The Ex-Day Behavior of Preferred and Common Stocks

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Abstract

This paper examines the effects of investor level taxes on ex-dividend day behavior. Using fifteen years of historical data, we perform a quasi-experiment using the 2017 Tax Cuts and Jobs Act, which reduced corporate investors' tax rate on capital gains relative to dividends. We exploit variation in the portion of shares held by institutional investors to identify securities for which corporate investors set prices, and we leverage a market adjusted model to describe ex-day price drops. Using a cross-sectional methodology, we find that ex-day behavior among common stocks did not change around the TCJA but price drops decreased for preferred stocks held by corporate investors. We implement a matched-pairs design to show that this observation among preferred stocks is attributable to tax effects. These findings suggest that while short-term arbitrageurs are capturing dividends for common stocks, tax clienteles affect ex-day pricing for preferred stocks. We vet these conclusions by back testing a dividend capture strategy and looking at ex-day behavior outside of the TCJA. While we document support for the aforementioned results, we find evidence for tax clienteles among illiquid common stocks and show that arbitrageurs are capturing ex-day returns for the most liquid preferred stocks.

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Contents

1 Introduction

"This is too difficult for a mathematician. It takes a philosopher."

-Albert Einstein, on his tax returns

Academics and practitioners have long debated whether investor level taxes are relevant to corporate payout policy and asset pricing. Miller and Modigliani (1961) show that in a world without taxes a firm's payout policy should not affect its value, but imposing differential tax rates on dividends and capital gains could give rise to implicit taxes or lead to segmentation among investors. Understanding the role of investor level taxes is important to a firm's choice of payout policy, capital structure, and capital budgeting, and deciphering the truth behind this debate could reveal the efficiency costs of dividend taxation.

We investigate the effect of investor level taxes by looking at a stock's change in price when it loses rights to a dividend. After a firm declares a dividend, investors can purchase shares with rights to the dividend until the ex-dividend day ("ex-date" or "ex-day"), and shares transacted on and after the ex-date are purchased without rights to the dividend. In an efficient market without taxes and other frictions, a stock's price should fall by the dividend amount on the ex-date. A wide body of empirical work, however, has shown that share prices usually drop by amounts less or more than the dividend (Campbell & Beranek, 1955; Baker, 1959; Durand & May, 1960). Several theories have been offered to explain this phenomenon. Elton and Gruber (1970) propose that investors' relative tax rates on dividends and capital gains determine a stock's ex-day change in price, while Kalay (1982) argues that deducing the marginal investor's tax status from ex-day behavior alone is not feasible. An expected price drop of greater or less than the dividend would offer a profit-making opportunity, and such opportunities should disappear as short-term arbitrageurs push ex-day price drops toward the dividend amount. Michaely and Vila (1995) merge these two ideas to propose that tax preferences, trading constraints, and risk explain ex-day price drops while other theories build on the work of Kalay (1982) but focus on non-tax factors that may influence ex-day behavior. We examine these different theories using ex-dividend data from common and preferred stocks. Since the market for common stock is vastly larger than that for preferred stock, only three ex-days studies (McInish & Puglisi, 1980; Eades, Hess, & Kim, 1984; Stickel, 1991) have focused on preferred equity, and since they were conducted more than 28 years ago, one contribution of this paper is an update to the ex-day literature with more recent data (Scholes, Wolfson, Erickson, Maydew, & Shevlin, 2002). Testing ex-day theories on preferred stock is compelling due to its relatively low price volatility, high dividend yields, and large cross-sectional differences in ownership.[1]

This paper proposes using the 2017 Tax Cuts and Jobs Act (TCJA) to identify the effect of investor-level taxes.[2] Since the TCJA reduced corporate investors' tax preferences for dividends over capital gains while keeping constant the tax preferences of individual investors, our empirical design uses variation in securities' ownership structure to see whether a discrete change in the tax code affected ex-day behavior among securities where corporate investors are the marginal stockholders. Consistent with the tax clientele theory of Elton & Gruber (1970), we find that ex-day price drops decreased after the TCJA for preferred stocks where corporate investors are relatively more important in setting prices; for common stocks, we find that ex-day behavior did not change after the TCJA, which suggests that tax clienteles do not determine ex-day price drops for the asset class.

While this design makes for a fairly clean observational study, the TCJA could have coincided with other confounding effects, such as changes in risk, and these factors could drive our results. To alleviate this concern, we exploit a useful feature of the TCJA: it changed corporate investors' tax preferences for conventional preferred stock (CPS) without changing their preferences for trust preferred stock (TPS), and since these two types of preferred stock are similar in their risk characteristics, this detail of the TCJA makes possible a "pseudo"

[1] We find that the median volatility of returns for preferred stock is less than one-fifth of that for common stock, and the average dividend yield for preferred stock is nearly three-times larger than that for common stock. Preferred stock varies greatly in the portion of shares held by retail versus institutional investors, such as insurance companies, which offers a cross-sectional study on the effect of ownership on ex-day behavior.

[2] We are not aware of any pre/post study in the ex-day literature that has focused on the TCJA due to the availability of data from after its enactment in January of 2018.

matched pairs design that isolates tax effects by controlling for possible confounders. The results from this test are consistent with our previous findings for preferred stocks, which leads us to conclude that tax clienteles exist in the preferred equity market, and the tax status of these clienteles affects security pricing.

To broaden our analysis, we also examine ex-day behavior outside of the TCJA using data from ex-dividend events over the last fifteen years. We back test returns from trading around ex-days to test the predictions of Kalay (1982) and find that while short-term arbitrageurs are capturing dividends for common stock, these predictions fail to hold for preferred stock. Even after a series of robustness checks on transaction costs and trading volumes, we find that there are excess returns from trading around ex-days for preferred stock. Back-testing this strategy tests market efficiency, but it does little to decipher the tax and non-tax factors that determine a stock's ex-day change in price. To this end, we perform a long-horizon regression over the same period. These results affirm our view for preferred stocks that tax clienteles determine ex-day price drops, but they lead us to form a nuanced view for common stocks. We find evidence for the presence of short-term arbitrageurs among more liquid common stocks and tax clienteles among less liquid common stocks. Since abnormal trading volumes are increasing in the portion of shares held by investors who are dividend tax-advantaged, we conclude that the tax-induced dynamic trading theory of Michaely and Vila (1995) describes the ex-day behavior of common stocks.

The remainder of this paper is organized as follows. Section II gives the motivation for using the TCJA as the foundation for our empirical design. Section III describes the literature on investor level taxes and provides the theoretical basis for using an ex-dividend study. Section IV presents our methodology. Section V details our sample selection, outlines our test statistics, and describes our data. Section VI presents our results, and Section VII summarizes our conclusions.

2 Motivation for Empirical Design

According to Miller and Modigliani (1961), a firm's dividend policy should not affect its value if capital markets are perfectly efficient. Holding constant a firm's investment policy, choosing to retain earnings or pay them out in dividends should not change a stock's value. This prediction assumes that markets are frictionless and investors face the same tax rate on dividends and capital gains. In the U.S., however, different groups of investors are taxed at various rates on these two sources of income (see Table 1). While the tax rate on capital gains is approximately the same for individual and corporate stockholders, corporate investors are dividend tax-advantaged since capital gains are taxed as ordinary income while dividends benefit from a Dividends Received Deduction (DRD),[3] which reduces their applicable tax rate on dividends to 10.5%.[4] Individual stockholders usually face the same tax rate on dividends and capital gains of 20%[5,6] while pension funds and other institutions are tax-free.

Table 1: Maximum Marginal Tax Rates on Dividends and Capital Gains

	Tax Rate	
	Dividends	Capital Gains
Individual Investors	20.0%	20.0%
Corporate Investors	10.5%	21.0%
Pensions and Other Investors	0.0%	0.0%

Notes:
(a) Dividends are qualified dividends, and capital gains are long-term in nature.

[3]The DRD allows some or all of the dividends a corporate investor receives to be deducted from taxable income. The amount that can be deducted depends on the portion of stock owned by the corporate stockholder. Section 243(a) of the Internal Revenue Code stipulates that 50% of the dividend can be deducted if it owns 20% of the entity distributing the dividend. This deduction increases to 65% if it owns greater than 20%, and if it owns greater than 80%, the corporate stockholder can fully deduct the dividend.

[4]With a corporate tax rate of 21%, a DRD of 50% implies an effective rate of 21% x $(1 - 50\%)$, or 10.5%.

[5]Throughout this paper, we use individuals' maximum marginal tax rates. We assume that capital gains are long-term in nature (i.e., assets were held for over a year) and dividends are qualified dividends (i.e., dividends were issued by a U.S. corporation that, for common stocks, had been held for at least 60 days before the ex-date, and, for preferred stocks, had been held for at least 90 days before the ex-date).

[6]For individual investors, dividends were historically taxed at a higher rate than long-term capital gains. Since 2003, however, the maximum individual tax rate on qualified dividends (20%) has been equal to the tax rate on long-term capital gains (20%). Short-term capital gains and non-qualified dividends are still taxed at the individual stockholder's ordinary income tax rate.

In a world where investors face heterogeneous tax rates on dividends and capital gains, there are several explanations for how investor-level taxes affect capital markets (Hanlon & Heitzman, 2010). Miller and Modigliani (1961) propose that investors could form "clienteles" that hold different types of securities based on firms' payout policies. Investors who face a low tax rate on dividends could hold stocks with high dividend yields, and those who face a high tax rate on dividends could hold stocks with low dividend yields. Investors' preferences for dividends relative to capital gains should determine the stocks they choose to hold. Another theory argues that the tax treatment of dividends vis-à-vis capital gains is irrelevant to asset pricing since non-taxable and tax-indifferent investors are the relevant price setters.[7] Stockholders who face different tax rates on dividends and capital gains are infra-marginal so changes in tax rates on these two sources of income should not affect a firm's value.

Our paper tests for the effects of investor level taxes by examining a recent change in the tax code. We focus on the 2017 Tax Cuts and Jobs Act (TCJA), which changed corporate investors' tax preferences for dividends relative to capital gains by reducing their tax rate on capital gains from 35% to 21% while adjusting the DRD so that their tax rate on dividends, net of the DRD, remained 10.5% (see Table 2).[8] By lowering corporate investors' tax rate on capital gains while keeping constant their tax rate on dividends, the TCJA affords us the opportunity to test whether a change to corporate investors' tax preferences affects security pricing. This question is interesting because the assets managed by corporate investors have grown as a fraction of total financial assets in the last several years.[9] Insurance companies now play a key role in many asset classes, as property and casualty and life insurers alone hold roughly 26.0% of the market for preferred equity (U. S. Chamber of Commerce, 2019).

[7] Tax-indifferent investors face the same tax rates on dividends and capital gains.

[8] The TCJA adjusted the DRD to 50% from 70% such that corporations' effective tax rate on dividends after the Act ($21\% \times [1-50\%] = 10.5\%$) is the same as that from before the Act ($35\% \times [1-70\%] = 10.5\%$).

[9] According to the Financial Stability Board (2019), the portion of financial assets held by insurance companies, pension funds, and other financial intermediaries has grown from 42.9% of total assets in 2002 to 47.9% in 2017. The fraction of assets held by hedge funds, trust companies, finance companies, and other investment funds, in particular, has increased from 21.8% in 2002 to 30.5% in 2017.

Table 2: Changes in Tax Rates around the TCJA

	Tax Rate	
	Dividends	Capital Gains
Pre-TCJA		
Individual Investors	20.0%	20.0%
Corporate Investors	10.5%	35.0%
Post-TCJA		
Individual Investors	20.0%	20.0%
Corporate Investors	10.5%	21.0%

Notes:
(a) Dividends are qualified dividends, and capital gains are long-term in nature.
(b) Preferred stock is conventional preferred stock, which benefits from the DRD.

3 Literature Review

Methods of Testing for Tax Effects

There are three main ways to test for whether investor level taxes affect capital markets: long horizon returns studies, event studies, and ex-day pricing studies. Tests of long horizon returns look at whether investors require compensation to hold shares that pay tax-disadvantaged dividends.[10] While Black and Scholes (1974) document no relationship between dividend yield and stock returns, subsequent studies (Naranjo, Nimalendran, & Ryngaer, 1998) have shown mixed results.[11] Event studies look at security prices around a change in the tax code. They were developed as an improvement on studies of long-horizon returns because it is easier to control for variables such as risk and information effects over short pockets of time (Hanlon & Heitzman, 2010). The researcher can more easily draw causal links to tax effects since other potentially confounding variables are assumed to remain constant over the observation period. The ideal event is an unexpected change in tax

[10]Brennan (1970) develops the first theoretical framework based on a three-factor model: $E[R_j] = \gamma d_j + \alpha_0\beta + \alpha_1 R_f$ where R_j is the firm's pre-tax return, d_j is the firm's expected dividend yield, β is the covariance between the firm's and market's returns, and R_f is the risk-free rate. γ represents the dividend tax premium and is a function of investor level taxes on dividends compared to capital gains (Brennan, 1970).

[11]Taxes alone are insufficient to explain the direction and magnitude of the relationship between long-run returns and dividend yield (Hanlon & Heitzman, 2010).

rates that satisfies several requirements: the change is economically significant, it is permanent in nature, and it does not coincide with changes in other variables that might affect asset prices (Hanlon & Heitzman, 2010). This body of literature has presented convincing evidence that investor level taxes affect asset prices. In one of the first event studies, Ayers, Cloyd, and Robinson (2002) consider the 1993 announcement of a hike in individual investors' tax rates on dividends and find that stock prices declined less for firms with high ownership by corporate investors since these stockholders were unaffected by the change in tax rates.[12] While event studies are an improvement on tests of long horizon returns, a potential problem with these studies is that tax events are assumed to be exogenous even though they are often correlated with other developments in the economy that affect markets. For example, a proposal to reduce tax rates may coincide with initiatives to reduce regulation, and both changes may affect asset prices. Ex-dividend day studies are a better way to investigate tax effects. These studies look at a stock's change in price after it loses rights to a dividend, which is thought to be a function of the tax status of a stock's price setting investors (Elton & Gruber, 1970), and they are an improvement on event studies since they focus on one-day intervals instead of weeks or months as for event studies. Researchers can more easily isolate tax effects from other factors that affect markets because ex-day pricing is relatively uncorrelated with other developments in the economy.

The methodology used in this paper combines an ex-day study with a pre/post design.[13] We focus on a stock's dividend drop ratio (DDR), which is defined as its change in price after going ex-dividend divided by the dividend amount. Despite fifty years of research, there is no consensus regarding why DDRs are usually less than one, but three competing theories have been offered to explain this phenomenon: the tax clientele theory, the short-selling theory, and the market microstructures theory.

[12] Ayers et al. (2002) document that stock prices declined more for high dividend yield stocks as compared to those with low dividend yields, which suggests that individuals' tax rates on dividends affect returns.

[13] Our pre/post design is distinct from an event study since we are not interested in stock price reactions to the change in tax code itself; instead, we compare ex-day behavior in the *years* before and after the change.

Theories of Ex-Day Behavior

Elton and Gruber (1970) propose the tax clientele theory, which holds that a stock's decline in price on the ex-day reflects the after-tax value of dividends vis-à-vis capital gains to its marginal investors. In a rational market, an investor should be indifferent between buying or selling a stock immediately before or after it goes ex-dividend,[14] which means that a stock's ex-day change in price should depend on the value of dividends compared to changes in price, or capital gains.[15] Since individual investors have historically faced higher tax rates on dividends than on capital gains, the tax clientele theory offers that individual investors' dividend tax misgiving explains why ex-day price drops have historically been less than the dividend amount. Although Elton and Gruber (1970) proposed the idea of tax clienteles five decades ago, a wide body of subsequent work (Green & Rydqvist, 1999; Whitworth & Rao, 2010; Armstrong & Hoffmeister, 2012) has supported their theory. In our study of the TCJA, the tax clientele theory predicts that DDRs should fall after the TCJA for securities where corporate investors set prices since the TCJA lowered their tax preference for dividends over capital gains.

Although it is intuitively appealing, the tax clientele theory does not answer why DDRs are less than one even in markets with dividend tax-advantaged and tax-indifferent investors or why DDRs are consistently less than one in the U.S. even after the 2003 Jobs and Growth Tax Relief Reconciliation Act (JGTRRA) equalized individual investors' tax rates on (qualified) dividends and (long-term) capital gains. The short-selling theory offers another explanation. Kalay (1982) argues that the tax status of a security's marginal stockholders should not affect its ex-date price drop since short-term, tax-indifferent arbitrageurs will engage in dividend capture strategies around the ex-date and drive the stock's change in price toward

[14] A stockholder who sells stock before the ex-date loses rights to the dividend but expects to sell the stock at a price higher than that after the stock goes ex-dividend. A stockholder who sells stock after the ex-date retains rights to the dividend but expects to sell the stock at a price lower than that before the stock goes ex-dividend. In an efficient market, investors should be indifferent between these two choices.

[15] As derived in the Appendix, the formula for a stock's expected DDR is $\frac{P_B - \bar{P}_A}{D} = \frac{1-\tau_d}{1-\tau_g}$, where P_B is the cum-dividend price, $\bar{P}_A$ is the expected ex-dividend price, D is the dividend amount, τ_g is the investor's tax rate on capital gains, and τ_d is the investor's tax rate on dividends (Elton & Gruber, 1970).

the dividend amount.[16] An expected price drop less (more) than the dividend would offer an arbitrage opportunity to these investors who could buy (sell short) the stock cum-dividend and sell (buy) the stock ex-dividend. These opportunities should disappear as arbitrageurs bid up (push down) cum-dividend prices and the selling (buying) pressure causes ex-dividend prices to decline (rise). Instead of revealing the marginal investor's tax preferences, Kalay (1982) holds, DDRs different from one reflect transaction costs, short selling constraints, and other market frictions. Supporting this theory, many papers have revealed the importance of transaction costs (Lakonishok & Vermaelen, 1986; Blau, Fuller, & Van Ness, 2011; Dasilas, 2009) and short-selling constraints (Jia, Kalay, & Mayhew, 2010; Thornock, 2010). In our study of the TCJA, the short-selling theory predicts that DDRs should not change in response to the TCJA since corporate investors are infra-marginal.

Despite its empirical strengths, the short-selling theory cannot explain why DDRs are significantly less than one even among securities with very low transaction costs. A third explanation involves microstructures, which are factors specific to markets and asset classes that may cause ex-day behavior to depart from theory. Proposing the first of these ideas, Bali and Hite (1998) hypothesize that price discreteness precluded DDRs from being equal to one before 2001 since U.S. stock markets used price ticks of one-eighths and one-sixteenths instead of decimals; these discontinuities should have caused ex-date price drops to equal the dividend amount rounded up to the nearest price tick. This market microstructure theory lost favor after U.S. stock markets adopted decimal price ticks and DDRs did not move closer to one (Graham, Michaely, & Roberts, 2003). Frank and Jagannathan (1998) offer another market microstructure theory based on bid-ask bounces around ex-dates,[17] but other studies

[16] In the U.S., short-term capital gains are taxed as ordinary income, which means that short-term investors are tax-indifferent with respect to dividends and capital gains.

[17] Frank and Jagannathan (1998) study the Hong Kong stock market, where DDRs are far less than one even though dividends and capital gains are tax-free. The authors hypothesize that since retail investors struggle to collect and reinvest dividends, market makers buy stock from individual stockholders before the ex-date and sell stock back to these investors on the ex-date, and these abnormal trading volumes cause most transactions before the ex-date to execute at bid prices and those on the ex-date to execute at ask prices. This theory claims that bid-ask bounces explain why, in the absence of taxes, DDRs tend to be less than one. Kadapakkam (2000) challenges this theory by showing that DDRs in the Hong Kong stock market approached one after it moved to electronic settlement, which effectively reduced transaction costs.

(Koski & Scruggs, 1998; Jakob & Ma, 2002) have presented mixed results.

These explanations for a stock's ex-day price drop are not mutually exclusive. Investors may form tax clienteles, but short-term arbitrageurs could still capture dividends around ex-dividend days and make it difficult to decipher the tax status of a stock's marginal investors from looking at ex-day behavior alone. Dividend capture strategies could be feasible for only a subset of securities, such as those with high dividend yields and sufficient liquidity; in this case, the short-selling theory may be appropriate in explaining the ex-day behavior of some stocks while the tax clientele theory may be better for others. Related to this idea, the tax-induced dynamic trading theory of Michaely and Vila (1995) combines the tax clientele and short-selling theories to show that, in addition to tax preferences and transaction costs, ex-day price drops are related to risk. Empirical studies of this theory (Michaely & Murgia, 1995; Wu & Hsu, 1996; Michaely & Vila, 1996; Dhaliwal & Li, 2006) have shown that ex-day trading volumes are positively correlated with the heterogeneity of tax rates across investors and negatively correlated with the variance of returns. For each of these explanations, market microstructures almost certainly affect stocks' ex-day changes in price. This paper seeks to decipher the relative accuracy and importance of these theories for different securities.

4 Methodology

4.1 Back-Test of a Dividend Capture Strategy

In the first part of our empirical design, we back-test a dividend capture strategy. We measure excess returns from buying stock on the cum-date and selling stock on the ex-date to see whether there are profit making opportunities for a skilled institutional trader.[18,19]

[18]We do not back-test returns from short selling stock on the cum-date and buying stock on the ex-date since mean DDRs for our sample are less than one.

[19]The dividend capture literature on preferred stocks is considerably less developed than that on common stocks. Whereas the market value of all U.S. equities is approximately $30 trillion, the market value of preferred stocks is roughly $272 billion (U.S. Chamber of Commerce, 2019), and since preferred stocks are often thinly traded, the size of the asset class poses a challenge to empirical studies. Just one study (McInish & Puglisi, 1980) has back-tested this strategy on preferred stocks.

We begin our methodology in this way because it gives us a simple way to test the efficiency predictions of Kalay (1982). The short-selling theory predicts that there should be no excess returns from a dividend capture strategy (after transaction costs) while the tax clientele theory holds that excess returns are plausible. If dividend capture yields positive excess returns, we can reject the short-selling theory, and, on this basis, we can test whether it is the existence of tax clienteles that creates such profit opportunities or whether non-tax factors play a role. The strategy's gross return from ex-dividend observation i is

$$R^{gross} = \frac{-P_i^{cum} + P_i^{ex} + D_i}{P_i^{cum}} \tag{1}$$

where P_i^{cum} is the price of the stock on the cum-date, P_i^{ex} is the price of the stock on the ex-date, and D_i is the dividend amount per share. The excess return from each observation is the gross return minus the daily return from holding a 30-day treasury bill on the ex-date. We account for transaction costs by assuming that the trader purchases stock on the cum-date at the ask price and sells stock on the ex-date at the bid price.[20]

Back-testing a dividend capture strategy helps us sanity check the short-selling theory's predictions, but it does little to decipher the tax and non-tax factors that determine a stock's ex-day change in price. The next two subsections explore these relationships by using an identification strategy that reveals which ex-day theories, if any, accurately predict DDRs for preferred and common stocks. This analysis is complementary to our back-test of returns since it allows us to test not only the short-selling theory but also the theory of tax clienteles.

4.2 Long-Horizon Study

Our long-horizon study asks whether investors' tax preferences affect ex-day behavior. As Hanlon and Heitzman (2010) point out, "if the relative tax preference of dividends to the

[20]We also assume that the institutional trader faces the same effective tax rate on dividends and capital gains. This strategy's income from both dividends and capital gains is short-term in nature, so both sources of income are taxed at the corporate statutory tax rate. This assumption also accounts for pass-through entities, such as hedge funds, that act on behalf of tax-free institutions.

price-setting investors varies across firms, then variation should be observed in the price of the dividends across firms partitioned by the investors' tax status" (p. 101). There are many conceivable ways to assess the tax status of a stock's price-setting investors, but we use the fraction of shares held by institutional investors to identify whether a security's stockholders prefer dividends to capital gains.[21] This identification strategy "has produced the most consistent evidence that dividend taxes affect security returns," and its logic is simple (Hanlon & Heitzman, 2010, p. 101).[22] Institutional investors include corporations like insurance companies and banks, and since these investors are dividend tax-advantaged, the marginal stockholders of securities with high institutional ownership should have a preference for dividends over capital gains; likewise, the marginal investors of securities with low institutional ownership (or high ownership by individuals) should be dividend tax-indifferent. We use the following regression equation modified from Dhaliwal and Li (2006)"

$$\text{DDR}_i = \beta_0 + \beta_1 \text{Inst}_i + \beta_2 \text{Yield}_i + \beta_3 \ln(\text{MktCap}_i) + \beta_4 \ln(1 + \text{Var}_i) + \epsilon_i \tag{2}$$

where DDR_i is the dividend drop ratio for ex-dividend observation i. Inst_i is the percentage of stock owned by the top-10 institutional holders of the security as of the cum-date.[23] Yield_i is the dividend amount divided by the cum-price, MktCap_i is the security's market capitalization as of the cum-date, and Var_i is the variance of daily returns for the security over days [-45,-6] and [+6,+45], where day 0 is the ex-date.[24]

Holding that a stock's DDR is determined by the tax preferences of its marginal investors,

[21] Institutional ownership is defined as the percentage of stock owned by institutional investors, such as corporations, insurance companies, pension funds, endowments, and mutual funds, according to Form 13F Filings made to the Securities and Exchange Commission (SEC).

[22] Dhaliwal, Erickson, Frank, and Banyi (2003) and Dhaliwal, Erickson, and Heitzman (2004) find that the relationship between dividend yield and stock returns is stronger when institutional investors own fewer shares, and Sialm (2009) shows that the portion of expected returns attributable to dividend yield increases nearly one-to-one with the fraction of shares held by non-institutional investors.

[23] We use the fraction of shares held by the top-10 institutional stockholders, not by *all* institutional stockholders, due to the availability of data for preferred stocks. Table 23 shows that these two measures are nearly perfectly correlated (Pearson correlation coefficient is 0.9993) among common stocks.

[24] See Appendix for detail on our choice of explanatory variables.

the tax-clientele theory predicts that DDRs should be increasing in Inst_i.[25] Stocks whose investors have a preference for dividends over capital gains should have DDRs greater than one, and those whose investors are tax-indifferent should have DDRs equal to one. Kalay (1982) suggests the opposite relationship. Short-selling activities depend on tax-indifferent arbitrageurs interacting with investors who are not tax-indifferent, and since individual investors face the same tax rate on dividends and capital gains, arbitrageurs must interact with corporate stockholders whose expected price drops are not equal to one.[26] The short-selling theory predicts that DDRs should be decreasing in Inst_i for this reason.

Yield_i, MktCap_i, and Var_i are included as control variables. Yield_i identifies the portion of a stock's expected return that is attributable to dividend income.[27] The use of dividend yield as an identification strategy has shown consistent evidence for the importance of investor level taxes[28] and their role in determining ex-day behavior.[29] The tax-clientele theory predicts a positive sign for Yield_i since high dividend yield stocks should be held by investors who are dividend tax-advantaged and whose tax status implies price drops of greater than one. The short-selling theory also predicts a positive sign for Yield_i since high dividend yields should enable tax-indifferent arbitrageurs to capture dividends and drive DDRs closer to one. MktCap_i is included as a proxy for liquidity since researchers (Stickel, 1991; Karpoff & Walking, 1998) have shown empirically that short-term traders can better engage in dividend capture activities when transaction costs are low.[30] The short-selling theory expects a

[25] Elton and Gruber (1970) show that a stock's expected DDR is $\frac{1-\tau_d}{1-\tau_g}$, which means that the expected DDR when $\tau_d < \tau_g$ is greater than when $\tau_d = \tau_g$.

[26] Elton and Gruber (1970) show that a stock's expected DDR is greater than one when $\tau_d < \tau_g$.

[27] As Elton and Gruber (1970) explain, "the lower a firm's dividend yield the smaller the percentage of his total return that a stockholder expects to receive in the form of dividends and the larger the percentage he expects to receive in the form of capital gains" (p. 71).

[28] Ayers et al. (2002) find that stocks with higher dividend yields experienced more negative stock price reactions around the announcement of an increase in individual tax rates on dividends. Lang and Shackelford (2000) find that non-dividend-paying stocks had significantly higher abnormal returns than dividend-paying stocks following the 1997 cut to the individual tax rate on capital gains. Auerbach and Hassett (2007) find that the most positive price reactions were associated with high dividend-paying stocks and stocks that paid no dividends following a reduction in the individual tax rate on dividends.

[29] Looking at ex-day behavior around major changes in the tax code between 1926 and 2005, Whitworth and Rao (2010) show that ex-day behavior among the highest yield stocks is heavily tied to corporate tax rates while ex-day behavior among the lowest yield stocks depends more on individual rates.

[30] As shown in the Appendix, Kalay (1982) gives the theoretical bounds for a DDR as a function of "round

positive sign for MktCap_i, and the tax-clientele theory does not postulate a direct relationship between liquidity and DDRs. Var_i is included as a proxy for risk. The short-selling and tax-induced dynamic trading theories predict a negative sign for Var_i since volatility makes it difficult for arbitrageurs to capture dividends around ex-dates (Michaely & Vila, 1995).

4.3 Pre/Post Study

While our long-horizon study describes the relationship between DDRs and various factors, it is difficult to determine whether tax effects are properly accounted for by the variables in our regression equation. We propose a pre/post study of ex-day behavior as an improvement on this design. Similar quasi-experiments exist in the ex-day literature for common stocks,[31] but we are not aware of such a design in the literature on preferred stocks. We focus on the 2017 Tax Cuts and Jobs Act (TCJA), which changed corporate investors' tax preferences for dividends vis-à-vis capital gains (see table 2). In the same way as other pre/post studies,[32] institutional ownership is used as an indicator for dividend tax-advantaged status. We propose the following difference in differences regression equation to assess whether changes to corporations' tax status affects ex-day behavior:

$$\begin{aligned}\text{DDR}_i = \beta_0 + \beta_1 \text{TCJA}_i \times \text{Inst}_i + \beta_2 \text{TCJA}_i + \beta_3 \text{Inst}_i + \beta_4 \text{Yield}_i \\ + \beta_5 \ln(\text{MktCap}_i) + \beta_6 \ln(1 + \text{Var}_i) + \epsilon_i\end{aligned} \tag{3}$$

where TCJA_i is a dummy variable equal to 1 if the observation falls after the enactment of the TCJA and 0 otherwise. Unlike event studies, we do not partition our sample around the *announcement* of the change in tax rates; instead, we choose the TJCA's *enactment* date

trip" transaction costs in a dividend capture strategy (p. 1062).

[31] Armstrong and Hoffmeister (2012) focus on a tax change in 1991 that reduced the tax rate on dividends for qualified public utility stocks, and for affected stocks, the authors document a significant change in DDRs.

[32] Several studies use institutional ownership to show that the marginal investor's tax preferences affect the degree to which a stock responds to changes in investor level taxes. Ayers et al. (2012) find that common stocks with lower institutional ownership experienced significantly greater negative abnormal returns after a proposal to increase individuals' tax rate on dividends, and Barkhordar and Ahmad (2014) find that institutional ownership influenced ex-day behavior after a reduction in the individual tax rate on dividends.

since we are interested in the tax rates attaching to an ex-dividend observation, not the release of information about a future change in rates.[33] Inst_i, Yield_i, MktCap_i, and Var_i are measured in the same way as from before and are included as control variables.

The main variable of interest in this regression is $\text{TCJA}_i \times \text{Inst}_i$, which gives the change in DDRs after the TCJA that is attributable to a stock's ownership structure.[34] Since the TCJA lowered corporate investors' preferences for dividends over capital gains without changing individuals' tax preferences, the tax clientele theory predicts that DDRs should decrease in response to the TCJA for securities where corporate investors are the price-setting investors and not change among securities for which individuals set prices. So long as our samples contain significant variation in the portion of shares held by corporate investors, the tax clientele theory predicts a negative sign for $\text{TCJA}_i \times \text{Inst}_i$ for this reason. The short-selling theory does not predict any change in DDRs around the TCJA since it did not affect the extent to which tax-indifferent arbitrageurs can capture dividends.

While the previous regression looks at a discrete change in the tax code and attempts to draw causality between tax effects and changes in DDRs, it is still possible that non-tax factors changed alongside the TCJA's enactment and that these factors drive our results. For example, the TCJA may have changed sentiment and led investors to bid more aggressively for securities about to go ex-dividend. To address this problem, we exploit a feature of the TCJA that allows us control for potential confounders. We perform a "pseudo" matched pairs study of two types on preferred stock: conventional preferred stock (CPS) and trust preferred stock (TPS).[35] While all references to "preferred stock" up until this point relate to CPS, we introduce TPS in this section as a benchmark asset due to its unique tax treatment. The TCJA decreased corporate investors' tax preferences for CPS dividends over capital gains,

[33] In most event studies, authors are careful to define the event date not as the time when a change was enacted but rather as the date on which the market became aware of the change and updated security prices to reflect the new information. These studies carefully examine pre-trends leading up to the event date to understand when information becomes priced-in to the market.

[34] We note that TCJA_i gives the change in DDRs after the TCJA that is attributable to other factors.

[35] See Appendix for a description of these securities.

but, for TPS, corporate investors' tax preferences did not change (see table 3).[36] This feature allows us to test the tax clientele theory, which predicts that for securities where corporate investors are the marginal stockholders, DDRs for CPS should drop after the TCJA while DDRs for TPS should stay the same.

Table 3: Maximum Marginal Tax Rates on CPS and TPS Dividends

	Security Type	
	CPS	TPS
Pre-TCJA		
Individual Investors	20.0%	39.6%
Corporate Investors	10.5%	35.0%
Post-TCJA		
Individual Investors	20.0%	39.6%
Corporate Investors	10.5%	21.0%

Notes:
(a) CPS dividends are qualified dividends, and capital gains are long-term in nature.
(b) Assumes maximum marginal tax rate on ordinary income for individual stockholders.

The underlying assumption of this design is that the only difference between CPS and TPS is their tax treatment. Following Dunbar and Veliotis (2012), we believe that this assumption is reasonable since the two samples have relatively similar risk characteristics.[37] As demonstrated by table 25, the median volatility of returns is almost identical between the samples of CPS and TPS, and the two groups of securities are similar in size. If our assessment is accurate and the two asset classes indeed have the same risk, this design isolates tax effects as the source of any differences we observe around the TCJA. We test for such effects using the following difference in differences regression equation:

$$\begin{aligned} \text{DDR}_i = \beta_0 + \beta_1 \text{TCJA}_i \times \text{Type}_i + \beta_2 \text{Inst}_i \times \text{Type}_i + \beta_3 \text{TCJA}_i + \beta_4 \text{Type}_i \\ + \beta_5 \text{Inst}_i + \beta_6 \text{Yield}_i + \beta_7 \ln(\text{MktCap}_i) + \beta_8 \ln(1 + \text{Var}_i) + \epsilon_i \end{aligned} \tag{4}$$

[36] Dividends from CPS benefit from the dividends received deduction (DRD), while those from TPS are fully taxed as ordinary income. In lowering the corporate statutory tax rate, the TCJA did not change corporate stockholders' relative tax rates on TPS dividends and capital gains.

[37] Dunbar and Veliotis (2012) use a matched-pair design between CPS and TPS to control for risk.

where Type_i is a dummy variable equal to 1 if the security is a CPS and 0 if it is a TPS. All other variables are defined in the same way as from before. The main variable of interest in this equation is $\text{TCJA}_i \times \text{Type}_i$, which represents the unique change in DDRs for CPS after the enactment of the TCJA after controlling for ownership, dividend yield, size, and price volatility. For CPS held by corporate stockholders, the tax clientele theory expects a negative sign for $\text{TCJA}_i \times \text{Type}_i$. It does not predict any change in DDRs for CPS held by tax-indifferent investors, and while observations from these securities will add noise to our regression, we should still observe a significant relationship with $\text{TCJA}_i \times \text{Type}_i$ if corporate investors are the marginal stockholders for a reasonable share of securities in our sample. The tax clientele theory predicts a positive sign for $\text{Inst}_i \times \text{Type}_i$ since corporate investors are dividend tax-advantaged for CPS but tax-indifferent for TPS. The variable TCJA_i represents the change in DDRs for TPS after the TCJA, so the tax clientele theory does not predict a significant relationship with TCJA_i. Type_i indicates whether DDRs are significantly different for CPS as compared to TPS in general.

4.4 Regression Methodology

In each of our regressions, we are careful to account for cross-sectional correlation in residuals. This correlation is problematic in many economic settings since unmodeled market phenomena may similarly affect errors across observations from different firms and assuming independence can lead to highly inflated t-statistics or understated standard errors. This source of heteroskedasticity is likely to be a problem when analyzing panel data on DDRs since they may be correlated at different points in time due to various factors, including macroeconomic events that affect investor sentiment toward dividend paying stocks,[38] unofficial changes to investors' tax rates,[39] and market microstructures. We account for cross sectional correlation in our computation of standard errors by clustering observations by

[38] Barkhordar and Ahmed (2014) observe that DDRs increase during recessionary periods.

[39] Falling equity markets may produce losses that investors can use to offset future gains, effectively reducing investors' tax rates on capital gains.

quarter.[40] Clustering by quarter is fair since we can assume that economic conditions are fairly constant during a given quarter. We considered other ways to address cross-sectional correlation, such as performing cross-sectional regressions by quarter and then averaging the coefficients from each cross-sectional regression. We ran our regressions using this methodology, and we make note where our results are substantially different from clustering the observations by quarter. Neither of these procedures account for correlation between observations of the same firm in different periods (Peterson, 2009).

5 Data

5.1 Sample Selection

Sample of Common Stocks

We obtained data on dividend events and pricing series from the Centre for Research and The Security Prices (CRSP). Information on institutional ownership was provided by the Thomson-Reuters S-34 database through the Wharton Research Data Services (WRDS).[41] Institutions included in this database are insurance companies, banks, pension funds, mutual funds, and hedge funds, among others. Our sample contains dividend events for all stocks traded on the major U.S. exchanges (NYSE, AMEX, and NASDAQ) between January 2004 and December 2018. We chose 2004 as the starting point since the maximum individual tax rates on qualified dividends and long-term capital gains equalized after 2003, and there might be a lag between the change in tax rates and portfolio restructuring.[42] We include only regular taxable dividends that are paid in cash to ordinary shareholders (CRSP share codes 10 and 11) on a monthly, quarterly, semi-annual, or annual basis (CRSP distribution

[40]For cases where the same security has two ex-dividend events in the same quarter, we keep only the event closest to quarter-end. Our results are the same when we keep only the first event.

[41]Thomson-Reuters compiles this information at the security level from institutional holders' Form 13F filings with the Securities and Exchange Commission (SEC).

[42]Using 2004 as the starting point also eliminates market microstructure effects from the New York Stock Exchange (NYSE) decimalizing its quotation prices starting in January 2001.

codes 1222, 1232, 1242, and 1252) since institutional traders can develop strategies around these events and because recurring dividends permit both across- and within-security studies. We exclude non-cash dividends due to their variable tax treatment. We also exclude dividends of American Depository Receipts (ADRs), exchange traded funds (ETFs), real estate investment trusts (REITs), unit investment trusts, and closed-end funds due to these securities' complex distribution requirements and different tax treatment. From this sample (n = 79,700), we eliminate observations for which no stock was traded on the ex-date (n = 1,794) or the business day preceding the ex-date (n = 2,757), which follows Elton and Gruber (1970). In these cases, regulations require that brokers mechanically adjust the stock price downward by the full amount of the dividend, which produces a DDR equal to one. Since the minimum tick size for stocks trading above $1 is $0.01 on the major U.S. exchanges, we eliminate observations with dividends less than $0.01 (n=347), which follows the methodology used by Chetty, Rosenberg, and Saez (2005); Zhang, Farrell, and Brown (2008); and Barkhordar and Ahmad (2014). We eliminate observations for which the share price was less than $5 (n=1,591) for two reasons: stocks trading for less than $5 per share often have wide bid-ask spreads, which introduces noise into our computation of DDRs, and firms with share prices less than $5 are often distressed so cash distributions can change underlying credit risk, which may affect ex-date behavior. Following Chetty et al. (2005), Zhang et al. (2008), and Graham et al. (2003), we remove events with dividend yields less than 0.01 percent (n = 2,631) since small price movements can cause DDRs to take extreme values when the dividend is small in comparison to the stock price. Observations for which the cum-date market capitalization was less than $100 million (n = 0) are eliminated due to the wide bid-ask spreads observed among illiquid stocks. We also eliminate observations with institutional ownership exceeding 100 percent (n = 73), which may result from record-keeping errors or double counting. In the end, our sample of common stocks contains 70,507 ex-dividend events for 2,294 distinct firms.[43]

[43]We note that these figures are computed on the sample before truncating by dividend yield.

Sample of Preferred Stocks

We are not aware of a database that contains the universe of preferred stocks, so we constructed our own sample. We include all preferred stocks in the Standard & Poor's (S&P) U.S. Preferred Stock Index, the oldest and largest index of preferred stocks.[44] Securities included in the index are fixed, floating, and variable preferred stocks, cumulative and non-cumulative preferred stocks, preferred stocks with callable or conversion features, and trust preferred stocks traded on major U.S. stock exchanges. Securities with mandatory conversion or scheduled maturity within the next 12 months and those with a market capitalization less than $100 million or that have traded fewer than 250,000 share per month are excluded. CRSP does not contain information on preferred stocks, so we obtained data on dividend events and pricing series from S&P Capital IQ. Institutional ownership data were collected from the Thomson-Reuters S-34 database. Our sample contains dividend distributions from preferred stocks between January 2004 and September 2019.[45] We include only regular taxable dividends that are paid in cash on a monthly, quarterly, semi-annual, or annual basis. We exclude trust preferred stock (TPS) from our sample since it is treated as debt for tax reporting purposes and does not benefit from the Dividends Received Deduction.[46] From this sample (n =7,604), we eliminate observations with dividends less than $0.01 (n=0) and dividend yields less than 0.1% (n=3). We exclude observations for which no stock was traded on the ex-date (n = 0) or the business day preceding the ex-date (n = 223). We eliminate observations for which the share price was less than $5 (n=16) and those for which the level of institutional ownership exceeds 100 percent (n = 0). In the end, our sample of preferred stocks contains 7,362 ex-dividend events for 211 distinct firms.[47]

[44] A list of index constituents was made available through an academic data request to S&P Dow Jones Indices since constituent-level information is not publicly available. We received 19 lists containing the index's constituents as of year-end for the years 2006 to 2019 and merged these lists while removing duplicate entries.

[45] While our sample of common stocks includes observations through December 2018, S&P Capital IQ is more up-to-date than CRSP, so our sample of preferred stocks contains more recent ex-dividend events.

[46] We note that we later include TPS observations in some of regression analysis.

[47] We note that these figures are computed on the sample before truncating by dividend yield.

5.2 Test Statistics

The Model

In a perfectly efficient market, the DDR for a dividend distribution is a stock's instantaneous change in price after going ex-dividend divided by the dividend amount. Changes in price, however, are not instantaneous when a stock goes ex-dividend. A stock loses rights to the dividend when the market closes on the business day before the ex-day ("cum-date" or "cum-day"), and the first trade after the stock goes ex-dividend is not executed until the market opens on the following business day. This feature complicates our computation of DDRs since relevant information may have changed overnight, and price movements between the market closing and when it opens may, in part, reflect these changes. One may brush aside this concern as trivial, but market microstructure effects at open on the ex-date pose a more serious problem. Regulations require that all orders on the books of U.S. exchanges be reduced by the dividend amount when a stock goes ex-dividend, so opening prices on the ex-date bias DDRs toward one. One way to address this problem is to use a stock's closing price on the ex-day instead of its opening price. Graham, Michaely, and Roberts (2003) point out, however, that using closing prices is problematic since "the entire ex-day price movement occurs between the closing price of the cum-day and the opening price of the ex-day, [so] using closing prices on the ex-day adds noise and reduces our ability to make accurate inferences" (p. 2624). Elton and Gruber (1970) mitigate this problem by discounting the closing price on the ex-date by the one-day returns of similar stocks before computing DDRs, and Balasubramaniam and Henker (2005) use intra-day prices on the ex-date as an alternative to closing prices. Following Whitworth and Rao (2010); Chetty et al. (2005); Zhang et al. (2008); and Barkhordar and Ahmad (2014), we compute the DDR for an ex-dividend observation as the beta-adjusted difference between the cum-date closing price and ex-date closing price divided by the dividend amount. We discount the closing price on the ex-date by the stock's expected return,[48] which we estimate using a market

[48] We note that our computation of DDRs assumes the closing price on the cum-date to be the base price

model with value-weighted daily returns[49] over a benchmark period.[50] This is

$$DDR_i = \frac{P_i^{cum} - \hat{P}_i^{ex}}{D_i}, \text{ where } \hat{P}_i^{ex} = \frac{P_i^{ex}}{1 + (\hat{a}_i + \hat{\beta}_i R_m^{ex})} \tag{5}$$

where P_i^{cum} and P_i^{ex} are the closing bid prices on the cum-dividend and ex-dividend days, respectively.[51] D_i is the amount of the dividend per share. R_m^{ex} is the daily return between the cum- and ex-dates for the corresponding market index, and the coefficients $\hat{a}_i$ and $\hat{\beta}_i$ are estimated by regressing the stock's daily returns against the daily returns of the corresponding index over the benchmark period.

A Problem with Interpreting Results

According to Hanlon and Heitzman (2010), "recent research documents extreme volatility in ex-dividend day pricing" (p. 102). While most studies find that mean DDRs are significantly less than one, there is wide variance in DDRs,[52] which Eades et al. (1984) attribute to two sources of noise: variance of price changes and dividend yield. The authors explain,

> If two firms have equal variance of price changes but one firm has a \$1.00 dividend and the other has a \$0.10 dividend, the variance of the price ratio of the \$1.00 dividend firm is only 1% of the variance of the price ratio of the \$0.10 dividend firm. The result is that the simple average of the two price ratios assigns far too much weight to the low dividend security (Eades et al., 1984, p. 7).

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and discounts the closing price on the ex-date using a market model. Alternatively, we could use the closing price on the ex-date as the base price and discount the closing price on the cum-date using a market model. Since the period of time between the cum-date and ex-date is short, the difference in approaches is negligible.

[49] Value-weighted daily returns for common and preferred stocks are taken from the CRSP value-weighted index and the U.S. Preferred Stock Index, respectively. We note that it may be problematic to use such indices to estimate securities' expected returns since the indices include the securities themselves.

[50] The benchmark period contains days -45 through -6 and days +6 through +45, where day 0 is the ex-date. Following most of the literature, we exclude the event window (i.e., days -5 through +5) from the benchmark period since the event periods often contain abnormal returns and volumes.

[51] Using average transaction prices in our computation of DDRs may be problematic since abnormal trading volumes around the ex-date may cause most transactions before the ex-date to execute at the bid-price and transactions on the ex-date to execute at the ask-price (Frank & Jagannathan, 1998). To address this problem, we use bid-to-bid prices in our computation. We performed our analysis using mid-to-mid and ask-to-ask prices, and our results are substantially the same.

[52] The mean DDR (year 2005) for the sample in Zhang et al. (2008) is 0.757 with standard deviation 4.62.

Since ex-day price movements for low dividend, high variance stocks have outsized effects on DDRs, parameter estimates may depend significantly on the ex-day behavior of a small set of observations even though DDRs should not depend on the size of the dividend or the variance of daily returns. This noise may complicate our interpretation of regression results.

We investigate whether the factors identified by Eades et al. (1984) indeed add heteroskedasticity to our data or whether there are other effects, such as time-lags between cum-dividend and ex-dividend prices, an imperfect risk model, transaction costs, and bid-ask spreads. It is difficult to parse out signal from noise in our sample of ex-dividend distributions since we do not know the true DDRs for these events; to work around this problem, we analyze a sample of "placebo" dividend distributions for which we *do* know what the average DDR should be, and we leverage this sample to reduce noise in our actual sample. Our procedure is straightforward. We compute DDRs for a sample of placebo dividend distributions, which contains a random selection of dates on which the selected securities did not actually pay dividends. The null hypothesis of this analysis is that the mean DDR will be equal to 0 because we should not observe abnormal returns on a random selection of trading days. For each placebo observation, we use our market-adjusted model to calculate a DDR, where the denominator is equal to the stock's dividend for the corresponding quarter.[53]

The results from this analysis are presented in table 4. The top portion of the exhibit gives summary statistics for the sample after imposing the aforementioned requirements for our sample selection,[54] which removes roughly 16% of the observations (see line (2) in table 4). The mean of this sample is greater than 0 at the 1% significance level, and its standard deviation is large. Focusing on the sample's standard deviation after imposing the various criteria, we can see that observations with small dividends and low dividend yields, in addition to those with volatile share prices, add noise to our computation of DDRs.

[53] We also perform the analysis without using the market-adjusted model and instead calculated DDRs by simply dividing the raw change in price by the dividend amount. The results are roughly the same as those from using the market-adjusted model but the DDRs have wider variance.

[54] Restrictions include trading requirements (stock must have traded on the ex-date and the business day immediately before the ex-date), dividend requirements (dividend amount and dividend yield must be greater than $0.01 and 0.1%, respectively) and share price requirements (share price must be greater than $5).

There are several ways to reduce this noise. One way is to truncate the sample by dividend yield, dividend size, or volatility, as shown in lines (3), (4), and (5) of table 4, respectively. Requiring yields to be greater than 0.5% brings the mean much closer to 0 and significantly reduces noise, and removing observations with dividends smaller than $0.15 and variance greater than 1×10^{-4} has a similar effect. Despite these benefits, truncating the sample eliminates more than half of the observations. An alternative to truncating the sample is to winsorize the data by DDR, which is shown in line (6) of table 4 and is common throughout the literature (Graham, Michaely, & Roberts, 2003; Zhang et al., 2008).[55] This operation reduces the sample's standard deviation by approximately the same amount as truncating, but the mean remains significantly different from zero.

Truncating by dividend yield is clearly superior to truncating by dividend size and price volatility since it eliminates more noise while retaining more observations, but it is not clear whether truncating by dividend yield is superior to winsorizing. While truncating eliminates more noise, winsorizing retains roughly double the number of observations. Since our sample size is still large in both cases, we decide to truncate the sample by dividend yield. We acknowledge that this decision is subjective, so we perform all of the analysis in this paper using both truncated and winsorized samples, and we make note where results from the two samples are substantially different.

Following Michaely (1991), we correct for heteroskedasticity in our computation of average DDRs with the following covariance matrix of disturbances for each ex-day observation:

$$\Omega_{ij} = \begin{cases} \sigma_i^2/d_i^2 & \text{if } i = j \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

where σ_i^2 is the variance of daily returns over the benchmark period and d_i is the dividend yield for security i on the cum-date. We compute average DDRs using a weighted average

[55] Winsorizing the data at the kth level replaces all values below the kth percentile with the value at the kth percentile, and replaces all values above the (1-k)th percentile with the value at the (1-k)th percentile.

where the weight for each observation is the inverse of its corresponding term in equation 6:

$$\overline{DDR} = \frac{\sum_{i=1}^{n}(d_i^2/\sigma_i^2) \times DDR_i}{\sum_{i=1}^{n}(d_i^2/\sigma_i^2)} \tag{7}$$

Dividend Drop Ratios Over Time

Tables 5 and 6 show DDRs over time for the samples of preferred stocks and common stocks, respectively. Consistent with the literature (Zhang et al., 2008; Chetty et al., 2005), we document significant variance in DDRs. For preferred stocks, we find that the mean DDR is 0.8484, and that for common stocks is 0.9426, which is consistent with the recent literature[56] but is generally larger than the mean DDR reported in older literature.[57] We also find that DDRs of common stocks are significantly more volatile. Whereas the standard deviation of DDRs for preferred stocks is 0.3322, that figure for common stocks is 1.2260. For preferred stocks and especially for common stocks, DDRs appear to spike during recessionary periods, such as 2008 to 2009, and when markets are generally volatile, such as 2016.

5.3 Data Description

Table 7 provides descriptive statistics for the explanatory variables used in this paper. For preferred stocks, the distributions of Inst and Yield are roughly symmetric. The distributions of MktCap and Var are skewed due to a number of observations that take extreme values. For common stocks, the distribution of Inst is roughly symmetric, Yield is slightly skewed toward large values, and MktCap and Var are both highly skewed. To reduce the distortion caused by outliers, we use the logarithm of MktCap and the logarithm of one plus Var in our analysis. Even though the distributions of explanatory variables are skewed and non-normal, the assumption of normality should not be problematic since the sample size is large. Comparing the sample of preferred and common stocks, the median of Inst among

[56] Zhang et al. (2008), for example, reports a weighted average DDR for common stocks of roughly 0.9.
[57] Elton and Gruber (1970), for example, find the average DDR for their sample to be 0.7780.

preferred stocks is 26.09% compared to 38.99% for common stocks. The average of Yield for preferred stocks is much larger than that for common stocks.[58], and the average of MktCap for common stocks is nearly 20-times greater than for preferred stocks, which suggests that our sample of common stocks is considerably more liquid. While the mean of Var among preferred and common stocks is roughly similar, Var among preferred stocks is considerably more skewed, which tells us that volatility for a representative common stock in our sample is considerably greater than for the representative preferred stock, as evidenced by values at the 50^{th}, 75^{th}, and 95^{th} percentiles. This characteristic is similar to that reported for the samples used in Stickel (1985) and Brown and Warner (1985).

Table 8 gives the Pearson correlations between the explanatory variables. For the sample of preferred stocks, Inst is slightly negatively correlated with Yield and not meaningfully correlated with MktCap or Var. For the sample of common stocks, MktCap and Yield are negatively correlated with each other while the correlations between all other explanatory variables are minimal.

6 Results and Discussion

6.1 Empirical Results

Back-Test of Dividend Capture

Tables 9 and 10 give average daily returns from back-testing a dividend capture strategy on common and preferred stocks, respectively. The investor earns the risk-free rate of return for days on which no ex-dividend events take place,[59] and she earns the average rate of return when there is more than one event. The first two columns give pre- and post-tax returns

[58] This figure for our sample of common stocks is greater than that in Lakonishok and Vermaelen (1986).

[59] This assumption is reasonable since it is misleading to benchmark against the returns of a risk-free portfolio if, for example, the strategy is only performed for a small number of days each year. We use a 30 day treasury bill as the benchmark risk-free asset.

assuming no transaction costs,[60] and the next two columns give returns after transaction costs. Since our data include bid prices but not ask prices for preferred stocks, we cannot model transaction costs for preferred stocks using bid-ask spreads as we do for common stocks.[61] To work around this problem, we regress bid-ask spreads from common stocks against trading volume and share price volatility and then use the corresponding regression coefficients to estimate bid-ask spreads for each preferred stock observation (see table 11).[62] We use a t-statistic to test the equality between the mean risk-free return and the strategy's mean return. While the discussion below focuses on pre-tax returns net of transaction costs, our conclusions are the same for the other measures of returns presented in tables 9 and 10.

We find that dividend capture yields negative excess returns for common stocks (5% significance level) but positive excess returns for preferred stocks (5% significance level) compared to the returns of a risk-free portfolio. In other words, tax-indifferent arbitrageurs are already capturing dividends for common stocks, which is consistent with the ex-day literature[63] and agrees with the efficiency predictions of Kalay (1982), but they are not capturing dividends for preferred stocks since money is left on the table.[64]

We test several assumptions to understand the sensitivity of our results. We first consider the way we estimate transaction costs for preferred stocks. Our procedure assumes that transaction costs are similar between common and preferred stocks after controlling for liquidity and share price volatility, but this assumption may be unfair due to idiosyncratic factors. As a robustness check, we repeat the analysis using a fixed transaction cost for each

[60] In the case without transaction costs, we use bid-to-bid prices. As a robustness check, we compute returns using mid-to-mid and ask-to-ask prices, and the results are substantially the same.

[61] For common stocks, we model transaction costs by assuming that the purchase of stock is executed at the ask-price and the sale of stock is executed at the bid-price.

[62] Our regression results predict that bid-ask spreads for the preferred stocks are roughly double those for common stocks, which makes sense because preferred stocks are considerably less liquid.

[63] Lakonishok and Vermaelen (1986) find that trading volumes for common stocks peak around ex-dates as short-term arbitrageurs buy stock cum-dividend and sell stock ex-dividend, especially for liquid, high dividend yield stocks. Building on this work, Blau, Fuller, and Van Ness (2011) find evidence not only for abnormal trading volumes but also for heightened short selling around ex-dividend days, and Dasilas (2009) finds similar results looking at the Greek stock market between 2000 and 2004.

[64] This finding for preferred stocks contradicts McInish and Puglisi (1980), who find that a dividend capture strategy on preferred stocks does not beat a passive buy-and-hold strategy.

preferred stock observation. Figure 1 plots net pre-tax returns and their corresponding 95% confidence intervals using various assumptions for the average cost of a round-trip transaction. This plot shows that returns are significantly positive when round-trip transaction costs are less than roughly 0.3% of the ex-price, and since table 10 predicts that the actual figure is less than 0.1%, we conclude that excess returns are still positive under most reasonable estimates for transaction costs. We also test the sample's composition of securities by computing returns from capturing dividends for only a subset of stocks, such as those with high dividend yields or large dividends. Table 12 demonstrates that, for preferred stocks, returns are even more positive (1% significance level) when looking only at stocks with high dividend yields or large dividends, and, for common stocks, returns are still negative (5% significance level) irrespective of the sample on which we back-test the strategy. As an additional robustness check, we modify the trading window. Whereas before we assume a two-day window in which stock is purchased on the cum-date and sold on the ex-date, here we consider returns from three-day and four-day windows around the cum- and ex-dates. Table 13 shows that our results are robust to different trading windows at the 5% significance level.

In summary, our back-test of a dividend capture strategy offers support for the short-selling theory in describing the ex-day behavior of common stocks but not for preferred stocks. Even after a variety of checks, we find that arbitrageurs are not capturing dividends for preferred stocks and that there are excess returns to be made from trading around ex-days for the asset class. We cannot conclude from this result alone that since the predictions of the short-selling theory fail to hold the tax clientele theory must therefore describe the ex-day behavior of preferred stocks. Microstructures or other non-tax factors could be driving our results. Our long-horizon study sheds more light on these findings.

Long-Horizon Study

We perform our long-horizon regression on the samples of common and preferred stocks partitioned by market capitalization[65] since certain ex-day theories may be better for ex-

[65] See Appendix for detail on our choice of market capitalization as a proxy for liquidity.

plaining the behavior of more or less liquid stocks.[66] Partitioning our sample is especially important for our analysis of common stocks since there is significant heterogeneity in liquidity across this sample (see table 7). Table 14 shows the results for common stocks. Across the full sample, DDRs are increasing in Yield and MktCap and decreasing in Var at the 1% significance level. This result is consistent with the short-selling theory, which predicts that short-term arbitrageurs can better engage in dividend capture and drive DDRs closer to one among securities with high dividend yields, low transaction costs, and stable prices. DDRs are also decreasing in Inst at the 5% significance level, but this relationship depends on the securities' liquidity. The coefficient for Inst is positive for less liquid stocks and negative for more liquid stocks, both at the 1% significance level. This result is interesting because it suggests different explanations for ex-day behavior depending on a stock's liquidity. For more liquid stocks, the short-selling theory may explain ex-day behavior since dividend capture relies on tax-indifferent arbitrageurs interacting with dividend tax-advantaged stockholders around ex-dates to drive DDRs *down* toward one. This explanation also fits with our finding that the mean DDR for more liquid stocks is slightly greater than one. Tax clienteles appear to influence ex-day behavior for less liquid stocks. Since trading constraints may preclude tax-indifferent arbitrageurs from trading around ex-days among these securities, their DDRs may still reflect the marginal investor's tax status, and since corporate investors prefer dividends over capital gains, DDRs are increasing in institutional ownership. We note that the r^2 values in this regression and in subsequent regressions are very low, which is expected in the context of other studies that document significant volatility in ex-day pricing.[67]

We also find that the mean DDR for more liquid common stocks is considerably greater

[66] The literature has demonstrated that DDRs often depend on a stock's transaction costs and short-selling constraints. Stickel (1991), for example, observes that ex-day abnormal returns are positive among less liquid stocks but roughly zero among more liquid stocks. Jia, Kalay, and Mayhew (2010) show that abnormal trading volumes on the cum-date depend on transaction costs imposed by options exchanges, and, in one of the only ex-dividend papers looking at the short selling market, Thornock (2010) shows that the prices charged by lenders to borrow shares increase around ex-days most notably for less liquid stocks as the supply of shortable shares falls.

[67] Zhang et al. (2008), for example, reports r^2 values between 0.0113 and 0.0125 even after winsorzing the data to remove outliers, and Chetty et al. (2005) reports r^2 values between 0.0010 and 0.0030.

than that for less liquid common stocks (see table 14). Ignoring the regression results and focusing on this metric alone, this difference could be attributable to three factors: transaction costs, tax effects, and microstructures. For transaction costs to *fully* explain the difference, the average round-trip transaction cost for less liquid securities would have to be roughly 0.4461% of the ex-price.[68] We find that the actual round-trip transaction cost for less liquid securities is actually 0.1924% of the ex-price (i.e., far less than 0.4461%),[69] which means that transaction costs alone are not enough to explain why the mean DDR of less liquid stocks is considerably less than one. Tax effects and microstructures must explain at least some of the discrepancy between mean DDRs of more and less liquid securities, and, interpreted in combination with the positive coefficient for Inst among less liquid securities, we can be confident that tax clienteles influence the ex-day behavior of less liquid common stocks.

Table 15 shows the same results for preferred stocks. Irrespective of liquidity, we find that DDRs are increasing in Inst (1% and 5% significance levels for less and more liquid stocks, respectively), which suggests that the tax clientele theory explains the ex-day behavior of the asset class. Since preferred stocks are considerably less liquid in general, this finding reconciles with the results from our analysis of common stocks since tax-indifferent arbitrageurs struggle to engage in dividend capture strategies for illiquid securities. There is not a significant relationship with Yield, which goes against the short-selling theory, and the fact that DDRs are increasing in MktCap is not necessarily consistent with the short-selling theory since dividend tax-advantaged investors may gravitate toward more liquid securities.[70] Unlike for common stocks, mean DDRs for preferred stocks are not materially different for more or less liquid stocks, which offers further support for our claim that the tax clientele theory describes ex-day price drops for preferred stocks.

The relationships we outline above provide weak evidence for or against the different

[68] For this calculation, we solve for $\bar{T}/\bar{D} = 1 - \overline{DDR}$, where $\bar{T}$ is the average round-trip transaction cost, $\overline{D}$ is the average dividend amount per share, and $\overline{DDR}$ is the unweighted average DDR.

[69] This computation assumes that stock is purchased at the ask price on the cum-date and sold at the bid price on the ex-date, which provides an upper bound on transaction costs.

[70] This proposition is not unreasonable since institutional investors often allocate large amounts of capital and avoid taking large positions in individual securities.

theories of ex-day behavior since our long-horizon regressions do little to draw *causal* links between the tax status of the marginal investor and ex-day price drops. Our results could be attributable to tax effects, but other variables could also covary with stocks' ownership structures and lead to these relationships. The next section describes the core part of our empirical design: a quasi-experiment using a discrete change in the tax code that better isolates tax effects and allows us to make causal conclusions.

Pre/Post Study

In this section we use the Tax Cuts and Jobs Act (TCJA) to test whether a change in corporate investors' tax preferences causes a structural shift in ex-day behavior among securities where corporate investors set prices. Whereas we use observations from as early as 2004 in our long-horizon study, we choose a different observation period here since we seek to have roughly the same number of observations before and after the enactment of the TCJA. We decided on January of 2016 as the starting point, and the availability of data from CRSP and S&P Capital IQ determined the ending point; the sample spans through December of 2018 for common stocks and September of 2019 for preferred stocks.

As shown in table 16, we find that DDRs fell after the TCJA among preferred stocks with high institutional ownership but they did not change for common stocks. While the coefficient for TCJA $\times$ Inst is insignificant for common stocks, DDRs for preferred stocks are decreasing in TCJA $\times$ Inst at the 1% significance level. This finding among preferred stocks is consistent with the tax clientele theory which predicts that DDRs should have decreased after the TCJA was enacted among securities where corporate investors are important in setting prices, and it fits with our previous conclusion that the tax clientele theory describes the ex-day behavior of preferred stocks. Since the short-selling theory does not predict any change in DDRs around the TCJA, these findings lend support for the short-selling theory in describing the behavior of common stocks. The coefficient for TCJA is significant beyond the 10% level for neither sample, which tells us that DDRs did not meaningfully change around the TCJA for reasons other than ownership structure. The direction and significance of the coefficients for Inst, Yield, and MktCap are the same as those from our long-horizon study for both samples. DDRs among common and preferred stocks are decreasing and increasing in Inst, respectively (both at the 1% significance level), and the coefficients for Yield and MktCap are positive (1% significance level) for both samples. These results provide additional support for our conclusion that tax clienteles influence ex-day behavior among preferred stocks while the short-selling theory better describes that for common stocks.

Our pseudo matched pairs design helps us understand if DDRs among preferred stock fell after the TCJA due to tax factors or whether outside determinants changed in tandem with the TJCA and caused DDRs to decline. As previously discussed, we use TPS as a benchmark asset for CPS to control for possible confounders since the two types of preferred stock are subject to the same risks but only for CPS did the TCJA change corporate investors' tax preferences. As shown in table 17, DDRs are decreasing in TCJA × Type at the 1% significance level while the relationship with TJCA is insignificant; in other words, DDRs specifically from CPS fell following the enactment of the TCJA,[71] which is consistent with the predictions of the tax clientele theory.[72] The coefficient for Inst × Type is positive (5% significance level), which supports the tax clientele theory since corporate investors are dividend tax-advantaged for CPS but tax-indifferent for TPS. Since the coefficient for Type is not significant, we can be confident that this relationship is specific to ownership structure. Consistent with our previous analysis and in support of the tax clientele theory, the coefficient for Inst is positive (1% significance level), and while the coefficient for MktCap is positive (1% significance level), the coefficients for Yield and Var are not significant, which may be attributable to noise from including TPS and CPS in the same sample.

Synthesizing the results from our three empirical tests, we find consistent evidence for the following conclusions. The tax clientele theory of Elton and Gruber (1970) describes

[71] This finding is robust to choosing starting dates of June 2015, June 2016, or January 2017.

[72] For securities where corporate investors are the marginal stockholders, DDRs should have decreased after the TCJA among CPS but not for TPS since the TCJA did not change corporate investors' tax preferences with respect to TPS dividends and capital gains. For securities where individuals are the marginal stockholders, there should have been no change.

the ex-day behavior of preferred stocks. Even after sensitizing our results to a variety of assumptions, there are excess returns (after transaction costs) to be made from a dividend capture strategy on this asset class. Using ex-dividend events from the past two decades, we find that DDRs are higher among securities where corporate investors are important in setting prices, and, as the tax clientele theory predicts, DDRs from this cohort of preferred stocks fell after the TCJA was enacted. We can attribute this change to tax effects based on our pseudo matched pairs design. We document different results for common stocks. While the tax clientele theory seems to describe the ex-day behavior of less liquid common stocks, the short-selling theory of Kalay (1982) better describes the behavior of more liquid common stocks and of common stocks in general. Back-testing a dividend capture strategy on the asset class shows that short-term arbitrageurs are already capturing dividends. Consistent with the short-selling theory, we find that DDRs are decreasing in the portion of shares held by institutional investors, and DDRs from common stocks did not change after the enactment of the TCJA. We do not rule out the market microstructures theories; these features likely explain why DDRs are consistently less than one in our samples even though neither individual nor corporate investors are tax-advantaged with respect to capital gains.

6.2 Robustness Checks

Institutional Holdings

The interpretation of our results relies on the validity of using institutional ownership as an indicator for dividend tax-advantaged status; our conclusions are only accurate in so far as the marginal investor for stocks with high institutional ownership prefers dividends to capital gains and the marginal investor for stocks with low institutional ownership is dividend tax-indifferent. There are several potential problems with this identification strategy. Chetty and Saez (2005), for example, suggest that institutional ownership is a noisy proxy for the marginal investor's tax status since institutions include corporations, insurance companies, pension funds, endowments, and mutual funds, which have different tax characteristics. While some of these entities are tax-exempt, the earnings of others are fully taxable. Chetty and Saez (2005) argue that this heterogeneity among institutions' tax treatment makes it difficult to decipher the tax status of the marginal investor from institutional holdings alone. Another problem is that this strategy makes the assumption that institutions allocate capital based primarily on their tax preferences when, in fact, non-tax factors such as risk preferences and corporate structure may also influence asset allocation (Hanlon & Heitzman, 2010).[73]

To see whether these factors negate our conclusions, we test other measures of ownership that have less heterogeneity in the tax treatment of investors. We collected data from S&P Capital IQ on the portion of shares held by insurance companies (Insur), taxable corporations such as banks (PrivCorp), tax-free institutions such as mutual funds (TaxFree), and individual investors (Indiv) for our sample of common stocks.[74] Each of these variables alone is an improvement on using institutional ownership since the tax status of each metric's investors is more homogeneous; we can be reasonably confident, for instance, that insurance companies are all dividend tax-advantaged and tax-free institutions are all dividend tax-indifferent. Tables 18 and 19 give summary statistics for and correlations between these ownership metrics. In general, our sample of common stocks has fairly low ownership by insurance companies, private corporations, and retail investors and high ownership by tax-free institutions such as mutual funds. Insur and TaxFree are both positively correlated with Inst, and Indiv is negatively correlated with Inst, which suggests that stocks with higher institutional ownership have fewer individual investors, and vice versa.

Our robustness check tests whether the results from our long-horizon regression on common stocks are robust to our choice of ownership metric. We found before that DDRs were decreasing in Inst across our full sample (see table 14), which agreed with the short-selling theory because dividend capture activities depend on tax-indifferent arbitrageurs interacting

[73] For example, institutional investors may be hesitant to invest in Limited Liability Companies (LLCs) due to the hassle of filing K1s with the IRS.

[74] These data are not available for our sample of preferred stocks, so our robustness check is limited in scope to common stocks.

with dividend tax-advantaged investors (i.e., corporate investors as opposed to individuals). To vet this result, we use equation 2 but replace Inst with the new explanatory variables: Insur, PrivCorp, TaxFree, and Indiv.[75] If the short-selling theory indeed describes the ex-day behavior of common stocks, we predict that the coefficients for Insur and PrivCorp will be negative since insurance companies and other corporations are dividend tax-advantaged and short-term arbitrageurs must engage with these two groups to capture dividends. The coefficients for TaxFree and Indiv should not be significant since the expected DDRs of securities with tax-indifferent investors are equal to one.

Consistent with the short-selling theory, table 20 shows that DDRs are decreasing in Inst and PrivCorp at the 5% significance level while DDRs are not significantly related to TaxFree or Indiv. When Insur and PrivCorp are combined into one variable, the corresponding coefficient is -6.2345 with a t-value of 2.6323 (5% significance level). We conclude from these results that our conclusions are robust to using different proxies for dividend tax-advantaged status. Despite its potential shortcomings, we can be reasonably confident in our use of total institutional ownership as an identification strategy for dividend tax-advantaged status among commons stocks. Although we are unable to perform this robustness check on our sample of preferred stocks given the limitations of our data, we assume that using institutional ownership is reasonable for preferred stocks as well.

Returns and Trading Volumes around Ex-Dates

Throughout this paper, we focus on a stock's behavior on the ex-date or the day before the ex-date and ignore the days leading up to and after a stock going ex-dividend. We exclude the event period (i.e., days -5 through +5, where day 0 is the ex-date) when calculating a stock's beta-adjusted change in price, we record most of our explanatory data only as of the

[75] Whereas we have historical data for institutional ownership, S&P Capital IQ does not provide historical data on Insur, PrivCorp, TaxFree, or Indiv; we only have one observation per security taken as of the fourth quarter of 2019. Given these limitations, we include ex-dividend observations from only the most recent quarter of our observation period (i.e., Q4 of 2018). The underlying assumption of this analysis is that each security's ownership structure did not change between the last quarter of 2018 when an ex-dividend event took place and the last quarter of 2019 when ownership data were collected.

cum-date, and our back-test assumes a narrow trading window around the ex-date. While these decisions are well motivated, a stock's behavior in the days surrounding the ex-date is still of interest to the researcher since it be used to vet the feasibility of a dividend capture strategy and suggest the presence of short-term traders. We compute excess returns and abnormal trading volumes for the five days leading up to and five days after a security's ex-date. Excess returns are equal to the difference between the mean portfolio return on day t and the mean risk-free return.[76] We test abnormal trading volumes by comparing the mean trading volume on day t to the mean trading volume recorded over days $[-45, -6]$ and $[+6, +45]$, where day 0 is the ex-date.[77]

As shown in tables 21 and 22, excess returns and abnormal trading volumes are significantly positive on the ex-date and the day before the ex-date for both common and preferred stocks. Positive excess returns on the ex-date reflect ex-day price drops being consistently less than the dividend amount while positive excess returns on the cum-date and abnormal trading volumes suggest that short-term arbitrageurs capturing dividends for at least some of the securities in our samples. For common stocks, we observe positive excess returns and abnormal trading volumes on both sides of the ex-date. The story is similar for preferred stocks, but trading windows are wider. Excess returns are significantly positive in the days leading up to and including the ex-date and negative in the days after the ex-date, which tells us that short-term traders are purchasing stock not only on the cum-date but also in the days leading up to the ex-date, and they are selling stock in the subsequent days (see table 21). One explanation for this difference between preferred and common stocks is that common stocks are more liquid so arbitrageurs can purchase and sell large amounts of stock on the cum- and ex-dates but for preferred stocks arbitrageurs must begin purchasing stock in the days before the cum-date and then gradually sell stock after the ex-date.

This test calls into question our previous conclusions for preferred stocks. Our back-test

[76] The risk-free portfolio contains 30-day treasury bills.

[77] Trading volume on day t is equal to the number of shares transacted on day t multiplied by the corresponding price per share.

told us that short-term traders are not capturing dividends since there are excess returns (after transaction costs) from a dividend capture strategy, but abnormal trading volumes around the ex-date suggest the presence of arbitrageurs. After performing a variety of tests to understand this result, we find that differences in liquidity reconcile these findings.[78] We partition our sample of preferred stocks into deciles based on market capitalization and observe that the only cohorts for which daily trading volumes are abnormal are the top-two deciles (t-values 13.7993 and 16.8944). For all other deciles trading volumes are not abnormal and cum-date excess returns are not different from zero at the 5% significance level. In other words, only for a small subset of preferred stocks is their liquidity enough for arbitrageurs to capture dividends. We conclude that while the tax clientele theory describes the behavior of most preferred stocks, there is still a subset of securities — namely, those with the greatest liquidity — for which the short-term traders are capturing dividends.

To understand how these relationships depend on ownership structure, we partition our samples into deciles based on the fraction of shares held by institutional investors. Our results are roughly the same across all deciles of preferred stocks, but, for common stocks, we find that ex-day excess returns and abnormal trading volumes are significantly more positive among cohorts with higher institutional ownership. This result is consistent with the tax induced dynamic trading theory of Michaely and Vila (1995), which postulates that trading volumes should be increasing in the heterogeneity of tax rates among a stock's investors. Combined with our earlier findings that tax clienteles affect ex-day price drops among less liquid common stocks while arbitrageurs capture dividends for more liquid stocks, this robustness check leads us to conclude that the tax induced dynamic trading theory describes the ex-day behavior of common stocks.

Market-Adjusted Model

We calculate a stock's DDR using the market-adjusted model described by equation

[78] Table 22 shows that the average daily trading volume for common stocks is roughly 45-times greater than that for preferred stocks.

5, and while this approach is common throughout the literature (Whitworth & Rao, 2010; Chetty et al., 2005; Zhang et al., 2008; Barkhordar & Ahmad, 2014), a potential shortcoming of the model is that it fails to account for the time between a stock going ex-dividend and shareholders receiving the dividend in cash. Investors buying stock on the cum-date purchase two assets: the underlying stock without the dividend and a contract to receive the dividend on the payment date. The value of this contract is not just the amount of the dividend but rather the dividend amount discounted to reflect the lag between the ex-date and the payment date. A stock's price should fall by the value of this contract when it goes ex-dividend, which means that equation 5 should divide the ex-day change in price by the present value of the dividend, not its notional amount. Mathematically, this is

$$D\hat{D}R_i = \frac{P_i^{cum} - \hat{P}_i^{ex}}{\delta_i D_i}, \text{ where } \hat{P}_i^{ex} = \frac{P_i^{ex}}{1 + (\hat{a}_i + \hat{\beta}_i R_m^{ex})} \tag{8}$$

where δ_i is the discount factor assuming a daily discount rate equal to the return from holding a 30-day treasury bill and all other variables are the same as from before.

To understand the sensitivity of our results to this misspecification of the model, we compute the number of days between the ex-date and payment date for each observation in our sample and calculate DDRs based on the equation above. As shown in figure 2, the average lag between the ex-date and payment date is fairly short; for common stocks, the ex-date is roughly 20 days before the payment date on average, and for preferred stocks the figure is 17 days. The modified DDRs are therefore roughly the same as those calculated using our original market-adjusted model; modified DDRs for common and preferred stocks are 0.8016% and 0.4956% greater than the original figures. This result tells us that our findings are robust to this misspecification of the model.

7 Conclusion

The relevance of investor level taxes to asset pricing is a hotly contested topic in the corporate finance and tax accounting literatures; there is little consensus regarding the way that investor level taxes affect firm valuation, capital allocation, or capital structure. Ex-day studies make up a wide body of work meant to address these questions, and their empirical results offer support both for and against the idea that investors' tax preference affect ex-day behavior. This paper engages in the debate by leveraging the 2017 Tax Cuts and Jobs Act's change to corporate investors' tax preferences. We use variation in the portion of shares held by institutional investors to test whether ex-day price drops changed among securities where corporate investors are relatively important in setting prices. We also examine panel data from the last fifteen years to vet our findings from this quasi-experiment.

This paper presents evidence that tax clienteles affect ex-day pricing for preferred stocks. While there is some evidence for the presence of short-term arbitrageurs, we show that these activities are limited in scope to the most liquid preferred stocks and that institutional traders are not capturing ex-day returns for most of the asset class. This result stands up to a litany of robustness checks on trading constraints, which tells us that transaction costs alone cannot explain why tax clienteles affect ex-day price drops for preferred stocks. For common stocks, we document support for the tax-induced dynamic trading theory. Trading volumes significantly increase around ex-dates, and excess returns are significantly positive on the cum-date. While arbitrageurs are capturing dividends for most securities, we show that tax clienteles affect ex-day behavior for the least liquid common stocks. Abnormal trading volumes are increasing in the portion of shares held by corporate investors, which lends further support for investors' tax preferences, in addition to trading constraints and risk, determining ex-day price drops. We do not rule out that market microstructures influence ex-day behavior for either asset class.

The findings in this paper — namely, support for the tax clientele and tax-induced dynamic trading theories — have implications for all market participants. The direction for managers is clear: since investors' tax preferences affect asset pricing and therefore costs of capital, firms whose stockholders are mostly corporations should pay out more of their earnings in dividends as compared to those with mostly individual shareholders. Firms should seek to issue securities that fit their investors' tax preferences. In light of the results from our back-test, corporate investors should interact with short-term traders to sell stock cum-dividend and repurchase their shares ex-dividend in order to maximize wealth. For preferred stocks, short-term arbitrageurs should heed our findings and develop strategies to capture dividends for the asset class by purchasing stock ex-dividend and selling stock cum-dividend, especially among high dividend yield securities.

Future research in this area should prioritize data that directly express the tax status of a stock's marginal investors. Potential directions include examining variations in corporate investors' tax rates at the firm level, exploiting differences in tax treatment for various corporate structures at the state level, and considering market shocks that give rise to widespread losses that investors can use to offset future taxable gains.

8 Tables and Figures

8.1 Tables

Table 4: Descriptive Statistics from "Placebo" DDR Analysis

	Mean	S.D.	n	% Total	
Raw Sample	0.8002	90.8361	13,549	100%	(1)
(-) Trading Requirements	0.8859	96.2447	12,063	89%	
(-) Div > \$0.01	0.0246	11.6712	12,037	89%	
(-) Share Price > \$5	0.0196	11.7389	11,866	88%	
(-) Div Yield > 0.1%	0.0827	5.8880	11,379	84%	
Adjusted Sample	0.0827	5.8880	11,379	84%	(2)
(-) Div Yield > 0.2%	0.0761	4.4826	10,104	75%	
(-) Div Yield > 0.3%	0.0638	3.1514	8,618	64%	
(-) Div Yield > 0.4%	0.0323	2.5782	7,144	53%	
(-) Div Yield > 0.5%	0.0171	2.3081	5,685	42%	
Adjusted for Div Yield	0.0171	2.3081	5,685	42%	(3)
(-) Div > \$0.05	0.1260	5.1582	10,298	76%	
(-) Div > \$0.075	0.1590	4.6067	8,657	64%	
(-) Div > \$0.10	0.1159	4.1384	7,625	56%	
(-) Div > \$0.15	0.0485	2.7227	5,218	39%	
Adjusted for Div Size	0.0485	2.7227	5,218	39%	(4)
(-) Var $< 5 \times 10^{-4}$	0.0120	4.8793	9,212	68%	
(-) Var $< 4 \times 10^{-4}$	0.0487	4.6601	8,170	60%	
(-) Var $< 3 \times 10^{-4}$	0.0256	4.4964	6,622	49%	
(-) Var $< 2 \times 10^{-4}$	-0.0431	3.6772	4,200	31%	
(-) Var $< 1 \times 10^{-4}$	-0.0608	2.6262	1,179	19%	
Adjusted for Variance	-0.0608	2.6262	1,179	19%	(5)
Winsorized at 2.5% Level	0.0862	2.4341	11,379	84%	(6)

Notes:
(a) Sample contains a random selection of placebo ex-dividend distributions from common stocks between 2002 and 2006. Securities did not actually pay dividends on these days.
(b) For each placebo observation, we use our market-adjusted model to calculate the DDR, where the denominator is equal to the stock's dividend for the corresponding time period.
(c) Lines (3), (4), and (5) give summary statistics after truncating the sample from line (2) by increasingly stringent requirements on dividend yield, dividend size, and variance, respectively.
(d) Line (6) gives summary statistics after winsorizing the sample from line (2) by DDR at the 2.5% level.

Table 5: Dividend Drop Ratios for Preferred Stocks

Year	Median	Median	S.D.	n
2004	0.8452	0.8378	0.2867	115
2005	0.8409	0.8258	0.3114	172
2006	0.8368	0.7926	0.3009	234
2007	0.8557	0.7827	0.3456	308
2008	0.8916	0.7686	0.8069	339
2009	0.8095	0.8118	0.7202	301
2010	0.8634	0.9343	0.5898	330
2011	0.8631	0.8746	0.3417	371
2012	0.8425	0.8396	0.2913	461
2013	0.8159	0.8518	0.3109	671
2014	0.8323	0.8314	0.2986	718
2015	0.8092	0.8488	0.3055	738
2016	0.8760	0.8902	0.4080	851
2017	0.8211	0.8742	0.2864	928
2018	0.8260	0.8360	0.3110	997
Total	0.8356	0.8484	0.3322	7,534

Notes:
(a) DDRs are computed using the sample truncated by dividend yield at 0.5%.
(b) Mean and S.D. are calculated based on weighted least squares where, for each observation, the ratio of the squared dividend yield to the variance of daily returns is the weight.
(c) n represents the number of discrete ex-dividend observations in the corresponding year.

Table 6: Dividend Drop Ratios for Common Stocks

Year	Median	Mean	S.D.	n
2004	0.8169	0.9032	1.2316	1,977
2005	0.8005	0.8775	1.4630	2,095
2006	0.7940	0.8956	1.2241	2,116
2007	0.8775	0.8538	1.3256	2,214
2008	0.8152	0.8828	2.0153	2,478
2009	0.9926	1.0908	1.4160	2,121
2010	1.0132	1.1114	1.1514	1,986
2011	0.9058	0.9436	1.2121	2,100
2012	0.9051	0.9758	0.7885	2,460
2013	0.9518	0.9867	1.3811	2,260
2014	0.9385	0.9922	1.2242	2,395
2015	0.8158	0.9183	1.3306	2,572
2016	0.8523	0.9391	1.3044	2,717
2017	0.8185	0.8430	1.2664	2,303
2018	0.8289	0.8975	1.2169	2,365
Total	0.8762	0.9426	1.2260	34,159

Notes:
(a) DDRs are computed using the sample truncated by dividend yield at 0.5%.
(b) Mean and S.D. are calculated based on weighted least squares where, for each observation, the ratio of the squared dividend yield to the variance of daily returns is the weight.
(c) n represents the number of discrete ex-dividend observations in the corresponding year.

Table 7: Distribution of Explanatory Variables Around Ex-Dividend Date

Preferred Stocks

	Mean	S.D.	5^{th}	25^{th}	50^{th}	75^{th}	95^{th}
$Inst_i$	0.2489	0.1518	0.0123	0.1241	0.2609	0.3474	0.5029
$Yield_i$	0.0165	0.0070	0.0069	0.0141	0.0159	0.0185	0.0237
$MktCap_i$	506	570	116	180	304	617	1,486
$Var_i \times 10^4$	3.8310	17.032	0.0718	0.1699	0.3345	0.8512	7.0063

Common Stocks

	Mean	S.D.	5^{th}	25^{th}	50^{th}	75^{th}	95^{th}
$Inst_i$	0.3853	0.1417	0.1388	0.2990	0.3899	0.4752	0.6085
$Yield_i$	0.0064	0.0059	0.0069	0.0033	0.0053	0.0080	0.0144
$MktCap_i$	10,063	30,877	151	509	1,712	6,189	42,709
$Var_i \times 10^4$	5.2741	23.270	0.8152	1.6775	2.8688	5.3220	16.228

Notes:
(a) Summary statistics are performed on the samples before truncating by dividend yield.
(b) Inst_i is the fraction of shares held by the top-10 institutional investors on the cum-date.
(c) Yield_i is the dividend amount divided by the cum-date share price.
(d) MktCap_i is the security's market capitalization (in millions USD) on the cum-date.
(e) Var_i is the variance of daily returns over days [-45, -6] to [+6, +45], where day 0 is the ex-date.

Table 8: Pearson Correlation of Explanatory Variables Around Ex-Dividend Date

Preferred Stocks

	$Inst_i$	$Yield_i$	$MktCap_i$	Var_i
$Inst_i$	–	-0.1817	-0.0651	-0.0372
$Yield_i$	-0.1817	–	-0.0509	0.0695
$MktCap_i$	-0.0651	-0.0509	–	-0.0093
Var_i	-0.0372	0.0695	-0.0093	–

Common Stocks

	$Inst_i$	$Yield_i$	$MktCap_i$	Var_i
$Inst_i$	–	-0.0040	0.0008	0.0005
$Yield_i$	-0.0050	–	-0.1264	-0.0929
$MktCap_i$	0.0008	-0.1264	–	0.0246
Var_i	0.0005	-0.0929	0.0246	–

Notes:
(a) Pearson correlations are performed on the samples before truncating by dividend yield.
(b) Inst_i is the fraction of shares held by the top-10 institutional investors on the cum-date.
(c) Yield_i is the dividend amount divided by the cum-date share price.
(d) MktCap_i is the security's market capitalization (in millions USD) on the cum-date.
(e) Var_i is the variance of daily returns over days [-45, -6] to [+6, +45], where day 0 is the ex-date.

Table 9: Average Daily Returns from Dividend Capture Strategy on Common Stocks

Year	**No Transaction Costs**		**W/ Transaction Costs**		**Risk Free**
	No Taxes	W/ Taxes	No Taxes	W/ Taxes	No Taxes
2004	0.1776%	0.1073%	-0.1215%	-0.0734%	0.0033%
2005	0.2736%	0.1653%	-0.0067%	-0.0040%	0.0082%
2006	0.2582%	0.1560%	0.0332%	0.0201%	0.0130%
2007	0.0505%	0.0305%	-0.1862%	-0.1125%	0.0127%
2008	0.0995%	0.0601%	-0.2532%	-0.1529%	0.0041%
2009	0.1946%	0.1176%	-0.0493%	-0.0298%	0.0003%
2010	0.1011%	0.0611%	-0.0445%	-0.0269%	0.0003%
2011	0.0772%	0.0466%	-0.0488%	-0.0295%	0.0001%
2012	0.1370%	0.0827%	0.0037%	0.0022%	0.0002%
2013	0.1539%	0.0929%	0.0272%	0.0164%	0.0001%
2014	0.0477%	0.0288%	-0.1317%	-0.0796%	0.0000%
2015	0.0986%	0.0596%	-0.1042%	-0.0629%	0.0000%
2016	0.2183%	0.1319%	0.0862%	0.0521%	0.0005%
2017	0.2464%	0.1488%	0.0965%	0.0583%	0.0022%
2018	0.0805%	0.0486%	-0.1176%	-0.0710%	0.0047%
Mean	0.1443%***	0.0872%***	-0.0578%**	-0.0349%**	0.0033%***
(t-stat)	(5.9190)	(5.8278)	(-2.5612)	(-2.6522)	(45.3797)

Notes:
(a) Table tests whether the mean of returns is the same as the mean return from holding a risk-free portfolio.
(b) Strategy is performed on sample truncated by dividend yield at 0.5%. Strategy assumes the purchase of stock on the cum-date and sale of stock on the ex-date. On days where no ex-dividend observation takes place, strategy earns the risk-free rate.
(c) Columns corresponding to no transaction costs assume purchase and sale of stock at bid prices. We model transaction costs by assuming that the purchase of stock is executed at the ask price and the sale of stock is executed at the bid price.
(d) We assume a 39.6% marginal tax rate on non-qualified dividends and short-term capital gains.
(e) 1%, 5%, 10% significance levels are denoted by ***, **, *, respectively.

Table 10: Average Daily Returns from Dividend Capture Strategy on Preferred Stocks

Year	**No Transaction Costs**		**W/ Transaction Costs**		**Risk Free**
	No Taxes	W/ Taxes	No Taxes	W/ Taxes	No Taxes
2004	0.0901%	0.0544%	0.0400%	0.0242%	0.0034%
2005	0.0190%	0.0115%	-0.0300%	-0.0181%	0.0082%
2006	0.0645%	0.0390%	0.0042%	0.0026%	0.0130%
2007	0.0371%	0.0224%	-0.0289%	-0.0175%	0.0127%
2008	0.1246%	0.0753%	0.0537%	0.0324%	0.0041%
2009	0.3449%	0.2083%	0.2733%	0.1651%	0.0003%
2010	0.0873%	0.0527%	0.0189%	0.0114%	0.0003%
2011	0.1119%	0.0676%	0.0222%	0.0134%	0.0001%
2012	0.1098%	0.0663%	0.0082%	0.0049%	0.0002%
2013	0.1262%	0.0762%	0.0037%	0.0022%	0.0001%
2014	0.1561%	0.0943%	0.0303%	0.0183%	0.0000%
2015	0.1106%	0.0668%	-0.0144%	-0.0087%	0.0000%
2016	0.0872%	0.0527%	-0.0304%	-0.0184%	0.0005%
2017	0.1458%	0.0880%	0.0052%	0.0032%	0.0022%
2018	0.1141%	0.0689%	-0.0302%	-0.0182%	0.0047%
Mean	0.1153%***	0.0697%***	0.0274%**	0.0166%**	0.0033%***
(t-stat)	(10.7708)	(10.5613)	(2.3698)	(2.1558)	(45.3497)

Notes:
(a) Table tests whether the mean of returns is the same as the mean return from holding a risk-free portfolio.
(b) Strategy is performed on sample truncated by dividend yield at 0.5%. Strategy assumes the purchase of stock on the cum-date and sale of stock on the ex-date. On days where no ex-dividend observation takes place, strategy earns the risk-free rate.
(c) Columns corresponding to no transaction costs assume purchase and sale of stock at bid prices. Since we only have bid prices for preferred stocks, we regress bid-ask spreads for common stocks against market capitalization (as of cum-date) and volume (average daily trading volume over days [-45,-6] and [+6,+45], where day 0 is the ex-date) and use these regression coefficients to estimate bid-ask spreads for each preferred stock observation.
(d) We assume a 39.6% marginal tax rate on non-qualified dividends and short-term capital gains.
(e) 1%, 5%, 10% significance levels are denoted by ***, **, *, respectively.

Table 11: Regression Coefficients From Regression of Bid-Ask Spreads for Common Stocks

Dependent Variable: Bid-Ask Spread as % Ex-Price	
Intercept	0.4193***
	(173.8712)
log(Volume)	-0.0482***
	(-125.4078)
log(1 + Variance)	0.4469***
	(15.6991)
Mean	0.1344%
r^2	0.3329
Sample Size	33,574

Notes:
(a) Regression is performed on sample of common stocks truncated by dividend yield at 0.5%. Volume is the average daily trading volume (in shares) over days [-45,-6] and [+6,+45], where day 0 is the ex-date. Variance is the variance of daily returns over the same period.
(b) The data span from January 2004 to December 2018.
(c) 1%, 5%, 10% significance levels are denoted by ***, **, *, respectively.
(d) t-values are included in parentheses.

Table 12: Average Daily Pre-Tax Returns After Transaction Costs by Sample Criterion

	Common Stocks		Preferred Stocks	
Criterion	Mean	(t-stat)	Mean	(t-stat)
Yield > 0.5%	-0.0578%**	(-2.5612)	0.0274%**	(2.3698)
Yield > 1.0%	-0.0781%***	(-2.8182)	0.0295%***	(2.5731)
Yield > 2.0%	-0.0256%**	(-2.5572)	0.0350%***	(3.3925)
Dividend > $0.01	-0.0578%**	(-2.5612)	0.0274%**	(2.3698)
Dividend > $0.25	-0.0790%***	(-3.9133)	0.0305%***	(2.6531)
Dividend > $0.50	-0.0780%***	(-4.0754)	0.0321%***	(3.0536)

Notes:
(a) Table tests whether the mean returns are same as those from holding a risk-free portfolio for trading strategy executed on different samples of securities according to criterion.
(b) Strategy is performed on sample truncated by dividend yield at 0.5%. Strategy assumes the purchase of stock on the cum-date and sale of stock on the ex-date. On days where no ex-dividend observation takes place, strategy earns the risk-free rate.
(c) Columns corresponding to no transaction costs assume purchase and sale of stock at bid prices. For common stocks, we model transaction costs by assuming that the purchase of stock is executed at the ask-price and the sale of stock is executed at the bid-price. Since we only have bid prices for preferred stocks, we regress bid-ask spreads for common stocks against market capitalization (as of cum-date) and volume (average daily trading volume over days [-45,-6] and [+6,+45], where day 0 is the ex-date) and use these regression coefficients to estimate bid-ask spreads for each preferred stock observation.
(d) We assume a 39.6% marginal tax rate on non-qualified dividends and short-term capital gains.
(e) 1%, 5%, 10% significance levels are denoted by ***, **, *, respectively.

Table 13: Average Daily Pre-Tax Returns After Transaction Costs by Trading Window

Days before / after		**Common Stocks**		**Preferred Stocks**	
Cum-Date	Ex-Date	Mean	(t-stat)	Mean	(t-stat)
0	0	-0.0578%**	(-2.5612)	0.0274%**	(2.3698)
1	0	-0.0313%**	(-2.4571)	0.0227%***	(2.8945)
0	1	-0.0242%**	(-2.0662)	0.0256%***	(2.8733)
1	1	-0.0333%**	(-2.2646)	0.0214%**	(2.2049)

Notes:
(a) Table tests whether the mean returns are same as those from holding a risk-free portfolio for trading strategy executed on different samples of securities according to criterion.
(b) Strategy is performed on sample truncated by dividend yield at 0.5%. Strategy assumes the purchase of stock on the cum-date and sale of stock on the ex-date. On days where no ex-dividend observation takes place, strategy earns the risk-free rate.
(c) Columns corresponding to no transaction costs assume purchase and sale of stock at bid prices. For common stocks, we model transaction costs by assuming that the purchase of stock is executed at the ask-price and the sale of stock is executed at the bid-price. Since we only have bid prices for preferred stocks, we regress bid-ask spreads for common stocks against market capitalization (as of cum-date) and volume (average daily trading volume over days [-45,-6] and [+6,+45], where day 0 is the ex-date) and use these regression coefficients to estimate bid-ask spreads for each preferred stock observation.
(d) We assume a 39.6% marginal tax rate on non-qualified dividends and short-term capital gains.
(e) 1%, 5%, 10% significance levels are denoted by ***, **, *, respectively.

Table 14: Long-Horizon Regression Coefficients for Common Stocks

Dependent Variable: Dividend Drop Ratio			
	Full Sample	Low Liquidity	High Liquidity
Intercept	0.3149***	0.6656***	1.0973***
	(3.4122)	(9.6651)	(18.2197)
Inst	-2.1146**	1.1128***	-6.3882***
	(-1.8430)	(3.1445)	(-4.3581)
Yield	8.6111***	7.4876***	9.9677***
	(5.2181)	(3.6602)	(3.7125)
log(MktCap)	6.8053***		
	(7.3619)		
log(1+Var)	-1.8674***	-1.4798**	-9.1552***
	(-4.7925)	(-2.4789)	(-4.6818)
$\overline{\text{DDR}}$	0.9446	0.8634	1.0080
r^2	0.0038	0.0007	0.0043
Sample Size	34,149	16,787	17,362

Notes:
(a) Sample is partitioned at the 50th percentile of MktCap.
(b) Regression is performed on sample truncated by dividend yield at 0.5%. Coefficients and standard errors are estimated by clustering the sample by quarter.
(c) Sample spans from January 2004 through December 2018.
(d) 1%, 5%, 10% significance levels are denoted by ***, **, *, respectively.
(e) t-values are included in parentheses.

Table 15: Long-Horizon Regression Coefficients for Preferred Stocks

Dependent Variable: Dividend Drop Ratio			
	Full Sample	Low Liquidity	High Liquidity
Intercept	0.5289***	0.7668***	0.8246***
	(5.5251)	(13.8107)	(18.2197)
Inst	1.8058**	2.6001***	3.2300**
	(2.2967)	(3.5895)	(2.3235)
Yield	4.0125	2.6364	1.4693
	(1.3231)	(1.0326)	(0.3248)
log(MktCap)	4.1399***		
	(3.9177)		
log(1+Var)	8.3242***	7.2481***	6.0838***
	(5.1275)	(9.5341)	(3.5332)
$\overline{\text{DDR}}$	0.8495	0.8188	0.8720
r^2	0.0124	0.0132	0.0219
Sample Size	7,322	3,622	3,659

Notes:
(a) Sample is partitioned at the 50th percentile of MktCap.
(b) Regression is performed on sample truncated by dividend yield at 0.5%. Coefficients and standard errors are estimated by clustering the sample by quarter.
(c) Sample spans from January 2004 through December 2018.
(d) 1%, 5%, 10% significance levels are denoted by ***, **, *, respectively.
(e) t-values are included in parentheses.

Table 16: Pre/Post Regression Coefficients

Dependent Variable: Dividend Drop Ratio		
	Common Stocks	Preferred Stocks
Intercept	0.5556***	0.6065***
	(15.2712)	(19.1016)
TCJA × Inst	-0.9587	-2.1829***
	(-0.2391)	(-2.7253)
TCJA	-3.6756	5.0579*
	(-0.5054)	(1.7746)
Inst	-1.7376***	1.5199***
	(-3.3426)	(4.9720)
Yield	6.9492***	1.2083***
	(9.0443)	(2.7558)
log(MktCap)	5.5571***	3.4761***
	(13.9843)	(7.5236)
log(1+Var)	-9.5506	1.6375
	(-0.5023)	(0.7032)
$\overline{DDR}$	0.8939	0.8622
r^2	0.0028	0.0033
Sample Size	7,251	2,682

Notes:
(a) Regression is performed on sample truncated by dividend yield at 0.5%. Standard errors are estimated by clustering the sample by quarter.
(b) Sample spans from January of 2016 through December of 2018 for common stocks and from January of 2016 through September of 2019 for preferred stocks.
(c) TCJA is a dummy variable that takes the value 1 if the observation falls after the enactment of the TCJA (1 January 2018) and 0 otherwise.
(d) Preferred stock sample contains only conventional preferred stock.
(e) 1%, 5%, 10% significance levels are denoted by ***, **, *, respectively.
(f) t-values are included in parentheses.

Table 17: Pseudo Matched Pairs Regression Coefficients for Preferred Stocks

Dependent Variable: Dividend Drop Ratio	
Intercept	0.5318***
	(5.4656)
TCJA × Type	-7.4501***
	(-2.1673)
Inst × Type	3.4451**
	(2.0188)
TCJA	-1.4461
	(-0.0293)
Type	1.7976
	(0.5731)
Inst	4.6168***
	(3.8464)
Yield	4.4254
	(1.4872)
log(MktCap)	4.2113***
	(4.3034)
log(1+Var)	8.3163
	(1.1307)
$\overline{DDR}$	0.8543
r^2	0.0126
Sample Size	8,060

Notes:
(a) Regression is performed on sample truncated by dividend yield at 0.5%. Standard errors are estimated by clustering the observations by quarter.
(b) The data span from January 2016 to September 2019.
(c) TCJA is a dummy variable that takes the value 1 if the observation falls after the enactment of the TCJA (1 January 2018) and 0 otherwise.
(d) Type is a dummy variable that takes the value 1 if the security is conventional preferred stock and 0 if the security is a trust preferred stock.
(e) Preferred stock sample contains both conventional preferred stock and trust preferred stock.
(f) 1%, 5%, 10% significance levels are denoted by ***, **, *, respectively.
(g) t-values are included in parentheses.

Table 18: Distribution of Ownership Metrics for Common Stocks

	Mean	S.D.	5^{th}	25^{th}	50^{th}	75^{th}	95^{th}
Inst	0.3386	0.1269	0.1287	0.2596	0.3370	0.4133	0.5393
Insur	0.0016	0.0168	0.0000	0.0004	0.0011	0.0028	0.0130
PrivCorp	0.0078	0.1640	0.0000	0.0001	0.0023	0.0807	0.4724
TaxFree	0.6052	0.2844	0.0011	0.4019	0.6826	0.8382	0.9553
Indiv	0.0829	0.1433	0.0014	0.0068	0.0265	0.0867	0.3940

Notes:
(a) Summary statistics are performed on the samples before truncating by dividend yield.
(b) Inst is the fraction of shares held by the top-10 institutional investors on the cum-date. Insur, PrivCorp, TaxFree, and Indiv give the fraction of shares held by insurance companies, taxable corporations (incl. insurance companies and banks), tax-free institutions, and individual investors, respectively, as of the fourth quarter of 2019. These data are provided by S&P Capital IQ.
(c) Summary statistics for Inst are different from those in table 7 since these statistics relate to observations from only the last quarter of 2019.

Table 19: Pearson Correlation of Ownership Metrics for Common Stocks

	Inst	Insur	PrivCorp	TaxFree	Indiv
Inst	-	0.1595	-0.0094	0.3890	-0.2171
Insur	0.1595	-	0.5977	-0.3937	0.0060
PrivCorp	-0.0094	0.5977	-	-0.4098	0.0468
TaxFree	0.3890	-0.3937	-0.4098	-	-0.5268
Indiv	-0.2171	0.0060	0.0468	-0.5268	-

Notes:
(a) Pearson correlations are performed on the sample truncated by dividend yield at 5%. Sample contains ex-dividend observations only from January 2018 through December 2018 due to the availability of data.
(b) Inst is the fraction of shares held by the top-10 institutional investors on the cum-date. Insur, PrivCorp, TaxFree, and Indiv give the fraction of shares held by insurance companies, taxable corporations (incl. insurance companies and banks), tax-free institutions, and individual investors, respectively, as of the fourth quarter of 2019. These data are provided by S&P Capital IQ.

Table 20: Long-Horizon Regression Coefficients for Common Stocks by Ownership Metric

Dependent Variable: Dividend Drop Ratio					
Intercept	549405**	0.5007**	0.4395*	0.5508*	0.5528
	(2.4540)	(2.2872)	(1.9004)	(1.8581)	(1.3498)
Inst	-1.4245***				
	(-5.6950)				
Insur		-3.0185**			
		(-1.9660)			
PrivCorp			-6.2924**		
			(-2.3164)		
TaxFree				-1.2888	
				(-0.6716)	
Indiv					2.2612
					(0.7462)
Yield	3.8376**	4.4135**	3.9235**	4.6094**	3.9521*
	(1.9520)	(1.9000)	(1.8210)	(1.8659)	(1.7899)
log(MktCap)	4.9149***	5.0673**	5.0041***	5.3889***	4.5265**
	(2.7673)	(2.4359)	(2.5077)	(2.9251)	(2.2654)
log(1+Var)	-8.8763	-9.2999	-9.0693	-9.0438	-9.5279
	(-0.5966)	(-0.6199)	(-0.6068)	(-0.6384)	(-0.6409)
$\overline{\text{DDR}}$	0.8578	0.8578	0.8578	0.8578	0.8578
r^2	0.0029	0.0031	0.0041	0.0031	0.0031
Sample Size	793	793	793	793	793

Notes:
(a) Regression is performed on sample truncated by dividend yield at 0.5%. Coefficients and standard errors are estimated by clustering the sample by quarter.
(b) Sample contains ex-dividend observations only from January 2018 through December 2018 due to the availability of data. (c) Inst is the fraction of shares held by the top-10 institutional investors on the cum-date. Insur, PrivCorp, TaxFree, and Indiv give the fraction of shares held by insurance companies, taxable corporations (incl. Insurance companies and banks), tax-free institutions, and individual investors, respectively, as of 22 February 2020. These data are provided by S&P Capital IQ.
(d) 1%, 5%, 10% significance levels are denoted by ***, **, *, respectively.
(e) t-values are included in parentheses.

Table 21: Excess Daily Returns around Ex-Dates

Trading day	Preferred Stocks			Common Stocks		
relative to ex-day	Excess Return	t-value	Sig Level	Excess Return	t-value	Sig Level
-5	0.0039%	0.2306	0.8176	0.0118%	0.8633	0.3880
-4	0.0400%	2.1646	0.0304	-0.0112%	-0.8519	0.3943
-3	0.0320%	2.6407	0.0083	0.0205%	1.6789	0.0932
-2	0.0741%	4.2952	$< 10^{-4}$	0.0215%	1.6461	0.0998
-1	0.1459%	10.2314	$< 10^{-4}$	0.0723%	5.8598	$< 10^{-4}$
Ex-day	0.1440%	18.3261	$< 10^{-4}$	0.2058%	16.8131	$< 10^{-4}$
+1	-0.0261%	-1.7421	0.0815	0.0453%	0.5914	0.8952
+2	-0.0048%	-2.2712	0.0378	0.0360%	1.6541	0.0931
+3	-0.0586%	-3.0629	0.0022	0.0203%	1.5861	0.1127
+4	-0.0439%	-2.3109	0.0209	0.0432%	1.4902	0.1005
+5	0.0766%	2.4679	0.0136	0.0221%	1.8073	0.0707

Notes:
(a) Returns are computed on the samples truncated by dividend yield at 0.5%.
(b) Excess return is equal to the difference between the mean portfolio return on day t and the risk-free portfolio's mean return on day t. The risk-free portfolio contains 30-day treasury bills.
(c) t-value tests for the equality between the excess return and zero.

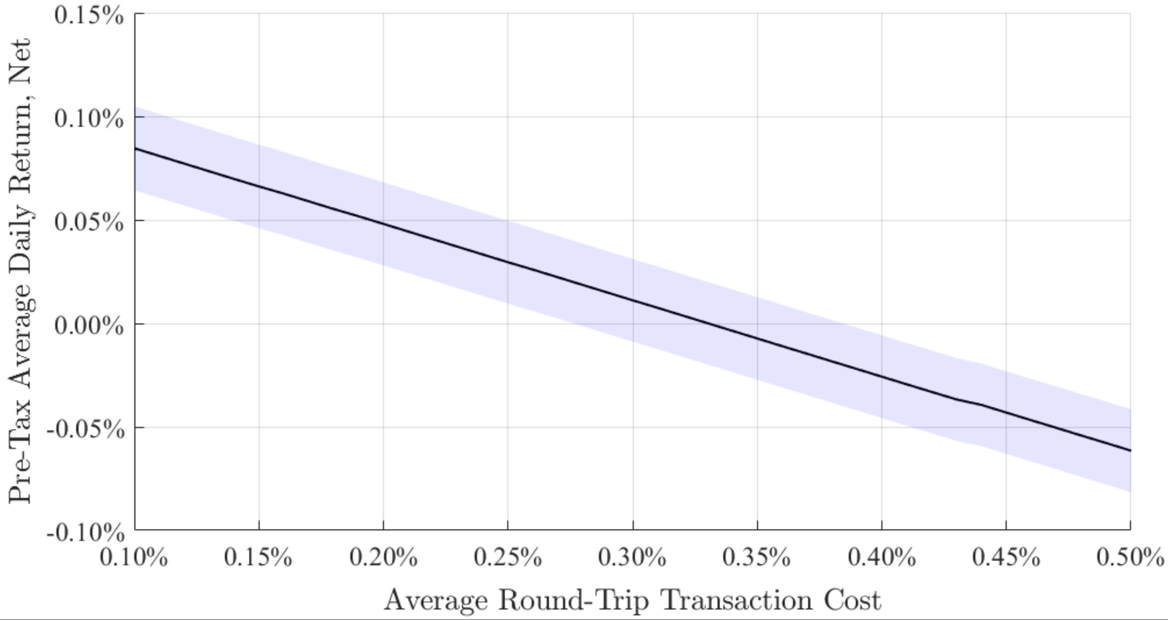
Table 22: Abnormal Trading Volumes around Ex-Dates

Trading day relative to ex-day	Preferred Stocks Daily Volume	Preferred Stocks t-value	Preferred Stocks Sig Level	Common Stocks Daily Volume	Common Stocks t-value	Common Stocks Sig Level
-5	1.6305	1.1947	0.2323	73.1955	4.2631	$< 10^{-4}$
-4	1.5473	-0.0177	0.9859	72.4598	3.5599	0.0004
-3	1.5296	-0.3171	0.7512	70.6233	1.9191	0.0550
-2	1.6797	1.5613	0.1185	70.7334	2.0544	0.0399
-1	1.7365	3.0446	0.0023	74.0007	5.0839	$< 10^{-4}$
Ex-day	2.0650	5.0357	$< 10^{-4}$	71.5374	2.8700	0.0041
+1	1.6352	1.5537	0.1203	69.0060	0.4289	0.6682
+2	1.5777	0.5048	0.6137	68.3372	-0.2071	0.8363
+3	1.6252	1.4568	0.1452	67.6927	-0.8285	0.4074
+4	1.4924	-1.2191	0.2229	67.2055	-1.3664	0.1718
+5	1.7255	2.0843	0.0372	68.1646	-0.3813	0.7035

Notes:
(a) Volumes are computed on the samples truncated by dividend yield at 0.5%.
(b) Daily volume is equal to the mean trading volume for the securities in our sample on day t in millions of dollars. Trading volume on day t is equal to the number of shares transacted on day t multiplied by the corresponding price per share.
(c) t-value tests for the equality between the daily volume and the mean volume recorded over days [-45, -6] and [+6, +45], where day 0 is the ex-date.

8.2 Figures

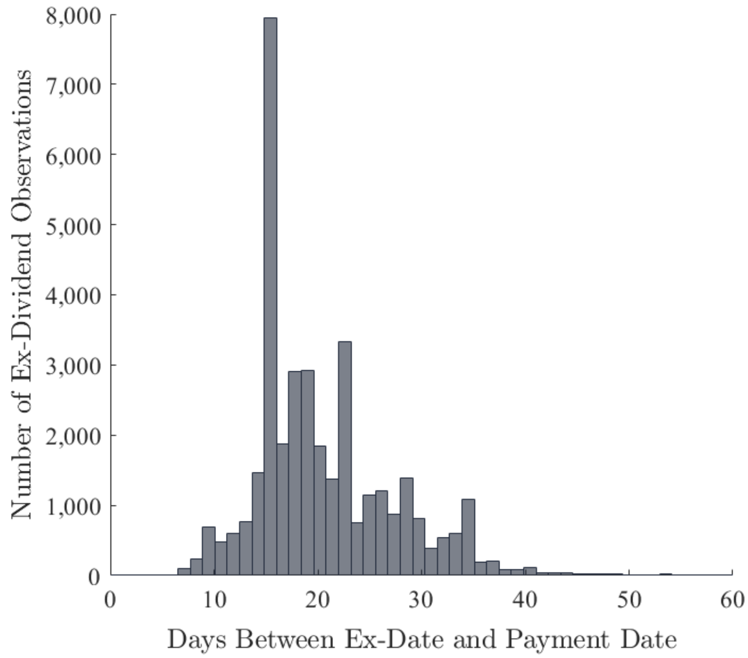
Figure 1: Sensitivity of Dividend Capture Returns to Transaction Costs (Preferred Stocks)



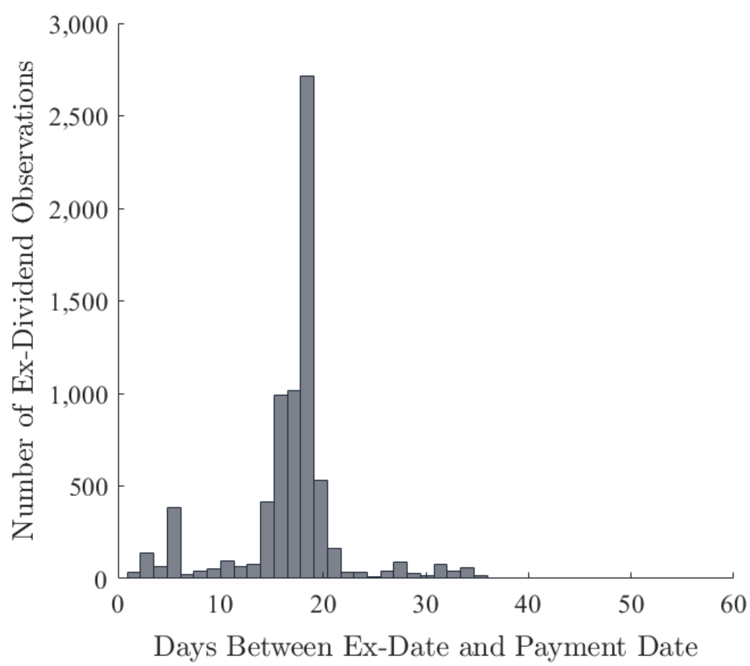
Notes:
(a) Plot shows pre-tax average daily returns (net) from a dividend capture strategy on preferred stocks assuming a fixed transaction cost (as a percent of the ex-price) per round-trip trade.
(b) Shaded area signifies 95% confidence interval.

Figure 2: Histograms of Days Between Ex-Date and Payment Date

(a) Common Stocks



(b) Preferred Stocks



Notes:
(a) Plots show the number of business days between the ex-dividend day and the day on which the dividend is distributed to shareholders.

9 Appendix

9.1 Derivations

Tax Clientele Theory of Elton and Gruber (1970)

Elton and Gruber (1970) derive a formula for a stock's expected DDR in a market without transaction costs and where all trading is intra-group. They define the following variables:

$\bar{P}_A$	stock's expected price after the stock goes ex-dividend
P_B	stock price before the stock goes ex-dividend
P_C	price at which the stock was purchased
D	the dividend amount per share
t_g	the marginal investor's tax rate on capital gains
t_d	is the marginal investor's tax rate on dividends

The authors start with the assumption that a stockholder should be indifferent between selling stock immediately before or after the ex-date. Mathematically, this is

$$P_B - \tau_g(P_B - P_C) = \bar{P}_A - \tau_g(\bar{P}_A - P_C) + D(1 - \tau_d) \tag{9}$$

since a stockholder selling a share before the ex-date receives P_B but generates a tax liability of $\tau_g(P_B - P_C)$, and a stockholder selling a share after the ex-date receives $\bar{P}_A$ and $D(1-\tau_d)$ but generates a tax liability of $\tau(\bar{P}_A - P_C)$. Rearranging this expression gives a stock's predicted DDR:

$$\frac{P_B - \bar{P}_A}{D} = \frac{1 - \tau_d}{1 - \tau_g} \tag{10}$$

An investor should also be indifferent between *buying* the stock immediately before or after the ex-date. A similar expression can be derived from analyzing the trade-off from the buyer's perspective.

Short Selling Theory of Kalay (1982)

Kalay (1982) builds on this derivation in a world with transaction costs. The author claims that an expected price drop of less (more) than the dividend would offer an arbitrage opportunity to these investors who could buy (sell short) the stock cum-dividend and sell (buy) the stock ex-dividend. These opportunities should disappear as arbitrageurs bid up (push down) cum-dividend prices and selling (buying) causes ex-dividend prices to decline (rise). Mathematically, an expected price drop by more than the dividend would offer a profit making opportunity if

$$(1-\tau_d)[P_B - \bar{P_A} - D - \alpha\bar{P}] > 0 \tag{11}$$

where $\bar{P} = (\bar{P_A} + P_B)/2$ and $\alpha\bar{P}$ is the expected transaction cost of a round-trip trade. Similarly, an expected price drop by less than the dividend would offer a profit making opportunity if

$$(1-\tau_d)[D - (P_B - \bar{P_A}) - \alpha\bar{P}] > 0 \tag{12}$$

Combining the expressions above gives

$$|D - (P_B - \bar{P_A})| \leq \alpha\bar{P} \tag{13}$$

This result allows Kalay (1982) to derive the theoretical bounds for a DDR as a function of round-trip transaction costs. This is

$$1 - \frac{\alpha\bar{P}}{D} \leq \frac{P_B - \bar{P_A}}{D} \leq 1 + \frac{\alpha\bar{P}}{D} \tag{14}$$

9.2 Choice of Variables

This section outlines the logic behind our choice to use the portion of shares held by a stock's top-10 institutional investors and market capitalization as explanatory variables.

Institutional Ownership

We define institutional ownership as the fraction of shares held by the top-10 institutional investors due to the availability of data. While the Thomson-Reuters S-34 database contains data on nearly our entire sample of common stocks, it contains data on only a small fraction of our sample of preferred stocks. After searching several databases, we found that S&P Capital IQ provides the richest data on institutional ownership for preferred stocks. A shortcoming of this data source is that it does not include the fraction of shares held by *all* institutional investors; rather, it includes only the fraction of shares held by the top-n institutional holders for $n = [1, 10]$. For this reason, we define institutional ownership as the portion of stock held by the top-10 institutional shareholders for both common and preferred stocks so that our data are consistent between samples.

To understand whether the fraction of shares held by the top-10 institutional holders is a good proxy for the portion of shares held by all institutional holders, we calculate the correlation between different measures of institutional ownership for common stocks, as shown in table 23. We find that the fraction of shares held by the top-10 institutional holders is nearly perfectly correlated with the total institutional ownership, which gives us confidence in the validity of using this metric for common stocks. We make the assumption that this relationship also holds for our sample of preferred stocks.

Table 23: Pearson Correlations of Proxies for Institutional Ownership for Common Stocks

	Top 5 Inst Shlds	Top 10 Inst Shlds	All Inst Shlds
Top 5 Inst Shlds	–	0.9993	0.9964
Top 10 Inst Shlds	0.9993	–	0.9985
All Inst Shlds	0.9964	0.9985	–

Note: Data from sample of common stocks.

Liquidity

Following Karpoff and Walking (1998), we consider several measures of liquidity, including bid-ask spreads,[79] market capitalization, shares outstanding, average daily trading volume, and share price. We compute the Pearson correlations between these proxies for liquidity and bid-ask spreads for our sample of common stocks. We find that only share price is meaningfully correlated with bid-ask spreads. Since bid-ask spreads are only one component of a stock's liquidity and given the weak correlation with most proxies for liquidity, we decided on a proxy for liquidity based more on intuition than on the results from table 24.

Table 24: Pearson Correlations of Proxies for Liquidity

	MktCap	ShOut	Volume	Price	Bid-Ask
MktCap	–	0.8446	-0.0329	0.1915	-0.0491
ShOut	0.8446	–	0.0028	0.0303	-0.0536
Vol	-0.0329	0.0028	–	0.0167	-0.1080
Price	0.1915	0.0303	0.0167	–	0.2056
Bid-Ask	-0.0491	-0.0536	-0.1080	0.2056	–

(a) Pearson correlations are performed on the sample before truncating by dividend yield.
(b) MktCap and ShOut are the security's market capitalization and number of shares outstanding on the cum-date.
(b) Vol is the security's average daily trading volume (in dollars) over days [-45, -6] to [+6, +45], where day 0 is the ex-date.
(c) Price is the security's share price on the cum-date.
(d) Bid-Ask is the security's bid-ask spread on the cum-date.

[79] While CRSP contains data on bid-ask spreads for our sample of common stocks, we are not aware of a source containing bid-ask spreads for preferred stocks.

9.3 Conventional Preferred Stock and Treasury Preferred Stock

Conventional preferred stock (CPS) and treasury preferred stock (TPS) are similar in the benefits and risks they provide to investors. Both types of securities provide regular streams of income to stockholders, and they are usually junior in priority to debt claims on a business and senior to common equity. Despite these similarities, CPS and TPS differ in their form and tax treatment. Whereas CPS is usually issued by the parent company, TPS is issued by a special-purpose vehicle that lends proceeds from issuing TPS to the parent company and receives interest from the parent at the TPS dividend rate. This entity, in turn, distributes the interest payments to TPS holders as dividends. In most cases, TPS receives a guarantee from the parent that makes it rank *pari passu* with the CPS. While interest paid to the entity issuing the TPS is tax deductible for the parent, dividends paid to holders of CPS are not tax deductible.

Table 25: Distribution of Explanatory Variables Around Ex-Date for CPS and TPS

Conventional Preferred Stocks (n = 8,067)							
	Mean	S.D.	5^{th}	25^{th}	50^{th}	75^{th}	95^{th}
$Inst_i$	0.2489	0.1518	0.0123	0.1241	0.2609	0.3474	0.5029
$Yield_i$	0.0165	0.0070	0.0069	0.0141	0.0159	0.0185	0.0237
$MktCap_i$	506.20	570.70	116.10	180.80	304.20	616.90	1,486
$Var_i \times 10^4$	2.5970	14.1519	0.0725	0.1677	0.3254	0.8074	6.4818
Trust Preferred Stock (n = 352)							
	Mean	S.D.	5^{th}	25^{th}	50^{th}	75^{th}	95^{th}
$Inst_i$	0.2275	0.1128	0.0344	0.1423	0.2555	0.3023	0.4357
$Yield_i$	0.0128	0.0071	0.0025	0.0049	0.0158	0.0179	0.0192
$MktCap_i$	643.3	1,103	182.7	210.7	401.8	622.4	4,078.5
$Var_i \times 10^4$	1.9491	9.89713	0.0646	0.1618	0.3087	0.8060	5.0834

Notes:
(a) Summary statistics are performed on the samples before truncating by dividend yield.
(b) $Inst_i$ is the fraction of shares held by the top-10 institutional investors on the cum-date.
(c) $Yield_i$ is the dividend amount divided by the cum-date share price.
(d) $MktCap_i$ is the security's market capitalization on the cum-date.
(e) Var_i is the variance of daily returns over days [-45, -6] to [+6, +45], where day 0 is the ex-date.

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