baseline method.

To address the role of discount rate news, we apply the VAR decomposition proposed by Vuolteenaho [91] to compute cash flow shocks from underlying return shocks and VAR model estimates. To implement the approach, we follow Vuolteenaho [91] and Michaely et al. [76] in selecting the VAR state variables as $z_t = (r_t, \theta_t, roe_t)'$, where r_t is the log stock return, θ_t is the log book-to-market ratio, and roe_t is the log (GAAP) return on equity. VAR slope parameters

[13] Stock returns embed information concerning future cash flow to *equity holders*, whereas theory hypothesizes that corporate policy decisions relate to uncertainty regarding cash flow from assets or 'firm cash flow.' Stock-return-based measures of cash flow news can therefore be biased in the presence of leverage, and the severity of the bias varies cross-sectionally with leverage. Since firm-level debt returns are generally unavailable, we use the return on the 5-year Treasury Note as the debt return in each month in computing unlevered returns. In addition to analyzing measures based on unlevered returns, we also include firm leverage as a control in our main econometric models.

are estimated using pooled data over the full sample period. We follow Vuolteenaho [91] and Michaely et al. [76] and market-adjust all variables in the VAR system by subtracting the cross-sectional average for the contemporaneous month. The Appendix provides additional discussion and presents corresponding VAR slope estimates. These are qualitatively similar to those reported by Vuolteenaho [91] and Michaely et al. [76]. This **VAR decomposition** method uses quarterly, rather than monthly or daily returns, and applies a log transform to returns. Both features potentially impact measures relative to the baseline method. To distinguish the effects of these aspects of the decomposition procedure from the effects of firm-level return predictability, we compute a set of measures using quarterly cross-sectionally de-meaned log returns as shocks. This **quarterly log returns** approach is equivalent to forcing VAR slopes to zero in the VAR decomposition method. A final **accounting data** approach constructs measures from quarterly cash flow shocks computed as residuals from a regression of firm-level quarterly EBITDA divided by lagged assets on a set of firm-year dummies.

1.4.4 Sample description

Table 1 presents descriptive statistics for our corporate policy measures of central interest, as well as for a subset of our alternative return-based measures. We require cash, leverage, dividends, size, market-to-book, profitability, DSVOL, USVOL, and VOL to be available for inclusion in our sample, which includes roughly 102,000 firm-year observations over the period 1983 – 2017. Approximately 35% of the firm-year observations are associated with a non-zero dividend and 43% repurchase shares. The average (median) firm in our sample has a cash-to-assets ratio of approximately 19.5% (9.8%) and a leverage ratio of approximately 17% (12%). The distributional properties of our variables qualitatively match those reported in prior studies, such as Chay and Suh [23] (focusing on corporate payout), Bates et al. [11]

(cash holdings), and Lemmon et al. [72] (leverage). Cash and leverage are positively skewed in pooled data, with cash exhibiting the greater degree of skewness. Summary statistics computed by year (not explicitly reported) confirm well-documented aggregate trends in payout and cash holdings, including the secular decrease in the proportion of firms paying dividends, the increase in the proportion of firms repurchasing shares, and the increase in average firm cash holdings.

The pooled mean of cash flow news volatility using the baseline method is approximately 15% (monthly). Upside cash flow news volatility is on average greater than downside volatility. This suggests that cash flow news is positively skewed for the typical firm. The pooled mean of SKEW is approximately 0.5, confirming this intuition. Basing measures on the VAR decomposition alters some statistical properties for our measures. The pooled mean of cash flow news volatility decreases. This is intuitive because the VAR method filters out return variation due to expected return news. The skewness properties of the VAR-based measures also differ: average downside and upside volatility are approximately equal under this approach, and the pooled mean of SKEW is much smaller. These differences are not primarily driven by the effects of state variables and predictable variation in the VAR decomposition, but rather to the use of log rather than simple returns and quarterly versus monthly data. Panel D emphasizes this point by presenting statistics for measures computed based on quarterly cross-sectionally demeaned log returns (without the VAR filter), which have similar properties to the VAR-based measures.

Panel A of Table 2 reports pooled pairwise Pearson correlations among various return-based measures constructed using the baseline approach, and between these return-based measures and a number of key firm characteristics. Not surprisingly, pairwise correlations among VOL, DSVOL, and USVOL are high. The correlation between DSVOL and VOL (0.854) is significantly lower than the correlation between USVOL and VOL (0.976). The correlation between DSVOL and USVOL is 0.725. SKEW and U/DVOL have a correlation coefficient of 0.929, consistent with Chen et al. [24]'s finding of a strong positive relation between these measures. The pairwise correlations between the VOL measure and firm characteristics indicate that firms with greater volatility in cash flow news are less profitable, smaller, and operate in markets with greater product market fluidity. Contemporaneous correlations with market-to-book and investment activity are relatively small. Similar insights obtain for the sided-volatility measures and the measures of skewness in cash flow news. These correlations indicate that certain characteristics, such as (smaller) firm size and (greater) product market fluidity are associated with greater firm cash flow risk, including greater downside volatility and more negatively skewed cash flow news.

Panel B of Table 2 shows pairwise correlations for return-based measures depending on the method used to construct cash flow shocks. Columns correspond to the various measures produced under the baseline method using monthly data. Rows correspond to specified alternative approaches. Each entry in the table represents the pairwise correlation between the risk measure listed in the row header and the baseline risk measure. Comparing correlation values in a particular column is informative regarding the degree of affinity across alternative methods for that particular measure. Generally, the correlations between the baseline measures and the measures under the firm-specific mean, market-adjusted, and unlevered return methods are positive and high. Because these alternative methods yield measures that are highly correlated with the baseline measures, panel regression results discussed below focus on the baseline measures. We obtain similar results for the alternative variations.

Correlations with the baseline measures are lower for the VAR decomposition method, particularly for skewness measures. However, this is also true for measures constructed using quarterly, cross-sectionally demeaned log returns. This illustrates that the sampling frequency and log transformation jointly impact the properties of our measures at least as much as filtering for predictable variation in expected returns. In the final row of the panel, we present correlations between our return-based measures and measures constructed from accounting data. The return-based measures and the corresponding accounting-based measures are positively correlated for VOL and DSVOL. However, accounting-based measures of USVOL and the two skewness proxies are essentially uncorrelated with corresponding measures constructed from stock returns. Results that follow in our discussion of payout, liquidity, and leverage policies focus on return-based measures, and in particular on the baseline measures and measures obtained using the VAR decomposition method. Section 1.7 of the paper discusses robustness of results to alternative approaches, including further exploration of the distinction between return-based and accounting-based measures.

1.5 Payout Decisions

1.5.1 The propensity to pay

We first examine the decision to pay cash out to shareholders by analyzing the propensity to pay considered by Fama and French [34], Hoberg and Prabhala [54], and Chay and Suh [23], among others. Table 3 presents estimation results for the propensity to pay dividends (Panels A and B) and repurchase shares (Panel C). For comparison with previous literature, Panel A shows results for pooled panel logits including various return-based measures along with a benchmark set of control variables similar to those considered by Fama and French [34] and Hoberg and Prabhala [54]: profitability, size, asset growth, and market-to-book. All variables are lagged by one period. We include year effects and cluster standard errors at the firm level. Column (1) of Panel A confirms results in Fama and French [34]. Profitability and size relate positively to the propensity to pay dividends, while asset growth and market-to-book relate negatively. Column (2) incorporates the return-based measure VOL. The coefficient on VOL is negative and highly significant, indicating that firms with more volatile cash flow news are less likely to pay a dividend. This confirms results previously reported by Hoberg and Prabhala [54] and Chay and Suh [23].

Columns (3) – (5) explore the role of asymmetries in the distribution of cash flow news. When the SKEW variable in column (3) is added to the model, the associated coefficient estimate is positive and significant: firms with less negatively skewed cash flow news are more likely to pay a dividend, controlling for volatility and other firm characteristics. The alternative measure U/DVOL displayed in column (4) produces similar results. Results in column (5) provide a different perspective concerning the role of asymmetric cash flow news by decomposing VOL into downside and upside components. The coefficients on both downside and upside components of volatility are negative and significant. However, the magnitude of the coefficient on downside volatility is approximately three times larger than that on the upside component. The fact that the propensity to pay dividends is more sensitive to downside volatility is consistent with the direction of results for skewness conditional on total volatility: more negatively skewed cash flow news is associated with a lower propensity to pay.

Asymmetries in cash flow news are economically, as well as statistically, significant. Because the U/DVOL asymmetry measure is a log ratio, the corresponding coefficient carries a convenient interpretation as an elasticity. The slope estimate in Panel A indicates that each 1% increase in the U/DVOL measure is associated with an increase in the propensity to pay of approximately 0.6%, all else equal. To further probe the economic significance of our results, we conduct computations in which we evaluate the model-implied probability of paying a dividend for alternative empirical percentiles of a specified variable of interest, with all other covariates (including year and industry dummies) fixed at corresponding firm-year values.

We do this for each firm-year in the sample and report pooled averages of the corresponding predicted probabilities. Table 4 shows results associated with estimates from the benchmark model in Panel A of Table 3 including the focal variables VOL and SKEW, along with firm controls and year effects (the column (3) specification).

Results show that marginal effects associated with VOL are quite large: increasing VOL from the 10th to the 90th percentile, all else equal, decreases the propensity to pay by over 60 percentage points (from approximately 69% to about 3%). Increasing *SKEW* from the 10th to the 90th percentile, all else equal, has a smaller but still economically significant effect: the predicted propensity to pay rises from around 30% to 43%. Among the other variables included in the model, the economic significance of SKEW is smaller than that for ROA and SIZE, but larger than that for CAPEX and M/B.

The second panel (Panel B) of Table 3 provides results for an extended specification. The model incorporates additional lagged firm characteristics including cash holdings, leverage, research and development expenditures, asset tangibility, and the RE/TE proxy for the earned-versus-contributed capital mix. In addition, we add industry fixed effects based on two-digit SIC codes and the lagged dependent variable. We retain year fixed effects and standard errors are again clustered at the firm level. Not surprisingly, given the persistence of dividend payout, the lagged dependent variable is highly significant. A number of additional firm characteristics are significant, generally in economically expected directions. The general pattern of results for our return-based measures remains similar to that for the simpler specification for volatility and skewness.[14] Volatility is negatively associated with payout, and firms with more negatively skewed cash flow news are less likely to pay a dividend. Under the extended model, downside and upside volatility have opposite signed coefficients,

[14] In unreported additional tests, we estimate the models of Panels A and B including the fluidity measure of Hoberg et al. [55] over the more limited sample period for which this measure is available. We obtain similar results for our key return-based measures. We are grateful to Gerard Hoberg for making these data available.

in contrast to the simpler specification of Panel A, with downside volatility having the larger impact. This finding suggests that payout policy is affected by several aspects of uncertainty about future cash flows and that the potential for large decreases in future cash flow exerts the largest impact.

Panel C of Table 3 reports results when the dependent variable is the propensity to repurchase shares rather than pay a dividend. The model is the extended specification of Panel B. We omit results for repurchases using the simpler specification in order to conserve space, although they are qualitatively similar. We obtain similar findings with respect to the sign and significance of coefficients on measures of cash flow uncertainty for the propensity to repurchase shares. Higher volatility is associated with a lower propensity for buy-backs, and, conditional on volatility, more negatively skewed cash flow news is associated with a lower propensity to repurchase. One noticeable difference in results for repurchases from results for dividends is that upside volatility is not related to the likelihood of repurchasing shares. Relative to results for the propensity to pay dividends, the key coefficients in Panel C are generally smaller in magnitude, implying economically weaker effects. As a final remark, we note that the specifications reported in Table 3 do not include a firm fixed effect. In additional untabulated analyses, we estimate a panel logit model with firm fixed effects and obtain qualitatively similar results using this approach.

Table 5 presents results for the propensity to pay dividends using measures based on the VAR decomposition to isolate the components of return variation that reflects cash flow news. The left side of the table shows estimates for the VAR-based measures. The right side of the panel presents the estimates for quarterly log return measures for comparison. For both sets of measures, the same pattern of results holds for total volatility, the skewness measures, and downside volatility as shown earlier using the baseline measures. Greater upside volatility has a negative relation with the likelihood of dividend payment using the

VAR-based measures. This contrasts with a positive estimate under the baseline measures. The quarterly log return measure also produces a negative (but insignificant) coefficient for USVOL. This shows that differences between results using baseline measures and the VAR-based measures are primarily attributable to constructing measures using quarterly data and log returns, and not to the return decomposition determined by the VAR coefficients. Irrespective of the approach applied, we consistently find that the marginal effect of downside volatility on the propensity to pay is much larger than the marginal effect of upside volatility. In unreported additional results, we verify that results for the propensity to repurchase are qualitatively similar to those in Panel C of Table 3.

1.5.2 The quantity of payout

The quantity of payout represents a second important aspect of policy. Studying the level of payout is important because, as Hoberg and Prabhala [54] note, "Virtually the entire supply of dividends in any one year comes from companies that already pay dividends." (p. 102) To study dividend changes, we create an indicator variable representing an increase (decrease) in dividends that takes the value of one if the firm increases (decreases) its nominal per share dividend amount in the corresponding year, and is zero otherwise. As a robustness check, we compute an alternative dividend increase (decrease) indicator based on whether the nominal total dividend paid in the current year exceeds that for the prior year. The dividend increase measure is defined for the set of firm-years in our sample for firms that pay a dividend in the current year and thus includes both initiations of dividends and firms that paid a higher dividend in the current year than the prior year. Similarly, our dividend decrease measure includes both omissions and a decrease by firms that paid a dividend in both the current and prior year.[15]

Table 6 reports panel logit estimation results for the propensity to increase (Panel A) or decrease (Panel B) dividends. The specification is similar to the expanded logit specification applied to analyze the propensity to pay, except that we exclude the lagged dependent variable since we do not expect strong persistence in dividend increase and decrease indicators. (Including the lagged dependent variable yields similar results.) The point estimate of the coefficient associated with the volatility of cash flow news in column (1) of Panel A is positive, which seems puzzling. Upon incorporating a measure of skewness, however, this coefficient becomes negative as expected, although insignificant. Asymmetries in cash flow news appear relevant for dividend changes. More positively skewed cash flow news is associated with a greater propensity to increase dividends. Similarly, we obtain opposite-signed effects upon splitting volatility into downside and upside components. All else equal, greater upside (downside) volatility is associated with a higher (lower) propensity to increase dividends. The associated slope estimates are highly significant.

Panel B of Table 6 reports results for dividend decreases. We highlight several aspects of these results. First, VOL has a positive and significant coefficient indicating that firms with especially volatile returns are more likely to decrease their dividends. Second, the skewness of cash flow news is negatively related to the likelihood of a dividend decrease, conditional on total volatility. Thus more negative skewness in cash flow news leads to a higher probability of reducing dividends. Finally, splitting volatility into downside and upside components delivers significant effects in the expected direction: greater downside volatility is associated with a greater likelihood of a decrease in payout, while the opposite is true for greater upside volatility. Overall, the results in Table 6 indicate that measures of skewness and sided risk

[15] [55] separate initiations/omissions from increases/decreases in dividends. The results of our analysis for dividend changes are robust to their separation. In our sample, there are 1,751 initiations, 20,084 other increases in dividends, 1,712 omissions, and 10,546 other decreases in dividends. Many of the changes are small in magnitude.

measures have strong and predictable relations with the decision to change payout.

1.6 Cash and Leverage Policies

1.6.1 Cash holdings

We begin our investigation of cash holdings policy with a relatively simple, benchmark model in the spirit of Opler et al. [81] and Bates et al. [11]. Specifically, we first estimate a pooled OLS model with year and industry dummies, along with a set of firm characteristics similar to those considered in the aforementioned papers. As with earlier payout models, all firm variables are lagged one period and standard errors are clustered at the firm level.[16]

The precautionary motivation for holding cash predicts a positive relation between cash holdings and uncertainty. Column (1) of Table 7 Panel A confirms this conjectured relation using total volatility (VOL) as the uncertainty measure. Columns (2)–(4) of this panel explore the role of asymmetries in cash flow news. The skewness of cash flow news is negatively related to cash holdings, controlling for volatility. This finding obtains for both the SKEW and U/DVOL measures, and implies that firms with more negatively skewed cash flow news retain more cash. Column (4) splits volatility into downside and upside components. Consistent with the precautionary motive for holding cash, greater downside volatility is associated with greater cash holdings. In contrast, greater *upside* volatility is associated with lower cash holdings, although the slope estimate for upside volatility is substantially lower in magnitude relative to the corresponding estimate for downside volatility.

To assess the economic significance of these results, we focus on column (2), which includes

[16]The numbers of observations in the cash regressions are less than the number in earlier models of corporate payout. This is caused by requiring the presence of the acquisition variable from Compustat (following Bates et al. [11]) for the cash regressions.

VOL and the SKEW measure. The associated slope estimates imply that a one standard deviation increase in VOL is associated with an approximately 1.50% increase in cash holdings, all else equal. This increase is around 15% of median cash holdings in our sample. Turning to skewness, a one standard deviation decrease in SKEW (more negative skewness) is associated with an increase in cash holdings of approximately 1.11%, which corresponds to about an 11% increase in cash holdings relative to the median cash level. These results imply that the impact of the skewness of cash flow news is an economically significant determinant of cash holdings levels with marginal effects that are on the same order as those associated with the (total) volatility measure. Finally, point estimates in column (4) for downside and upside volatility imply large differences in economic effects associated with these components with downside volatility have the dominant impact on cash holdings. A one standard deviation increase in DSVOL increases cash by almost 30% relative to the median cash flow balance, while a one standard deviation increase in USVOL decreases cash by about 13%.

Columns (5)-(8) of Panel A of Table 7 report results for a specification is identical to that in columns (1)-(4), except for adding the lagged dependent variable to capture persistence in cash holdings. The coefficient on VOL in column (5) is negative, rather than positive as in column (1). This seems puzzling; however, the corresponding estimate becomes positive (and significant) as expected in column (6) once SKEW is included in the model. Otherwise, the general pattern of results for the risk measures in columns (6)-(8) follows that of results in columns (2)-(4). The dynamic model allows us to estimate the speed of adjustment in cash policy and to contrast short run versus long run effects for variables of interest. Under the dynamic model, the slope coefficient β captures the short run effect and the quantity $\beta/(1-\rho)$ represents the long run effect, where ρ denotes the coefficient on the lagged dependent variable. The pooled OLS estimate of ρ is approximately 0.65 and is highly significant, confirming times series persistence in firm cash levels. The ρ estimates imply that long-run effects are inflated by a factor of nearly 3 relative to corresponding short run effects. These long run effects are quite meaningful. For example, a one standard deviation decrease in SKEW corresponds to an increase in cash holdings of approximately 2.4%, which is roughly 25% of the median cash position.

The specifications in Panel A do not explicitly account for unobserved heterogeneity among firms. The left-hand portion of Panel B therefore shows results for a traditional (static) fixed effects model. The pattern of results is similar to those for the baseline specification on the left-hand side of Panel A: cash holdings are positively related to VOL, negatively related to measures of skewness, positively related to downside volatility, and negatively related to upside volatility. The right-hand portion of Panel B presents results for a model that includes *both* a firm fixed effect and the lagged dependent variable. Estimation of such a model can be challenging. Both pooled OLS and traditional fixed effects estimates are generally biased and inconsistent [80]. The bias of the fixed effects estimator disappears as the panel data length "T" becomes large; however, various studies argue that it can be significant for panel data sets often analyzed in empirical corporate finance [38]. Panel B reports results for a bias-corrected dynamic panel estimator, due to Everaert and Pozzi [33]. The approach starts with the initial, biased fixed-effect estimates and iteratively adjusts these estimates using a bootstrap procedure to obtain unbiased estimates. The resulting estimates are qualitatively similar to those for the dynamic panel data without a fixed effect. The coefficient on the lagged dependent variable falls as expected, since OLS estimates are biased upward in the presence of a firm fixed effect. This implies slightly smaller long run effects. In other respects, however, results are very similar.

Panel C shows results using VAR-based measures. The left-hand portion of Panel C presents results for dynamic model estimated by OLS, and the right-hand portion presents results for the bias-corrected dynamic panel approach. The VAR-based measures produce qualitatively similar results for our main asymmetry measures of interest. The slope coefficients on SKEW and U/DVOL remain negative and significant as in previous results. Similarly, the slope coefficients on DSVOL and USVOL are statistically significant with positive and negative signs, respectively.

1.6.2 Leverage

Many papers have analyzed the determinants of firm leverage. Empirical approaches as well as conclusions vary considerably. As with our analysis of cash holdings, we consider multiple econometric approaches. Table 8 provides results.[17] All of our models include the following (lagged) firm controls, motivated by prior literature: OCF, CASH, R&D, DEPRN, TANG, SIZE, M/B, and DIV. (See the Appendix for variable definitions.)

Panel A of Table 8 shows results for two specifications. The left-hand side of Panel A contains results for a model that includes lagged leverage, dummies for two-digit SIC industry classification, and lagged firm controls. Estimation is by pooled OLS. The right-hand side of Panel A reports results for a traditional (static) fixed effects model. We obtain a positive and significant coefficient for the VOL measure of firm cash flow risk under both the pooled and fixed effects approaches. While this result is not consistent with theoretical literature, the direction and significance of the coefficient on firm risk in the empirical capital structure literature is not well established.[18] Intuition suggests that firms with more negatively skewed

[17]The results we present uses market leverage as dependent variable. Our results are robust to alternative leverage definitions. Alternative leverage measures include book leverage, defined as book value of debt divided by book value of total assets, and leverage ratio adopted by Keefe and Yaghoubi [64]. Keefe and Yaghoubi [64] argue that traditional measures of leverage ratio treat operating liabilities as negative equity. Hence, they propose a leverage measure as

$$\text{MDR} = \frac{\text{DLTT} + \text{DLC}}{\text{DLTT} + \text{DLC} + \text{ME}}$$

which does not consider the effect of operating liabilities.

[18]Castanias [22], Bradley et al. [18], Faulkender and Petersen [36], Xu [95], and Levine and Wu [73] find

cash flow news should employ lower leverage, all else equal. The dynamic model estimated by pooled OLS generates a positive coefficient on SKEW, consistent with this prediction. The fixed effects estimator; however, generates the opposite result: more negatively skewed cash flow news is associated with *more* leverage. The pooled OLS and fixed effect approaches also generate opposite-signed estimates for coefficients on the downside and upside components of volatility. The dynamic model estimated by pooled OLS yields a negative and significant coefficient for downside volatility, consistent with theoretical predictions. The slope coefficient associated with upside volatility is positive. However, the fixed effects model produces an opposite pattern of results.

Both pooled OLS and static fixed estimates of slope parameters are potentially biased in capital structure models. The former is potentially biased due to the importance of unobserved heterogeneity across firms in explaining capital structure. The traditional fixed effects estimator is biased when there is unobserved heterogeneity and capital structure is persistent [80]. Panel B shows results using an econometric approach that delivers consistent estimates when the model includes both the lagged dependent variable and firm-level fixed effects. Specifically, we report results for the approach of Elsas and Florysiak [32] that also accommodates a fractional dependent variable, which is potentially important for leverage. A nontrivial fraction of firms (14.8% in our sample) exhibit zero (measured) leverage [89], and this clustering of observations at a boundary point can exacerbate biases associated with estimating linear panel data models when the measured dependent variable is a bounded ratio (Cook et al. [26], Ramalho and da Silva [82]). The Elsas and Florysiak [32] approach provides unbiased and consistent for (unbalanced) dynamic panel data models with fractional dependent variables. The estimator takes the form of a doubly-censored

a negative relationship between leverage ratio and cash flow volatility, while Friend and Lang [43] find a positive relationship. Leary and Roberts [68], Lemmon et al. [72], Frank and Goyal [41], and Antoniou et al. [4] do not find that volatility exerts a consistent impact on leverage. For a more extensive review and accompanying literature see Keefe and Yaghoubi [64], Frank and Goyal [41], and Kale et al. [62].

Tobit estimator (with censoring at 0 and 1), that accounts for the fractional nature of the dependent variable via a latent variable approach. We refer readers to Elsas and Florysiak [32] for additional details.

The left-hand side Panel B shows results for the baseline measures. The right-hand shows results for measures based on the VAR decomposition. Standard errors are clustered by firm. The left-hand side of Panel B shows that applying the Elsas and Florysiak [32] estimator produces slope coefficients for our measures of interest that generally accord with theory and intuition. In particular, firms with more negatively skewed cash flow news use less debt as expected. Also, the slope coefficient for downside volatility is negative as expected, whereas that for upside volatility is positive and significant. Finally, although the point estimate for VOL in column (1) remains positive when VOL is included alone (among our measures of interest), the coefficient on VOL becomes negative as expected in columns (2)–(3) when included alongside a skewness measure. Including measures of the asymmetry in cash flow news therefore helps resolve an apparently incongruous result concerning the relation between leverage and cash flow volatility. [19]

The right-hand side of of Panel B of Table 8 shows results for the Elsas and Florysiak [32] estimator using measures based on the VAR decomposition of Vuolteenaho [91]. Results for our main measures of interest are qualitatively similar to those obtained under the baseline measures. In particular, total cash flow volatility (VOL) is negatively related to leverage, measures of skewness relate positively to leverage, conditional on volatility, and the decomposition of total volatility in column (8) reveals that downside (upside) volatility relates negatively (positively) to firm leverage.

[19] In Table 8, we use levered stock returns to compute volatility. This raises the possibility that the results in Panel B for leverage are attributable entirely to measuring risk with levered returns. We also reproduced the results using unlevered returns (as discussed in footnote 13) and the method of Elsas and Florysiak [32]. The same results are obtained for skewness and the sided volatility measures. Thus the use of levered returns to compute the uncertainty measures is not a primary factor in the relationships documented in Panel B.

To discuss the economic significance of our results, we focus on estimates on the left-hand side of Panel B, associated with the Elsas and Florysiak [32] approach for baseline measures. The estimate of the parameter ρ capturing persistence in the dependent variable is roughly 0.75. This implies that the long-run significance for our leverage estimates is roughly 4 times that of the short-run effect. To appreciate the economically important role of asymmetries, consider the slope estimate for SKEW in column (2) of Panel B of Table 8. This estimate implies that a one standard deviation increase in skewness is associated with an approximately 40 basis point increase in leverage, all else equal (including cash flow volatility). This effect may seem modest; however, it is a short run effect, and the corresponding long run effect implies an increase in leverage of approximately 1.6%, which is roughly 13% of median leverage in our pooled sample. Estimates in column (4) contrast the effects of the downside and upside components of volatility. Our estimates imply that a one standard deviation increase in downside (upside) volatility is associated with a decrease (increase) in leverage of approximately 1% (0.77%) in the short run. Long-run effects are roughly four times this magnitude based on our estimates.

1.6.3 Endogeneity via feedback effects

Endogeneity can arise from a variety of sources, including omitted variables, simultaneity, and measurement error. Previously discussed dynamic panel data models for cash and leverage address several potential sources of endogeneity. For example, these models accommodate unobserved, time-invariant heterogeneity across firms that is potentially correlated with explanatory variables. They also permit bona fide dynamic behavior, as would be expected under models of partial adjustment in leverage and other corporate policies. However, a subtle weakness of approaches considered to this point is that they assume explanatory variables to be *strictly exogenous*, i.e., uncorrelated with model shocks at all leads and lags, conditional on the unobserved time-invariant firm effect. Among other restrictions, this prohibits feedback effects or 'reverse causality' from the dependent variable to future values of the explanatory variables. Feedback effects are potentially relevant in many corporate finance settings, including the policies we examine. For example, unanticipated shocks to firm leverage could impact the future values of a variety of firm variables included in our models, including the future properties of cash flow uncertainty. Grieser and Hadlock [49] emphasize the importance of strict exogeneity for the consistency of many panel estimators in a finance context, and note that few published studies explicitly address the issue.[20]

We estimate an alternative set of dynamic panel data models under a weaker set of assumptions to address feedback concerns. In particular, we estimate the following model:

$$Y_{i,t} = \sum_{p=1}^{P} \rho_p Y_{i,t-p} + \beta' X_{i,t-1} + \psi' Z_{i,t-1} + \lambda_t + \alpha_i + \eta_{i,t}, \tag{1.8}$$

where Y denotes the corporate policy of interest, X denotes our uncertainty measures of focal interest, Z is a vector including a constant and additional controls, and $\eta_{i,t}$ denotes a shock. The term α_i explicitly recognizes the inclusion of a time-invariant firm effect in the model, and λ_t captures year effects. The model of Eq. (1.8) permits more than one lag in the dependent variable for reasons discussed below.

In order to relax the assumption that explanatory variables $X_{i,t}$ and $Z_{i,t}$ are strictly exogenous, we apply the 'system GMM' estimation approach of Arellano and Bover [6] and Blundell and Bond [15], who build upon earlier contributions of Holtz-Eakin et al. [56] and Arellano and Bond [5]. To introduce the approach, consider the first-differenced form of Eq.

[20] There are exceptions, including, for example, Wintoki et al. [93], who apply system GMM approaches similar to those we consider below in the context of addressing feedback from firm performance to corporate governance and specifically board structure.

(1.8), ignoring year effects for simplicity:

$$\Delta Y_{i,t} = \sum_{p=1}^{P} \rho_p \, \Delta Y_{i,t-p} + \beta' \Delta X_{i,t-1} + \psi' \Delta Z_{i,t-1} + \Delta \eta_{i,t}, \tag{1.9}$$

The first-difference transformation removes the firm effect. However, OLS remains inconsistent for Eq. (1.9) because $\Delta Y_{i,t-1}$ is mechanically correlated with $\Delta \eta_{i,t}$. We assume that the (lagged) explanatory variables $X_{i,t-1}$ and $Z_{i,t-1}$ are *predetermined*, such that model shocks $\eta_{i,t}$ are uncorrelated with current and past values of these variables, but they are potentially correlated with *future* values of the variables. Importantly, this permits feedback from Y to future values of X and Z.

We now make the additional assumption that shocks $\eta_{i,t}$ in Eq. (1.8) are serially uncorrelated. Under this assumption, suitably lagged levels of variables serve as valid instruments for the endogenous variables in Eq. (1.9), which permits consistent estimation of slope parameters. For example, although $Y_{i,t-1}$ is correlated with $\Delta \eta_{i,t}$, $Y_{i,t-2}$ is uncorrelated with $\Delta \eta_{i,t}$ and therefore a viable instrument. Additional lagged levels of $Y_{i,t}$ are also valid instruments. Similar logic implies that $X_{i,t-2}$ and $Z_{i,t-2}$ of the predetermined regressors are valid instruments for the first-differenced model, as are additional past lagged levels. Additional moment conditions may be exploited under the assumption that differences $\Delta X_{i,t}$ and $\Delta Z_{i,t}$ are uncorrelated with α_i. In particular, lagged differences of these variables can be used as instruments in the (non-transformed) levels equation (Eq. (1.8)). Similarly, under a stationarity assumption discussed in Blundell and Bond [15], lagged differences of the dependent variable can serve as instruments in the levels equation. The system GMM estimator exploits the additional moment conditions associated with the levels equation in addition to those available for the first-differenced equation. The additional levels equations and associated instruments are particularly important when the dependent variable $Y_{i,t}$ is persistent, as is the case for corporate leverage, for example. In such cases, GMM estimates that employ lagged levels as instruments in the first-differenced equations can be substantially biased. Intuitively, this occurs because lagged levels become weak instruments in the differenced equation. Incorporating the additional moment conditions alleviates the bias (Blundell and Bond [16]).

The assumption that shocks $\eta_{i,t}$ are uncorrelated is critical. It is, therefore, important to choose a sufficient number of lags of the dependent variable (p in our notation) to well-capture the dynamics of the dependent variable. We include two or three lags in reported results, depending on the specification. Models with fewer lags generally produce similar results for our variables of interest; however, in some cases serial correlation tests suggest that the dynamics are inadequately captured for these models. We implement the system GMM estimator by including the lagged levels $Y_{i,t-2} \ldots Y_{i,t-6}$, $X_{i,t-2}$, $X_{i,t-3}$, $Z_{i,t-2}$ and $Z_{i,t-3}$ as instruments in the differenced equations, and lagged differences $\Delta Y_{i,t-1}$, $\Delta X_{i,t-1}$ and $\Delta Z_{i,t-1}$ as instruments in the levels equations.[21] Year effects are included in the model and treated as strictly exogenous.

Table 9 presents estimation results for cash flow uncertainty measures of primary interest. These results are qualitatively similar to previous results obtained under more restrictive assumptions. Taking results for cash holdings (columns (1)–(4)) as an example, the estimated slope coefficient on cash flow volatility (VOL) is negative, but statistically insignificant. Conditional on VOL and other controls, the slope coefficient on SKEW is negative and significant as expected, and including SKEW results in a positive rather than negative estimate

[21] For additional discussion and technical results pertaining to system GMM estimates of dynamic panel data models see e.g., Blundell and Bond [15], Bond [17] or the textbook treatment in Wooldridge [94]. We report results for the optimal 'two-stage' system GMM estimates, applying robust standard errors, implemented via Stata's 'xtdpd' procedure. To conserve space, we do not explicitly spell out the matrices of moment conditions for the system GMM estimator. Presentations of these matrices and further explication may be found in the aforementioned references. We truncate the number of included lags for predetermined variables to avoid an excessively large number of instruments in the system. We obtain similar results under modest perturbations of the number of included lags.

for the slope on VOL. Similar results obtain in column (3) using the alternative U/DVOL asymmetry measure and in this case the corresponding slope estimate for VOL becomes both positive and weakly significant. Column (4) confirms that the slope coefficients on DSVOL (USVOL) are positive (negative), with the magnitude of the slope coefficient on DSVOL 4–5 times greater than that on USVOL. These results are similar to those previously reported in Table 7. Likewise, results for leverage (columns (5)–(8)) are similar to those reported for the dynamic panel estimator of Elsas and Florysiak [32] (Panel B of Table 8). The latter approach assumes that explanatory variables are strictly exogenous, but Table 9 shows that we obtain similar findings using the system GMM approach that treats explanatory variables as predetermined. Although this section focuses on cash and leverage policies, columns (9)–(12) of Table 9 illustrate that we obtain qualitatively similar results for firms' propensity to pay a dividend under a linear probability variant of the dynamic panel data model that accommodates feedback effects from payout shocks to future explanatory variables. The bottom portion of Table 9 shows the number of lags included in each model and the p-value associated with the test of the null hypothesis that $\text{Corr}(\Delta\eta_t, \Delta\eta_{t-2}) = 0$, an implication of the key model assumption that $\eta_{i,t}$ is uncorrelated. We find no evidence of significant correlation in these tests.

The system GMM results indicate that our main conclusions are robust to weakening the assumption of strict exogeneity to permit realistic feedback from corporate policies to explanatory variables. Although this is comforting, we caution that this robustness does not imply that our analysis is free from all potential endogeneity concerns. Cash flow uncertainty measures remain exposed to potential bias associated with measurement error. To the extent that this generates an attenuation bias, our results are conservative. In addition, despite our efforts to control for a wide range of firm characteristics suggested by existing empirical literature, it remains possible that the models omit a relevant variable that is correlated with our cash flow uncertainty measures. Ultimately, it would be ideal to introduce convincing external instruments to alleviate such concerns. However, as in many corporate finance settings, it is very difficult to identify highly convincing external instruments in the models we consider. To underscore the associated difficulty, we note that many of our explanatory variables, which are drawn from a large body of prior literature, are subject to endogeneity concerns. A consistent estimator requires identifying at least as many valid external instruments as there are endogenous regressors – an extremely difficult task.

1.7 Robustness and Extensions

1.7.1 Daily returns versus monthly returns

Our baseline return-based measures utilize monthly returns. The choice of monthly returns is based on a trade-off between the increased accuracy that high-frequency data afford in estimating properties of cash flow news versus potential biases induced by trading frictions and associated microstructure effects, which become more severe at higher sampling frequencies. To illustrate the robustness of our key results to the choice of daily versus monthly returns, Table 10 shows results for the propensity to pay dividends, substituting daily returns for monthly returns in constructing cash flow uncertainty measures. These results are analogous to those in Panel B of Table 3.

The pattern of results in Table 10 is largely the same as in Table 3: the propensity to pay is negatively related to VOL, positively related to the two skewness measures, negatively related to downside volatility, and positively related to upside volatility. In untabulated results, we also examine the impact of substituting uncertainty measures based on daily returns for analyses of the propensity to repurchase, cash holdings, and leverage and obtain similar results.

1.7.2 Measuring cash flow uncertainty with accounting data

Results to this point employ measures of cash flow uncertainty constructed from stock returns. It is possible to conduct a similar analysis using uncertainty measures constructed from accounting data. Does this distinction matter empirically concerning the relation between uncertainty measures and corporate policies? The simple answer to this question is 'yes:' results are often *not* robust to the use of accounting-based measures. As a concrete example, slope coefficients for the asymmetry measures SKEW and U/DVOL in cash regressions are often insignificant and in some cases take an unexpected sign. The lack of robustness of results to the use of accounting-based measures is perhaps not surprising given the weak correlations between return-based and accounting-based measures reported in Table 2.

Section 1.3 outlines the conceptual merits of return-based measures relative to those based on accounting data. Here we further examine the characteristics of firms with different cash-flow skewness properties, contrasting results under return-based skewness measures with those under accounting-based measures. Specifically, we sort our sample into deciles based on a specified skewness measure (return-based or accounting-based) at each fiscal year end. We then compute the (equal-weighted across firms and fiscal year ends) decile portfolio averages for various firm characteristics for each fiscal year. Lastly, we present time-series average of these cross-sectional averages.

Panel A of Table 11 presents results when firms are sorted using our baseline return-based SKEW measure. The first column shows the average value of SKEW for each decile. By construction, there is a monotonic ordering from decile 1 with the most negative skewness to decile 10 with the most positive skewness. The second column shows that sorting based on SKEW yields a similarly monotonically increasing pattern in the alternative U/DVOL asymmetry measure. This is not surprising given the high correlation between SKEW and U/DVOL. The third column presents the average accounting-based SKEW value for each decile. The extreme high and low deciles of return skewness also have the highest and lowest average accounting-based SKEW values, but there is little variation in the average accounting-based SKEW value across the second through the ninth deciles of firms. Similar results obtain for the accounting-based U/DVOL measure (column 4). These results emphasize that a ranking of firms based on SKEW constructed using stock returns differs significantly from a similar ranking based on SKEW constructed using accounting data.

The right-hand portion of Panel A presents decile averages for five firm characteristics computed using end of previous (fiscal) year values. These characteristics are operating cash flow, size, the market/book ratio for assets, R&D expense scaled by assets, and capital expenditure scaled by assets. The fifth column shows that the lowest (highest) decile with the most negative (positive) skewness has the lowest (highest) average profitability. The other eight deciles all have similar profitability. The sixth column shows that the firms in the highest skewness deciles are on average smaller. The return skewness deciles also map monotonically into M/B ratios: negative skewness of returns is paired with low M/B while the highest positive skewness is paired with the highest average M/B (column 7). This monotonic pattern for M/B is consistent with the common interpretation of high M/B firms as 'growth' firms. Column 8 similarly shows that firms with high positive skewness typically have large R&D expenses and that firms with negative skewness in their returns tend to conduct less R&D. The final column shows that investment in new fixed assets increases across the ten deciles. Overall, these results characterize a typical firm with high positive SKEW based on stock-returns as a firm with smaller size, high M/B, high R&D, and high capital expenditures. Such firms would seem to be precisely the type of firms with the potential to realize extreme positive cash flow outcomes in the future.

Panel B of Table 11 presents contrasting results when decile portfolios are formed based on SKEW computed from accounting data. We focus discussion on the right-hand portion of this panel that shows relations with firm characteristics. The fifth column shows the average OCF for each decile. Accounting-based SKEW sorts are roughly similar to sorting by profitability in the most recent year. This is not ideal given that we endeavor to measure *skewness* in performance outcomes, as opposed to the level of profitability. The sixth column shows the surprising result that higher skewness of accounting profits is associated with larger firms. There is no consistent relationship between M/B and skewness based on past accounting profits (column 7). Casual thinking suggests that firms with higher R&D intensity would have more positive skewness. Column 8 of Panel B shows that, in contrast to this intuition, accounting-based SKEW is highest for firms with the lowest R&D intensity. The final column of Panel B shows a mild tendency for Capex to increase with skewness. These results indicate that high positive skewness in accounting profitability is associated with large firms with low R&D intensity. Accounting-based SKEW values are essentially unrelated to M/B and have only a weak association with investment in fixed assets. Our interpretation of this evidence is that skew measures based on stock returns better capture firm attributes likely to be associated with similarly skewed *future* cash flow outcomes. Recall that return-based cash flow shocks reflect revisions in expectations of the entire (discounted) stream of future cash flows. A related interpretation of our results is that such shocks differ materially from shocks to current period accounting outcomes. Given the apparent issues associated with accounting-based asymmetry measures, we are less concerned with the fact that corporate policy regression results differ for such measures relative to measures based on stock returns.

1.7.3 NYSE versus non-NYSE firms

Previous literature finds that the sample composition matters in empirical corporate finance studies (see, for example, Begenau and Palazzo [13], Fama and French [34], Graham and Leary [46]). More specifically, Graham and Leary [46] examine cash holdings over a roughly 100 year period. Their paper documents substantial differences in liquidity policies between NYSE firms and non-NYSE firms, especially since 1980. We briefly examine the impact of this split on our results. A simple comparison of pooled averages reveals that NYSE firms hold less than half the cash held by non-NYSE firms (10.49% vs 23.78%) over our sample period. Measures of future firm performance also differ between the two groups of firms. Volatility is on average 50% higher for non-NYSE firms than NYSE firms, downside volatility is 40% higher, upside volatility is 65% higher, and the skewness measures are both about 250% higher.

We next estimate the extended model from Panel A of Table 7 separately for NYSE and non-NYSE firms. Results are presented in Table 12. Columns (1)-(4) report results for firms listed on the NYSE, and columns (5)-(8) report results for non-NYSE firms. The slope coefficient on the traditional total volatility (VOL) measure of cash flow risk is positive as expected for NYSE-listed firms. Measures of cash flow skewness (columns (2) and (3)) also impact cash retention in the expected direction, and including these measures materially increases the economic significance of VOL. For non-NYSE firms, the slope coefficient when VOL is included without measures of skewness is negative, rather than positive, although it is statistically insignificant (columns (5)). Upon adding measures of skewness to the model (columns (6) and (7)), these measures are highly significant in the expected direction, and the slope coefficient on VOL becomes positive (although still insignificant). Models that split volatility into upside and downside components (columns (4) and (8)) reveal statistically and economically significant differences between the two components for both NYSE and non-NYSE firms. Effects are more stark for non-NYSE firms, however. Broadly, the results in Table 11 indicate that asymmetries in cash flow news are important for both sets of firms, but are relatively more important for non-NYSE listed firms.

1.7.4 Asymmetries in expected return news

The analysis to this point focuses on the role of asymmetries in the distribution of cash flow news. Here we briefly discuss an extension that also considers the role of asymmetries in firm-level *expected return* news, either separately or in conjunction with asymmetry measures for cash flow news. Conceptually, it is somewhat difficult to characterize clear ex ante hypotheses concerning asymmetries in expected return news and corporate policies. Should firms adopt more conservative policies if expected returns are more positively skewed? It is perhaps not clear, because patterns of expected return variation might reflect either time-varying risk (discount rates) or effects driven by sentiment/mispricing (or both). As discussed in Vuolteenaho [91], the VAR state variables used to decompose returns into cash flow and expected return news, which include lagged returns, the book-to-market ratio, and a profitability measure, are intended to capture key cross-sectional return patterns, including price-momentum and reversal effects and the value and profitability anomalies. An extensive and ongoing literature debates the question of whether these empirical anomalies reflect risk or mispricing.

Empirically, we construct uncertainty measures analogous to those constructed for cash flow news (VOL, DSVOL, SKEW, etc.) based on expected return shocks $\hat{\epsilon}_{i,t}^{ER}$ rather than cash flow shocks. We then re-estimate our corporate policy models both 1) substituting these expected return measures for the cash flow news measures, all else equal; or 2) incorporating expected return uncertainty measures in addition to corresponding cash flow uncertainty measures. Results for these expected return uncertainty measures are relatively weak. For example, in extended specifications that include both sets of uncertainty measures, we tend to find that previously documented coefficient patterns for cash flow uncertainty measures are robust to the extended model, whereas expected return uncertainty measures are often insignificant. Explicit results are available upon request from the authors.

1.8 Conclusion

We examine how corporate policy decisions depend on asymmetries in firm cash flow distributions. We propose a variety of measures of asymmetries, including decompositions of total variance into upside and downside components, and several direct measures of skewness. Downside and upside variance differentially affect firms' payout, cash, and leverage decisions, and we consistently find that corporate policies are more sensitive to downside volatility relative to upside. In similar fashion, corporate policies depend upon skewness conditional on volatility. Theoretical treatments of corporate policies such as leverage and cash holdings emphasize the importance of potential cash shortfalls. Our results accord with this theory: firms with more negatively skewed cash flow distributions adopt more conservative corporate policies. Overall, our evidence indicates that corporate policies depend on asymmetries in cash flow distributions, and that variance fails to completely capture the aspects of cash flow uncertainty relevant for policy choices.

1.9 Tables

Table 1: Summary Statistics for Corporate Policy and Cash Flow Uncertainty Measures

This table presents descriptive statistics of uncertainty measures and corporate policy variables for the sample period 1983-2017. For each variable, we report the pooled sample size (N), the mean, standard deviation (SD), skewness (SKEW), minimum (MIN), maximum (MAX), and selected percentiles, denoted, e.g., P50 for the 50-th percentile. All statistics are based on pooled data. Panel A shows statistics for our main financial policy variables. Panel B shows statistics for our cash flow news measures computed using the baseline method. Panels C and D show results for measures constructed using the VAR decomposition method (Panel C) and based on cross-sectionally de-meaned quarterly stock returns (Panel D). See Section 4.3 of the paper for details concerning different ways of constructing the measures. The sample includes all the firm-year observations in the CRSP-Compustat merged dataset from 1983 to 2017 with the following exceptions. (1) We exclude the utility (SIC 4900 - 4949) and financial (SIC 6000 - 6999) firms; (2) we only include firms traded on NYSE, AMEX, and NASDAQ with CRSP share codes of 10 or 11; (3) we exclude the firm year observations with less than $5 million of total assets and less than $2.5 million of book equity; and (4) we require cash, leverage, dividends, size, market-to-book ratio, return-on-assets, and baseline volatility measures (DSVOL, USVOL, and VOL) to be not missing. Lastly, we winsorize all variables at the 1st and 99th percentile. Detailed definitions of variables are provided in the Appendix.

	N	MEAN	SD	SKEW	MIN	P10	P25	P50	P75	P90	MAX
					Panel A: Financial policies						
DIV	102,313	0.347	0.476	0.643	0.000	0.000	0.000	0.000	1.000	1.000	1.000
REP	102,313	0.430	0.495	0.281	0.000	0.000	0.000	0.000	1.000	1.000	1.000
CASH	102,313	0.195	0.236	1.755	0.000	0.009	0.028	0.098	0.271	0.536	1.000
MLEV	102,313	0.169	0.173	1.074	0.000	0.000	0.016	0.120	0.267	0.428	0.694
					Panel B: Cash flow news measures, baseline method						
VOL	102,313	0.153	0.081	1.603	0.047	0.073	0.097	0.134	0.186	0.255	0.483
DSVOL	102,313	0.092	0.040	0.780	0.029	0.046	0.062	0.085	0.116	0.148	0.213
USVOL	102,313	0.116	0.073	1.925	0.031	0.050	0.067	0.096	0.141	0.206	0.436
SKEW	102,313	0.555	1.013	0.554	-1.620	-0.661	-0.121	0.482	1.128	1.831	3.770
U/DVOL	102,313	0.166	0.357	0.208	-0.671	-0.280	-0.074	0.150	0.391	0.632	1.125
					Panel C: VAR decomposition method						
VOL	81,076	0.118	0.051	0.897	0.042	0.061	0.078	0.107	0.148	0.190	0.278
DSVOL	81,076	0.078	0.047	1.055	0.013	0.028	0.042	0.066	0.103	0.144	0.228
USVOL	81,076	0.084	0.035	0.917	0.000	0.045	0.058	0.078	0.104	0.132	0.213
SKEW	81,076	0.254	0.988	-0.310	-2.168	-1.121	-0.435	0.329	1.027	1.488	2.197
U/DVOL	81,048	0.182	0.542	0.056	-1.241	-0.487	-0.163	0.176	0.523	0.858	1.652
					Panel D: Quarterly log returns method						
VOL	102,161	0.131	0.053	0.696	0.048	0.069	0.088	0.121	0.165	0.207	0.281
DSVOL	102,161	0.084	0.046	0.836	0.015	0.033	0.048	0.075	0.112	0.150	0.220
USVOL	102,161	0.091	0.036	0.645	0.030	0.049	0.063	0.084	0.114	0.143	0.191
SKEW	102,161	0.140	0.542	-0.221	-1.164	-0.598	-0.242	0.167	0.556	0.833	1.231
U/DVOL	102,138	0.152	0.505	0.144	-1.131	-0.465	-0.174	0.137	0.463	0.789	1.550

Table 2: Cross-Correlations

This table presents pooled correlations for the sample period 1983–2017. Panel A presents the correlations between our main measure and key firm characteristics including *ROA*, *OCF*, *SIZE*, *M/B*, *CAPEX*, *TANG*, and *Product Market Fluidity* from Hoberg et al. [55]. The correlation calculated based on any pair of variables is based on the availability of both. Panel B presents the correlations between our main measures and other variations of measures. In each column of Panel B, we present the correlations between cash flow uncertainty measures constructed with our baseline method and cash flow uncertainty constructed with VAR decomposed return, quarterly logged return, and accounting-based methods. The variable *FLUIDITY* is adorned with a † symbol to emphasize that correlations for this variable are based only on the overlapping portion of our sample period for which the measure is available (1999–2010).

Panel A: Correlations between baseline measures and firm characteristics

	VOL	*DSVOL*	*USVOL*	*SKEW*	*U/DVOL*
VOL	1.000				
DSVOL	0.854	1.000			
USVOL	0.976	0.725	1.000		
SKEW	0.534	0.111	0.677	1.000	
U/DVOL	0.437	-0.019	0.603	0.929	1.000
ROA	-0.410	-0.468	-0.349	-0.081	0.024
OCF	-0.387	-0.446	-0.328	-0.079	0.035
SIZE	-0.461	-0.441	-0.434	-0.283	-0.187
M/B	0.159	-0.008	0.217	0.235	0.336
CAPEX	-0.028	-0.080	-0.004	0.049	0.097
TANG	-0.139	-0.156	-0.120	-0.030	-0.011
FLUIDITY†	0.281	0.282	0.259	0.097	0.091

Panel B: Correlations between baseline measures and measures based on alternative methods

	VOL	*DSVOL*	*USVOL*	*SKEW*	*U/DVOL*
Firm-specific mean	0.999	0.934	0.985	0.901	0.709
Market-adjusted returns	0.981	0.936	0.987	0.868	0.873
Unlevered returns	0.917	0.911	0.925	0.968	0.966
VAR decomposition	0.776	0.801	0.599	0.127	0.285
Quarterly log returns	0.823	0.847	0.701	0.235	0.381
Accounting-based	0.388	0.425	0.024	-0.133	-0.033

Table 3: Propensity to Pay

This table presents propensity to pay regression results using our baseline return-based method of describing the uncertainty about cash flow news. We employ pooled MLE to estimate alternative versions of the following general model:

$$log\left(\frac{p(Y_{i,t}=1)}{1-p(Y_{i,t}=1)}\right)=\beta' X_{i,t-1}+\psi' Z_{i,t-1}+\lambda_t+\epsilon_{i,t},$$

where i indexes firm and t indexes time. Y denotes the dependent variable which varies across panels as described below. X is a vector containing uncertainty measures of focal interest, and λ_t is a year dummy. Z denotes a vector containing control variables for our propensity to pay model. In some cases, Z includes a set of industry dummies based on two-digit SIC codes, indicated by a 'Yes' field for 'Industry Effects' in results. In Panel A, the dependent variable equals one if a firm pays dividend in a year, and zero otherwise. All uncertainty measures are constructed using our baseline method. We adopt a benchmark specification in Panel A following Fama and French [34] and Hoberg and Prabhala [54] by controlling *ROA*, *SIZE*, *M/B*, and *CAPEX*. Panel B uses the same dependent variable as Panel A. In Panel B, we adopt an extended model following Hoberg and Prabhala [54], Chay and Suh [23], and Hoberg et al. [55] and control for *LEV*, *CASH*, *ROA*, *M/B*, *SIZE*, *CAPEX*, *R&D*, *MISS R&D*, *TANG*, and *RE/TE*. In Panel C, the dependent variable equals one if a firm repurchases in a year, and zero otherwise. We use the same extended model as in Panel B. Detailed definitions of variables are listed in the appendix. Standard errors are clustered at firm level. t statistics are reported in parentheses. *, **, *** indicates 10%, 5%, and 1% significance level, respectively.

Panel A: Propensity to pay dividends - benchmark model

	(1)	(2)	(3)	(4)	(5)
VOL		-23.518***	-25.170***	-24.935***	
		(-34.81)	(-36.57)	(-36.13)	
SKEW			0.255***		
			(12.90)		
U/DVOL				0.624***	
				(11.54)	
DSVOL					-30.937***
					(-31.62)
USVOL					-9.605***
					(-13.85)
ROA	7.473***	6.334***	5.881***	5.734***	5.325***
	(39.10)	(29.39)	(27.38)	(26.68)	(24.80)
SIZE	0.566***	0.350***	0.363***	0.354***	0.357***
	(32.59)	(20.06)	(20.58)	(20.11)	(20.11)
CAPEX	-2.826***	-2.068***	-2.129***	-2.179***	-2.224***
	(-10.27)	(-7.34)	(-7.53)	(-7.69)	(-7.85)
M/B	-0.270***	-0.200***	-0.218***	-0.233***	-0.251***
	(-11.09)	(-7.88)	(-8.39)	(-8.65)	(-9.44)
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	88,470	88,470	88,470	88,470	88,470

Panel B: Propensity to pay dividends - extended model

	(1)	(2)	(3)	(4)	(5)
VOL		-6.289***	-8.214***	-8.162***	
		(-12.92)	(-15.92)	(-15.87)	
SKEW			0.244***		
			(9.70)		
U/DVOL				0.714***	
				(10.31)	
DSVOL					-18.463***
					(-17.71)
USVOL					1.270**
					(2.15)
DIV	6.021***	5.880***	5.883***	5.895***	5.864***
	(114.47)	(112.28)	(111.44)	(111.11)	(111.16)
ROA	6.447***	6.374***	5.985***	5.782***	5.515***
	(21.47)	(20.47)	(19.02)	(18.23)	(17.40)
SIZE	0.330***	0.269***	0.283***	0.274***	0.271***
	(25.69)	(20.01)	(20.70)	(20.18)	(19.89)
CAPEX	-3.718***	-3.579***	-3.563***	-3.672***	-3.632***
	(-10.82)	(-10.21)	(-10.08)	(-10.39)	(-10.26)
M/B	-0.210***	-0.195***	-0.215***	-0.236***	-0.246***
	(-8.69)	(-8.33)	(-9.07)	(-9.59)	(-10.16)
CASH	-0.243**	-0.070	-0.035	-0.016	-0.002
	(-2.06)	(-0.58)	(-0.29)	(-0.13)	(-0.01)
LEV	-2.926***	-2.656***	-2.597***	-2.555***	-2.488***
	(-17.59)	(-15.80)	(-15.56)	(-15.38)	(-14.92)
R&D	-4.645***	-4.171***	-4.005***	-3.936***	-3.753***
	(-8.64)	(-7.80)	(-7.54)	(-7.44)	(-7.18)
MISS R&D	0.030	0.039	0.035	0.033	0.028
	(0.61)	(0.77)	(0.70)	(0.66)	(0.55)
TANG	1.009***	0.999***	0.975***	0.982***	0.971***
	(7.80)	(7.57)	(7.40)	(7.47)	(7.36)
RE/TE	0.113***	0.064**	0.060**	0.060**	0.054**
	(4.17)	(2.57)	(2.41)	(2.40)	(2.26)
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	88,283	88,283	88,283	88,283	88,283

Panel C: Propensity to repurchase - extended model

	(1)	(2)	(3)	(4)	(5)
VOL		-1.960***	-2.512***	-2.496***	
		(-11.40)	(-12.87)	(-13.07)	
SKEW			0.071***		
			(6.32)		
U/DVOL				0.210***	
				(6.65)	
DSVOL					-5.393***
					(-12.31)
USVOL					0.054
					(0.26)
REP	2.271***	2.251***	2.251***	2.253***	2.247***
	(102.49)	(101.70)	(101.68)	(101.72)	(101.43)
ROA	1.571***	1.456***	1.383***	1.345***	1.307***
	(18.04)	(16.63)	(15.75)	(15.18)	(14.93)
SIZE	0.220***	0.195***	0.198***	0.196***	0.191***
	(31.75)	(27.07)	(27.27)	(27.08)	(26.55)
CAPEX	-1.091***	-0.986***	-0.990***	-1.032***	-1.006***
	(-6.20)	(-5.60)	(-5.62)	(-5.86)	(-5.72)
M/B	-0.033***	-0.026**	-0.033***	-0.040***	-0.048***
	(-3.25)	(-2.52)	(-3.25)	(-3.81)	(-4.62)
CASH	0.357***	0.428***	0.436***	0.434***	0.439***
	(6.24)	(7.34)	(7.46)	(7.43)	(7.53)
LEV	-1.273***	-1.172***	-1.152***	-1.140***	-1.113***
	(-16.44)	(-15.09)	(-14.83)	(-14.64)	(-14.28)
R&D	-1.272***	-1.194***	-1.169***	-1.170***	-1.111***
	(-6.97)	(-6.57)	(-6.45)	(-6.47)	(-6.18)
MISS R&D	-0.015	-0.018	-0.022	-0.024	-0.027
	(-0.54)	(-0.66)	(-0.79)	(-0.85)	(-0.98)
TANG	-0.041	-0.070	-0.081	-0.078	-0.098
	(-0.57)	(-0.98)	(-1.13)	(-1.09)	(-1.36)
RE/TE	0.025***	0.015***	0.014***	0.013***	0.011**
	(4.81)	(2.85)	(2.68)	(2.62)	(2.20)
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	88,339	88,339	88,339	88,339	88,339

Table 4: Economic Significance of Benchmark Model

We report the economic effects for the propensity to pay dividends based on Logistic regression coefficient estimates from Table 3 Panel A, specification (3). The dependent variable equals one if the firms is a dividend payer in a year and zero otherwise. To calculate predicted probability, we apply the estimated coefficients from the model in Table 3, $\hat{\beta}$, $\hat{\psi}$, and $\hat{\lambda}_t$, to

$$p\left(Y_{i,t}=1\right)=\frac{\exp\left(\hat{\beta}' X_{i,t-1}+\hat{\psi}' Z_{i,t-1}+\hat{\lambda}_t\right)}{1+\exp\left(\hat{\beta}' X_{i,t-1}+\hat{\psi}' Z_{i,t-1}+\hat{\lambda}_t\right)}$$

for each firm-year observation. Each variable in $X_{i,t-1}$ and $Z_{i,t-1}$ is fixed at the 10th, 25th, 50th, 75th, and 90th percentile with the other variables held at their median values. λ_t is set at observed value of each observation. Next, we calculate and report the pooled average of the predicted probabilities. The row labeled *75-25* presents the difference between the propensity to pay at 25th and 75th percentile, and the percentage difference is reported in the bracket below. The row labeled *90-10* presents the difference between the propensity to pay at 10th and 90th percentile, and the percentage difference is reported in the bracket below.

Pctl	*VOL*	*SKEW*	*ROA*	*SIZE*	*CAPEX*	*M/B*
10	68.6%	29.4%	15.1%	19.4%	37.0%	37.9%
25	56.2%	32.2%	28.2%	25.6%	36.5%	37.0%
50	35.4%	35.4%	35.4%	35.4%	35.4%	35.4%
75	13.9%	38.9%	41.8%	47.5%	33.4%	32.2%
90	3.1%	42.9%	49.4%	59.2%	30.4%	26.9%
75-25	-42.3%	6.8%	13.6%	21.9%	-3.0%	-4.8%
Pct diff	-75.2%	21.0%	48.2%	85.7%	-8.2%	-12.9%
90-10	-65.5%	13.5%	34.3%	39.8%	-6.6%	-11.0%
Pct diff	-95.4%	45.7%	226.6%	205.2%	-18.0%	-29.1%

Table 5: Propensity to Pay Dividends: Robustness to Alternative Measures

This table presents additional propensity to pay regression results based on alternative measures. We estimate the following model:

$$log\left(\frac{p(DIV_{i,t}=1)}{1-p(DIV_{i,t}=1)}\right) = \rho\, DIV_{i,t-1} + \beta' X_{i,t-1} + \psi' Z_{i,t-1} + \lambda_t + \epsilon_{i,t},$$

where i indexes firm and t indexes time. The dependent variable DIV is an indicator that takes the value one when a firm pays a dividend in a particular firm-year, and zero otherwise. X is the vector containing our uncertainty measures, Z is a vector containing control variables for each financial policy of interest, and λ_t is a year dummy. Z includes a set of industry dummies based on two-digit SIC codes, which is emphasized by a 'Yes' field for 'Industry FE' in presented results. Columns 1 to 4 presents the results with uncertainty variables calculated using VAR decomposed returns. Columns 1 to 4 presents the results with uncertainty variables calculated using quarterly log returns demeaned at each cross-section. In each panel, Columns (1)-(4) present results in which all uncertainty measures are constructed with the cash flow news obtained by VAR Decomposition similar to Vuolteenaho [91] and Michaely et al. [76]; Columns (5)-(8) present results in which all uncertainty measures are constructed based on quarterly log returns. More detailed constructions of the uncertainty measures are described in Section 4. We adopt the extended model and control for *LEV*, *CASH*, *ROA*, *M/B*, *SIZE*, *CAPEX*, *R&D*, *MISS R&D TANG*, and *RE/TE* by following Hoberg and Prabhala [54], Chay and Suh [23], and Hoberg et al. [55]. Detailed definitions of variables are listed in the appendix. t statistics are reported in parentheses. *, **, *** indicates 10%, 5%, and 1% significance level, respectively.

	VAR-based measures				Quarterly log return based measures			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VOL	-9.115***	-8.201***	-8.233***		-9.481***	-8.964***	-8.911***	
	(-13.60)	(-11.97)	(-11.98)		(-16.48)	(-15.46)	(-15.30)	
SKEW		0.193***				0.365***		
		(7.39)				(9.29)		
U/DVOL			0.370***				0.413***	
			(7.17)				(9.16)	
DSVOL				-10.477***				-12.114***
				(-11.79)				(-15.49)
USVOL				-1.626*				-1.301*
				(-1.73)				(-1.65)
DivDum	6.007***	6.018***	6.019***	6.023***	5.856***	5.861***	5.858***	5.866***
	(101.96)	(101.53)	(101.46)	(101.76)	(112.88)	(111.98)	(111.93)	(112.03)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	70,878	70,878	70,878	70,878	88,145	88,145	88,145	88,145

Table 6: Propensity to Change Dividends

This table presents propensity to pay regression results. We estimate the following model:

$$log\left(\frac{p(Y_{i,t}=1)}{1-p(Y_{i,t}=1)}\right) = \rho\, Y_{i,t-1} + \beta' X_{i,t-1} + \psi' Z_{i,t-1} + \lambda_t + \epsilon_{i,t},$$

where i indexes firm and t indexes time. Y is the dependent variable reflecting changes in payout status as described below. X is a vector containing our uncertainty measures of focal interest, Z is a vector containing control variables for each financial policy of interest, and λ_t is a year dummy. Z includes a set of industry dummies based on two-digit SIC codes, which is emphasized by a 'Yes' field for 'Industry FE' in presented results. In Columns 1 to 4, the dependent variable equals one if a firm increases its dividend in a year, and zero otherwise. In Columns 5 to 8, the dependent variable equals one if a firm decreases its dividend in a year, and zero otherwise. A firm is considered as increasing its dividends if its dividend per share is higher than the previous year. A firm is considered as decreasing its dividends if its dividend per share is lower than the previous year. All the uncertainty measures are constructed with our baseline method. Following Chay and Suh [23], Hoberg and Prabhala [54], and Hoberg et al. [55], we control for control for *LEV*, *CASH*, *ROA*, *M/B*, *SIZE*, *CAPEX*, *R&D*, *MISS R&D TANG*, and *RE/TE*. Detailed definitions of variables are listed in the appendix. t statistics are reported in parentheses. *, **, *** indicates 10%, 5%, and 1% significance level, respectively.

	Propensity to increase dividends				Propensity to decrease dividends			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VOL	1.519***	0.551	0.531		3.097***	4.246***	4.179***	
	(3.78)	(1.27)	(1.25)		(7.85)	(10.04)	(9.92)	
SKEW		0.117***				-0.141***		
		(6.26)				(-7.87)		
U/DVOL			0.338***				-0.379***	
			(6.66)				(-7.62)	
DSVOL				-6.405***				10.495***
				(-7.05)				(12.00)
USVOL				5.222***				-2.071***
				(9.32)				(-4.08)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	32,448	32,448	32,448	32,448	32,439	32,439	32,439	32,439

Table 7: Cash Models

This table presents regression results for cash holdings. We estimate variations of the following general model:

$$CASH_{i,t} = \rho\, CASH_{i,t-1} + \beta' X_{i,t-1} + \psi' Z_{i,t-1} + \lambda_t + \epsilon_{i,t},$$

where i indexes firm, t indexes time and $\epsilon_{i,t} \equiv \alpha_i + \eta_{i,t}$, which permits the possibility of a time-invariant firm effect. The dependent variable $CASH$ is cash and short term investment divided beginning period book assets. X is the vector containing our uncertainty measures, Z is the vector containing control variables for each financial policy of interest, and λ_t is year dummy. In some cases, Z includes a set of industry dummies based on two-digit SIC codes, which is emphasized by a 'Yes' field for 'Industry FE' in presented results. Models that explicitly incorporate a firm effect α_i are designated by a 'Yes' field for 'Firm Effects' in presented results. Following Opler et al. [81] and Bates et al. [11], we include *LEV*, *DIV*, *OCF*, *SIZE*, *ACQN*, *M/B*, *NWC*, *CAPEX*, *R&D*, and *MISS R&D* as controls for firm characteristics. Detailed definitions of the control variables are listed in the appendix. Panel A presents results with uncertainty measures constructed with our baseline measures. Panel A Columns 1 to 4 report regression results from a benchmark specification where we run pooled regression with year fixed effects. Panel A Columns 5 to 8 reports regression results from an extended model where we include industry fixed effects, year fixed effects, and lagged dependent variable. Industries are defined based on 2-digit SIC codes. Panel B presents results for alternative econometric specifications, still using our baseline measures. Panel B Columns 1 to 4 present firm fixed effects estimators. Panel B Columns 5 to 8 present Tobit estimators for dynamic panel model following Elsas and Florysiak [32]. Panel C presents results with uncertainty measures constructed with cash flow news component obtained by VAR decomposition similar to Vuolteenaho [91] and Michaely et al. [76]. Columns 1 to 4 presents results with our extended model where where we include industry fixed effects, year fixed effects, and lagged dependent variable. t statistics are reported in parentheses. *, **, *** indicates 10%, 5%, and 1% significance level, respectively.

Panel A: Pooled OLS

	Benchmark model				Extended model			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VOL	0.099*** (5.63)	0.182*** (8.86)	0.197*** (9.88)		-0.034*** (-3.26)	0.025** (2.06)	0.033*** (2.80)	
SKEW		-0.011*** (-9.75)				-0.007*** (-11.24)		
U/DVOL			-0.039*** (-12.91)				-0.026*** (-14.32)	
DSVOL				0.715*** (15.74)				0.397*** (14.49)
USVOL				-0.169*** (-8.25)				-0.186*** (-13.55)
CASH					0.661*** (92.76)	0.660*** (92.01)	0.659*** (91.90)	0.658*** (91.05)
LEV	-0.242*** (-31.64)	-0.244*** (-31.76)	-0.247*** (-32.03)	-0.248*** (-32.17)	-0.117*** (-29.04)	-0.119*** (-29.44)	-0.122*** (-29.90)	-0.123*** (-30.26)
DIV	-0.034*** (-11.60)	-0.032*** (-10.87)	-0.032*** (-10.80)	-0.027*** (-9.02)	-0.013*** (-8.87)	-0.012*** (-8.04)	-0.011*** (-7.99)	-0.009*** (-6.02)
OCF	-0.099*** (-11.49)	-0.091*** (-10.45)	-0.084*** (-9.49)	-0.082*** (-9.30)	-0.002 (-0.30)	0.004 (0.71)	0.009 (1.57)	0.010* (1.72)
SIZE	-0.002** (-2.10)	-0.002*** (-2.73)	-0.002** (-2.29)	-0.001 (-1.55)	-0.008*** (-18.65)	-0.009*** (-19.46)	-0.008*** (-18.94)	-0.008*** (-18.06)
ACQN	-0.133*** (-20.16)	-0.129*** (-19.52)	-0.124*** (-18.76)	-0.123*** (-18.65)	-0.115*** (-21.54)	-0.112*** (-20.94)	-0.109*** (-20.32)	-0.108*** (-20.31)
M/B	0.033*** (27.94)	0.034*** (28.25)	0.036*** (28.49)	0.036*** (28.92)	0.018*** (22.36)	0.018*** (22.84)	0.019*** (23.38)	0.020*** (23.87)
NWC	0.198*** (34.24)	0.199*** (34.47)	0.201*** (34.85)	0.203*** (35.26)	-0.095*** (-22.64)	-0.094*** (-22.39)	-0.092*** (-22.00)	-0.090*** (-21.54)
CAPEX	-0.139*** (-11.66)	-0.136*** (-11.36)	-0.130*** (-10.86)	-0.129*** (-10.80)	-0.245*** (-27.45)	-0.243*** (-27.23)	-0.239*** (-26.76)	-0.238*** (-26.74)
R&D	0.479*** (24.67)	0.473*** (24.42)	0.471*** (24.29)	0.462*** (23.83)	0.172*** (13.36)	0.169*** (13.09)	0.168*** (13.02)	0.164*** (12.64)
MISS R&D	0.018*** (6.22)	0.019*** (6.38)	0.019*** (6.50)	0.019*** (6.62)	0.000 (0.28)	0.001 (0.47)	0.001 (0.63)	0.001 (0.72)
Industry FE	No	No	No	No	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	82,947	82,947	82,947	82,947	82,947	82,947	82,947	82,947

Panel B: Fixed effects model and dynamic panel estimator of Everaert and Pozzi [33]

	Fixed effects estimator				Everaert and Pozzi [33] estimator			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VOL	0.010	0.065***	0.071***		-0.037***	0.026**	0.035***	
	(0.61)	(3.42)	(3.81)		(-3.29)	(2.05)	(2.80)	
SKEW		-0.006***				-0.007***		
		(-7.13)				(-10.00)		
U/DVOL			-0.021***				-0.024***	
			(-8.58)				(-12.25)	
DSVOL				0.349***				0.305***
				(8.85)				(10.98)
USVOL				-0.108***				-0.154***
				(-5.44)				(-11.34)
CASH					0.607***	0.606***	0.606***	0.606***
					(98.60)	(98.65)	(98.72)	(98.71)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	82,763	82,763	82,763	82,763	72,934	72,934	72,934	72,934

Panel C: VAR-based measures

	Pooled OLS				Everaert and Pozzi [33] estimator			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VOL	0.012	-0.008	-0.014		0.049**	0.037*	0.034	
	(0.72)	(-0.45)	(-0.84)		(2.27)	(1.74)	(1.38)	
SKEW		-0.004***				-0.003***		
		(-7.14)				(-3.51)		
U/DVOL			-0.011***				-0.008***	
			(-8.99)				(-4.35)	
DSVOL				0.122***				0.154***
				(5.94)				(4.67)
USVOL				-0.122***				-0.099***
				(-5.06)				(-3.22)
CASH	0.686***	0.685***	0.685***	0.685***	0.470***	0.470***	0.470***	0.469***
	(86.30)	(86.02)	(85.97)	(86.08)	(33.74)	(33.59)	(40.09)	(35.22)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	66,467	66,467	66,467	66,467	58,995	58,995	58,995	58,995

Table 8: Leverage Models

This table presents regression results for firm leverage policy. We estimate variations of the following general model

$$Y_{i,t} = \rho\, Y_{i,t-1} + \beta' X_{i,t-1} + \psi' Z_{i,t-1} + \lambda_t + \epsilon_{i,t},$$

where i indexes firm, t indexes time and $\epsilon_{i,t} \equiv \alpha_i + \eta_{i,t}$, which permits the possibility of a time-invariant firm effect. The dependent variable *LEV* is defined as long-term debt plus debt in current liabilities divided by market value of assets. X is a vector containing our uncertainty measures of focal interest, Z is a vector containing control variables, and λ_t is a year dummy. In some cases, Z includes a set of industry dummies based on two-digit SIC codes, which is emphasized by a 'Yes' field for 'Industry FE' in presented results. Models that explicitly incorporate a firm effect α_i are designated by a 'Yes' field for 'Firm Effects' in presented results. Following Frank and Goyal [41], Lemmon et al. [72], and Xu [95], we control for *CASH*, *DIV*, *OCF*, *SIZE*, *M/B*, *TANG*, *DEPRN*, *R&d*, and *MISS R&D*. Detailed definitions of the control variables are listed in the appendix. Panel A presents results with uncertainty measures constructed with our baseline measures. In Columns 1 to 4, we adopt an OLS estimator while controlling industry and year fixed effects, and lagged dependent variable. In Columns 5 to 8, we adopt a firm fixed effect model with year dummies. Panel B presents results based on a dynamic panel estimator following Elsas and Florysiak [32]. Columns 1 to 4 present results for this model using uncertainty measures constructed with our baseline method. Columns 5 to 8 present results for the same model with uncertainty measures constructed with cash flow news component obtained by VAR decomposition similar to Vuolteenaho [91] and Michaely et al. [76]. t statistics are reported in parentheses. *, **, *** indicates 10%, 5%, and 1% significance level, respectively.

Panel A: Baseline measures

	Pooled OLS				Fixed effects			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VOL	0.044*** (8.59)	0.021*** (3.48)	0.013** (2.19)		0.079*** (5.66)	0.157*** (10.13)	0.193*** (12.62)	
SKEW		0.003*** (7.93)				-0.009*** (-12.70)		
U/DVOL			0.012*** (11.63)				-0.041*** (-20.27)	
DSVOL				-0.146*** (-10.35)				0.515*** (16.52)
USVOL				0.104*** (14.83)				-0.100*** (-7.01)
LEV	0.855*** (303.48)	0.856*** (304.66)	0.858*** (305.69)	0.858*** (306.15)				
CASH	-0.013*** (-8.24)	-0.013*** (-8.23)	-0.013*** (-8.46)	-0.013*** (-8.44)	-0.076*** (-19.88)	-0.074*** (-19.37)	-0.071*** (-18.34)	-0.070*** (-18.30)
DIV	-0.006*** (-7.86)	-0.006*** (-8.39)	-0.006*** (-8.48)	-0.007*** (-9.73)	-0.014*** (-5.42)	-0.013*** (-5.11)	-0.013*** (-4.96)	-0.011*** (-4.42)
OCF	-0.001 (-0.55)	-0.004* (-1.92)	-0.007*** (-3.59)	-0.007*** (-3.52)	-0.103*** (-19.90)	-0.094*** (-18.27)	-0.079*** (-15.82)	-0.086*** (-16.96)
SIZE	0.002*** (9.19)	0.002*** (9.88)	0.002*** (9.53)	0.002*** (8.75)	0.042*** (25.49)	0.041*** (25.14)	0.041*** (25.17)	0.042*** (25.63)
M/B	-0.000* (-1.79)	-0.001*** (-3.22)	-0.001*** (-5.35)	-0.001*** (-5.92)	-0.014*** (-24.62)	-0.012*** (-22.03)	-0.010*** (-17.43)	-0.010*** (-17.76)
TANG	0.032*** (15.19)	0.032*** (14.86)	0.031*** (14.58)	0.030*** (14.34)	0.088*** (12.45)	0.090*** (12.74)	0.093*** (13.11)	0.093*** (13.17)
DEPRN	-0.047*** (-4.40)	-0.042*** (-3.94)	-0.039*** (-3.63)	-0.037*** (-3.45)	0.033 (1.12)	0.022 (0.77)	0.011 (0.38)	0.014 (0.49)
R&D	-0.018*** (-4.78)	-0.017*** (-4.60)	-0.017*** (-4.65)	-0.015*** (-4.21)	-0.016 (-1.35)	-0.014 (-1.17)	-0.011 (-0.93)	-0.011 (-0.96)
MISS R&D	0.006*** (7.75)	0.006*** (7.58)	0.006*** (7.39)	0.006*** (7.34)	0.006 (1.37)	0.006 (1.42)	0.006 (1.44)	0.007 (1.58)
Firm FE	No	No	No	No	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	89,173	89,173	89,173	89,173	89,173	89,173	89,173	89,173

Panel B: dynamic panel estimator of Elsas and Florysiak [32]

	Baseline measures				VAR-based measures			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VOL	0.014**	-0.018**	-0.022***		-0.039***	-0.020	-0.023*	
	(1.99)	(-2.25)	(-2.75)		(-3.10)	(-1.53)	(-1.77)	
SKEW		0.004***				0.005***		
		(8.00)				(10.69)		
U/DVOL			0.012***				0.009***	
			(9.79)				(9.55)	
DSVOL				-0.252***				-0.172***
				(-14.03)				(-11.66)
USVOL				0.104***				0.154***
				(12.48)				(9.52)
LEV	0.767***	0.771***	0.775***	0.778***	0.784***	0.793***	0.793***	0.796***
	(211.08)	(210.07)	(208.42)	(209.56)	(201.69)	(199.08)	(197.30)	(198.95)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	89,173	89,173	89,173	89,173	71,561	71,561	71,561	71,561

Table 9: Dynamic Panel Data Models without the Strict Exogeneity Assumption

This table presents estimation results for the following dynamic panel data model:

$$Y_{i,t} = \sum_{p=1}^{P} \rho_p \, Y_{i,t-p} + \beta' X_{i,t-1} + \psi' Z_{i,t-1} + \lambda_t + \alpha_i + \eta_{i,t},$$

where i indexes firm and t indexes time. The dependent variable Y is the corporate policy variable of interest as described below. X is a vector containing cash flow uncertainty measures of focal interest, Z is a vector containing control variables for each financial policy of interest (including a constant), λ_t is a year dummy, α_i is a time-invariant firm effect, and $\eta_{i,t}$ denotes a shock assumed to be serially uncorrelated. Columns (1)-(4) present results in which the dependent variable is firm cash holdings ($Y_{i,t} = CASH_{i,t}$). Columns (5)-(8) present results in which the dependent variable is firm leverage ($Y_{i,t} = LEV_{i,t}$). Columns (9)-(12) present results in which the dependent variable is an indicator taking the value of one if the firm pays a dividend in the corresponding fiscal year ($Y_{i,t} = DIV_{i,t}$). Estimation is based on the two-step 'system GMM' approach of Arellano and Bover [6] and Blundell and Bond [15]. We treat the cash flow uncertainty measures $X_{i,t}$ and included firm controls $Z_{i,t}$ as predetermined rather than strictly exogenous. Our implementation employs the lagged levels $Y_{i,t-2} \ldots Y_{i,t-6}$, $X_{i,t-2}$, $X_{i,t-3}$, $Z_{i,t-2}$ and $Z_{i,t-3}$ as instruments in the differenced equations, and lagged differences $\Delta Y_{i,t-1}$, $\Delta X_{i,t-1}$ and $\Delta Z_{i,t-1}$ as instruments in the levels equations. See Section 1.6.3 for additional discussion concerning the approach. The table presents slope estimates β associated with cash flow uncertainty measures of interest and the slope estimate $\hat{\rho}_1$ associated with Y_{t-1}. (Estimates for additional lags of $Y_{i,t}$ are omitted to conserve space.) All cash flow measures are constructed using the baseline method described in Section 4. Firm controls are the same as those in Table 7 for cash, Table 8 for leverage, and Table 3 Panel B for dividends, except that we omit *MISS R&D*. The bottom portion of the table reports the number of lags included in each model and the p-value associated with a test of the null hypothesis $\text{Corr}(\Delta\eta_t, \Delta\eta_{t-2}) = 0$ consistent with the underlying model assumptions (labeled *p-val (Corr.)*). The sample period is 1983–2017 with allowance for lags included in the model. Detailed definitions of variables are listed in the appendix. t statistics are reported in parentheses for uncertainty measures (t-statistics for Y_{t-1} are omitted to conserve space but are highly significant). *, **, *** indicates 10%, 5%, and 1% significance level, respectively based on robust standard errors.

Variable	Cash Holdings ($Y_{i,t} = CASH_{i,t}$)				Leverage ($Y_{i,t} = LEV_{i,t}$)				Dividends ($Y_{i,t} = DIV_{i,t}$)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VOL	-0.004	0.023	0.046*		0.037***	0.009	0.009		-0.058***	-0.160***	-0.167***	
	(-0.15)	(0.84)	(1.71)		(2.74)	(0.63)	(0.63)		(-3.22)	(-7.59)	(-7.97)	
SKEW		-0.002**				0.003***				0.010***		
		(-2.14)				(4.04)				(7.55)		
U/DVOL			-0.015***				0.009***				0.030***	
			(-4.58)				(4.50)				(8.40)	
DSVOL				0.309***				-0.178***				-0.442***
				(5.41)				(-5.87)				(-8.86)
USVOL				-0.095***				0.104***				0.066***
				(-3.45)				(6.82)				(3.36)
Y_{t-1} ($\hat{\rho}_1$)	0.487***	0.488***	0.490***	0.488***	0.747***	0.753***	0.757***	0.760***	0.836***	0.834***	0.833***	0.828***
	(32.45)	(32.80)	(32.99)	(33.16)	(62.66)	(63.62)	(63.96)	(65.69)	(76.83)	(78.61)	(78.93)	(76.56)
Lag Order (p)	3	3	3	3	2	2	2	2	2	2	2	2
p-val (Corr.)	0.445	0.532	0.624	0.628	0.700	0.828	0.857	0.712	0.813	0.721	0.759	0.821
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	64,927	64,927	64,927	64,927	78,439	78,439	78,439	78,439	77,716	77,716	77,716	77,716

Table 10: Propensity to pay dividends - daily return based measures

This table presents regression results with daily stock return based measures. The dependent variable equals one if a firm pays dividend in a year, and zero otherwise. We adopt the extended model in Table 3 Panel B, where we control for industry fixed effects, year fixed effects and lagged dependent variable. Following Chay and Suh [23], Hoberg and Prabhala [54], and Hoberg et al. [55], we control for control for *LEV*, *CASH*, *ROA*, *M/B*, *SIZE*, *CAPEX*, *R&D*, *MISS R&D*, *TANG*, and *RE/TE*. Detailed definitions of variables are listed in the appendix. t statistics are reported in parentheses. *, **, *** indicates 10%, 5%, and 1% significance level, respectively.

	(1)	(2)	(3)	(4)
VOL	-5.356***	-5.704***	-6.004***	
	(-9.98)	(-10.69)	(-11.03)	
SKEW		0.080***		
		(4.30)		
U/DVOL			0.884***	
			(5.47)	
DSVOL				-17.204***
				(-10.90
USVOL				5.905***
				(5.09)
DIV	5.904***	5.907***	5.917***	5.908***
	(111.70)	(111.66)	(111.17)	(111.85)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	88,283	88,283	88,283	88,283

Table 11: Accounting based measures vs. return based measures

This table shows how accounting based and return-based uncertainty measures are associated with firm characteristics. The firm characteristics we examine include *OCF*, *ASSET*, *M/B*, *R&D*, and *CAPEX*. More detailed definitions of these variables can be found in the appendix. At the end of each fiscal year, we create decile portfolios based on SKEW measures with group 1 being the lowest (most negative SKEW) and group 10 being the highest (most positive SKEW). Next, we calculate the cross-sectional average characteristics of each group for SKEW and U/DVOL. Lastly, we calculate and present time-series average of all the cross-sectional group averages. Panel A shows results with sorting on return-based SKEW groups. Panel B shows results with sorting on accounting-based SKEW groups.

Panel A: Group formed with return-based SKEW									
	Return-based measure		Accounting-based measure		Firm characteristics				
	SKEW	*U/DVOL*	*SKEW*	*U/DVOL*	*OCF*	*ASSET*	*M/B*	*R&D*	*CAPEX*
1	-1.157	-0.602	0.084	0.078	0.055	4.496	1.260	0.039	0.054
2	-0.459	-0.229	0.281	0.294	0.085	4.541	1.402	0.039	0.059
3	-0.043	-0.045	0.321	0.328	0.096	4.728	1.539	0.041	0.061
4	0.286	0.092	0.345	0.364	0.102	4.371	1.636	0.045	0.065
5	0.570	0.214	0.332	0.360	0.098	3.816	1.756	0.050	0.067
6	0.834	0.332	0.321	0.346	0.101	3.520	1.897	0.053	0.069
7	1.083	0.450	0.297	0.315	0.097	2.635	2.069	0.061	0.073
8	1.334	0.583	0.308	0.320	0.104	2.418	2.193	0.064	0.077
9	1.616	0.728	0.396	0.459	0.116	1.801	2.366	0.063	0.080
10	2.098	0.879	0.414	0.485	0.122	1.511	2.324	0.061	0.081

Panel B: Group formed with accounting-based SKEW									
	Accounting-based measure		Return-based measure		Firm characteristics				
	SKEW	*U/DVOL*	*SKEW*	*U/DVOL*	*OCF*	*ASSET*	*M/B*	*R&D*	*CAPEX*
1	-2.218	-1.934	0.555	0.145	-0.065	1.592	1.971	0.090	0.064
2	-1.529	-1.920	0.551	0.150	-0.053	2.272	1.911	0.086	0.053
3	-1.180	-1.093	0.535	0.149	-0.020	2.614	1.809	0.071	0.054
4	-0.238	-0.119	0.575	0.189	0.081	2.827	1.546	0.048	0.060
5	0.793	0.468	0.572	0.221	0.143	4.288	1.790	0.040	0.066
6	1.163	1.190	0.661	0.319	0.208	5.402	2.163	0.036	0.078
7	1.292	1.951	0.691	0.329	0.196	4.428	1.947	0.035	0.083
8	1.414	2.200	0.679	0.310	0.178	3.531	1.806	0.035	0.079
9	1.579	2.216	0.677	0.296	0.167	3.563	1.720	0.033	0.077
10	2.012	2.028	0.638	0.265	0.148	3.887	1.625	0.031	0.076

Table 12: Cash Models for NYSE vs. Non-NYSE Firms

This table presents regression results for NYSE and non-NYSE firms separately. The dependent variable of the results are cash. We adopt the extended model in Panel A of Table 7, where we control for industry fixed effects, year fixed effects and lagged dependent variable. Following Opler et al. [81] and Bates et al. [11], we include *LEV*, *DIV*, *OCF*, *SIZE*, *ACQN*, *M/B*, *NWC*, *CAPEX*, *R&D*, and *MISS R&D* as controls for firm characteristics. Detailed definitions of the control variables are listed in the appendix. t statistics are reported in parentheses. *, **, *** indicates 10%, 5%, and 1% significance level, respectively.

	NYSE				Non-NYSE			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VOL	0.045**	0.071***	0.076**		-0.056***	0.010	0.023	
	(2.53)	(3.61)	(3.96)		(-4.61)	(0.69)	(1.60)	
SKEW		-0.003***				-0.008***		
		(-4.21)				(-9.38)		
U/DVOL			-0.011***				-0.030***	
			(-5.83)				(-12.04)	
DSVOL				0.239***				0.392***
				(6.78)				(11.63)
USVOL				-0.067***				-0.200***
				(-3.14)				(-12.57)
CASH	0.678***	0.678***	0.678***	0.678***	0.654***	0.652***	0.652***	0.650***
	(44.41)	(44.40)	(44.39)	(44.29)	(80.27)	(79.39)	(79.21)	(78.44)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,589	27,589	27,589	27,589	55,167	55,167	55,167	55,167

Chapter 2

Do U.S. Firms Payout Too Much to their Long-term Detriment?

2.1 Introduction

The total payout by publicly-traded U.S. firms increased, in real terms, from $108 Billion in 1984 to $1.5 Trillion in 2018. Such high payout raises concerns about firms' financial resources left to support investment and innovation. Lazonick [66], for example, supports this view and argues that S&P500 companies used, on average, 91% of their net income from 2003 to 2012 to finance their payout policies, which left limited amount for investment. Almeida et al. [2] find that a subset of firms which repurchase to boost EPS and that such firms reduce contemporaneous investment, R&D, and employment. Recent studies counter these findings. Fried and Wang [42] and Farre-Mensa et al. [35] argue that the aggregate cash distribution is overstated without accounting for the external financing that firms raise. Asness et al. [8], Fried and Wang [42], and Roe [84] examine the relation between repurchases, investment in physical capital, and R&D at the *aggregate* level and find no evidence of a reduction in response to repurchases. While macro analysis using aggregated data is suggestive, such analysis cannot determine whether large payouts cause long-term harm to the paying firms.

Our paper aims to fill this gap by testing whether transferring abnormally large amounts of cash to shareholders has detrimental effects on the firm's ability to invest and innovate.

Unlike prior studies, our paper (i) focuses on *firm-level* analysis as payout decisions are made at the firm-level, (ii) identifies firms with an unexpectedly large payout as firms who could potentially suffer negative effects of payout, and (iii) examines a longer window to determine if the impact on investment and innovative activities is temporary or a long-term effect. To address these issues, we first identify potentially overpaying firms and then identify a reasonable benchmark for evaluating the behavior of these firms. We find that the firms initiating large payout do not reduce investment and innovation relative to an appropriate benchmark. Furthermore, we find that firms initiating large payout do not suffer long-term declines in profitability, value, or sales growth.

We consider the firms that payout most in their respective industry as potentially distributing abnormally large amounts of cash to shareholders and hurting investment and innovation activity. Specifically, we subtract the median total payout [1] for the corresponding 2-digit SIC code from each firm's total payout to calculate the firm's industry adjusted payout. We then flag firms in the top 20% of industry adjusted payout ratios each year as high payers. We drop the high payers that are also in the top 20% of industry adjusted payout ratios in the prior three years so that all the high payers we study are transitioning from "normal" payers to high payers. We select a control firm for each high payer. We identify a control firm that (a) lies between the 40th and the 60th percentile of the industry adjusted payout ratio distribution and (b) is matched to the high payout firm based on selected characteristics, including industry, size, profitability, and cash balances. Matching on these characteristics allows us to ensure that high payers and their controls are similar in industry, size, and ability to payout. We employ two matching schemes – the broad matching scheme, which matches on industry and size, and the tight matching scheme, which matches on industry, size, profitability, and cash balance. Our main findings are qualitatively similar with both

[1] dividends plus repurchases scaled by assets

matching algorithms.

Using this classification scheme, we examine whether high payout firms experience economically and statistically significant reductions in their investment in physical capital and innovative activities relative to the control group over a three-year period after the time they are labeled as high payers. We measure investment in physical capital using CAPEX and the scope of innovative activities with R&D spending. We also examine the impact of high payout on profitability, cash balances, Tobin's Q, and the growth rate in sales in the years following a firm being categorized as a high payer. Our examination relies on a series of difference-in-differences tests using the high payout firms and the control firms. On balance, our evidence conflicts with the critics of modern corporate payout policy.

Our main results can be summarized as follows. Focusing on the short run first, we document that high payout firms invest in physical capital at the same (tight matching) or higher rate (broad matching) as the control firms in the year in which they are labeled as high paying firms. More importantly, we find that high payout firms invest 1% more than matching firms in the long run using both matching schemes. We also find that paying out an abnormally large amount of cash does not negatively affect long run spending on innovative activities. Our results show that the R&D expenditures of high paying firms and control firms are not significantly different from each other in both the short run and long run. These findings do not support the concerns raised in prior studies regarding the negative impact of excessive payouts on expanding physical capacity and innovation [e.g., 2, 66]. Our findings confirm that the conclusions from the macro analysis of Asness et al. [8], Fried and Wang [42], and Roe [84] hold at the firm level.

Next, the paper examines whether firms' valuations and profitability are negatively affected as a result of paying out large amounts of cash to shareholders. We first observe that high paying firms have higher profitability, cash balances, and Tobin's Q relative to the control firms before the initiation of the large payout when we only match on industry and size. Second, after controlling for profitability and cash balance, we find that high paying firms maintain their profitability and control firms experience a decline. Cash, Tobin's Q, and sales growth decline for both high payers and their matches, but the high payout firms decline by a smaller amount for cash and sales growth than the control group and by the same amount in Q. To provide a more complete picture of high payers, we redo our main analyses for the firms that persistently pay high amounts and firms that pay high amounts in a single year (or transitory high payers). Our findings show that there is a long run decline in investment and R&D for both transitory high payers and their matched firms and that the downward trend is not significantly different. Furthermore, profitability and Tobin's Q are not different for the transitory high payers and their control firms. For the persistent high payers, we find that the reduction in investment and R&D over time is smaller than the decline for their control firms. Additionally, profitability, cash balances, and Q are higher for the persistent high payers than for their control firms. Overall, these results are not consistent with criticisms of modern payout policy.

We also split our sample of persistent high payout firms according to how the payout was financed. The three possibilities are financed by issuing equity, financed by issuing debt, and internally financed payout. We split the persistent high payers into groups based on the percentage of total payout over t to $t+3$ that is linked to one of these financing choices. We track the investment behavior of the three groups over time. If the persistent high payers have access to capital markets and can issue equity or debt to finance large payouts, then these firms are unlikely to be constrained from funding their desired level of investment or R&D. Firms that internally finance payout, however, could face more constraints on their investment and innovative activities. Using the tight matching scheme and focusing on persistent high payers, we find that the control firms for all three financing groups experience declines in CAPEX, R&D, profitability, and Tobin's Q. The equity and debt financed persistent high payers behave in the same manner as their control firms. However, the internally financed persistent high payers invest more than their matched firms, earn higher profits, and have higher Q's despite their large payouts. Overall, our results suggest that paying out large amounts of cash to shareholders does not appear to be detrimental to firms' long-term ability to invest, innovate, and grow.

Finally, we split our sample based on the change in leverage for the high payout firms. We split into two groups – one with large increases in leverage, and the other with decreases, no change, or small increases in leverage. Critics of modern payout policy would predict that the firms with large increases in leverage should be more financially constrained, reduce investment and innovation, and suffer loss of profitability and value. Our analysis shows that the high payout firms with large leverage increases invest at the same rate as control firms, spend in the same manner on R&D as control firms, maintain the same profitability as control firms, and experience the same value changes as control firms. Thus high payers with large leverage increases exhibit the same behavior and performance as peer firms. This finding is inconsistent with criticisms of firms' payout policy.

We believe our paper contributes to several strands in the finance literature. There is a growing literature expressing concerns about U.S. firms distributing excessive amount of cash to shareholders which can potentially harm firms' long-term growth. Lazonick [66] argues that S&P500 firms devote an enormous amount of cash to stock repurchases to boost stock prices because a big portion of corporate executives' pay is tied to stock-based options and stock awards. Lazonick concludes that the massive wave of repurchases is negatively affecting stable growth, employment, and income equality in the U.S. economy.[2] Almeida

[2]The short-termism critique is not new. Other discussion of these points in the financial press and policy literature include the letter from Lawrence Fink cited at the beginning of the paper. See also The Economist [90] discusses some flaws in buybacks and suggests that share repurchases can potentially create perverse incentives to pay out too much cash resulting in a reduction in firms' ability to invest and innovate and an

et al. [2] find that firms conducting EPS-induced repurchases reduce their CAPEX, research and development spending, and employment by 10%, 3%, and 5%, respectively, in the four quarters following EPS-induced repurchases. Asness et al. [8] and Fried and Wang [42] examine the relation between repurchases and investments at the aggregate level. They provide descriptive evidence suggesting that net investment has not declined over time and that there appears to be a positive correlation between repurchases and net investment at the macro level. Roe [84] conducts a similar analysis of aggregate R&D and finds that R&D and innovation do not appear to decline in response to repurchases.

While these studies provide suggestive results, they do not track investing behavior beyond the current year, do not examine the impact of payout on other policies, do not track the long-term value effect, and generally implement their analyses at the macro level. We contribute to this discussion by conducting a *micro-level* analysis and by tracking the investment policies over time as well as other important financial attributes such as profitability, cash holdings, and firm value. Using a control group identified based on our matching algorithms, we compare the investment of high payout firms with control firms to test whether overpaying firms' investment and innovation over time are diminished by the act of large payouts. Our paper provides evidence that there is no long-term negative impact of large payouts by firms that choose to payout.

Our paper also contributes to short-termism literature. Prior studies show that short-termism can arise in various situations [30, 45, 48, 59, 87], leads to less investment and innovation, destroys long-term benefit of investors, and negatively impacts the national economy [7]. The literature has identified two possible channels through which payout could contribute to short-termism. First, prior studies find evidence on the use of repurchases as a means to meet or beat analysts' EPS forecasts at the expense of bypassing value-creating

increase financial distress risk.

investment opportunities and long-term growth. Hribar et al. [57] document that stock repurchases are disproportionately more frequent among firms where reported EPS would have otherwise fallen short of analysts' forecasts. Graham et al. [47] survey more than 400 CFOs about the factors driving financial disclosure decisions. More than 78% of these executives are willing to make small or moderate sacrifices in long-term value-maximizing investment opportunities to manage earnings. The second channel is that managers could use payout to influence stock prices in the short run and also influence their own welfare by establishing an external reputation. Trying to meet or beat earnings benchmarks can lead to better short-term stock performance [2, 57].

Recent studies cast doubt on prior findings that U.S. firms are afflicted by short-termism which harms corporate investment in physical capital and innovation. Fried and Wang [42] argue that payout figures provide an incomplete picture of firm capital flows because a fraction of payouts can be offset by equity issuance or debt issuance. Once capital inflows from shareholders to the firm are accounted for, shareholder payouts amount to about 22% of firm net income in contrast to prior estimate of 91% of net income [66]. Focusing on the investment angle, Kaplan [63] argues that if the prediction that short-termism causes underinvestment is correct, one would expect to see an increase in profitable investments by other investors such as venture capital firms and private equity firms. The empirical evidence, however, does not appear to support this conjecture. Finally, Crane et al. [27] provide empirical evidence that institutional investors increase corporate payout as a governance mechanism. The relationship between payout and investment should be negative with firms paying out more to mitigate the incentive to over-invest. The high amount of payout should imply a higher valuation since payout helps reduce agency costs. Our paper contributes to the short-termism literature by demonstrating that long-term investment decisions of the firms are not adversely affected by today's payout policies and by demonstrating that high payout firms do not experience a significant decline in their profitability or value relative to their peer firms.

The rest of this paper is organized as follows. Section 2.2 describes the identification of our sample of high payout firms, the methodology used throughout this paper, and a comparison of high paying firms and a matched control sample. Section 2.3 reports the main empirical results using gross payout. Section 2.4 examines the role of externally financing payout. Finally, Section 2.5 concludes.

2.2 Sample and Methodology

2.2.1 Identifying High Payout Firms

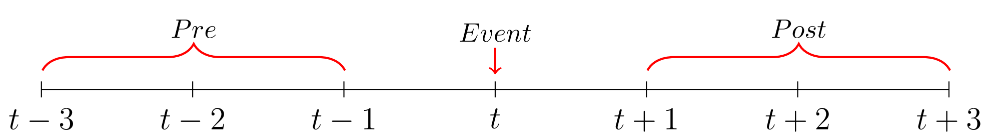
We start with all US firms recorded in the CRSP-Compustat Merged dataset from fiscal year 1984 to 2017. We pick 1984 as the starting point of our sample because of two regulatory changes. First, the SEC instituted Rule 10B-18 or safe harbor rule in 1982. The majority of repurchase activity has occurred since that time, and corporate payout choices have changed significantly [34, 39, 61]. Second, better quality repurchase data is available beginning in 1984 due to changes to the statement of cash flows by FASB. We exclude all utilities (SIC between 4000 and 4949) and financial firms (SIC between 6000 and 6999). To mitigate potential problems caused by outliers, we drop all firms with assets less than \$5 million or total book equity less than \$2.5 million [54, 55]. This gives us 15,419 unique GVKEYs over 33 fiscal years.

We focus on the total amount of cash that firms distribute to their shareholders. We define total payout as the sum of dividends and repurchases. Following the payout literature, dividends is measured by the dividend payout to common shareholders recorded in Compustat

[23, 34, 54]. We measure repurchases following Grullon et al. [50] which utilize information in the statement of cash flows. Since open market repurchases are difficult to track [10, 34, 88], we adopt the simple approach in Grullon et al. [50]. To facilitate comparisons across our panel of data, we scale our payout measures (total payout, dividends, and repurchases of common shares) by total assets.

We focus on the firms that pay out the largest amount of cash. These firms are at the center of the short-termism debate because their large payouts are potentially detrimental to investment and performance. At the end of each fiscal year, we calculate the median total payout scaled by lagged assets for each industry using 2-digit SIC codes. We subtract the industry median rate from the total payout rate of each firm to calculate the industry adjusted payout rate.

We utilize an event study framework in our empirical analysis. The event year t is the fiscal year in which a firm initiates high payout. Relative to the fiscal year t, we define the period $[t-3, t-1]$ as the *Pre-event* period and the period $[t+1, t+3]$ as the *Post event* period. The definition of *Pre*, *Event*, and *Post* years can be illustrated using the following figure.



We average the industry adjusted payout rates over the interval $[t-3, t-1]$ and refer to this as the *pre-event* payout. We require that firms have available data from $t-3$ to $t+3$. We consider firms in the top 20% of industry adjusted payout rate for each year as paying out large amounts of cash. We drop the firms that are also in the top 20 percentile during $[t-3, t-1]$. We further drop all the firms with missing OCF and Cash during $[t-3, t-1]$. Our procedure allows us (i) to identify the year in which a firm starts to payout a high amount, (ii) to identify that year as the event year, and (iii) to track the firm through time to determine if the unusually high payout adversely affects investment, innovation, profitability, and value. We also determine whether the high payout persists or simply occurs in that one year. Since we require that firms stay in the sample from $t-3$ to $t+3$, our earliest event year is 1987, and our last event year is 2014. We end up with 3,510 firms from 1987 to 2014 that distribute large amounts of cash to shareholders. We refer to these firms as high payout firms or high payers.

Table 1 describes some characteristics of our sample of high payout firms using the average figure from the *pre-event*. The average total payout in the *pre-event* period is slightly less than 1% and is composed of slightly more than half dividends. As expected, the distribution of payout is skewed to the right. The average total assets and average market capitalization for the high payers are about $3 billion and $3.7 billion respectively. The distributions of these variables are also right skewed. The ratio of operating cash flow to total assets is about 15%. The average (median) high payer has a cash to assets ratio of 23% (14.6%). The average high payers spends just over 10% of its assets on new physical capital (CAPEX) and just less than 10% on R&D. We code R&D as zero for the firms which do not report a value. The average (median) Tobin's Q is 2.06 (1.55). Average or median sales growth figures that are double digit indicate that typical firm has a reasonably growing businesses. The average (median) book value of leverage is 17.5% (14.5%) indicating that the high payout firms are only moderately leveraged. The 90th percentile value for book leverage is only 39% which indicates that the high payers typically do not rely on borrowed funds to finance their assets. Finally, the average (median) age since inception is 37 (23) years, and the cut-off for the lowest quartile is 13 years[3]. The average (median) age since listing is about 15 (12) years. Thus the majority of high payers are reasonably mature firms.

[3] We thank Prof. Gustavo Grullon for providing this data.

2.2.2 Identifying a Control Sample for the High Payout Firms

Our empirical inference relies on a comparison between each high payer and an otherwise similar matching or control firm whose payout is around the industry median. This approach allows us to control for common payout determinants in the empirical literature [34, 75] without imposing model specification assumptions. At the end of each fiscal year t, we select the firms whose total payout is between the 40^{th} and the 60^{th} percentiles in their respective industry as our potential pool for matching. We match on both industry and firm size as proxied by book value of assets. We assign percentile ranks to all firms based on $Size_{t-1}$. For each high payer in year t, any firms from the matching pool that are in the same industry and are within ± 10 percentile of the $Size_{t-1}$ of the high payer is selected as potential matches.

To ensure that each control firm is only matched to one high paying firm and to achieve the maximum number of matched firms possible, we begin with the high payers that received one matching firm. Next, if any of the control firms are matched to multiple high payers, we randomly assign the matching firm to one of the high payers. Finally, we turn to the high payers that receive multiple matches based on our criteria. We randomly select one control firm if a high payer is matched with multiple potential firms. We repeat this process until no additional matching is possible. The remaining high payers are unmatched. We end up with $2,973$ high payers with a matched firm out of $3,510$ high payers (84.7%) and with 537 high payers without a matched firm (15.3%).

Panel A of Table 2 summarizes the characteristics of high payout firms and their matching firms in the *pre-event* period and in the event year when we match based on industry and size. We report key average characteristics for the high payers and their matches respectively in *pre-event* and event year from 1987 to 2014. Namely, for each high payer and its control, we first calculate the average of the variables of interest in the *pre*-period. We then average within each event year for high payers and control firms respectively. Lastly, we report the average across all the event years for the *pre-event* characteristics. We repeat the process for the event period, except that we do not average characteristics within the *event*-period since it only covers one year. The columns labeled "H" and "M" present the mean characteristics of high payers and their matching firms, respectively. The columns labeled "Diff" reports the average difference between high payers and their matches for *pre-event* years and for the event year. T-statistics for the hypothesis that the average difference is zero are reported in the parentheses.

The first row of Panel A of the table reports the average size for high payers and their matches using industry and size to identify the matches. The average size of high payers and their matches are not statistically different in either year since size is a matching criterion. In the second, third, and fourth rows of Panel A, we compare three payout measures for the $2,973$ high payers and their matching firms to verify that our method in fact identifies high payers that substantially increased their payout in event years. For the average *pre-event* year, total payout for the high payers and their matches are different by a small but significant amount; however in the event year, the high payers' total payout is much larger than the control firms (8.0% of assets vs 0.4% of assets). This difference is both statistically and economically significant. Next, we examine common dividends scaled by total assets. In *pre-event* years, the high payers pay a modestly higher dividend. In event years, high payers increase their dividends by almost 150% while the control firms continue to pay the same dividend. The event year difference in dividends between high payers and matching firms is about 1.3% of assets and is statistically significant. The third payout variable is repurchases scaled by total assets. For the high payers, repurchases increase by more than tenfold in event years. The difference in repurchases in the *pre-event* year between high payers and control firms is small but statistically significant; however, the event year difference is very large and significant. Thus our method of identifying high payers does in fact identify firms that payout much more than average for their industries and identifies the year in which significant increases in payout occurred. Additionally, total payout, common dividends, and repurchases of common shares all exhibit the same basic pattern, although percentage changes in repurchases are much larger than dividends. The above discussion focuses on gross payout or payout without regard to the possibility of stock issues. Issuance of equity and other access to capital is discussed in section 5.1.

Following the payout measures, we examine the ability of firms to payout funds to shareholders. We measure the ability to payout by profitability (operating cash flow/total assets) and by cash balances (cash itself plus short-term investments/total assets). Since operating cash flow and cash balances both exhibit considerable variability on an annual basis, we average OCF and cash over the three years of the *pre-event* period. The average OCF of the high payers for the *pre-event* period is approximately 4.5% higher than the average of the matching firms. Thus, on average, high payers have about a 40% higher profitability than their industry and size matched firms. The average ratio of cash to assets for the high payers is similarly 7.5% higher than for the matching firms. In other words, high payers also have about 40% more cash on hand than the matching firms in the *pre-event* period. The greater profitability and greater liquidity of the high payers relative to the control firms suggests that high payers payout large amounts because they have the ability to do so. These figures suggest two important matters. First, the large cash position of the high payers suggests that their total assets are inflated by possibly excess cash. Second, the initial attempt to construct a sample of matching firms may be incomplete because of the substantial difference in the ability to payout funds to shareholders. The next two paragraphs discuss these two issues.

With regard to the cash positions, a large literature documents that cash takes an increasingly important portion on firrms' balance sheets over recent financial history [11, 46, 61, 81]. Opler et al. [81] and Bates et al. [11] use net assets (total assets minus cash and short-term investment) as the scalar in their cash ratio definitions. Two firms with the same net assets may have vastly different total assets due to the difference in cash balances. Reductions in cash balances through payout can create a mechanical increase in the payout ratio and CAPEX ratio if we scale payout and CAPEX with total assets. To ensure that our results are not driven by the variation in the denominator of our ratios, we standardize firm level variables like payout, OCF, cash, and CAPEX by net assets. We define proxy variables for firm characteristics following the empirical corporate finance literature. See Table A1 in the Appendix for our precise variable definitions.

To address the problem noted above of incomplete matching, we construct another control sample for which we match on *pre-event* operating cash flow and cash balances as well as industry and size. The two additional characteristics on which we match will provide the benefit of more closely aligning the characteristics of the high payers and the matching firms but at the cost of fewer firms for which matches are possible. When using the four characteristics for matching, we obtain 1,429 matches or almost half of the matches in Panel A (48.1%) and about 40% of our initial sample of high payers. Panel B presents average characteristics for these 1,429 high payers and the respective matching firms for the *pre-event* and event periods. The size of the high payers and the matching firms continue to be comparable. The average *pre-event* profitability of the high payers as measured by OCF is approximately the same as the average of the matching firms. Thus matching on OCF eliminated the apparent difference in Panel A. Panel B also shows that even after matching on cash balances the high payers continue to have a larger cash balance than the average of the matching firms, although the difference in the *pre-event* year is less than half of the difference shown in Panel A. In results that are presented below, we use both matched samples. We refer to these as broad matching when only industry and size are used as matching attributes and tight matching when industry, size, OCF, and cash are used as matching attributes.

Panels A and B also list the average Tobin's Q for the high payout firms and the control firms. Under the broad matching scheme, high payers have an average Q that is substantially higher than the average for the matching firms by 0.21, and the difference is significantly different from 0. Panel B shows that tight matching eliminates the difference in Q with the average for both groups being 2.13. Since Q can reflect the influence of growth opportunities, differences in underlying profitability, and the potential influence of mispricing, we also include average sales growth as a further indication of differences in growth potential. Sales growth is larger for the control firms than for high payers under both matching schemes.

The last characteristic of the high payers presented in both panels is the book leverage ratio (book value of long-term debt plus debt in current liabilities divided by book value of assets). The reported averages in Panel A suggest two conclusions. First, both high payers and control firms on average have stable leverage ratios across the periods. Second, the average high payer has almost 9% lower book leverage than the average matched firm in the *pre-event* period. Thus in part, high payers may be substituting higher payout to equity holders for payout to creditors. Additionally, the results in Panel B using the tighter matching scheme provide similar conclusions that both high payers and their matches have stable leverage ratios and that high payers have lower book leverage than their matching firms, on average. However, in Panel B, the difference in high payers and control firms for the *pre-event* period decreases from 9% to about 5%. We defer discussion of leverage until section 5.2 below.

The above discussion compares the high payers with their matched firms. Panel C presents some descriptive information for the high payers for which there are matches and those for which a suitable match could not be located. Panel C compares the $2,973$ high payers for whom matches existed under the broad matching scheme with 537 high payers for whom there was not a match. In terms of *pre-event* characteristics, the unmatched firms are larger, have less cash, and have more leverage than the $2,973$ high payers with matches. There is no difference in *pre-event* profitability, and both *pre-event* and *event* year payout are not meaningfully different.

Panel D provides a similar comparison between the $1,429$ high payers with matches under the tight matching scheme and the $1,544$ firms that had matches under the broad scheme but did not under the tight scheme. Size and payout characteristics for both the *pre-event* period and the event year are similar indicating no noteworthy differences. However, profitability was higher, cash balances were lower, and leverage was higher for the unmatched high payers than for the high payers with matching firms. The higher profitability for the unmatched high payers suggests that profitability may have been the reason there was no matching firm. Overall, we conclude that the unmatched high payers were in many respects similar to the high payers with matches. Thus we concentrate our analysis on the high payers for which there is a matching firm to serve as a reference point in our analysis of investment, innovation, and value.

2.2.3 Methodology

We utilize an event study framework in our empirical analyses. We define an indicator variable for each of the Pre, $Event$, and $Post$ periods. We further define an indicator variable $High$ which equals 1 if a firm is classified as a high payer period and 0 if classified as a match. We begin by testing whether high payout is associated with low investment and innovation activity in the contemporaneous year using the following regression model and difference-in-difference (DID) approach.

$$y_{i,t} = \gamma High_i + \theta Event_t + \zeta(High_i \times Event_t) + \alpha_{t'} + \beta_j + \varepsilon_{i,t} \tag{2.1}$$

where i indexes firm, j indexes industry, t indexes event time, and t' indexes fiscal year. y is the dependent variable of interest (e.g., $CAPEX$). $\alpha_{t'}$ represents year fixed effects. β_j represents industry year fixed effects. We do not include any observations in the *Post*-period in this regression. Bertrand et al. [14] show that the serial correlation in a simple DID setting can lead to biased standard errors. Conventional DID standard errors understate the standard deviation of the estimators and overstate statistical significance. Following Bertrand et al. [14]'s suggestion, we average firm level variables over the *Pre*-period instead of including 3 years of observations in the regression. We further cluster standard errors at the firm level. The focus of this regression is on the interaction term. If high payers reduce investment or innovative activities as a consequence of the large payout, then the coefficient on the interaction term will be negative and significant.

To investigate the long-term effect of high payout, we utilize a similar framework and estimate the following regression model.

$$y_{i,t} = \gamma High_i + \delta Post_t + \eta(High_i \times Post_t) + \alpha_{t'} + \beta_j + \varepsilon_{i,t} \tag{2.2}$$

Similarly, we average firm level variables over both *Pre*- and *Post*-periods. Standard errors are also clustered at firm level. We do not include any observations in the *Event*-period when estimating this regression so that we are comparing the variables of interest before and after the event. As with equation (1), our focus is on the coefficient on the interaction term.

Our event framework and DID estimation closely follows Bertrand et al. [14] and Roberts and

Whited [83] with two modifications. First, we include industry and year fixed effects while Roberts and Whited [83] do not. The inclusion of the fixed effects changes the interpretation of an intercept in the context of our results. Second, many applications of the DID framework include other continuous control variables in regressions like equations (1) and (2). Since we use an elaborate matching scheme described in detail above as well as industry and year fixed effects, we do not include the typical set of control variables that might appear in a study of payout (like Chay and Suh [23] or Hoberg et al. [55]).

2.3 Short Run and Long Run Impact of High Payout

In this section, we investigate the short run and long run impact of high payout on firms' investment and innovative activities. We begin with examining the short run impact. Namely, we test whether high payers undertake significantly less capital investment or R&D in the year of high payment compared with their matches. Almeida et al. [2] document a negative relationship between payout and investment in the year of repurchase for firms that repurchase to avoid reporting a negative earnings surprise. If high payers cut investment to make the large payout in the event year, we expect to see that high payers make contemporaneously less investment than their matching firms. Next, we turn to the long run effect of high payout. We compare the investment and innovation of high payers and their matching firms in the *post event* period ($t+1$ through $t+3$). If high payout leads to a long run decline in firms' CAPEX and R&D, we expect to see that high payers invest less in these categories than the control firms in subsequent years.

2.3.1 Short Run Impact

To investigate the impact of high payout in the year of the payout, we estimate equation (2.1) with different dependent variables using the observations from event and *pre-event* periods. The dependent variables are total payout, CAPEX, and R&D expenses with each dollar figure scaled by the prior year's net assets. Following Bertrand et al. [14] we use the average firm characteristics during $t-3$ and $t-1$ when estimating Equation 2.1. To control for common factors over time, such as changes in macroeconomic conditions, we include year fixed effects. To control for time persistent factors associated within each industry, we include industry fixed effects. We further cluster standard errors at the firm level. Panel A of Table 3 presents the results. Columns (1) - (3) use the matched sample with the broad matching criteria (industry and size), and columns (4) – (6) use the matched sample with the tight matching criteria (industry, size, operating cash flow, and cash balance).

Column (1) reports the results with total payout as the dependent variable and using the broad matching criteria. The first coefficient is the difference between high payers and the control firms in the *pre-event* period. The estimate in Column (1) is positive and significant, which means that before the event year, high payers payout more than their matches but by a small amount (0.6%). The second coefficient captures the change in total payout for the matching firms over time. The estimate is insignificant and indicates that the matching firms do not change their payout in the event year. The third coefficient on the interaction term measures difference in the change in total payout during the event year between high payers and the control firms. The estimate is positive and significant. This means that relative to the matching firms, the total payout of high payers increases significantly in the event year. This result is expected and reflects our method of identifying high payers. Column (4) reports the results for the matched samples using total payout as the dependent variable and the tight matching criteria. While the magnitudes of the coefficients vary slightly, columns

(1) and (4) yield the similar result that high paying firms payout about 10% more than the control firms in the event year.

Results reported in Column (2) demonstrate how CAPEX is related to high payout using the broad matching criteria. High payers invest 1% less than their matching firms before the year of high payout. The negative coefficient on Event indicates that investment declines by about 2% for the matching firms during the event year. However, the estimated coefficient on the interaction term is positive and significant which shows that high payout is not associated with a cut in investment relative to comparable firms. Column (5) reports the results using the tight matching criteria. The coefficient on Event suggests that the control firms decrease their CAPEX by close to 2%. The DID coefficient is insignificant and indicates that high payers' investment mirrors the investment of the matching firms. The hypothesis that high payouts cause firms to curtail investment predicts that the interaction term will have a negative coefficient. Thus our regression results indicate that on average high payout firms invest the same or more than comparable firms not less. This result is robust to the matching criteria used to construct the matched sample. Additionally, these results conflict with Almeida et al. (2016). The difference in our results and their results may be attributed to different methodologies and especially to different samples. Almeida et al. (2016) focus on firms that used repurchases to increase earnings per share and avoid a negative earnings surprise while our sample is composed of firms that make large payouts to their shareholders irrespective of the particular quarterly or annual forecast of earnings per share.

Columns (3) and (6) investigate the impact of high payout on R&D as a measure of innovative activity. Column (3) uses the broad matching criteria, and column (6) uses the tight matching criteria. The coefficient on Event indicates that the matching firms decrease their R&D in the event year. The estimated coefficient on the interaction term indicates that there is no significant difference in R&D between high payers and matches as a consequence of the large payout in the event year. The hypothesis that high payouts cause firms to curtail innovation predicts a negative coefficient. Our matched sample approach rejects this hypothesis for the event year under both matching criteria. Overall, we do not find a significant negative impact of high payout relative to the matching firms on either investment or innovative activity in the time period that is contemporaneous with the high payout.

2.3.2 Long Run Impact

This section examines the impact of high payout on a firm's long run investment policy. The criticisms of Lazonick [66] and others suggests that excessively large payouts to shareholders permanently reduce investment and damage long-term value which hurts both the firm and the economy at large. We adopt a similar setup as in the last section and estimate Equation (2.2). We also include average firm characteristics during the *pre-event* period and *post event* period in the regression. We do not include information from the event year in this regression so that we are comparing the variables of interest before and after the year of high payout.

We estimate equation (2.2) and present the results in Panel B of Table 3. Columns (1) and (4) present the results with total payout as the variable of interest and using the two different matching criteria. The coefficient on the interaction of High and Post is positive and significant which indicates that high payers continue, on average, to pay out more than the control firms after the year of high payment. However, the difference in payout is much smaller than the difference in total payout for the event year (3% for the longer run vs 10% in the year high payout was initiated). This implies that the high payers on average reduce payout from t to t + 3 but only partially. Thus, on average, only part of the payout increase in the event year is persistent. These results describe the average high payer relative to its matching firm. Section 3.4 directly examines the persistence of high payout.

The next question we examine is whether high paying firms reduce their investment and innovative activities after the year of high payment. Critics of large payouts by large publicly held corporations contend that investment and R&D fall as a consequence of high payout. Columns (2) and (5) present results of our DID regressions with CAPEX as the dependent variable and using the two different matching schemes. The estimated coefficient on High is negative and significant. This result is consistent with the short run results discussed above and indicates that prior to the year of the large payout high payers invested less than their matching firms. The estimated coefficient on Post is also negative and significant which indicated that the matching firms reduce CAPEX by about 3% over time. Finally, the estimated coefficient on the interaction term is positive and significant. This means that high payers invest about 1% more after the year of high payout than their matches. The results indicate that high payout does not lead to a long run cut in investment by the high payout firms relative to the control firms.

Another way to isolate the effect of a large payout on investment is to compare the average change for the matching firms directly to the average change for the high payers. The average change in investment for the control firms from *pre-event* to *post event* is simply the coefficient on Post. In column (5), the coefficient is -3.7%. The average change from pre to *post event* for the high payers is the sum of the coefficients on Post and on the interaction term. The average change for high payers as reported in the last row of the panel is -2.6% (1.1% high than the matching firms). High payers do experience a reduction in investment of about 2.5% as the firm goes through time; however, the reduction for high payers is substantially smaller than the reduction for the matching firms. Kahle and Stulz [61] document a decreasing trend in public firms' CAPEX and profitability and an increasing trend in intangible assets. Asness et al. [8] show a similar trend in capital investment for the Russell 3000 firms. Amini and Kumar [3] connect the decline in CAPEX with industry concentration. We observe similar decline in CAPEX and profitability in both high payers and controls, and the decline is more pronounced for the control firms. We also investigate the impact of large payouts on R&D in the *post event* period. The results in Column (3) and (6) indicate that R&D is also very similar between high payers and matches after the large payout in that both groups of firms reduce their R&D across the seven year period. The analysis of the impact of high payout on investment and R&D is consistent across the two matching strategies.

Thus the results in Table 3 are not consistent with high payout having a negative impact on investment or innovative activities. Thus our firm level evidence confirms the aggregate level evidence presented by Asness et al. [8], Roe [84], and Fried and Wang [42]. However, our evidence goes beyond those papers and establishes that firm level investment and innovation do not decrease concurrent with or subsequent to large payouts. Thus neither individual firms nor the economy in the aggregate show evidence of the reputed negative effects of payout.

Using a simple cash flow identity, one might question how it is possible that the high payout firms might be able to dramatically increase their payout (perhaps both in the event and subsequent periods) without decreasing investment and R&D. In fact, the DID framework indicates that investment actually increases relative to the matching firms for the high payers. Three possible answers to this question are ability to raise external funds, higher profits, or higher cash balances. The next section addresses the impact of high payout on profitability, cash balances, and firm value. The role of access to external financing is discussed in section 4.1.

2.3.3 Long-term Impact on Valuation and Profitability

Criticism of large payout implies that long-term corporate viability is compromised by the payouts. In this section, we use our DID framework to examine the long run effects of payout on operating cash flow, cash balances, and Tobin's Q to assess whether long run viability is affected. We use the scaled values of operating cash flow and cash balances reported in Table 2 to measure the effect of payout on those variables. We use Q or market value of assets to book value to measure valuation and/or growth opportunities. Table 4 presents the results using estimates of equation (2) and the same format as Panel B of Table 3. Columns (1) through (4) report results using the broad matching scheme (industry and size), and columns (5) through (8) report results using the tight matching scheme (operating cash flow and cash balance in addition to industry and size). Significantly negative coefficients for the interaction term (High x Post), would be consistent with the notion that high payouts have a negative impact on the long-term profitability, cash holdings and/or valuation (or growth opportunities) of the firm.

The positive and significant coefficients for $High$ for OCF, Cash and Tobin's Q regressions for the broad matching scheme in columns (1), (2), and (3), respectively, suggest that the high payers are more profitable and generate higher cash flows, hold larger cash balances, and have higher growth opportunities and/or higher valuations relative to their industry and size peers. After we match on Cash and OCF, the smaller set of high payers and controls, as expected, have similarly high levels of OCF and Cash, but also have similarly high levels of Q as the high payers, as evidenced by the insignificant coefficients for High for the OCF, Cash, and Q, in columns (5), (6) and (7), respectively.

For the tight match in columns (5), (6) and (7), wherein the control firms have the similarly high OCF, Cash and Tobin's Q as the high payers, the control firms exhibit a significant decline in their OCF, Cash and Q as evidenced by the significantly negative coefficients for Post. Since these firms are not high payers, this decline is not associated with the payouts, but more likely a part of the secular trend for the more profitable firms in the represented industries. The coefficients for Post in columns (1), (2), and (3) for the broad match are either insignificant or exhibit smaller declines because the larger set of control firms in these regressions have, on average, lower levels of OCF, Cash and Q in the *pre* period as discussed above.

The high payers using the tight match exhibit significantly smaller declines in OCF and Cash as compared to the control firms in the post period, as evidenced by the positive coefficients for the OCF and Cash regressions for the interaction term in columns (5) and (6), despite having similarly high values in the *pre-event* period as discussed above. In contrast, the high payers suffer similar declines in Tobin's Q as evidenced by the insignificant coefficient for the interaction term for the Q regression for the tight match in column (7). This suggests that there are significant and similar declines in growth opportunities for the high payers relative to their control firms which have similarly high growth opportunities before the initiation of the high payouts. However, the decline in OCF for the high payers relative to the control is an insignificant 0.008, as estimated by the sum of the coefficients of Post and the interaction term. The insignificant decline in OCF for the high payers with the tight match suggests that these firms do not suffer a decline in their profitability. And despite the higher payout, their cash does not decline as much as for the control firms who do not initiate the higher payouts, as evidenced by the positive coefficient of the interaction term in column (5).

Columns (4) and (8) report the results for the DID regressions for Sales Growth for the broad match and the tight match, respectively. The significant negative coefficients for High in both regressions suggest that the sales growth for High Payers in the *pre* period is less than the sales growth for the control firms, even though their Q ratios are similar or higher, respectively. These results are consistent with the results for Q and Sales Growth in Panels A and B of Table 2. The significant negative coefficients for *Post* in both regressions suggest large significant declines in sales growth for the control firms in the post period, consistent with the declines in Q in the post period. The significant positive coefficient for the interaction term for the tight match suggests that the decline in sales growth for the High Payers in the tight match is less than the decline in sales growth for the control firms. These results confirm the conclusions drawn from the Q regressions that high payers and the matched controls are from industry-size combinations that are expecting significant declines in their growth opportunities.[4]

The overall picture that emerges is that the high payers have higher operating cash flow, higher cash balances and higher growth opportunities relative to their industry and size peers before the initiation of the high payout. The high payers are from a subset of industry-size combinations that are facing significant declines in their growth opportunities. From this set of firms which have higher operating cash flows, higher cash, and higher growth opportunities and are now looking at significant expected declines in their growth opportunities, the firms not expecting a corresponding decline in profitability initiate higher payouts. The firms who are expecting their profitability and cash flows to decline along with their growth opportunities do not initiate the high payouts.

2.3.4 Does Persistence in High Payout Matter?

The above results document that high payers payout 10% more than matching firms in the event year and continue to payout about 3% more than matching firms in the subsequent three years. Within the sample of high payers, there is considerable variation in the per-

[4] As a robustness check, we use alternative definition of *post event* period which covers $[t+1, t+5]$. We use the same matched high payers and re-estimate the results in Table 3 and 4 and obtain similar results.

sistence of payout. The results reported above may not adequately reflect the implications of high payout because those results ignore persistence and the persistent high payers may be the firms who most damage themselves from excessive payouts. This section examines whether firms that persistently payout large amounts of cash invest and innovate less and consequently suffer in terms of subsequent performance where performance is measured by operating cash flow, Q, and sales growth.

The first step in assessing the impact of persistence is to determine a reasonable criterion for classifying the high payout as persistent. We classify high payers in the event year as persistent or transitory based on how many times in the subsequent three years the firm has industry adjusted payout in the top 20% of firms in that fiscal year. We classify firms that are high payers in the event year but do not have payout in the top 20% in any of the three subsequent years as transitory high payers. We classify firms that continue to fall in the top 20% of industry adjusted payout in two or three of the subsequent years as persistent high payers. We drop the firms that only fall in the top 20% one time in the subsequent three years. For the broad matching scheme with 2,973 high payout firms, the sample is composed of 1,178 transitory high payers (39.6%), 1,052 persistent high payers (35.4%), and 743 firms not categorized and dropped (25%). For the tight matching scheme with 1,429 high payers, the sample is composed of 566 transitory high payers (39.6%), 497 persistent high payers (34.8%), and 366 firms not categorized and dropped (25.6%). We estimate equation (2) again separately for transitory and persistent high payers.

Table 5 separately compares the payout and investment behavior of the transitory high payers relative to their matching firms and persistent high payers to their matching firms. Panel A presents our DID estimates for the transitory high payers, and Panel B presents results for the persistent high payers. The structure of the table follows the pattern used in Table 3 with columns (1) – (3) reporting results using the broad matching scheme and columns (4)

– (6) reporting results using the tight matching scheme. In the interest of brevity, we focus on the results using the tight matching scheme.

Column (4) states that total payout for the high payers in the *pre-event* period was about 0.5% higher than the matching firms for both transitory and persistent high payers and that during the post period the matching firms for both groups increased their payout by approximately 1.5%. Both of these results parallel the full sample results presented in Panel B of Table 3. As expected, the *post event* payout experiences were different. Transitory high payers reduced their total payout by 1% of assets relative to their control firms in the *post event* period while persistent high payers continued to payout about 8.5% more than their control firms. This difference in payout behavior confirms that our sorting of high payers into transitory and persistent groups based on frequency of high payout accords with the difference in the amount of their payout.

Column (5) examines the investment behavior of transitory versus persistent high payers. Column (5) in Panel A shows that transitory firms had a similar *pre-event* level of investment to their matching firms. In contrast, Panel B shows that persistent high payers invested 2% less than their matching firms in the *pre-event* period. CAPEX of the control firms for both groups of high payers declined by roughly 3-4% in in the *post event* period. These results for the two groups are similar to each other and also similar to the results in Table 3. The interaction coefficient in Panel A is insignificant which implies that transitory high payers and their matching firms behave in the same manner in the *post event* period. The interaction term for persistent high payers has a coefficient that is positive and significant and indicates that high payers invested more than matching firms in the *post event* period. The coefficient for the persistent high payers suggests that high payers have about 1.5% higher CAPEX than matching firms. In other words, CAPEX declined by 4.2% for the matching firms but by only 2.5% by the persistent high payers (comparison of the Post coefficient with the imputed change in investment the last row Panel B). The argument that excessive payout causes firms to curtail investment predicts that the interaction term should have a negative coefficient and that the coefficient should be more negative for the persistent high payers than for the transitory high payers and that investment by the persistent high payers should decline by more than the control firms. The results do not support this conclusion. Finally, column (6) examines the results for R&D. The estimates in column (6) suggest that R&D declines by approximately 4% for the matching firms in the *post event* period and that high payers do not behave differently than the control firms. Thus there is no evidence that persistence in large payouts is harming investment or innovative activity.

Table 6 presents the results for operating cash flow, cash balances, Q, and sales growth for the two groups of high payers. In the interest of brevity, we only report results for the tight matching scheme. As with Table 5, Panel A presents estimates for transitory high payers, and Panel B reports results for persistent high payers. Column (1) begins the comparisons of transitory and persistent high payers with operating cash flow. Panel A shows that transitory high payers have a similar profitability to their matching firms in the *pre-event* period, that the profitability of the matching firms does not change from the *pre-event* to *post event* period, and that the high payers *post event* profitability is not different from their control firms. Panel B shows that persistent high payers have a similar *pre-event* cash flow as their matching firms, that the matching firms have a substantial decline in profitability in the post period, and that the persistent high payers have a much higher *post event* profitability than the control firms. The imputed change in profitability from combining the coefficients on Post and the DID term, shown in the last row of Panel B, indicates that operating cash flow for the persistent high payers does not change from the *pre-event* to *post event* period while the cash flow for the matching firms declines by 7.5%. Thus column (1) refutes the hypothesis that persistent high payers experience abnormal declines in profitability relative to their matched firms. In fact, the persistent high payers appear to significantly outperform their peers. The observed results are consistent with high payouts being the result of high performance rather than a cause of low subsequent performance.

The results above are consistent with Michaely et al. [76]'s results on the information content of payout. Michaely et al. [76] show that in the long run there is no difference in the level of profitability before and after dividend changes but that cash flow risk declines after dividends increase or shares are repurchased. We demonstrate that profitability, measured by OCF, does not change in the firms that increased their payout persistently by a large amount. Instead, it is the control group that experiences a decline in their profitability.

Column (2) of Table 6 estimates equation (2) for cash balances. Panel A shows that *pre-event* cash for transitory high payers is not different from the matching firms and that the matching firms experience a substantial decline in cash during the *post event* period. In addition, the coefficient on the interaction term shows that cash for the high payers in the *post event* period declines by a larger amount than the matching firms. In contrast, Panel B shows a different result for persistent high payers. Panel B shows that control firms for the persistent high payers also experience a substantial decline in cash of 6.6% but that the interaction term has a coefficient that is positive, significant, and large at 7.7%. The imputed change in cash in the last row of Panel B shows that cash balances for the average persistent high payer does not change despite the large payout and despite the fact that cash balances at comparable firms are declining. Thus high payment does not appear to be impairing the liquidity of the persistent high payers.

Column (3) of Table 6 estimates equation (2) for Q. Panel A shows that *pre-event* Q for transitory high payers is not different from the matching firms and that the matching firms experience a substantial decline in Q of 0.3 during the *post event* period. In addition, the coefficient on the interaction term shows that Q for the transitory high payers in the *post* *event* period behaves in the same manner as the control firms. In contrast, Panel B shows a different result for the persistent high payers. Panel B shows that control firms for the persistent high payers also experience a substantial decline in Q but that the interaction term has a coefficient that is positive and significant. In other words, Q declines for both the control firms and the persistent high payers but declines much less for the high payers. This result is consistent with the view that the matching firms for the persistent high payers experienced a large decline in the value of their growth opportunities but that the persistent high payers experienced a much smaller decline in the value of their growth opportunities (about 60% less). Thus the evidence is inconsistent with large payouts causing a reduction in value for the persistent high payers. Instead, the evidence is consistent with firms making large payouts when they have strong profitability and a loss of growth opportunities.

2.4 High Payout, Financing of Payout, and Leverage

2.4.1 Payout and the Issuance of New Securitiess

In the discussion of results above, we suggested that access to external funds might relax cash flow constraints as detailed in Fried and Wang [42] and explain why high paying firms were able to continue to support investment and innovation. External capital could come from equity issues as in Fried and Wang [42] or from debt issues as in Farre-Mensa et al. [35]. The possibility of both repurchasing shares and issuing shares in the same general time frame would not happen in a traditional Modigliani-Miller framework but is plausible in the presence of substantial agency costs (see Easterbrook [31]). The implications of both paying out funds through dividends and repurchases and issuing new equity claims in the same time frame suggests that the firm has access to the resources it needs to finance its investment and innovative activities and thereby enhance future performance. Debt issues to finance payout could similarly indicate that the high payout firms have access to external capital. Alternatively, if paying out large amounts of funds can be detrimental for firms, the effect would be concentrated in firms that internally financed and would not be present for firms with access to external capital. We investigate this possibility by splitting the persistent high payers into groups that describe how their consistent large payouts are financed (equity, debt, or internal) and examine CAPEX, R&D, profitability, and value conditional on financing using our DID framework.

We create a variable that measures the percentage of persistent high payout that is financed externally in the long run. We first calculate total equity financing over t to $t+3$ by summing new equity financing. New equity financing is the sum of total sales of common stock from year t to $t+3$ obtained from the cash flow statement. Next, we calculate the sum of total dollar payout from t to $t+3$. Finally, we compute the ratio of total equity financing to total dollar payout to capture the percentage of total payout that is financed by issuing equity. If this ratio is greater than or equal to 50% for a persistent high payer, we consider the long-term high payout as equity financed. We create a similar ratio for payout that is debt financed. New debt financing is the increase in debt level from the beginning of year t to the end of year $t+3$ where debt is defined as long-term debt plus debt in current liabilities. Internally financed payout occurs when the ratios of both equity financed payout and debt financed payout are less than 30%. Note that some firms will not be classified into any of these categories because the externally financed portion of payout falls between 30% and 50%.

Table 7 reports the results of our DID regression framework for equity financed payout in Panel A, debt financed payout in Panel B, and internally financed payout in Panel C. In the interest of economizing our presentation we present only the results with the tight matching scheme. We first discuss the payout behavior based on the method of financing and then examine the investment and innovative activities of the three groups. In each of the regressions for total payout, we see the same pattern of results. First, payout for the persistent high payers is between 0.5% and 1% more than the control firms during the *pre-event* period for all three financing groups. Second, control firms increase their payout by 1-2% in the *post event* period for all three financing groups. Third, during the *post event* period, high payers increase their payout substantially relative to the matching firms. In terms of the magnitude of the increase in payout relative to the control firms, debt financed persistent high payers increased their payout the least (6.8% relative to the matches) while the internally financed high payers increased their payout the most (9.3% relative to the matches). Thus in terms of payout the same general pattern is present for all three groups, and the internally financed high payers have the largest difference in behavior from the control firms.

In terms of investing behavior, equity and debt financed persistent high payers had CAPEX levels in both the *pre-event* and *post event* periods that were not different from their matching firms. However, for both debt and equity financed groups, both the persistent high payers and the control firms decreased the CAPEX between the *pre-event* and *post event* periods. The absence of a difference in the *post event* period between high payers and control firms should be expected because high payers can use external capital markets to supplement internal funds and relax cash flow constraints.

Internally financed persistent high payers exhibit a different pattern. The internally financed high payers invested 3.2% less than their matching firms in the *pre-event* period. During the *post event* period, the control firms for this group decreased their investment by about 4%. However, the interaction term in this regression is positive and significant indicating that the internally financed high payers invested substantially more than their control firms in the *post event* period. The imputed coefficient for CAPEX shows that the internally financed high payers decreased their CAPEX by 1.8% (vs 4.2% for the matched firms) in the *post event* period while they continued to payout large sums to shareholders.

In terms of innovative activities, debt and equity financed persistent high payers spent the same amount on R&D as their control firms in both the *pre-event* and *post event* periods. Internally financed high payers again exhibited different behavior. In the *pre-event* period, internally financed high payers spent almost 5% less on R&D than their matching firms. The matching firms reduced their R&D by 3.8% in the *post event* period. The internally financed high payers, however, increased their R&D spending by an almost equal amount. The imputed coefficient for the internally financed high payers shows that their R&D did not change from the *pre-event* to the *post event* period despite the decrease in R&D by the control firms. Thus the results for both investment and innovative activities for the internally financed persistent high payers show that the event of large payouts to shareholders did not reduce either CAPEX or R&D spending relative to the control firms.

Table 8 presents the results for operating cash flow, cash balances, Q, and sales growth for the high payers based on how the payout was financed. Panel A presents the results for equity financed high payers, Panel B for debt financed high payers, and Panel C for internally financed high payers. Column (1) of Panel A shows that equity financed high payers have the same underlying profitability as their matched firms in both the *pre-event* and *post event* periods. The control firms in Panel B experience a decline in operating cash flow of about 5% from *pre-* to *post event* while high payers have operating cash flow that is about 5% higher than the control firms. In other words, operating cash flow for the high payers does not change while cash flow decreases for the control firms. Similarly, for the internally financed high payers in Panel C, the matched firms have a 7.5% decline in operating cash flow while the high payers have an equal 7.5% higher operating cash flow. Thus for both debt financed and internally financed high payers, profitability does not change from *pre-* to *post event* while profitability of the control firms exhibits a significant decrease.

Column (2) shows for all three financing groups that cash balances drop for the control firms from the *pre-event* period to the post. The interaction term for the equity financed and internally financed groups show an offsetting increase in cash for the high payers in the *post event* period. Thus on net, cash balances for equity and internally financed high payers are stable across time despite the decline in cash for the control firms. Overall, the profitability and liquidity results show no tendency for declining performance or capacity to fund investment through time for high payers in any of the three financing categories.

Column (3) examines the impact of high payout on value separately for equity, debt, and internally financed high payers. The DID framework shows that Q declines for the control firms for the equity financed high payers (0.51), the debt financed high payers (0.29), and the internally financed high payers (0.37). The interaction terms indicate that the equity and debt financed high payers Q behave through time in the same manner as the control firms. In contrast, the interaction term for the internally financed high payers shows that their Q increases in the *post event* period by an offsetting amount. Thus the value of the internally financed high payers is unchanged by the event of large payouts despite the decrease in value of the matched firms during the *post event* period. Finally, column (4) shows that sales growth decreases from *pre-* to *post event* for the matching firms for all three financing categories and that high payers' sales growth behaves in the same manner. Thus Table 8 demonstrates that high payout firms both with externally financed payout and those that rely on internally financed payout perform equally or better than their matched firms in terms of profitability, value, and sales growth. Additionally, none of the three financing categories shows signs that high payout is triggering liquidity problems.

2.4.2 Leverage Change and Investment

The act of paying out cash to shareholders unequivocally reduces a firm's book value of equity. Thus, for a given debt level, payout increases its book leverage. This effect is instantaneous. A question arises about what the longer term impact of payouts is when some firms finance payout with equity issues while others finance with debt issues or internally finance. Additionally, any analysis that extends beyond the moment of payout to shareholders must also acknowledge that firms typically retain a portion of their income which increases a firm's equity position over time and reduces its leverage. Furthermore, debt eventually reaches maturity, and firm's repay creditors. To take account of the variety of factors that affect a firm's leverage, we examine the change in leverage for our sample of high payers over the four year period including years t through $t+3$. We calculate this by subtracting each firm's year $t-1$ fiscal year-end book leverage value from its year $t+3$ value to find the cumulative change in leverage over the four year period. We ask whether the high payout firms with the largest increases in leverage experience reductions in investment in physical capital, innovation, profitability, and value using our DID framework.

To examine leverage changes, we begin by looking at the distribution of leverage changes for the 1,429 high payers that have a matching firm under the tight matching scheme. We winsorize the four-year cumulative book leverage changes at the 1% and 99% levels. The resulting distribution of leverage changes spans from -29.5% up to +42.5%. Since our interest is identifying the high payout firms that also have large leverage increases, we split the data at the cut-off for the upper quartile of 7.8%. This separates the sample of high payers into two groups - high leverage increase firms with a change in leverage between +7.8% and 42.5% (or 357 firms) and firms that did not experience a large increase in leverage with leverage changes ranging between -29.5% and +7.7% (or 1,072 firms). We refer to these two groups as *Leverage Increasing* firms and *Leverage not Increasing* firms. Using this split of the sample of high payout firms, we focus on the impact of large leverage increases.

Table 9 displays the DID estimation with the *Leverage Increasing* high payers with matching firms in columns (1) - (3) and the *Leverage not Increasing* high payers with matching firms in columns (4) - (6). We first examine the two groups using our DID framework to assess the impact on leverage. Columns (1) and (4) report the results for the two groups. Columns (1) and (4) show that both groups of high payers have lower leverage than the respective control groups in the *pre-event* period and that leverage for both control groups does not change in the *post* period. Both of these conclusions are consistent with Panel B of Table 3. The interaction terms indicate that the two groups behave differently. For the *Leverage Increasing* group, the coefficient on the interaction term indicates that book leverage increases by an average of 12.5% relative to the matched firms. For the *Leverage Not Increasing* group, book leverage declines relative to the matched firms by an average of 3.1%. These results are consistent with our construction of the two groups of high payers.

Column (2) and (5) report the results for capital expenditure. Both groups invest less in the *pre-event* than the respective control groups, and the control firms reduce investment by about 4% in the *post event* period. For the leverage increasing high payers, the high payers exhibit the same behavior as the control firms. For the leverage not increasing high payers, the high payers invest relatively more than their matching firms as indicated by the positive and significant coefficient on the interaction term. Columns (3) and (6) report the results for R&D spending. Both control groups reduce their R&D spending in the post period, and the two groups of high payers behave in the same manner as their respective control firms. Thus on balance, the change in leverage during the event and post even period for the two groups appears to have no impact on the investing and innovative activities of high payout firms.

Table 10 reports the results of our analysis of profitability, cash balances, Tobin's Q, and sales growth separately for the two groups based on their leverage changes. Panel A reports results for the *Leverage Increasing* group, and Panel B reports results for the *Leverage not Increasing* group. Column (1) of Panel A shows that high payers that high payers that increase their leverage substantially have the same profitability as their matched firms in bot the *pre* and *post* periods. Column (1) of Panel B shows for the *Leverage not Increasing* group the that profitability of the control firms declines in the post period but that this group of high payers has higher profitability than their control group. Thus high paying firms that also increase leverage do not perform worse than their matched firms. High payout firms that do not substantially increase leverage appear to outperform their matched firms.

Column (2) in the two panels reports the results using cash balances as the dependent variable. For both groups, the control firms experience a decline in cash balances of 3-4%. For the leverage increasing firms, cash balances decrease by an additional 4.8% in the post period. In contrast, the interaction term for the leverage not increasing high payers is large and positive and indicates that their cash balances (like the their operating cash flow) does not change. Similar to profitability, the results for cash indicate that leverage increasing high payers do no worse than their peers while high payers which do not substantially increase leverage have more liquidity than their peers.

Column (3) in both panels reports the results using Tobin's Q as the dependent variable. The negative coefficient on *Post* in both panels indicates that Q declines for the control firms. The insignificant coefficient on the interaction term implies that Q does not behave differently for the high payers than for the two control groups. Thus there is no evidence to suggest that firm value is negatively impacted by payout for firms that concurrently increase their leverage.

2.5 Conclusion

During the past 30 years, there has been a decline in capital investment for US public firms which has provoked concerns that managers are excessively concerned with short-term results [e.g., 2, 37, 59, 66]. One part of the short-termist criticism is that firms are paying excessive amounts of cash to their shareholders and are forgoing valuable growth opportunities. Existing critiques of the short-termist hypothesis focus on macro level analysis of investment and R&D spending [8, 42, 84]. In this paper, we examine the short-term and long-term impact of large increases in payout on investment in physical capital and R&D at the firm level. A critical part of the analysis is to identify appropriate benchmarks for evaluating firms that make substantial increases in their payouts so that the link between payout, investment or innovation, profitability, and value can be assessed. We implement our analysis using a matched sample analysis of firms that substantially increase their payouts with firms from the same industry, similar size, similar profitability, and similar initial cash balances which do not substantially increase payouts. Using our matched sample comparisons and a difference-in-differences analysis, we do not find evidence supporting the view that high payout firms are systematically underinvesting and compromising long-term profitability and value. The firms that increase their payout do not show a decline relative to the matched sample. In fact, we find that high payout firms have 1% higher CAPEX than the control firms in the long run. High payout firms also spend a similar amount on innovative activities (measured by R&D spending).

The large payout increase observed in our sample is a joint effect of persistent high profitability and diminishing growth opportunities. We find that the high payers have higher operating cash flow, higher cash balances and higher growth opportunities relative to their peers before the initiation of the high payout. We also show that both the high payers and their peers face declining growth opportunities. The high payout firms have high profitability that persists and thus increase payout. In contrast, the control firms experience declining profitability and growth opportunities and do not initiate high payouts. Overall, the high payout by some public firms is not associated with a reduction in capital investment or R&D in the long run by those firms and is not a manifestation of short-termism. The secular decline in investment in the US public firms is likely the result of other economic factors and is not the result of large payouts to shareholders by the most profitable firms.

2.6 Tables

Table 1: *Pre-Event* Summary Statistics – High Payers

This table presents a summary of the average characteristics during the *pre-event* period for all the high payers. We consider firms in the top 20% of industry median adjusted payout rate for each year as paying out large amounts of cash. We drop the firms that are also in the top 20 percentile in the *pre-event* period. We further drop all the firms with missing OCF and Cash during the *pre-event* period. We end up with 3,510 high payers from 1987 to 2014. Total Asset and Market Cap are expressed in 2014 dollars in billions. Our Age (since inception) variable is based on the date of inception from Prof. Gustavo Grullon. We construct another age measure - Age (Since Listed) - as the number of years since a firm is first included in the CRSP database. Detailed definitions of variables can be found in the appendix.

	N	Mean	Std	P25	P50	P75
Total Payout/TA	3,510	0.009	0.011	0.000	0.005	0.015
Dividend/TA	3,510	0.006	0.009	0.000	0.000	0.010
Repurchase/TA	3,510	0.004	0.006	0.000	0.000	0.005
Total Asset	3,510	2.946	7.847	0.105	0.390	1.724
Market Cap	3,494	3.676	15.005	0.126	0.509	1.992
OCF/TA	3,510	0.158	0.152	0.098	0.156	0.224
Cash/TA	3,510	0.233	0.236	0.049	0.146	0.356
CAPEX	3,476	0.102	0.114	0.035	0.066	0.121
R&D	3,510	0.098	0.301	0.000	0.003	0.079
Q	3,494	2.060	1.525	1.175	1.546	2.275
SG	3,496	0.210	0.379	0.037	0.128	0.263
Leverage	3,510	0.174	0.157	0.031	0.145	0.273
Age (since inception)	2,771	37.104	35.134	13	23	49
Age (since listed)	3,510	14.785	14.666	5	10	22

Table 2: Summary Statistics – High Payers and Matching Firms

This table presents a summary of the characteristics of different groups of firms. We report key average characteristics for each group of firms respectively in *pre-event* and event year from 1987 to 2014. For each firm, we first calculate the average of the variables of interest in the *pre-event* period. We then average within each event year for high payers and control firms respectively. Lastly, we report the average across all the event years for the *pre-event* characteristics. We repeat the process for the event period, except that we do not average characteristics within the *event* period since it only covers one year. Panel A summarizes the characteristics of high payers and their matching firms when the match is based on industry and size (broad match). Panel B summarizes the characteristics of high payers and their matching firms when the match is based on industry, size, profitability, and cash level (tight match). The columns labeled “H” and “M” present the mean characteristics of high payers and their matching firms, respectively. The columns labeled “Diff” reports the average difference between high payers and their matches for *pre-event* years and for the event year. Total Asset are expressed in 2014 dollars in billions. T-statistics for the hypothesis that the average difference is zero are reported in the parentheses. Panel C summarizes average characteristics for the high payers for which there are matches and those for which a suitable match could not be located under the broad scheme. Panel D provides a similar comparison between the high payers with matches under the tight matching scheme and the firms that had matches under the broad scheme but did not under the tight scheme. T-statistics for the hypothesis that the average difference is zero are reported in the parentheses.

Panel A: Match on Industry and Size (# of Matches: 2,973)

	H		M		Diff	
	Pre	*Event*	*Pre*	*Event*	*Pre*	*Event*
Total Assets	3.052	3.181	2.906	3.032	0.146	0.149
					(1.05)	(1.01)
Total Payout/TA	0.012	0.080	0.004	0.004	0.008***	0.076***
					(11.91)	(21.74)
Dividend/TA	0.006	0.015	0.003	0.003	0.004***	0.013***
					(9.00)	(8.91)
Repurchase/TA	0.006	0.065	0.002	0.002	0.004***	0.063***
					(7.66)	(18.50)
OCF/TA	0.154	0.155	0.110	0.104	0.044***	0.051***
					(10.59)	(13.39)
Cash/TA	0.261	0.226	0.185	0.184	0.075***	0.042***
					(10.34)	(6.29)
OCF/NA	0.177	0.191	0.075	0.087	0.102***	0.104***
					(9.23)	(10.63)
Cash/NA	0.346	0.326	0.245	0.245	0.101***	0.081***
					(10.06)	(7.93)
Q	2.028	1.846	1.819	1.753	0.209***	0.093***
					(5.63)	(1.96)
SG	0.193	0.129	0.238	0.166	-0.045***	-0.037***
					(-4.75)	(-2.75)
Leverage	0.174	0.187	0.262	0.261	-0.088***	-0.074***
					(-17.16)	(-14.27)

Panel B: Match on Industry, Size, OCF, and Cash (# of Matches: 1,429)						
	H		M		Diff	
	Pre	*Event*	*Pre*	*Event*	*Pre*	*Event*
Total Assets	2.853	2.969	2.721	2.807	0.132	0.162
					(0.81)	(0.98)
Total Payout/NA	0.013	0.112	0.005	0.005	0.008***	0.107***
					(9.85)	(20.23)
Dividend/NA	0.007	0.017	0.002	0.003	0.005***	0.014***
					(8.57)	(8.15)
Repurchase/NA	0.006	0.095	0.002	0.002	0.004***	0.093***
					(5.47)	(17.52)
OCF/TA	0.139	0.141	0.142	0.125	-0.003	0.006
					(-0.98)	(2.37)
Cash/TA	0.299	0.255	0.256	0.246	0.043	0.009
					(7.58)	(1.52)
OCF/NA	0.152	0.170	0.159	0.130	-0.007	0.040***
					(-0.63)	(3.11)
Cash/NA	0.393	0.372	0.347	0.335	0.046***	0.037***
					(7.88)	(4.91)
Q	2.131	1.906	2.128	1.916	0.002	-0.010
					(0.07)	(-0.14)
SG	0.210	0.132	0.269	0.193	-0.059***	-0.061***
					(-5.14)	(-3.80)
Leverage	0.161	0.171	0.209	0.213	-0.048***	-0.042***
					(-6.30)	(-6.11)

Panel C: Unmatched High Payers on Industry and Size						
	Matched High Payers (2973)		Unmatched High Payers (537)		Diff	
	Pre	*Event*	*Pre*	*Event*	*Pre*	*Event*
Total Assets	3.052	3.181	4.310	4.395	-1.258*	-1.213*
					(-1.89)	(-1.86)
Total Payout/TA	0.012	0.080	0.014	0.078	-0.002	-0.002
					(-1.23)	(-0.30)
Dividend/TA	0.006	0.015	0.008	0.020	-0.002*	-0.005
					(-1.93)	(-1.60)
Repurchase/TA	0.006	0.065	0.006	0.058	0.000	-0.007
					(0.14)	(-1.10)
OCF/TA	0.164	0.155	0.163	0.159	0.001	-0.004
					(0.19)	(-0.45)
Cash/TA	0.261	0.226	0.163	0.145	0.098***	0.081***
					(6.08)	(5.74)
OCF/NA	0.202	0.191	0.192	0.198	0.009	-0.007
					(0.69)	(-0.50)
Cash/NA	0.346	0.326	0.206	0.195	0.140***	0.131***
					(6.22)	(6.03)
Q	1.964	1.844	1.576	1.549	0.387***	0.295***
					(3.96)	(3.51)
SG	0.163	0.129	0.146	0.114	0.016	0.015
					(0.58)	(0.64)
Leverage	0.174	0.187	0.219	0.228	-0.045***	-0.041***
					(-3.55)	(-3.06)

Panel D: Unmatched High Payers on Industry, Size, OCF, and Cash						
	Matched High Payers (1429)		Unmatched High Payers (1544)		Diff	
	Pre	*Event*	*Pre*	*Event*	*Pre*	*t*
Total Assets	2.773	2.884	3.325	3.476	-0.553	-0.592
					(-1.54)	(-1.57)
Total Payout/TA	0.011	0.078	0.013	0.082	-0.002	-0.004
					(-1.32)	(-0.71)
Dividend/TA	0.006	0.013	0.007	0.017	-0.001	-0.004*
					(-1.46)	(-1.76)
Repurchase/TA	0.005	0.065	0.006	0.065	-0.001	0.000
					(-0.78)	(0.00)
OCF/TA	0.152	0.140	0.177	0.169	-0.025***	-0.029***
					(-3.45)	(-4.27)
Cash/TA	0.301	0.257	0.223	0.196	0.078***	0.061***
					(4.51)	(4.08)
OCF/NA	0.186	0.170	0.219	0.212	-0.033***	-0.042***
					(-2.15)	(-2.86)
Cash/NA	0.396	0.375	0.299	0.280	0.096***	-0.095***
					(-4.05)	(-4.16)
Q	2.065	1.912	1.874	1.783	0.191*	0.129
					(1.79)	(1.56)
SG	0.174	0.132	0.151	0.121	0.023	0.012
					(0.89)	(0.60)
Leverage	0.160	0.170	0.187	0.202	-0.027***	-0.032***
					(-2.60)	(-3.30)

Table 3: Short Run and Long run Impact of High Payment

This table presents regression results estimating Equation (2.1) and Equation (2.2) with total payout, CAPEX, and R&D as dependent variables. Panel A presents results of estimating Equation (2.1), and Panel B presents results of estimating Equation (2.2). In both panels, columns (1) - (3) utilize the matched sample under the broad matching criteria. Columns (4) - (6) utilize the matched sample under the tight matching criteria. We include industry and year fixed effects, and we cluster standard errors at firm level in all the models. T-statistics are reported in the parentheses. Panel B also reports the sum of the estimated coefficients on *Post* and $High \times Post$ $(\delta + \eta)$. p-value for a test of statistical significance is also reported.

Panel A - Short Run Impact

	Broad Match			Tight Match		
	(1)	(2)	(3)	(4)	(5)	(6)
	Total Payout	*CAPEX*	*R&D*	*Total Payout*	*CAPEX*	*R&D*
High (γ)	0.006***	-0.010**	-0.028***	0.005***	-0.017***	-0.021*
	(17.45)	(-3.19)	(-3.47)	(11.10)	(-3.93)	(-1.67)
Event (θ)	-0.000	-0.023***	-0.018***	0.000	-0.018***	-0.026***
	(-0.68)	(-10.64)	(-4.16)	(0.55)	(-5.22)	(-3.75)
$High \times Event$ (ζ)	0.098***	0.013***	0.007	0.100***	0.006	0.011
	(60.05)	(4.47)	(1.36)	(42.42)	(1.27)	(1.16)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	11856	11740	11856	5708	5664	5708
adj. R^2	0.554	0.149	0.157	0.553	0.148	0.170

Panel B - Long run Impact

	Broad Match			Tight Match		
	(1) *Total Payout*	(2) *CAPEX*	(3) *R&D*	(4) *Total Payout*	(5) *CAPEX*	(6) *R&D*
High (γ)	0.006***	-0.010**	-0.028***	0.005***	-0.017***	-0.021*
	(18.88)	(-3.18)	(-3.47)	(12.02)	(-3.94)	(-1.67)
Post (δ)	0.013***	-0.030***	-0.021***	0.016***	-0.037***	-0.037***
	(17.88)	(-12.76)	(-4.49)	(14.50)	(-11.17)	(-5.87)
High $\times$ *Post* (η)	0.031***	0.011***	0.003	0.031***	0.011**	0.007
	(24.87)	(3.56)	(0.58)	(16.79)	(2.46)	(0.80)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	11848	11764	11848	5708	5676	5708
adj. R^2	0.251	0.165	0.167	0.243	0.173	0.184
$\delta + \eta$	0.044	-0.020	-0.018	0.047	-0.026	-0.030
p-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001

Table 4: Profitability and Valuation

This table presents regression results estimating Equation (2.2) with OCF, cash, Tobin's Q, and sales growth as dependent variables. Columns (1) - (4) utilize the matched sample under the broad matching criteria. Columns (5) - (8) utilize the matched sample under the tight matching criteria. We include industry and year fixed effects, and cluster standard errors at firm level in all the models. T-statistics are reported in the parentheses. We also reports the sum of the estimated coefficients on *Post* and $High \times Post$ $(\delta + \eta)$. p-value for a test of statistical significance is also reported.

	Broad Match				Tight Match			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OCF	*Cash*	*Q*	*SG*	*OCF*	*Cash*	*Q*	*SG*
High (γ)	0.102***	0.058***	0.202***	-0.038***	0.000	0.003	-0.035	-0.054***
	(9.00)	(7.61)	(5.66)	(-3.80)	(0.01)	(0.23)	(-0.61)	(-3.76)
Post (δ)	0.003	-0.014***	-0.130***	-0.104***	-0.039***	-0.043***	-0.369***	-0.145***
	(0.38)	(-3.60)	(-5.10)	(-11.30)	(-4.11)	(-6.71)	(-9.18)	(-11.52)
$High \times Post$ (η)	-0.019*	-0.008	-0.119***	0.015	0.031**	0.021**	0.068	0.037**
	(-1.94)	(-1.53)	(-3.51)	(1.33)	(2.13)	(2.50)	(1.24)	(2.15)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	11848	11848	11836	11832	5708	5708	5704	5704
adj. R^2	0.071	0.215	0.133	0.059	0.088	0.296	0.168	0.086
$\delta + \eta$	-0.016	-0.023	-0.248	-0.089	-0.008	-0.022	-0.301	-0.108
p-value	0.010	0.000	0.000	0.000	0.449	0.000	0.000	0.000

Table 5: Transitory and Persistent High Payers

This table presents regression results estimating Equation (2.2) with total payout, CAPEX, and R&D as dependent variables for transitory and persistent high payers. Panel A reports the results for transitory high payers, and Panel B reports the results for persistent high payers. We define the high payers that are not classified as high payers again in the *post* period as transitory high payers. We define the high payers that are classified as high payers two times or more in the *post* period as persistent high payers. We drop the high payers that are classified as high payers only once in the *post* period in this test. In both panels, columns (1) - (3) utilize the matched sample under the broad matching criteria. Columns (4) - (6) utilize the matched sample under the tight matching criteria. We include industry and year fixed effects, and cluster standard errors at firm level in all the models. T-statistics are reported in the parentheses. We also reports the sum of the estimated coefficients on *Post* and $High \times Post$ $(\delta + \eta)$. p-value for a test of statistical significance is also reported.

Panel A - Transitory High Payers

	Broad Match			Tight Match		
	(1)	(2)	(3)	(4)	(5)	(6)
	Total Payout	*CAPEX*	*R&D*	*Total Payout*	*CAPEX*	*R&D*
High (γ)	0.005***	-0.013**	-0.029**	0.004***	-0.009	-0.026
	(13.40)	(-2.53)	(-2.12)	(8.13)	(-1.29)	(-1.03)
Post (δ)	0.011***	-0.032***	-0.024**	0.012***	-0.027***	-0.035**
	(11.01)	(-8.52)	(-2.89)	(7.66)	(-5.68)	(-3.00)
$High \times Post$ (η)	-0.009***	0.010*	0.007	-0.011***	-0.000	-0.000
	(-9.12)	(1.81)	(0.67)	(-6.39)	(-0.02)	(-0.00)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4692	4664	4692	2256	2244	2256
adj. R^2	0.107	0.183	0.213	0.101	0.186	0.278
$\delta + \eta$	0.001	-0.023	-0.017	0.002	-0.028	-0.035
p-value	< 0.001	< 0.001	0.008	0.001	< 0.001	0.005

Panel B - Persistent High Payers

	Broad Match			Tight Match		
	(1)	(2)	(3)	(4)	(5)	(6)
	Total Payout	*CAPEX*	*R&D*	*Total Payout*	*CAPEX*	*R&D*
High (γ)	0.007***	-0.004	-0.016	0.006***	-0.018**	-0.021
	(10.66)	(-0.90)	(-1.62)	(6.53)	(-2.39)	(-1.40)
Post (δ)	0.014***	-0.028***	-0.014**	0.019***	-0.042***	-0.044***
	(12.47)	(-7.26)	(-2.03)	(9.88)	(-7.82)	(-4.81)
High $\times$ *Post* (η)	0.084***	0.012**	-0.004	0.086***	0.017**	0.015
	(33.80)	(2.56)	(-0.54)	(23.39)	(2.48)	(1.29)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4196	4172	4196	1984	1976	1984
adj. R^2	0.562	0.147	0.149	0.546	0.163	0.197
$\delta + \eta$	0.098	-0.016	-0.018	0.105	-0.025	-0.029
p-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001

Table 6: Profitability and Valuation - Transitory and Persistent High Payers

This table presents regression results estimating Equation (2.2) with OCF, cash, Tobin's Q, and sales growth as dependent variables for transitory and persistent high payers. To economize space, we only report the results using the sample under the tight matching criteria. Panel A reports the results for transitory high payers and Panel B reports the results for persistent high payers. We define the high payers that are not classified as high payers again in the *post* period as transitory high payers. We define the high payers that are classified as high payers two times or more in the *post* period as persistent high payers. We drop the high payers that are classified as high payers only once in the *post* period in this test. We include industry and year fixed effects, and cluster standard errors at firm level in all the models. T-statistics are reported in the parentheses. We also reports the sum of the estimated coefficients on *Post* and $High \times Post$ $(\delta + \eta)$. p-value for a test of statistical significance is also reported.

Panel A - Transitory High Payers

	(1) *OCF*	(2) *Cash*	(3) *Q*	(4) *SG*
High (γ)	-0.002	0.004	-0.097	-0.031
	(-0.06)	(0.21)	(-1.08)	(-1.20)
Post (δ)	-0.003	-0.030**	-0.285***	-0.133***
	(-0.15)	(-3.24)	(-4.88)	(-5.97)
$High \times Post$ (η)	-0.015	-0.027**	-0.079	0.013
	(-0.52)	(-2.06)	(-0.92)	(0.43)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	2258	2258	2258	2256
adj. R^2	0.171	0.301	0.197	0.064
$\delta + \eta$	-0.018	-0.057	-0.364	-0.120
p-value	0.441	< 0.001	< 0.001	< 0.001

Panel B - Persistent High Payers

	(1)	(2)	(3)	(4)
	OCF	*Cash*	*Q*	*SG*
High (γ)	0.014	0.001	0.106	-0.075***
	(0.73)	(0.04)	(1.08)	(-3.42)
Post (δ)	-0.075***	-0.066***	-0.408***	-0.161***
	(-5.77)	(-5.81)	(-5.80)	(-8.48)
High $\times$ *Post* (η)	0.081***	0.077***	0.240**	0.045*
	(4.34)	(5.31)	(2.60)	(1.78)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1986	1986	1986	1986
adj. R^2	0.083	0.360	0.189	0.128
$\delta + \eta$	0.006	0.012	-0.168	-0.116
p-value	0.652	0.243	0.011	< 0.001

Table 7: Financed High Payers

This table presents regression results estimating Equation (2.2) with total payout, CAPEX, and R&D as dependent variables for persistent high payers with different financing activity. To economize space, we only report the results using the sample under the tight matching criteria. Columns (1) - (3) report the results for the persistent high payers that have new equity finance taking more than 50% of total payout over $[t, t+3]$ (Equity Financed Persistent High Payers). Columns (4) - (6) report the results for the persistent high payers that have new debt finance taking more than 50% of total payout over $[t, t+3]$ (Debt Financed Persistent High Payers). Columns (7) - (9) report the results for the persistent high payers that have new equity and debt finance taking less than 30% of total payout over $[t, t+3]$ (Internally Financed Persistent High Payers). We include industry and year fixed effects, and cluster standard errors at firm level in all the models. T-statistics are reported in the parentheses. We also reports the sum of the estimated coefficients on *Post* and $High \times Post$ $(\delta + \eta)$. p-value for a test of statistical significance is also reported.

	Equity Financed			Debt Financed			Internally Financed		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Total Payout	*CAPEX*	*R&D*	*Total Payout*	*CAPEX*	*R&D*	*Total Payout*	*CAPEX*	*R&D*
High (γ)	0.005**	0.014	0.024	0.008***	-0.011	0.003	0.006***	-0.032***	-0.047**
	(2.30)	(0.64)	(0.42)	(3.42)	(-0.69)	(0.12)	(3.90)	(-3.54)	(-2.80)
Post (δ)	0.016***	-0.060***	-0.092**	0.010***	-0.030**	-0.027	0.020***	-0.042***	-0.038**
	(3.44)	(-4.09)	(-3.18)	(4.01)	(-2.64)	(-1.50)	(6.74)	(-5.57)	(-2.65)
$High \times Post$ (η)	0.078***	0.010	-0.028	0.068***	0.020	-0.002	0.093***	0.024**	0.034**
	(8.71)	(0.47)	(-0.60)	(8.74)	(1.21)	(-0.08)	(16.03)	(2.58)	(2.10)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	364	360	364	396	392	396	980	970	980
adj. R^2	0.488	0.148	0.182	0.492	0.274	0.331	0.561	0.166	0.174
$\delta + \eta$	0.095	-0.050	-0.120	0.078	-0.011	-0.029	0.113	-0.018	-0.005
p-value	< 0.001	0.002	0.001	< 0.001	0.387	0.086	< 0.001	0.001	0.527

Table 8: Profitability and Valuation - Financed High Payers

This table presents regression results estimating Equation (2.2) with OCF, Cash, Tobin's Q, and sales growth as dependent variables for persistent high payers with different financing activity. To economize space, we only report the results using the sample under the tight matching criteria. Panel A reports the results for the persistent high payers that have new equity finance taking more than 50% of total payout over $[t, t+3]$ (Equity Financed Persistent High Payers). Panel B reports the results for the persistent high payers that have new debt finance taking more than 50% of total payout over $[t, t+3]$ (Debt Financed Persistent High Payers). Panel C reports the results for the persistent high payers that have new equity and debt finance taking less than 30% of total payout over $[t, t+3]$ (Internally Financed Persistent High Payers). We include industry and year fixed effects, and cluster standard errors at firm level in all the models. T-statistics are reported in the parentheses. We also reports the sum of the estimated coefficients on *Post* and $High \times Post$ $(\delta + \eta)$. p-value for a test of statistical significance is also reported.

Panel A - Equity Financed High Payers

	(1)	(2)	(3)	(4)
	OCF	*Cash*	*Q*	*SG*
High (γ)	0.046	0.019	0.273	-0.005
	(0.64)	(0.47)	(0.92)	(-0.09)
Post (δ)	-0.086	-0.077**	-0.512**	-0.209***
	(-1.59)	(-2.78)	(-2.08)	(-4.05)
$High \times Post$ (η)	0.112	0.098**	0.209	0.023
	(1.51)	(2.53)	(0.70)	(0.31)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	364	364	364	364
adj. R^2	0.179	0.404	0.127	0.080
$\delta + \eta$	0.027	0.021	-0.303	-0.186
p-value	0.614	0.424	0.096	0.001

Panel B - Debt Financed High Payers

	(1) *OCF*	(2) *Cash*	(3) *Q*	(4) *SG*
High (γ)	0.004	-0.004	0.144	-0.012
	(0.19)	(-0.17)	(0.79)	(-0.34)
Post (δ)	-0.051**	-0.037*	-0.287*	-0.074**
	(-2.79)	(-1.93)	(-1.96)	(-2.18)
High $\times$ *Post* (η)	0.058**	0.036	0.063	0.017
	(2.31)	(1.33)	(0.32)	(0.36)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	396	396	396	396
adj. R^2	0.238	0.638	0.379	0.191
$\delta + \eta$	0.008	-0.001	-0.225	-0.056
p-value	0.656	0.958	0.085	0.102

Panel C - Internally Financed High Payers

	(1) *OCF*	(2) *Cash*	(3) *Q*	(4) *SG*
High (γ)	0.004	-0.003	-0.009	-0.095***
	(0.21)	(-0.12)	(-0.07)	(-3.37)
Post (δ)	-0.078***	-0.067***	-0.372***	-0.148***
	(-5.25)	(-4.06)	(-4.13)	(-6.25)
High $\times$ *Post* (η)	0.074**	0.083***	0.296**	0.028
	(3.28)	(3.74)	(2.35)	(0.82)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1986	1986	1986	1986
adj. R^2	0.083	0.360	0.189	0.128
$\delta + \eta$	0.006	0.012	-0.168	-0.116
p-value	0.652	0.243	0.011	< 0.001

Table 9: Leverage Changes

This table presents regression results estimating Equation (2.2) with leverage, CAPEX, and R&D as dependent variables for the high payers with different leverage policies. To economize space, we only report the results using the sample under the tight matching criteria. We define leverage change as the difference between leverage at $t-1$ and leverage at $t+3$. We rank the high payers by leverage change and the highest quartile is considered as significantly increasing their leverage ratios. Columns (1) - (3) report the results for the high payers that significantly increase their leverages. Columns (4) - (6) report the results for the rest of the matched high payers under the tight matching criteria. We include industry and year fixed effects, and cluster standard errors at firm level in all the models. T-statistics are reported in the parentheses. We also reports the sum of the estimated coefficients on *Post* and $High \times Post$ ($\delta + \eta$). p-value for a test of statistical significance is also reported.

	Leverage Increasing			Leverage not Increasing		
	(1)	(2)	(3)	(4)	(5)	(6)
	Leverage	*CAPEX*	*R&D*	*Leverage*	*CAPEX*	*R&D*
High (γ)	-0.056***	-0.016*	-0.024	-0.024***	-0.019***	-0.026*
	(-5.53)	(-1.70)	(-0.92)	(-4.07)	(-3.83)	(-1.74)
Post (δ)	0.003	-0.040***	-0.043**	-0.002	-0.038***	-0.031***
	(0.34)	(-6.05)	(-2.49)	(-0.41)	(-9.84)	(-3.75)
$Hight \times Post$ (η)	0.128***	0.012	-0.005	-0.031***	0.012**	0.007
	(13.14)	(1.25)	(-0.22)	(-6.84)	(2.44)	(0.62)
N	1404	1396	1404	4254	4220	4252
adj. R^2	0.268	0.202	0.209	0.314	0.177	0.169
$\delta + \eta$	0.131	-0.028	-0.048	-0.033	-0.026	-0.025
p-value	0.000	0.000	0.001	0.000	0.000	0.000

Table 10: Leverage Changes

This table presents regression results estimating Equation (2.2) with OCF, Cash, Tobin's Q, and sales growth as dependent variables for the high payers with different leverage policies. To economize space, we only report the results using the sample under the tight matching criteria. We define leverage change as the difference between leverage at $t-1$ and leverage at $t+3$. We rank the high payers by leverage change and the highest quartile is considered as significantly increasing their leverage ratios. Panel A reports the results for the high payers that significantly increase their leverages. Panel B reports the results for the rest of the matched high payers under the tight matching criteria. We include industry and year fixed effects, and cluster standard errors at firm level in all the models. T-statistics are reported in the parentheses. We also reports the sum of the estimated coefficients on *Post* and $High \times Post$ $(\delta + \eta)$. p-value for a test of statistical significance is also reported.

Panel A - Leverage Increasing

	(1)	(2)	(3)	(4)
	OCF	*Cash*	*Q*	*SG*
High (γ)	0.001	0.000	-0.109	-0.055*
	(0.05)	(0.01)	(-1.10)	(-1.89)
Post (δ)	-0.029	-0.030**	-0.334***	-0.157***
	(-1.33)	(-2.75)	(-5.21)	(-5.96)
$High \times Post$ (η)	0.025	-0.048**	-0.028	0.069**
	(0.88)	(-3.10)	(-0.31)	(2.00)
N	1404	1404	1404	1404
adj. R^2	0.117	0.353	0.224	0.115
$\delta + \eta$	-0.004	-0.078	-0.362	-0.088
p-value	0.842	0.000	0.000	0.000

Panel B - Leverage not Increasing

	(1)	(2)	(3)	(4)
	OCF	*Cash*	*Q*	*SG*
High (γ)	0.013	0.008	-0.021	-0.058***
	(0.62)	(0.61)	(-0.31)	(-3.47)
Post (δ)	-0.049***	-0.039***	-0.371***	-0.137***
	(-3.55)	(-5.38)	(-8.05)	(-9.45)
$High \times Post$ (η)	0.041**	0.037***	0.077	0.025
	(2.14)	(3.74)	(1.20)	(1.26)
N	4252	4252	4252	4252
adj. R^2	0.088	0.295	0.158	0.081
$\delta + \eta$	-0.008	-0.002	-0.294	-0.112
p-value	0.593	0.771	0.000	0.000

Appendices

Appendix A

Appendices for Chapter 1

A Variable Definitions

The following table defines policy and control variables employed in our empirical analysis.

Table A1: Variable Definitions

Name	Definition
Corporate policy variables:	
CASH	Cash and short term investments (CHE) divided by beginning of period book assets (AT).
DIV	A dummy variable equal to one if a firm pays a common dividend in a year, and zero otherwise.
LEV	Long-term debt plus debt in current liabilities divided by market value of assets. Market value of assets is book value of assets (AT) minus the book value of equity (BE) plus the market value of equity (ME).
REP	A dummy variable equal to one if a firm repurchases in a year, and zero otherwise.
Additional firm controls:	
ACQN	Acquisitions (AQC) divided by beginning of period book assets (AT).
ASSETS	Total book assets ((AT)).
CAPEX	Capital Expenditure (CAPX) divided by beginning of period total assets (AT). Long-term assets equals total assets (AT) minus total current assets (ACT).
DEPRN	Depreciation (DP) divided by beginning of period book assets (AT).
M/B	Book value of assets (AT) minus the book value of equity (BE)[1] plus the market value of equity (ME)[2] as the numerator of the ratio and book value of assets (AT) as the denominator.

Name	Definition
MISS R&D	Dummy variable set equal to one if R&D (XRD) is missing, and zero otherwise.
OCF	Earnings before interest, taxes, depreciation and amortization (OIBDP) divided by beginning of period book assets (AT).
R&D	R&D expenses (XRD) divided by beginning of period book assets (AT). Missing R&D values are set to zero.
RE/TE	Retained earnings (RE) divided by book equity (BE) [29].
ROA	Earnings before extraordinary items (IB) plus long-term and short-term interest expense (XINTD + XINST) plus income statement deferred taxes (TXDI) divided by beginning of period book assets (AT).
SIZE	Logarithm of total book assets (Ln(AT)).
TANG	Net plant, property, and equipment (PPENT) divided by book assets (AT).

B VAR Stock Return Decomposition Details

This appendix provides details regarding the estimates of the VAR model used to filter stock returns for expected return news. To describe the VAR approach, define the vector $z_t \equiv (r_t, x_t')'$, where r_t denotes log excess return and x_t denotes a vector of additional state variables governing the evolution of expected returns. (We suppress firm subscripts for notational simplicity.) The VAR takes the form:

$$z_t = \Gamma z_{t-1} + \epsilon_t, \tag{A.1}$$

where Γ denotes a matrix of VAR slope coefficients and ϵ_t is a vector-valued white noise shock with covariance matrix Σ.

Given the above VAR model, cash flow news and expected return news are computed as

$$\epsilon_t^{CF} = (e1' + \lambda')\epsilon_t \quad \text{and} \quad \epsilon_t^{ER} = \lambda'\epsilon_t, \tag{A.2}$$

respectively, where $\lambda' \equiv e1'\rho\Gamma(I - \rho\Gamma)^{-1}$ and $e1' = \begin{bmatrix} 1 & 0 & \ldots & 0 \end{bmatrix}$, and ρ equals the discount rate parameter in Eq. (1). Intuitively, the approach first computes expected return news directly and then backs out the cash-flow news as the difference between the unexpected return and expected return news. Given the matrix of VAR slopes λ and the parameter ρ (or, in practice, estimates), cash flow shocks are easily computed from Eq. (A.2).[3]

Following Michaely et al. [76], our main VAR implementation sets $z_t = (r_t, \theta_t, roe_t)'$, where r_t

[3] Given the VAR parameters, the variance of cash flow news and expected return news can be computed analytically. In particular, $\text{Var}(\epsilon^{CF}) = (e1' + \lambda')\Sigma(e1 + \lambda)$ and $\text{Var}(\epsilon^{ER}) = \lambda'\Sigma\lambda$. Instead of following this approach in our empirical work; however, we construct proxies for variance and other moments of interest (e.g., skewness and downside or upside variance) directly from time series of recent (estimated) shocks. There are two reasons for this. First, we have interest in partial and higher moments such that convenient analytical formula are lacking without strong distributional assumptions. Second, constructing proxies in this way allows our measures to adapt to realistic time-variation in the distributional characteristics of shocks.

is the log stock return, θ_t is the log book-to-market ratio, and roe_t is the log (GAAP) return on equity. Estimates are based on data from the COMPUSTAT quarterly fundamental file and CRSP monthly stock file from 1981–2017. We apply similar data processing steps to Vuolteenaho [91] and Michaely et al. [76] prior to estimation. We estimate the parameter ρ as the regression coefficient of the excess log ROE minus the excess log stock return, plus the lagged book-to-market ratio on the book-to-market ratio. This gives an estimate of approximately 0.985, similar to Vuolteenaho [91] and Michaely et al. [76]. Table B1 presents slope estimates and standard errors for our implementation of the VAR model. These estimates are qualitatively similar to those reported in Michaely et al. [76].

In additional unreported analyses, we explore the sensitivity of our measures to perturbations in the discount parameter ρ. Specifically, we compute measures for a grid of potential ρ values between 0.96 and 0.995. The corresponding measures are highly correlated with the VAR measures using our main ρ value of 0.985, and key results concerning the relations between corporate policies and VAR-based cash flow uncertainty measures are robust to alternative ρ values in this range. As a second robustness check, we estimate an alternative VAR(2) model of the form $z_t = \Gamma_1 z_{t-1} + \Gamma_2 z_{t-2} + \epsilon_t$ using the same state variables as in the main VAR(1) specification. Again, the resulting measures are highly correlated with the VAR-based measures applied in the main analysis and key results remain robust.

Table B1: VAR System Estimates

This table reports point estimates of a VAR describing the evolution of log stock returns and additional state variables. The model variables include market-adjusted quarterly log excess stock return (r), the market-adjusted log book-to-market ratio (θ), and market-adjusted log profitability, (roe). The parameters referenced in the table correspond to the following system:

$$z_{i,t} = \Gamma z_{i,t-1} + u_{i,t} \qquad \Sigma = E\left(u_{i,t}u_{i,t}^{'}\right)$$

Estimation is pooled across firms using weighted least squares, where observations are weighted such that each cross section receives an equal weight. For each parameter in Γ, we report the weighted least square estimates and associated standard errors (in parentheses). For the variance-covariance matrix (Σ), we report the variance and covariance estimates only. We use the COMPUSTAT quarterly fundamental file and CRSP monthly stock file from 1981 to 2017 for estimation.

	Transition Matrix (Γ)			Variance-covariance matrix (Σ)		
	r	θ	roe	r	θ	roe
r	0.033	0.012	0.210	0.048	-0.043	0.003
	(0.001)	(0.000)	(0.001)			
θ	0.108	0.947	-0.020	-0.043	0.084	0.006
	(0.002)	(0.000)	(0.003)			
roe	0.054	0.007	0.573	0.003	0.006	0.015
	(0.001)	(0.000)	(0.001)			

Appendix B

Appendices for Chapter 2

A Variable Definitions

The following table defines policy and control variables employed in our empirical analysis.

Table A1: Variable Definitions

Name	Definition
Total Assets (TA)	Dollar value (in billions) of total inflation adjusted assets (AT).
Net Assets (NA)	Assets (AT) minus cash and short-term investment (CHE).
Size	Dollar value (in billions) of total inflation adjusted assets (AT).
Book value of Equity	Stockholder's equity (SEQ) minus preferred stock plus balance sheet deferred taxes and investment tax credit minus post retirement asset (TXDITC). If stockholder's equity is not available, it is replaced by either common equity (CEQ) plus preferred stock par value (PSTK), or assets (AT) minus liabilities (LT). Preferred stock is preferred stock liquidating value (PSTKL) or preferred stock redemption value (PSTKRV), or preferred stock par value (PSTK). Market value of equity (ME) is defined as closing stock price multiplies with shares outstanding at fiscal year end.
Dividends	Total dividend payout to common shareholders (DVC) standardized by beginning period net assets.

Table A1: Variable Definitions

Name	Definition
Repurchases	Total repurchases standardized by beginning period net assets. Repurchase is measured by purchase of common stock (PRSTKCC). If this value is missing, substitute with the difference between total purchase of stock and purchase of preferred stock (PRSTKC − PRSTKPC).
Total Payout	Sum of dividend and repurchase.
OCF	Income statement operating income before depreciation (OIBDP) divided by beginning period Net Assets. If OIBDP is not available, substitute with income statement operating income after depreciation (OIADP) plus Depreciation (DP).
Cash	Cash and short term investments (CHE) divided by beginning period assets (AT).
Leverage	Total long-term debt (DLT) plus debt in current liabilities (DLC) divided by assets (AT).
CAPEX	CAPEX (CAPX) divided by beginning period *Net Assets*.
R&D	R&D expenses (XRD) divided by beginning period *Net Assets*. Missing values are set to zero.
MISS R&D	Dummy variable set equal to one if R&D (XRD) is missing, and zero otherwise.
Acquisition	Acquisitions (AQC) divided by beginning period book assets (AT).
Δ*IFA*	Increase in intangible assets divided by beginning period *Net Assets*. Intangible assets is calculated as Assets (AT) minus net PP&E (PPENT).
Tangibility	Net PP&E (PPENT) as a percentage of total fixed assets (AT−ACT).
NFA	Total fixed asset divided by beginning period *Net Assets*. Total fixed asset is defined as assets (AT) minus total current asset (ACT).

Table A1: Variable Definitions

Name	Definition
SG	Sales growth. Total sales (SALE) divided by last period total sales minus 1.
RE/TE	Retained earnings (RE) divided by book equity (BE).
Tobin's Q	Assets (AT) minus the book value of equity plus the market value of equity (ME) divided by assets (AT).
Age (since inception)	The number of years between a fiscal year end date and the date of initiation of a firm. The date of initiation of a firm is from Prof. Gustavo Grullon.
Age (since listed)	The number of years between a fiscal year end date and the first date a firm is included in the CRSP database.

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