JOURNAL OF FINANCIAL AND QUANTITATIVE ANALYSIS Vol. 52, No. 4, Aug. 2017, pp. 1765–1795
COPYRIGHT 2017, MICHAEL G. FOSTER SCHOOL OF BUSINESS, UNIVERSITY OF WASHINGTON, SEATTLE, WA 98195
doi:10.1017/S0022109017000394

https://doi.org/10.1017/S0022109017000394 Published online by Cambridge University Press

DRIPs and the Dividend Pay Date Effect

Henk Berkman and Paul D. Koch*

Abstract

On the day that dividends are paid, we find a significant positive mean abnormal return that is completely reversed over the following days. This dividend pay date effect has strengthened since the 1970s and is consistent with the temporary price pressure hypothesis. The pay date effect is concentrated among stocks with dividend reinvestment plans (DRIPs) and is larger for stocks with a higher dividend yield, greater DRIP participation, and greater limits to arbitrage. Over time, profits from a trading strategy that exploits this behavior are positively related to the dividend yield and spread and negatively associated with aggregate liquidity.

I. Introduction

Many studies examine stock prices around the dividend announcement day or the ex-dividend date. These events are of interest because they might contain value-relevant news associated with a dividend surprise or evoke trading to capture dividends.[1] In contrast, when the dividend pay date arrives, there is no tax-motivated trading and no new information about the amount or timing of this distribution. Nevertheless, we find striking evidence of a predictable price increase on the pay date that is completely reversed over the following days. This temporary inflation is concentrated among firms with dividend reinvestment plans (DRIPs).

A company-sponsored DRIP allows shareholders to automatically reinvest their dividend income into more shares of the firm, without paying brokerage costs

*Berkman, h.berkman@auckland.ac.nz, Business School, University of Auckland; Koch (corresponding author), pkoch@ku.edu, School of Business, University of Kansas. We acknowledge the helpful comments of an anonymous referee, Ferhat Akbas, Bob DeYoung, David Emanuel, Suzanna Emelio, Greg Freix, Kathleen Fuller, Brad Goldie, Ted Juhl, Michal Kowalik, Joe Lan, Paul Malatesta (the editor), Dimitris Margaritis, Alastair Marsden, Felix Meschke, Nada Mora, Peter Phillips, David Solomon, Ken Spong, Jide Wintoki, and seminar participants at the 2013 annual conferences of the Society of Financial Studies Finance Cavalcade, the 2013 Financial Management Association, and the 2012 Southern Finance Association, as well as the University of Auckland, the University of Canterbury, the University of Kansas, and the Federal Reserve Bank of Kansas City. We also acknowledge the excellent research assistance of Aaron Andra, Suzanna Emelio, and Evan Richardson. Please do not quote without permission.

[1] DeAngelo, DeAngelo, and Skinner (2009) review this literature.

https://doi.org/10.1017/S0022109017000394 Published online by Cambridge University Press

and sometimes at a discount. Firms with DRIPs tend to be larger, with higher institutional ownership and lower spreads. On average, 43% of all dividend-paying firms have company-sponsored DRIPs, but these firms represent 75% of the total market capitalization of all dividend-paying firms.

The fact that there is no new information on the dividend pay date, combined with the prevalence of DRIPs among U.S. stocks, creates an ideal setting to test the temporary price pressure hypothesis.[2] In this setting, we predict that liquidity suppliers should require a price increase on the dividend pay date to accommodate the increased demand for shares by uninformed (re-)investors. Ogden (1994) is the first to test this prediction. During the period 1962–1989, he finds a small but significant mean abnormal return of 7 basis points (bps) on the pay date, which accumulates to 20 bps over the following 3 days. However, he finds no significant price reversal after the pay date, and thus concludes that his evidence does not support the temporary price pressure hypothesis.

Figure 1 provides analysis similar to that of Ogden (1994) over 10-year subperiods spanning the years 1975–2012. Graph A plots the mean daily abnormal returns over the 2 weeks before and after dividend pay dates, for the tercile of stocks with the highest dividend yield, for every 10-year period since 1975. Graph B plots the analogous patterns in abnormal trading volume.

Figure 1 reveals a significant mean abnormal return on the dividend pay date (AR(0)), accompanied by a similar spike in abnormal trading volume (RVOL(0)). Both spikes have grown in magnitude during the 2 most recent decades, since the mid-1990s. For the tercile of high yield stocks, the mean AR(0) has increased from 12 bps in the mid-1970s to nearly 40 bps in the most recent decade. In addition, for the 2 most recent decades, there are several significant negative mean abnormal returns after day +1, indicating a reversal that accumulates to offset the temporary inflation around the pay date. We also find a significant abnormal return on day −3.[3]

The main goal of this paper is to test the temporary price pressure hypothesis by exploring how the magnitude of the pay date effect (AR(0)) varies across stocks and over time, with an emphasis on the role of company-sponsored DRIPs. For the period 2008–2012, we extend the analysis of Ogden by examining the divergent behavior of DRIP firms versus non-DRIP firms. We focus on this recent period because it reveals the greatest price pressure in Figure 1 and because we have accurate lists of DRIP firms for this time frame.[4]

[2]Other events that have been studied to test price pressure are more likely to have information content. For example, Mitchell, Pulvino, and Stafford (2004) examine price pressure around mergers. Studies of block sales and secondary distributions include Scholes (1972), Holthausen, Leftwich, and Mayers (1990), and Mikkelson and Partch (1986). Studies of changes in the Standard & Poor's (S&P) 500 Index include Harris and Gurel (1986), Schleifer (1986), Beneish and Whaley (1996), Kaul, Mehrotra, and Morck (2000), and Chen, Noronha, and Singal (2004). Hartzmark and Solomon (2013) analyze price pressure in the month that dividends are predicted.

[3]Yadav (2010) focuses his study on similar evidence of a price spike on day −3. He notes that the 3-day settlement period became effective in July 1995 with SEC Rule 15c6-1, and he suggests that this AR(−3) is due to shareholders who buy additional shares on day −3 and settle these trades with the dividend income received on day 0.

[4]We obtained annual lists of DRIP firms since 1996 from the American Association of Individual Investors (AAII). However, while we validate that these lists cover all DRIP firms for the most recent period, before 2008, they appear to omit many DRIP firms, so that the implied lists of "non-DRIP"

https://doi.org/10.1017/S0022109017000394 Published online by Cambridge University Press

FIGURE 1

Mean Abnormal Returns and Trading Volume around the Dividend Pay Date

Graph A of Figure 1 plots the mean abnormal returns for all 21 days in the event window $t = (-10,+10)$, around the dividend pay date (on day 0) for each 10-year period since 1975. Daily abnormal returns are obtained by subtracting the return on a benchmark portfolio matched to each stock by size and book-to-market ratio. Graph B plots the analogous patterns in the adjusted rank of volume (RVOL), obtained by ranking the 21 days in each window by trading volume and adjusting these ranks to range from −0.5 to +0.5 (i.e., RVOL(t) = RANK(t)/21 − 0.5). First, every quarter we select the top tercile of stocks by dividend yield. Second, every quarter we compute the cross-sectional mean AR(t) and RVOL(t) for each day (t) in the event window. Third, for each day in the window, we compute the time-series mean of the cross-sectional means across all quarters in every 10-year period since 1975. The 95% confidence interval is plotted for the mean AR(t) and RVOL(t) from the most recent decade, since this period has the widest interval (L95 (lower 95% confidence level) and U95 (upper 95% confidence level) for 2005–2012).

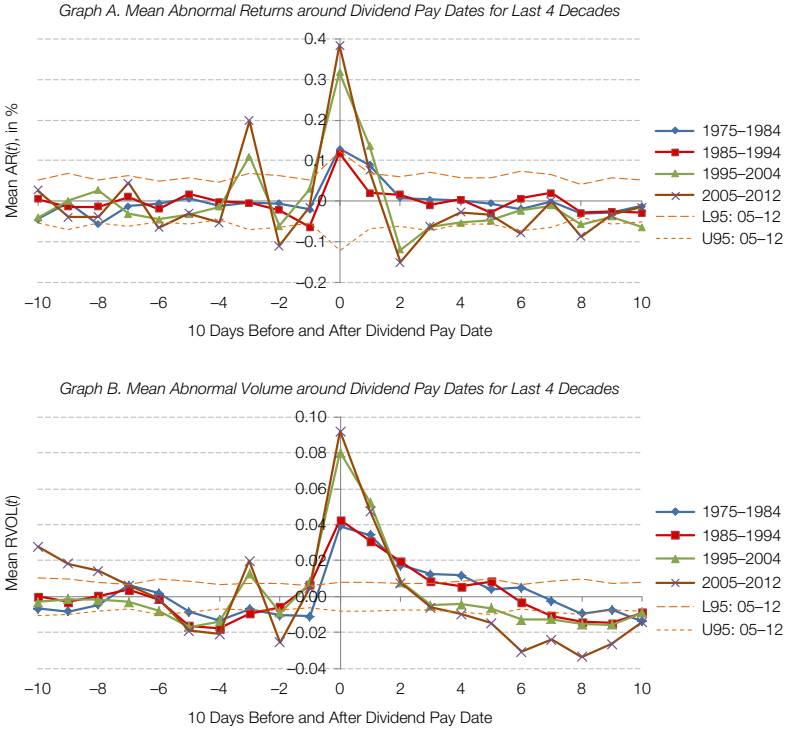


Figure 2 provides a first glance at our main results. Here, we examine the price patterns around the dividend pay date for the subsets of DRIP stocks or non-DRIP stocks in 3 portfolios: I) all dividend-paying stocks, II) high dividend yield stocks, and III) a subset of high yield stocks that are hard to arbitrage.[5] Graph A plots the mean cumulative abnormal returns (CARs) for the subsets of DRIP stocks in these 3 portfolios, while Graph B plots the mean CARs for the analogous subsets of non-DRIP stocks.

firms are corrupted by the inclusion of many DRIP firms before 2008. We have made an Internet Appendix (available at www.jfqa.org), which shows that our results are robust over the extended period 1996–2012 (see https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2172448).

[5]The second portfolio (II: HIGH_DY) includes the tercile of all dividend-paying stocks each quarter with the highest dividend yield, while the third portfolio (III: HARD_ARB) contains the top tercile of high yield stocks that are also in the bottom tercile by institutional ownership and the top tercile by bid–ask spread.

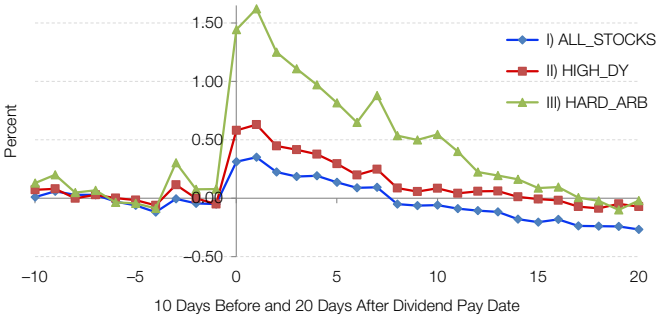
https://doi.org/10.1017/S0022109017000394 Published online by Cambridge University Press

FIGURE 2

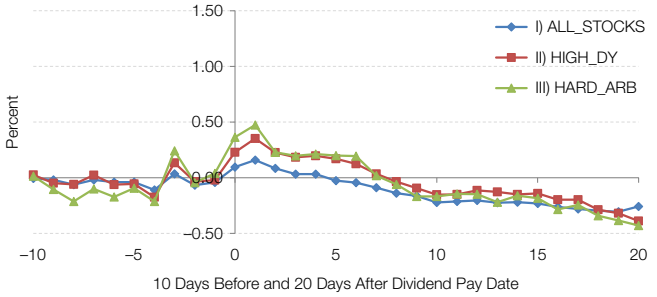
Mean CARs around Dividend Pay Date for DRIP Stocks or Non-DRIP Stocks

Figure 2 plots mean cumulative abnormal returns (CARs) across all 31 days in the event window (−10, +20), around the dividend pay date (on day 0), for the DRIP stocks or non-DRIP stocks in 3 portfolios. We first independently sort all dividend-paying stocks each quarter by dividend yield, institutional ownership in the prior quarter, and spread as a percentage of the closing price on day −10. Then we select 3 portfolios: I) ALL_STOCKS (all dividend-paying stocks each quarter), II) HIGH_DY (top 33% of all dividend-paying stocks each quarter by dividend yield), and III) HARD_ARB (top 33% by dividend yield, bottom 33% by institutional ownership, and top 33% by spread). Next, daily abnormal returns are computed by subtracting the return on a benchmark portfolio matched to each stock by size and book-to-market ratio. Then, for the DRIP stocks or non-DRIP stocks in each portfolio, we compute the cross-sectional average CARs for all 31 days in the event window, during every quarter in the period 2008–2012. Finally, for each portfolio, we compute the time-series mean of these cross-sectional averages across all quarters. Graphs A and B plot the resulting mean CARs for the DRIP stocks and non-DRIP stocks, respectively, in each portfolio.

Graph A. Mean CARs for Subsets of DRIP Stocks in 3 Portfolios



Graph B. Mean CARs for Subsets of Non-DRIP Stocks in 3 Portfolios



Graph A of Figure 2 reveals that the CAR for each portfolio of DRIP stocks is highest on day +1, before reversing toward 0 on subsequent days. For the portfolio of high yield DRIP stocks that are hard to arbitrage, the mean abnormal return on day 0 is 1.4% and the mean CAR reaches a peak that exceeds 1.5% on day +1. Then, for each portfolio, the series of negative abnormal returns beginning with day +2 accumulates to offset the temporary price spike on day 0, so that the mean CAR is reduced to 0 by day +20. This evidence confirms a reversal that completely offsets the temporary inflation around the pay date for these portfolios of DRIP stocks.

Graph B of Figure 2 indicates that the analogous 3 portfolios of non-DRIP stocks also display temporary inflation around the pay date, although it is much smaller in magnitude. One potential reason for the temporary (albeit smaller) inflation for non-DRIP stocks is that some brokerage houses allow retail clients to

https://doi.org/10.1017/S0022109017000394 Published online by Cambridge University Press

reinvest dividends automatically, even for stocks with no DRIP. Also, some shareholders of non-DRIP stocks may reinvest dividends on their own.[6]

These results imply that, on the pay date, the marginal investor is trying to "undo" the dividend payment by reinvesting the cash back into shares of the same company. This motivation behind the pay date effect contrasts with prior work, which shows that, in the period leading up to the ex-dividend date, the marginal investor is a dividend-seeking investor, as evidenced by price pressure in that period (e.g., see Hartzmark and Solomon (2013)). Thus, the source of the pay date effect can be viewed as the exact opposite of the impetus behind the price increase before the ex-dividend date, which reflects a preference by the marginal investor to receive the dividend.[7]

Figures 1 and 2 provide support for the temporary price pressure hypothesis and indicate an important role for DRIPs behind the pay date effect. This evidence motivates us to pursue further insights into the nature of this price pressure, by conducting four additional sets of tests.

Our first set of tests relates the magnitude of the pay date effect, AR(0), to cross-sectional variation in the demand for shares on the pay date. We begin by using a simple DRIP indicator variable as a proxy for the elevated demand on the pay date for the shares of firms with a company-sponsored DRIP. We find that AR(0) is significantly higher for the subset of DRIP firms, after controlling for the influence of other firm attributes. Next, we develop a proxy for firm-specific DRIP participation, based on the observation that a higher level of participation should result in a higher proportion of shares outstanding held by registered retail investors.[8] We conjecture that firms with greater DRIP participation (i.e., proxied by more registered retail investors) should have a larger pay date effect. Consistent with this conjecture, we show that i) the proportion of shares outstanding held by registered retail shareholders is significantly higher for DRIP stocks than for non-DRIP stocks, and ii) higher values for this proxy are associated with a significantly larger pay date effect (AR(0)) for DRIP stocks, but not for non-DRIP stocks.

Our second set of tests investigates whether there is less price pressure for the subset of DRIP firms that increases shares outstanding around the pay date. Firms that do not issue new shares are obliged to meet their DRIP commitments by buying back shares on the open market. Alternatively, DRIP firms may issue new shares as another way to meet their DRIP obligations, without exerting price pressure on day 0. As expected, we find that the subset of DRIP firms that issues new shares around the event has a significantly lower pay date effect, AR(0).

Our third set of tests examines whether short sellers try to exploit the temporary price increase around the pay date. For our sample of DRIP stocks, we find a significant spike in the abnormal volume of short selling at the time of the largest positive price spike, on day 0. In contrast, for non-DRIP stocks, there is no such

[6]In Figure B.1 of Internet Appendix B, we show that the results in Figure 2 are robust over the period 1996–2012.

[7]This evidence also raises the question of why investors wait to reinvest the dividend on the pay date at a high price, instead of selling before the ex-date and buying back after the pay date. We thank the referee for these insights.

[8]As we discuss in Section II.C, DRIP participation is effectively limited to retail investors. In addition, participating retail investors need to be registered shareholder of record, as opposed to the more common situation where the shares of retail investors are held in street name.

evidence of abnormal short volume around the pay date, consistent with the lower price pressure that we observe for these stocks.

Finally, we examine whether variation over time in the pay date effect for DRIP stocks is related to variation in the average cost of trading in the market. We begin by analyzing 3 alternative trading strategies that attempt to profit from the price spike on day 0. On any given day, these strategies prescribe holding the subset of DRIP stocks in each of our 3 portfolios, I–III, on their respective pay dates (i.e., buy at the close on day -1 and sell at the close on day 0). For every day (t) in the extended sample period 1996–2012, we first calculate the daily trading profits from each strategy as the cross-sectional mean abnormal return on the pay date, AR(0)_K$_t$, for the subset of DRIP stocks in each portfolio (K = I–III) that pays a dividend on that date. Within each quarter (n) in the sample period, we then aggregate the series of daily profits, AR(0)_K$_t$, to obtain the implied stream of quarterly profits measured by the CAR for each strategy during quarter n, CAR(0)_K$_n$, K = I–III.

Our three trading strategies yield streams of quarterly profits that are surprisingly large and stable over time. The CARs for each strategy are positive in at least 60 of the 68 quarters in the sample. They average 17.4% per quarter for portfolio I (ALL_STOCKS), 21.3% for portfolio II (HIGH_DY), and 19.3% for portfolio III (HARD_ARB). In addition, they tend to be higher during recessions, grow over time, are positively related to movements in the firms' dividend yield and spread, and are negatively associated with aggregate liquidity. This evidence corroborates the view that the pay date effect constitutes a liquidity premium for these portfolios of DRIP firms, in response to temporary price pressure on the pay date.

This paper contributes to several strands of literature. First, we build upon the body of work that explores the price pressure hypothesis, by investigating an ideal setting where temporary buying pressure stems from a perfectly predictable noninformation event. In doing so, we exploit a widely used tool to implement a popular investing strategy, DRIPs, which creates predictable retail demand on the dividend pay date. Second, we contribute to the anomalies literature by providing an example of postpublication return predictability that has become stronger over time, in contrast to the evidence presented in Schwert (2003) and McLean and Pontiff (2016). Furthermore, we show that the pay date effect is not limited to small stocks with low institutional ownership, which is also in contrast to most other anomalies (see, e.g., Boehmer and Kelley (2009), Chordia, Roll, and Subrahmanyam (2008)). Finally, this paper adds to the literature on limits to arbitrage by showing that, while the temporary inflation around the pay date is actively exploited by short sellers, their activity is insufficient to eliminate this price pressure (see Mitchell, Pulvino, and Stafford (2002), Stambaugh, Yu, and Yuan (2012)).

II. DRIPs: The Literature, Implementation, and Participation

A. Review of the Literature on DRIPs

The use of DRIPs expanded greatly in the 1970s (Pettway and Malone (1973)), but these plans have attracted little research in the academic literature. Ogden (1994) is the first to examine price pressure around the dividend pay date. He finds evidence of a small price impact that is somewhat larger for stocks with

https://doi.org/10.1017/S0022109017000394 Published online by Cambridge University Press

DRIPs, but he finds no evidence of a subsequent reversal. Moreover, he relies on published lists of firms with DRIPs for just 2 years (1984 and 1990), forcing him to make assumptions about which firms had DRIPs during the decade of the 1980s.

Two other working papers also explore price pressure around the dividend pay date. Blouin and Cloyd (2005) investigate price changes around the pay dates for closed-end funds during the years 1988–2003. They find a significant price increase around the pay date, but no significant reversal. Yadav (2010) examines price changes around dividend pay dates over the years 1997–2008. Using an incomplete list of 300 DRIP stocks, he finds that the mean abnormal return on the pay date is larger for his sample of DRIP stocks, compared to all stocks. In addition, similar to our result in Figure 1, he documents a significant abnormal return 3 days before the pay date. He attributes this price spike to shareholders who buy more shares on day −3 and then use their dividend income to settle the trades 3 days later. He focuses the remainder of his paper on potential microstructure determinants of this price spike on day −3.[9]

B. Transfer Agents and the Implementation of Company-Sponsored DRIPs

Firms commonly enlist a transfer agent to manage the ownership record for all investors who trade the company's shares. The transfer agent ensures that all ownership rights are properly allocated to the registered shareholders of record, including voting rights, the right to new shares issued from stock splits, stock dividends or rights offerings, and the right to cash dividends. Firms also typically rely on their transfer agent to administer company-sponsored DRIPs.

Details regarding the implementation of each DRIP vary somewhat across firms, and they are communicated to investors through a prospectus filed with the U.S. Securities and Exchange Commission (SEC) or a document distributed by the firm or the transfer agent. Two transfer agents that manage a substantial portion of all DRIPs sponsored by U.S. companies are Wells Fargo Shareowner Services and Computershare Trust Company. These two transfer agents have made DRIP documents available to the public.[10]

This DRIP documentation typically describes 3 important features about the purchase of shares involved in the DRIP: i) how the shares are to be purchased, ii) when the shares are to be purchased, and iii) what purchase price is to be charged to DRIP participants. First, at each dividend distribution, the company will direct the transfer agent to either purchase newly issued shares from the company or purchase existing shares in the open market. Second, if the transfer agent is told to purchase shares in the open market, it is typically directed to purchase

[9] Another body of work addresses other implications of DRIPs for both asset pricing and corporate finance. For example, Hansen, Pinkerton, and Keown (1985), Keown, Pinkerton, and Shalini (1991), and Peterson, Peterson, and Moore (1987) find only a modest market reaction to the firm's decision to adopt DRIPs. Scholes and Wolfson (1989) show how investors could benefit from certain discount features associated with DRIPs in the late 1980s. Dhillon, Lasser, and Ramirez (1992), Finnerty (1989), and Scholes and Wolfson (1989) examine firms' use of DRIPs to raise capital and conclude that DRIPs can help to mitigate the adverse price effects of new equity issues.

[10] The Web site for Computershare is https://www-us.computershare.com/investor/plans/planslist.asp?stype=drip, and the Web site for Wells Fargo is https://www.shareowneronline.com.

https://doi.org/10.1017/S0022109017000394 Published online by Cambridge University Press

the shares as soon as possible after receiving the funds. This common wording implies a fairly strong incentive for transfer agents to purchase shares on the dividend pay date (as soon as the dividend funds are received), in order to avoid litigation regarding any potential breach of fiduciary duty. Third, the price applied to every DRIP participant is typically the trade-weighted average price that applies to all shares bought to satisfy the DRIP, if the shares are purchased in the open market, or the closing price on the pay date if newly issued shares are purchased from the company. Internet Appendix A provides excerpts from the DRIP documents for two firms, which illustrate the responsibilities of the transfer agent and the relevant details common in these plans.

C. DRIP Participation and Broker Non-Votes in Shareholder Proxy Contests

We conjecture that the existence and implementation of company-sponsored DRIPs is a major force behind the pay date effect documented in this study. DRIP firms with a higher dividend yield and/or greater shareholder participation in their DRIP should have greater demand for their shares on the pay date, since the transfer agent must buy more shares to implement the DRIP. However, in designing tests of this conjecture, we are limited by the fact that no firm-specific data are available on the shareholder participation rates in company-sponsored DRIPs.[11]

Given this limitation, we pursue 2 approaches to examine how the temporary demand induced by DRIPs affects the pay date effect. Our first approach uses a simple DRIP indicator variable as a proxy for the elevated demand on the pay date for DRIP firms versus non-DRIP firms. Our second approach relies on 2 common features of company-sponsored DRIPs to develop a firm-specific proxy for cross-sectional variation in DRIP participation rates.

One feature is that roughly 95% of all DRIP firms limit the maximum dollar dividend amount that any individual shareholder can apply to purchase more shares through the DRIP. The typical limit ranges from $1,000 to $25,000 per quarter, which effectively excludes financial institutions, so that only retail investors can participate. Another feature is that firms require investors to become registered shareholder of record, in order to participate in a DRIP. This requirement helps firms to manage their retail ownership and results in all communication being made directly between the firm and its participating retail shareholders. It also enables the firm's transfer agent to administer the DRIP directly to participating retail shareholders.

It is noteworthy that the shares of retail investors who do not participate in a firm's DRIP, or who purchase stocks with no DRIP, are normally held in street name in retail brokerage accounts. This label means that the shares are registered in the name of the brokerage firm through which the stock is bought, rather than the investor who purchased the stock. In this case, all communication between the company and the investor is routed through the broker. This practice gives the brokerage house control over details involving shareholder rights for their

[11] We have had many conversations with companies, transfer agents, and brokerage houses to request data on firm-specific DRIP participation rates, the shareholdings of DRIP participants, and the timing and pricing of purchases made in the implementation of DRIPs. None of these entities are willing to share any data or discuss their DRIPs.

https://doi.org/10.1017/S0022109017000394 Published online by Cambridge University Press

https://doi.org/10.1017/S0022109017000394 Published online by Cambridge University Press

retail customers and reduces the cost of providing brokerage services. The typical brokerage house charges a fee of several hundred dollars to retail clients who ask to become shareholders of record, in order to discourage such requests. As a result of this practice, a small number of retail brokerage houses operate as the shareholders of record on behalf of most retail investors who do not participate in DRIPs, as well as retail investors who purchase stocks with no DRIP.

Given these features of DRIPs, we know that an increase in DRIP participation will, ceteris paribus, result in an increased proportion of shares held by retail investors who are shareholders of record. This discussion motivates our proxy for the firm's DRIP participation rate as *the proportion of shares held by registered retail shareholders* each quarter. Figure 3 illustrates our 2-step process to identify this proportion of registered retail shareholders. The first step is to obtain the proportion of shares held by *all* retail investors. We accomplish this first task by subtracting (from 1) the proportion of shares held by financial institutions that file 13F's each quarter. The second step requires that we identify the smaller proportion of shares held by retail investors who are registered shareholders of record. This second task is achieved by estimating its complement: The proportion of shares held by retail investors who are *not* registered shareholders of record (i.e., who hold their shares in street name).

For this second step, we use panel data on shareholder votes in proxy contests to elect members of the firm's board of directors. Importantly, these voting data include the category of broker non-votes, which reflects the proportion of a firm's shares that are held in street name by brokerage firms on behalf of non-voting shareholders. This proportion of shares classified as broker non-votes serves to measure the fraction of a firm's shares held by *nonregistered retail* shareholders, because i) these shares are held in street name (i.e., they are not registered), and ii) typical retail shareholders do not vote their shares, while most institutions vote their shares.[12]

Given these data on broker non-votes, we can estimate the proportion of shares outstanding that are held by *registered retail* shareholders each quarter by subtracting from 1 i) the proportion of shares held by *financial institutions* and ii) the proportion of remaining shares held by nonregistered retail shareholders (measured by broker non-votes), as follows:

$$\text{PART}_{in} = 1 - \text{PCT_INST}_{in} - \text{BROKER_NON}_{in}, \tag{1}$$

where PCT_INST_{in} = percentage of shares outstanding for stock i held by financial institutions during quarter n, obtained from the firms' quarterly 13F filings;

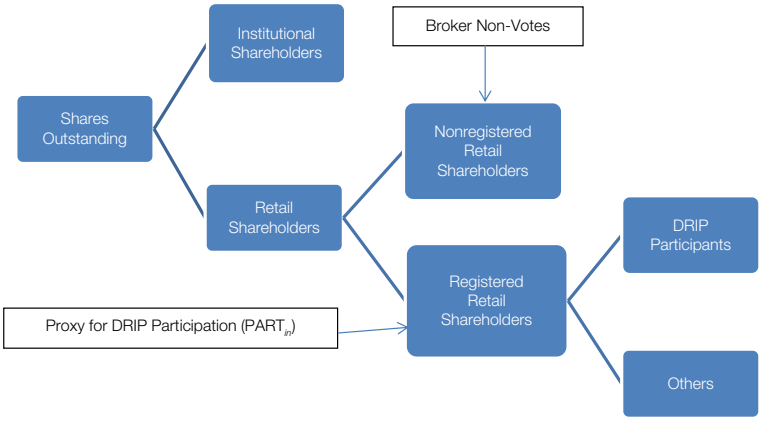
[12]The Broadridge Financial Solutions company processes the proxy votes for over 90% of public companies and mutual funds in North America. In a recent study in collaboration with PricewaterhouseCoopers (PwC), they report that roughly 70% of the shares held by retail investors are not voted, while only 10% of institutional shares are not voted (see Broadridge and PwC (2013)).

FIGURE 3
Proxy for Firm-Specific DRIP Participation Rates

Figure 3 illustrates the construction of our quarterly proxy for firm-specific DRIP participation rates, as the proportion of shares outstanding held by registered retail investors:

$$\text{PART}_{in} = 1 - \text{PCT_INST}_{in} - \text{BROKER_NON}_{in}, \quad (1)$$

where PCT_INST_{in} = percentage of shares outstanding for stock (i) held by financial institutions during quarter (n), obtained from firms' quarterly 13F filings, and BROKER_NON_{in} = percentage of shares outstanding classified as broker non-votes for stock (i) during quarter (n). We proxy a firm's DRIP participation rate each quarter by estimating the proportion of the firm's shares held by retail investors who are registered shareholders of record, since a basic requirement for investors to participate in a DRIP is to register their shares. The flow chart below shows that we construct this measure as the proportion of shares that remain after subtracting i) shares held by financial institutions and ii) shares classified as broker non-votes in proxy contests to elect the firm's board members (i.e., non-voting shares held in street name). It is appropriate to begin by subtracting institutional ownership and, thereby, to focus on retail investors, since institutions are excluded from participating in most DRIPs. It is also appropriate to further subtract broker non-votes as an estimate of the proportion of nonregistered retail shareholders, since typical nonparticipating retail shareholders hold their shares in street name and do not vote their shares. After subtracting this proportion of nonregistered retail investors, the remaining shares held by registered retail investors include the shares of DRIP participants.



BROKER_NON_{in} = percentage of shares outstanding classified as broker non-votes for stock i during quarter n.

The remaining shares held by registered retail investors include the shares of DRIP participants. We use this proxy to test 2 predictions behind the price pressure hypothesis. First, because PART_{in} includes the proportion of shares held by DRIP participants, it should be higher for DRIP firms than for non-DRIP firms, ceteris paribus. Second, if PART_{in} is a meaningful proxy for the additional demand for shares on the dividend pay date due to higher DRIP participation, then PART_{in} should be related to abnormal returns on the pay date, AR(0), for the subsample of DRIP firms. In contrast, for firms with no DRIP, this proxy (PART_{in}) has no bearing on DRIP participation or the demand for shares on the pay date and thus should be unrelated to AR(0).[13]

[13]Our proxy for DRIP participation is subject to some measurement error. For example, any *institutional* shares that are not registered and not voted (i.e., that appear in both PCT_INST and BROKER_NON) are "double counted" in equation (1), resulting in a downward bias for our proxy. We have also adjusted for this potential bias by adding 10% of PCT_INST_{in} back into PART_{in} (see footnote 12). Our results are not affected by this adjustment.

https://doi.org/10.1017/S0022109017000394 Published online by Cambridge University Press

https://doi.org/10.1017/S0022109017000394 Published online by Cambridge University Press

III. Data and Variables

A. Data

We analyze daily returns and trading volume for all New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and National Association of Securities Dealers Automated Quotations (NASDAQ) common stocks (Center for Research in Security Prices (CRSP) share code 10 or 11) during the period July 1975–Dec. 2012. We examine benchmark-adjusted abnormal returns to measure stock price performance (see Daniel, Grinblatt, Titman, and Wermers (1997)). The daily abnormal return is defined as the difference between the actual return on a stock and the return on an equal-weighted portfolio of all firms in the same size and book-to-market quintiles, obtained from Russ Wermers' Web site.[14]

We obtain the pay dates of all cash dividends from CRSP (DISTCD = 1200–1299). We apply the screens in Ogden (1994) to keep all dividend events for which i) the number of days between the ex-dividend day and the pay date is at least 10 and no more than 45, ii) the number of days between the ex-dividend day and the record date is at least 2 and no more than 7, and iii) there are at least 20 days between a firm's consecutive dividend pay dates.[15]

We have obtained annual lists of DRIP firms since 1996 from the American Association of Individual Investors (AAII). For 2012, the AAII list is almost identical to an analogous list of DRIP firms from Morningstar (97% of these DRIP firms appear on both lists). This cross-check validates the accuracy of the AAII lists over the recent period. However, from 2007 to 2008, the AAII lists indicate an unrealistic increase of 230 new DRIP firms, from a total of 392 to 622.[16]

We fail to find any reports in Factiva that corroborate this increase in 2008, suggesting that the AAII lists omit a large number of firms with DRIPs prior to 2008. Thus, we restrict our sample to the years 2008–2012 for our main analysis, where we compare the behavior of DRIP firms versus non-DRIP firms and thus require accurate lists of both types of firms. In Internet Appendix B, we show that our main results are robust over the extended period since 1996. Furthermore, in our analyses that focus on only DRIP stocks, we examine the extended period 1996–2012, for which we have the accurate lists of DRIP stocks from the AAII.

B. Variables

We begin by examining the following (cumulative) abnormal returns measured over 5 portions of the 21-day event window (−10, +10), as well as the ex-dividend date:

[14] Portfolio assignments for NYSE, AMEX, and NASDAQ stocks from CRSP are available since July 1975, based on the approach in Wermers (2003), at http://scholar.rhsmith.umd.edu/rwermers/.

[15] These screens help to ensure that we ignore events with coding errors and reduce the impact of ex-dividend day price effects on the pay date price effect. They eliminate 15,068 of the 232,322 events in the sample since 1975.

[16] The total number of company-sponsored DRIPs on the AAII list ranges from 600 to 1,300 in the years since 1996. However, roughly half of all DRIPs each year are sponsored by mutual funds, which are excluded in our analysis.

Return Measures around Dividend Pay Date

$AR(-3)_{in}$ = abnormal return for firm i on day -3, before the pay date in quarter n;

$AR(0)_{in}$ = abnormal return for firm i on day 0, the pay date in quarter n;

$CAR(0,+1)_{in}$ = cumulative abnormal return over days 0 and $+1$;

$CAR(+2,+10)_{in}$ = cumulative abnormal return over days $+2$ through $+10$;

$CAR(0,+10)_{in}$ = cumulative abnormal return over days 0 through $+10$;

$AR(EX_DIV)_{in}$ = abnormal return on the ex-dividend date for firm i in quarter n;

$AR(0)_{in}$–$AR(EX_DIV)_{in}$ = difference between AR(0) and AR(EX_DIV);

where $AR(t)_{in}$ = abnormal benchmark-adjusted return for stock i on day t relative to the dividend pay date in quarter n.

The timing of the first 5 measures is dictated by the evidence in Figure 1, which indicates significant positive abnormal returns on day -3 and day 0 and a significant negative abnormal return on day $+2$, followed by a series of smaller but significant negative abnormal returns in the ensuing days over the following 2 weeks (days $+2$ through $+10$).

Explanatory Variables

$DRIP_{in}$ = 1 if firm i has a company-sponsored DRIP in quarter n, or 0 otherwise;

$SIZE_{in}$ = market capitalization for firm i on day -10, 2 weeks prior to the pay date in quarter n, where market capitalization is taken from CRSP;

DIV_YIELD_{in} = percentage dividend yield for firm i, computed as the cash dividend amount from CRSP divided by the firm's closing stock price on day -10, 2 weeks before the pay date in quarter n, and multiplied by 100;

PCT_INST_{in-1} = percentage of total shares outstanding for firm i owned by institutional investors during the previous quarter $(n-1)$, taken from 13F filings;

$SPREAD_{in}$ = closing bid–ask spread for firm i, taken from CRSP, as a percentage of the closing price on day -10, 2 weeks prior to the pay date in quarter n;

$\ln(HILO_{in})$ = intraday stock return volatility for firm (i), measured as the natural log of the ratio of the daily high and low prices on day -10, multiplied by 100.

These explanatory variables are known at least 2 weeks prior to the pay date. Thus, the results in this paper lead to predictive trading strategies that can be easily implemented.

We examine 3 portfolios of stocks that vary in terms of dividend yield and the limits to arbitrage that they face. These portfolios are generated by first independently sorting all dividend-paying stocks each quarter by i) dividend yield, ii) institutional ownership in quarter $n-1$, and iii) percentage spread on day -10.

https://doi.org/10.1017/S0022109017000394 Published online by Cambridge University Press

https://doi.org/10.1017/S0022109017000394 Published online by Cambridge University Press

Then we construct portfolios I–III as follows:

I (ALL_STOCKS): All dividend-paying stocks each quarter;

II (HIGH_DY): Top 33% of all dividend-paying stocks each quarter by dividend yield;

III (HARD_ARB): Top 33% of all dividend-paying stocks each quarter by dividend yield, bottom 33% by institutional ownership, and top 33% by spread.[17]

IV. Main Results: The Pay Date Effect

A. Abnormal Returns for the Subsets of DRIP Stocks and Non-DRIP Stocks

Table 1 provides the average firm event returns over the 5 time frames defined previously, for the subsets of DRIP stocks and non-DRIP stocks in the first portfolio (I), which includes all dividend-paying firms each quarter. Table B.1 of Internet Appendix B provides analogous results for portfolios II (HIGH_DY) and III (HARD_ARB). We present 7 sets of means for 1) all stocks in the portfolio, 2) DRIP stocks, 3) non-DRIP stocks, 4) the difference of means across DRIP

TABLE 1

Average Behavior of Stock Prices around Dividend Pay Dates

Table 1 presents the average abnormal returns over different time frames around the dividend pay dates for all dividend-paying stocks during the sample period 2008–2012. The variables $AR(-3)_{in}$, $AR(0)_{in}$, $CAR(0,+1)_{in}$, $CAR(+2,+10)_{in}$, and $CAR(0,+10)_{in}$ are the percentage (cumulative) abnormal returns measured over different portions of the 21-day event window (−10,+10) around the pay date (on day 0) for the *i*th firm in the *n*th quarter. These abnormal returns are computed by subtracting the daily return on a benchmark portfolio matched to each stock by size and book-to-market ratio. $AR(EX_DIV)_{in}$ is the analogous abnormal return on the ex-dividend date, and AR(0) − AR(EX_DIV) is the mean of the difference between $AR(0)_{in}$ and $AR(EX_DIV)_{in}$. We provide 7 sets of results for 1) all stocks in portfolio I, 2) all DRIP stocks, 3) all non-DRIP stocks, 4) the difference of means across all DRIP stocks and all non-DRIP stocks, and 5)–7) the analogous results for a subset of matched pairs of all DRIP stocks and non-DRIP stocks. We describe the matching scheme in the text. We compute the average abnormal returns around the pay date for every portfolio, using a panel regression of each return measure on a constant term, with standard errors clustered by firm (*i*) and quarter (*n*). Analogous mean abnormal returns for the subsets of DRIP firms and non-DRIP firms in each portfolio are computed similarly. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Mean			Difference of Means (2)–(3)	Matched Pairs		
Variables	Portfolio I: All Stocks	All DRIP Stocks	All Non-DRIP Stocks	DRIP–Non-DRIP	DRIP	Non-DRIP	Mean Diff.
	1	2	3	4	5	6	7
NO_OF_FIRMS_PER_QTR	1,169***	507***	656***	−149***	130	130	0
$AR(-3)_{in}$ (%)	0.13***	0.12***	0.14***	−0.02	−0.02	0.18**	−0.14
$AR(0)_{in}$ (%)	0.24***	0.38***	0.13**	0.25***	0.53***	0.13**	0.40***
$CAR(0,+1)_{in}$ (%)	0.31***	0.44***	0.21**	0.24***	0.64***	0.25**	0.39***
$CAR(+2,+10)_{in}$ (%)	−0.39**	−0.40**	−0.39***	−0.01	−0.65**	−0.26*	−0.38*
$CAR(0,+10)_{in}$ (%)	−0.09	0.04	−0.18	0.23**	−0.02	−0.01	0.00
$AR(EX_DIV)_{in}$ (%)	0.15***	0.13***	0.17***	−0.04	0.18**	0.16***	0.02
AR(0) − $AR(EX_DIV)_{in}$	0.09**	0.26***	−0.04	0.29***	0.35***	−0.02	0.37**

[17] Other studies that use institutional ownership or transaction costs to examine the influence of limits to arbitrage on stock return performance include Asquith, Pathak, and Ritter (2005), Berkman, Dimitrov, Jain, Koch, and Tice (2009), Boehme, Danielsen, and Sorescu (2006), Diether, Malloy, and Sherbina (2002), Nagel (2005), and Sadka and Scherbina (2007).

stocks versus non-DRIP stocks, and 5)–7) the analogous results for a subset of matched pairs of DRIP firms versus non-DRIP firms within the portfolio.

The subset of matched pairs is generated every quarter, by first requiring matched firms to be in the same Fama–French 5-industry classification and then using logistic propensity scoring based on the following 4 firm characteristics: $\ln(\text{SIZE}_{in})$, DIV_YIELD_{in}, PCT_INST_{in-1}, and SPREAD_{in}. These 4 attributes regularly enter the quarterly logistic regressions with significant coefficients, while $\ln(\text{HILO}_{in})$ is rarely significant and is thus omitted from the logit model. We compute the average returns in Table 1, using a panel regression of each return measure on a constant term, with standard errors clustered by firm (i) and quarter (n).

First, consider the mean abnormal returns around the pay date for all dividend-paying stocks, in the left column of Table 1. Results indicate that an average of 1,169 U.S. stocks pay dividends each quarter. These stocks have a mean AR(–3) of 13 bps, a mean AR(0) of 24 bps, and a mean CAR(0,+1) of 31 bps. This price increase is completely reversed over the following 2 weeks, with a mean CAR(+2,+10) of −39 bps. All of these mean abnormal returns and CARs are significantly different from 0. Aggregating the CAR(0,+1) and the subsequent reversal, CAR(+2,+10), we obtain a mean CAR(0,+10) of −9 bps, which is not significantly different from 0 (t-ratio = −0.4). This evidence supports the temporary price pressure hypothesis.

The next 3 sets of results in Table 1 compare the analogous price patterns for the subsets of all DRIP stocks versus all non-DRIP stocks. This comparison indicates that the mean AR(0) and CAR(0,+1) are both significantly larger for DRIP firms versus non-DRIP firms. Importantly, for both DRIP stocks and non-DRIP stocks, the negative return reversal following the pay date effect, CAR(+2,+10), completely offsets the positive price spike around the pay date, so that the mean CAR(0,+10) is insignificant for both sets of firms. This evidence again indicates a price spike around the pay date for each set of firms that is completely neutralized over the following 2 weeks, further supporting the temporary price pressure hypothesis.

Finally, the analysis of matched pairs reported on the right side of Table 1 controls for differences in firm characteristics and yields similar results. For example, the subset of matched DRIP stocks has a mean AR(0) of 53 bps, which is significantly larger than the mean AR(0) of 13 bps for the matched set of non-DRIP stocks. The mean CAR(0,+1) for the matched pairs of DRIP stocks versus non-DRIP stocks displays comparable behavior. Once again, the price spike for both subsets of matched stocks is completely reversed over the following 2 weeks.

At the bottom of Table 1, we also present the mean abnormal return on the ex-dividend date, along with the mean difference between the abnormal returns on the pay date versus the ex-date.[18] For the subset of DRIP stocks, the mean AR(0)

[18]Hartzmark and Solomon (2013) provide evidence of temporary price pressure during the month that dividends are expected, which is followed by a reversal in the following month. They focus on the abnormal returns around the ex-dividend date and do not consider the pay date effect or the impact of DRIPs on their results.

https://doi.org/10.1017/S0022109017000394 Published online by Cambridge University Press

on the pay date is significantly *larger* than the mean abnormal return on the ex-date. In contrast, for the subset of non-DRIP stocks, the mean AR(0) on the pay date is *smaller* than that on the ex-date, although this difference is not significant.

Table B.1 of Internet Appendix B provides similar results for the successively smaller portfolios with a higher dividend yield (II) and greater limits to arbitrage (III). As we proceed to portfolios II and III, the price run-up and reversal around the pay date (AR(0), CAR(0,+1), and CAR(+2,+10)) grow larger in magnitude and the associated mean differences across DRIP stocks versus non-DRIP stocks become larger and more significant. These results corroborate the evidence in Table 1 and Figure 2.

B. Correlations across Abnormal Returns around the Pay Date

Table 2 presents the correlations across the abnormal return measures that reveal upward price pressure around the pay date (AR(0) and CAR(0,+1)) and subsequent price reversal following the pay date (CAR(+2,+10)). Each quarter, we first compute the pairwise cross-sectional correlations across these return measures for all dividend-paying stocks in portfolio I. We then calculate the time-series mean of every pairwise correlation across all quarters and present the results in Table 2. Mean Pearson correlations are provided above the diagonal, and mean Spearman correlations are below the diagonal. Table B.2 of Internet Appendix B presents the analogous results for portfolios II and III.

The correlations of interest are highlighted in the shaded areas of Table 2. These results indicate that the CAR around the pay date (CAR(0,+1)) is negatively correlated with the CAR over the following 2 weeks (CAR(+2,+10)). Furthermore, the magnitudes of these negative correlations increase as we proceed from portfolio I, in Table 2, to consider the finer subsets of stocks in portfolios II and III with a higher dividend yield and greater limits to arbitrage, in Table B.2. These results reinforce the evidence in Tables 1 and B.1, further indicating a systematic tendency for stock prices to increase around the pay date and reverse over the following 2 weeks, consistent with the price pressure hypothesis.

TABLE 2

Correlations across Return Measures over Different Time Frames around the Dividend Pay Date

Table 2 provides correlations across the return measures taken over 3 time frames around the dividend pay date: AR(0), CAR(0,+1), and CAR(+2,+10). We compute these correlations across all stocks, DRIP stocks, and non-DRIP stocks within portfolio I (all dividend-paying stocks) each quarter. The mean correlations are calculated in 2 stages. First, every quarter, we compute each pairwise cross-sectional Pearson or Spearman correlation across the dividend events for every group of stocks. Second, we compute the time-series mean for each pairwise cross-sectional correlation across all quarters in the sample period 2008–2012. The standard deviation of every time-series mean correlation is then used to construct the *t*-test of the null hypothesis that every mean correlation equals 0. The mean Pearson correlations are presented above the diagonal, and the mean Spearman correlations appear below the diagonal. ** indicates significance at the 5% level.

	Portfolio I: All Dividend-Paying Stocks			All DRIP Stocks			All Non-DRIP Stocks		
Variables	AR(0)	CAR(0,1)	CAR(2,10)	AR(0)	CAR(0,1)	CAR(2,10)	AR(0)	CAR(0,1)	CAR(2,10)
AR(0)	1.00	0.69**	−0.02	1.00	0.69**	−0.03	1.00	0.69**	−0.01
CAR(0,1)	0.66**	1.00	−0.06**	0.67**	1.00	−0.08**	0.65**	1.00	−0.06**
CAR(2,10)	−0.03**	−0.05**	1.00	−0.03	−0.05**	1.00	−0.02	−0.06**	1.00

https://doi.org/10.1017/S0022109017000394 Published online by Cambridge University Press

C. Firm Characteristics for the Subsets of DRIP Stocks and Non-DRIP Stocks

Table 3 presents the average firm characteristics for the subsets of all DRIP stocks and non-DRIP stocks in portfolio I. Columns 2–4 show that the average DRIP firm is significantly larger in size, and has smaller spreads and lower return volatility, compared with the average non-DRIP firm.[19] These relative attributes of the DRIP firms versus non-DRIP firms apparent in Table 3 remain fairly stable across the successively smaller subsets of DRIP firms and non-DRIP firms in portfolios II and III, provided in Table B.3 of Internet Appendix B. Importantly, this analysis shows that the DRIP firms responsible for the pay date effect are different from the typical firms involved in many other anomalies. Relative to non-DRIP firms, DRIP firms tend to be larger and have higher institutional ownership, smaller spreads, and lower volatility.

TABLE 3
Firm Characteristics for the Subsets of All DRIP Firms and All Non-DRIP Firms

Table 3 summarizes the descriptive statistics for the main firm characteristics analyzed in this study, for the subsets of DRIP stocks and non-DRIP stocks in portfolio I (ALL_STOCKS), which includes all dividend-paying stocks each quarter over the sample period 2008–2012. $SIZE_{in}$ is market capitalization of the ith firm on day −10, 2 weeks prior to the nth quarterly dividend pay date (on day 0). DIV_YIELD_{in} is the quarterly dividend amount, as a percentage of the closing price on day −10. PCT_INST_{in-1} is the percentage of total shares outstanding for stock i held by financial institutions in the previous quarter ($n-1$). $SPREAD_{in}$ is the daily closing spread, as a percentage of the closing share price on day −10. Finally, $ln(HILO_{in})$ is the natural log of the ratio of the daily high to the daily low taken on day −10, presented as a percentage (i.e., multiplied by 100). We present 7 sets of results for 1) all stocks in portfolio I, 2) all DRIP stocks, 3) all non-DRIP stocks, 4) the difference of means across all DRIP stocks and all non-DRIP stocks, and 5)–7) the analogous results for a subset of matched pairs of DRIP stocks and non-DRIP stocks within portfolio I. The matching scheme is described in the text. We compute the average firm characteristics for every portfolio using a panel regression of each variable on a constant term, with standard errors clustered by firm (i) and quarter (n). Analogous mean firm characteristics for the subsets of DRIP firms and non-DRIP firms in each portfolio, and their mean differences, are computed similarly. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Mean			Difference of Means (2)–(3)	Matched Pairs		
Variables	Portfolio I: All Stocks	All DRIP Stocks	All Non-DRIP Stocks	DRIP–Non-DRIP	DRIP	Non-DRIP	Mean Diff.
	1	2	3	4	5	6	7
NO_OF_FIRMS_PER_QTR	1,169***	507***	656***	−149***	130	130	0
$SIZE_{in}$ (in $millions)	7,316***	12,588***	3,241***	9,347***	3,602***	3,515***	87
DIV_YIELD_{in} (%)	0.77***	0.77***	0.77***	0.00	0.66***	0.71***	−0.05***
PCT_INST_{in-1} (%)	61.73***	62.71***	60.97***	1.74	60.15***	60.77***	−0.62
$SPREAD_{in}$ (%)	0.80***	0.58***	0.97***	−0.39***	0.82***	0.86***	−0.03
$ln(HILO_{in})$ (%)	3.76***	3.48***	3.98***	−0.50***	3.76***	3.83***	−0.07

[19] The last 3 columns of Table 3 present the results for the matched pairs analysis. As expected, 3 of the 4 matching variables (firm size, institutional ownership, and spread) are not significantly different across the matched pairs. On the other hand, the mean difference for the dividend yield is significant, but small in magnitude (at 5 bps).

https://doi.org/10.1017/S0022109017000394 Published online by Cambridge University Press

V. DRIPs, Demand or Supply, and the Pay Date Effect

A. Demand for Shares: DRIPs, DRIP Participation, and the Pay Date Effect

1. DRIPs and the Pay Date Effect

This section examines how the pay date effect depends upon cross-sectional variation in demand for shares around the pay date. We begin by using a DRIP indicator variable as a proxy for the elevated demand for DRIP firms versus non-DRIP firms, to explore the relation between AR(0) and firm attributes for all dividend-paying stocks over the period 2008–2012, as follows:

$$(2) \qquad \mathrm{AR}(0)_{in} = \beta_0 + \beta_1 \mathrm{DRIP}_{in} + \beta_2 \mathrm{DIV_YIELD}_{in} + \beta_3 \ln(\mathrm{SIZE}_{in}) + \beta_4 \mathrm{PCT_INST}_{n-1} + \beta_5 \ln(\mathrm{HILO}_{in}) + \varepsilon_{in}.$$

In Table 4, we present the results from estimating this panel regression model, with standard errors clustered by firm (i) and quarter (n). The main variable of interest is the DRIP dummy, which reveals a significant coefficient of 0.326 (t-ratio = 5.2). This result indicates that the abnormal return on the pay date (AR(0)) is approximately 33 bps higher for DRIP stocks relative to non-DRIP stocks, after controlling for other firm characteristics. The coefficients of the firm characteristics also indicate a significantly higher AR(0) for firms that face greater demand for shares on the pay date (due to a higher dividend yield), as well as for firms

TABLE 4

DRIPs, Firm Characteristics, and the Dividend Pay Date Effect

Table 4 analyzes the following relation between firm characteristics and the abnormal returns on the dividend pay date, AR(0), for all dividend-paying stocks (both with and without DRIPs) over the period 2008–2012:

$$(2) \qquad \mathrm{AR}(0)_{in} = \beta_0 + \beta_1 \mathrm{DRIP}_{in} + \beta_2 \mathrm{DIV_YIELD}_{in} + \beta_3 \ln(\mathrm{SIZE}_{in}) + \beta_4 \mathrm{PCT_INST}_{in-1} + \beta_5 \mathrm{SPREAD}_{in} + \beta_6 \ln(\mathrm{HILO}_{in}) + \varepsilon_{in}.$$

All variables are defined in Tables 1 and 3. We present the results from estimating this panel regression with standard errors clustered by firm (i) and quarter (n). Bold rows indicate the key variables of interest. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Variables	Coefficients	Estimates
Intercept	β_0	0.0694 3.5***
DRIP_{in}	**β_1**	**0.0326** **5.2*** **
$\mathrm{DIV_YIELD}_{in}$	β_2	13.98 2.1*
$\ln(\mathrm{SIZE}_{in})$	β_3	−0.042 −2.9***
$\mathrm{PCT_INST}_{in-1}$	β_4	−0.407 −2.2**
SPREAD_{in}	β_5	4.54 1.3
$\ln(\mathrm{HILO}_{in})$	β_6	2.61 2.8**
AVG_NO_OF_FIRMS_PER_QTR		1,212
Panel R^2		0.0068

https://doi.org/10.1017/S0022109017000394 Published online by Cambridge University Press

that face more severe limits to arbitrage (with smaller firm size, lower institutional ownership, and higher volatility).[20]

2. DRIP Participation and the Pay Date Effect

We next compare these firm characteristics, as well as our proxy for DRIP participation and its components, across the subsets of DRIP stocks versus non-DRIP stocks. Our proxy for DRIP participation relies on broker non-votes rendered in proxy contests to elect board members. These data are available from Equilar, Inc. (Redwood City, CA) for the years 2010–2012. For this sample period, we have 4,747 dividend events for firms with DRIPs and 4,987 events for firms without DRIPs.

In Panel A of Table 5, we show that this sample of events for DRIP firms has a mean AR(0) that is 15 bps higher than the analogous sample for non-DRIP firms. In addition, the average DRIP firm has lower institutional ownership, larger size, smaller spreads, and lower volatility. The average dividend yield is not significantly different across these groups of firms.

The main result of interest in Panel A of Table 5 pertains to our proxy for DRIP participation. As expected, the average proportion of shares held by registered retail investors (PART_{in}) is significantly higher for DRIP firms than for non-DRIP firms. However, the average level of PART_{in} remains large in magnitude for non-DRIP firms, at almost 21%. This result indicates that, for the typical firm, the group of registered retail shareholders includes many other investors besides those who participate in a DRIP (which must be 0 for non-DRIP firms).

This evidence suggests that there are other reasons for retail investors to become registered shareholders, besides DRIP participation. For example, PART_{in} may also be associated with other firm attributes such as the dividend yield, size, spread, and stock return volatility. We explore this issue by estimating the following regression model that measures the average difference in our proxy for DRIP participation across the subsets of DRIP stocks versus non-DRIP stocks, after accounting for the influence of these other firm characteristics:

$$\begin{aligned}(3)\quad \text{PART}_{in} &= \alpha_0 + \alpha_1 \text{DRIP}_{in} + \alpha_2 \text{BROKER_NON}_{in} + \alpha_3 \text{DIV_YIELD}_{in} \\ &\quad + \alpha_4 \ln(\text{SIZE}_{in}) + \alpha_5 \text{SPREAD}_{in} + \alpha_6 \ln(\text{HILO}_{in}) + \varepsilon_{in}.\end{aligned}$$

The left-hand side of Panel B in Table 5 reports the results for the sample of all DRIP stocks and non-DRIP stocks over the period 2010–2012. The t-ratios are based on standard errors clustered by firm (i) and quarter (n). The coefficient of the DRIP indicator variable (α_1) indicates that, after controlling for other firm characteristics, our proxy for DRIP participation is 3.8% greater for DRIP firms versus non-DRIP firms (t-ratio = 3.5). In addition, this proxy is significantly greater for firms with a higher dividend yield, smaller size, larger spread, and lower stock return volatility. We also note that, when we control for these other firm attributes, there is no significant relation between the proportion of

[20] We also estimate equation (2) for the extended sample period covering 1996–2012. Results are provided in Table B.4 of Internet Appendix B and are robust with respect to those in Table 4. In addition, we estimate this panel using the Fama–MacBeth (1973) approach. Results are in Table B.5 of Internet Appendix B and remain robust.

https://doi.org/10.1017/S0022109017000394 Published online by Cambridge University Press

https://doi.org/10.1017/S0022109017000394 Published online by Cambridge University Press

TABLE 5
DRIP Participation, Firm Characteristics, and the Pay Date Effect, AR(0)

Table 5 analyzes the following proxy for the participation rate in a firm's dividend reinvestment plan (DRIP):

$$\text{PART}_{in} = 1 - \text{PCT_INST}_{in} - \text{BROKER_NON}_{in},$$

where PCT_INST_{in} = percentage of shares outstanding for stock (i) held by financial institutions during quarter (n), and BROKER_NON_{in} = percentage of shares outstanding with proxy votes classified as broker non-votes. Data on broker non-votes, and thus our proxy for DRIP participation, are available for the period 2010–2012. In Panel A, we present summary statistics for various firm characteristics, including our proxy for DRIP participation, across the subsamples of DRIP firms and non-DRIP firms over the period 2010–2012. In Panel B, we estimate the following 2 panel regression models that describe i) the relation between our proxy for DRIP participation and firm characteristics and ii) the relation between the pay date effect AR(0) and our proxy for DRIP participation, as well as other firm characteristics:

$$(3)\quad \text{PART}_{in} = \alpha_0 + \alpha_1 \text{DRIP}_{in} + \alpha_2 \text{BROKER_NON}_{in} + \alpha_3 \text{DIV_YIELD}_{in} + \alpha_4 \ln(\text{SIZE}_{in}) + \alpha_5 \text{SPREAD}_{in} + \alpha_6 \ln(\text{HILO}_{in}) + \varepsilon_{in},$$

$$(4)\quad \text{AR(0)}_{in} = \beta_0 + \beta_1 \text{DRIP}_{in} + \beta_2 \text{PART}_{in} + \beta_3 \text{DRIP}_{in} \times \text{PART}_{in} + \beta_4 \text{BROKER_NON}_{in} + \beta_5 \text{DRIP}_{in} \times \text{BROKER_NON}_{in} + \beta_6 \text{DIV_YIELD}_{in} + \beta_7 \ln(\text{SIZE}_{in}) + \beta_8 \text{SPREAD}_{in} + \beta_9 \ln(\text{HILO}_{in}) + \nu_{in}.$$

We estimate the panel regression models in equations (3) and (4) with standard errors clustered by firm (i) and quarter (n). All variables are defined in Tables 1 and 3 (in Table B.3 of Appendix B, we document similar results when we estimate equations (3) and (4) using the Fama–MacBeth (1973) approach). Bold rows indicate the key variables of interest. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Summary Statistics for Our DRIP Participation Proxy and Firm Characteristics across the Subsets of DRIP Firms versus Non-DRIP Firms (2010–2012)

Variables	DRIP Firms	Non-DRIP Firms	Mean Difference
AR(0)_{in} (%)	0.17	0.02	0.15***
PCT_INST_{in-1} (%)	67.4	71.0	−3.6***
DIV_YIELD_{in} (%)	0.707	0.713	−0.006
SIZE_{in} (in $millions)	3,590	1,481	2,109***
SPREAD_{in} (%)	0.12	0.17	−0.05***
$\ln(\text{HILO}_{in})$ (%)	2.4	2.8	−0.4***
PART_{in} (%)	22.0	20.9	1.1***
BROKER_NON_{in} (%)	11.2	8.4	2.8***

Panel B. Estimation of 2 Panel Regression Models:

Equation (3): DRIP Participation and Firm Characteristics

Equation (4): Pay Date Effect, DRIP Participation, and Firm Characteristics

Dependent Variable for Equation (3): PART_{in}			Dependent Variable for Equation (4): AR(0)_{in}		
Intercept	α_0	0.596 9.8***	Intercept	β_0	0.050 0.3
DRIP_{in}	**α_1**	**0.038** **3.5*** **	**DRIP_{in}**	**β_1**	**−0.022** **−0.3**
_		—	**PART_{in}**	**β_2**	**−0.122** **−1.1**
_		—	**$\text{DRIP}_{in} \times \text{PART}_{in}$**	**β_3**	**0.618** **2.7****
BROKER_NON_{in}	α_2	0.010 0.1	BROKER_NON_{in}	β_4	0.060 0.1
_		—	$\text{DRIP}_{in} \times \text{BROKER_NON}_{in}$	β_5	0.324 0.5
DIV_YIELD_{in}	α_3	1.46 2.2**	DIV_YIELD_{in}	β_6	4.61 3.5***
$\ln(\text{SIZE}_{in})$	α_4	−0.028 −7.3***	$\ln(\text{SIZE}_{in})$	β_7	−0.002 −0.3
SPREAD_{in}	α_5	10.52 6.8***	SPREAD_{in}	β_8	3.37 0.5
$\ln(\text{HILO}_{in})$	α_6	−0.613 −4.0***	$\ln(\text{HILO}_{in})$	β_9	−0.676 −0.3
_		—	**$\beta_2 + \beta_3$** ***t*-statistic**		**0.496** **3.2*****
Panel R^2		0.148	Panel R^2		0.005
AVG_NO_OF_FIRMS_PER_QTR		804	AVG_NO_OF_FIRMS_PER_QTR		801

shares held by registered retail shareholders ($PART_{in}$) and the portion of nonvoting shares held in street name ($BROKER_NON_{in}$).[21]

Next, we test our prediction that $PART_{in}$ should be related to the pay date effect, $AR(0)_{in}$, for DRIP firms, but not for non-DRIP firms. We test this prediction using the following model:

$$\begin{aligned}(4)\quad AR(0)_{in} = {} & \beta_0 + \beta_1 DRIP_{in} + \beta_2 PART_{in} + \beta_3 DRIP_{in} \times PART_{in} \\ & + \beta_4 BROKER_NON_{in} + \beta_5 DRIP_{in} \times BROKER_NON_{in} \\ & + \beta_6 DIV_YIELD_{in} + \beta_7 \ln(SIZE_{in}) \\ & + \beta_8 SPREAD_{in} + \beta_9 \ln(HILO_{in}) + \upsilon_{in}.\end{aligned}$$

This specification allows the coefficients of 2 key variables, $PART_{in}$ and $BROKER_NON_{in}$, to differ across the subsets of DRIP stocks versus non-DRIP stocks. We argue that higher values of DRIP participation ($PART_{in}$) should *not* be informative for the subset of non-DRIP stocks (i.e., $\beta_2 = 0$), while higher DRIP participation should imply greater demand on the pay date and a higher AR(0) for the subset of DRIP stocks (i.e., $\beta_3 > 0$ and $\beta_2 + \beta_3 > 0$). Furthermore, after we control for the influence of $PART_{in}$ in this model, there is no reason to expect the proportion shareholders who do *not* participate in DRIPs (i.e., nonregistered retail shareholders, $BROKER_NON_{in}$) to have an independent impact on $AR(0)_{in}$, for either DRIP firms or non-DRIP firms (i.e., $\beta_4 = \beta_5 = 0$).[22]

We estimate equation (4) for the panel including all DRIP stocks and non-DRIP stocks over the period 2010–2012, with standard errors clustered by firm (i) and quarter (n). The results are presented on the right side of Panel B in Table 5. As expected, for non-DRIP stocks, there is no significant relation between our proxy for DRIP participation and the pay date effect (i.e., β_2 is insignificant). In contrast, there is a significant positive relation for DRIP stocks (i.e., $\beta_3 > 0$ and $\beta_2 + \beta_3 > 0$). In addition, after accounting for this association between $PART_{in}$ and $AR(0)_{in}$, we find no significant relation between $BROKER_NON_{in}$ and $AR(0)_{in}$, for either DRIP stocks or non-DRIP stocks (i.e., $\beta_4 = \beta_5 = 0$). We also find a significant positive relation between the dividend yield and AR(0) (i.e., $\beta_6 > 0$). Together, this evidence indicates that greater demand for DRIP stocks on the pay date, due to either a higher dividend yield or greater DRIP participation, is associated with a significantly larger pay date effect, AR(0).[23]

[21] We do not include institutional ownership in equation (3), since inclusion of variables PCT_INST_{in} and $BROKER_NON_{in}$ would completely explain the dependent variable (i.e., $PART_{in} = 1 - PCT_INST_{in} - BROKER_NON_{in}$).

[22] We do not include institutional ownership in equation (4), since inclusion of variables $PART_{in}$, PCT_INST_{in}, and $BROKER_NON_{in}$ would result in perfect collinearity (i.e., $PART_{in} = 1 - PCT_INST_{in} - BROKER_NON_{in}$).

[23] We also estimate both equations (3) and (4) using the Fama–MacBeth (1973) approach. Results are provided in Table B.6 of Internet Appendix B and are robust. In addition, in untabulated results, we find similar evidence when we estimate equations (3) and (4) for the subsets of all DRIP stocks and all non-DRIP stocks, separately.

https://doi.org/10.1017/S0022109017000394 Published online by Cambridge University Press

B. Demand for Shares: Changes in Shares Outstanding and the Pay Date Effect

We investigate the conjecture that there should be less price pressure for the subset of pay date events where firms issue more shares to meet the demand from their DRIP commitment, rather than buying shares on the open market. However, firms do not publicly disclose whether they issue new shares for the specific purpose of meeting their DRIP obligation.

In this section, we focus on the 43,635 pay date events by all DRIP firms over the period 1996–2012.[24] We then use CRSP daily data on shares outstanding (SHROUT) to identify the subset of DRIP firms that issues new shares over 2 time frames: On the pay date itself (i.e., on day 0) and over a longer event window that begins on the pay date and extends through the rest of the pay month. We consider these 2 alternative time frames because of potential delays in reporting changes in shares outstanding that may be updated by CRSP only at the month's end.[25]

By measuring the change in SHROUT over the longer window, we are assured of capturing changes that may occur on day 0 to help meet the firm's DRIP obligations, but that do not show up until the end of the month. Of course, this longer window may also weaken the power of our tests, since it is likely to include many instances where new shares are issued for purposes other than meeting the DRIP commitment, as well as instances where the number of shares outstanding is reduced (e.g., because of share repurchases).

First, we consider the relative frequencies of events when DRIP firms increase SHROUT, for each of these 2 time frames. For the short window (i.e., on day 0), there is an increase in SHROUT on 2.5% of the pay dates. For the longer window, DRIP firms experience an increase in SHROUT between the pay date and the end of the pay month for 19% of the pay date events.

Next, we formally analyze whether the magnitude of the pay date effect, AR(0), is smaller for the subset of events for which DRIP firms increase shares outstanding, while controlling for other firm attributes that are associated with AR(0), as follows:

$$(5)\quad \mathrm{AR}(0)_{in} = \beta_0 + \beta_1 \mathrm{DSHROUT}_{in} + \beta_2 \mathrm{DIV_YIELD}_{in} + \beta_3 \ln(\mathrm{SIZE}_{in}) + \beta_4 \mathrm{LPCT_INST}_{in} + \beta_5 \mathrm{SPREAD}_{in} + \beta_6 \ln(\mathrm{HILO}_{in}) + \varepsilon_{in},$$

where $\mathrm{DSHROUT}_{in}$ = a variable assigned a value of 1 for the subset of DRIP firms with an increase in shares outstanding, either on the pay date or during the longer event window that extends from the pay date to the end of the pay month.

[24] Since we focus on only DRIP firms in this analysis, it is appropriate to rely on our accurate lists of DRIP stocks from the AAII for the extended period since 1996. This sample of 43,635 pay dates excludes events when the DRIP firm changes shares outstanding during the event window (−10,+10), due to a stock split, stock dividend, or merger. This screen ensures that our analysis of the pay date effect is not confused by a dilution of shares from these other events.

[25] According to CRSP documentation, major changes in SHROUT should be recorded on the exact day of the event in the CRSP. However, firms may make smaller changes in SHROUT that the CRSP is not aware of, perhaps to satisfy DRIP obligations, or for stock grants and option exercises, or for share repurchases. Such smaller changes in SHROUT are often only recorded on the last day of the month, when the CRSP receives monthly updates from its data provider.

https://doi.org/10.1017/S0022109017000394 Published online by Cambridge University Press

This panel regression is estimated with standard errors clustered by firm (i) and quarter (n).

Two sets of regression results are provided in Table 6, for the analysis that considers an increase in shares outstanding over the 2 different time frames. Our main focus is on the coefficient of DSHROUT in Table 6, which is significantly negative in both sets of regression results. When we consider increases in SHROUT on the pay date, the subset of DRIP firms that issues new shares has a significantly smaller average pay date effect, by roughly 19 bps (i.e., $\beta_1 = -0.193$, t-ratio $= -2.7$). We also find a negative coefficient for the analogous subset of DRIP firms that increases SHROUT sometime over the longer window, between the pay date and the end of the pay month. This coefficient is smaller in magnitude and only marginally significant. Together, this evidence suggests that at least some firms manage their DRIP obligations by issuing new shares and, as a result, experience significantly less price pressure on the pay date.

TABLE 6

DRIPs, Changes in Shares Outstanding, and the Dividend Pay Date Effect

Table 6 examines the average difference in the abnormal returns on the pay date, AR(0), for the subset of DRIP firms that increases shares outstanding (SHROUT) around the pay date, while controlling for other firm characteristics, as follows:

$$\text{AR(0)}_{in} = \beta_0 + \beta_1 \text{DSHROUT}_{in} + \beta_2 \text{DIV_YIELD_K}_{in} + \beta_3 \ln(\text{SIZE}_{in}) + \beta_4 \text{PCT_INST}_{in} + \beta_5 \text{SPREAD}_{in} + \beta_6 \ln(\text{HILO}_{in}) + \varepsilon_{in}, \quad (5)$$

where $\text{DSHROUT}_{in} = 1$ if the DRIP firm increases shares outstanding around the pay date, and 0 otherwise. All other variables are defined in Tables 1 and 3. We measure the change in shares outstanding over 2 time frames: i) on the pay date (day 0) and ii) over the event window that extends from the pay date to the end of the pay month. The latter time frame represents a conservative approach, which ensures that we include changes in SHROUT that may occur on the pay date (day 0) but that may not be recorded by CRSP until the end of the month. This regression model is estimated for the sample of pay date events for all DRIP stocks each quarter over the period 1995–2012, for which CRSP shares outstanding is not missing for either time frame. The panel is estimated with standard errors clustered by firm (i) and quarter (n). *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

		Time Frame for Measuring Change in Shares Outstanding	
Variables	Coefficients	On Pay Date (Day 0)	From Pay Date (Day 0) until End of Pay Month
Intercept	β_0	0.666	0.674
t-ratio		1.5	1.5
DSHROUT	β_1	−0.193	−0.063
t-ratio		−2.7***	−1.7*
DIV_YIELD	β_2	29.20	29.26
t-ratio		4.2***	4.3***
ln(SIZE)	β_3	−0.026	−0.026
t-ratio		−1.9*	−1.9*
PCT_INST	β_4	−0.711	−0.711
t-ratio		−3.6***	−3.6***
SPREAD	β_5	3.66	3.62
t-ratio		0.5	0.5
ln(HILO)	β_6	12.97	12.99
t-ratio		4.3***	4.3***
No. of events		43,635	43,635
Panel R^2		0.041	0.041

C. Supply of Shares: Short Selling around the Pay Date

If sophisticated suppliers of liquidity try to exploit the temporary price increase around the pay date, then we would expect the volume of short selling to increase at the time of the largest positive price spike, on day 0. We investigate this

https://doi.org/10.1017/S0022109017000394 Published online by Cambridge University Press

possibility by examining daily movements in abnormal short volume ($ASV(t)_{in}$) over all 21 days in the event window $t=(-10,+10)$. This variable is constructed from Regulation SHO data on daily short volume, which is available for the 10 quarters covering the period Jan. 2005–June 2007, as follows:

$$(6) \qquad ASV(t)_{in} \quad = \quad (SV(t)/TV(t))_{in} - NORMAL(SV(t)/TV(t))_{in},$$

where $(SV(t)/TV(t))_{in}$ = ratio of short volume to total volume on day t, for stock i in quarter n; and NORMAL $(SV(t)/TV(t))_{in}$ = mean of $(SV(t)/TV(t))_{in}$ over days $t=+11$ through $+30$.[26]

For every day in the event window $t=(-10,+10)$, we examine the mean values of $ASV(t)_{in}$ for the subsets of DRIP stocks versus non-DRIP stocks in 2 portfolios: I) ALL_STOCKS and II) HIGH_DY. For a firm event to be included in this analysis, we require at least 1 day with nonzero shorting volume in the postannouncement window (+11,+30). This requirement reduces the sample to 6,451 events for portfolio I and 2,261 events for portfolio II.[27] As before, for every quarter (n), we first compute the cross-sectional average of $ASV(t)_{n}$ for each day (t) in the event window, and then we calculate the time-series mean of these cross-sectional averages over the 10 quarters in the sample period for which we have short sales data.

Results are plotted in Graphs A and B of Figure 4 for the subsets of DRIP stocks and non-DRIP stocks, respectively, in portfolios I and II. The confidence intervals for the mean $ASV(t)_{n}$ are obtained from the standard errors of the time-series means, for the subset of DRIP stocks or non-DRIP stocks in portfolio II.[28] For the 2 portfolios of DRIP stocks in Graph A, average abnormal short volume is positive on all but 1 day in the event window, and it is significantly greater than 0 on days −3 and 0. In addition, the magnitude of the spikes in abnormal short volume on these 2 days increases somewhat as we move from the portfolio of all DRIP stocks (I) to the subset of high yield DRIP stocks (II). For portfolio II, the average abnormal short volume is 1% of total volume on day 0.

For the analogous subsets of non-DRIP stocks in Graph B of Figure 4, we find no evidence of abnormal short selling around the pay date. The average abnormal short volume is small in magnitude for each day in the event window, and it is never significantly greater than 0. This result is consistent with the lower temporary inflation for these subsets of non-DRIP stocks that is documented in Table 1 and Figure 2. Together, this evidence supports the view that short sellers are attracted by the predictable price spikes around the pay date for DRIP stocks,

[26] Our daily short-sales data are obtained from the self-regulatory organizations (SROs) that made tick data on short sales publicly available starting on Jan. 2, 2005, as a result of Regulation SHO. Short sales data for the NYSE are available through the Trade and Quote (TAQ) database, and all other SROs make short sales data available on their Web sites. The end date for the Regulation SHO data in our sample is July 1, 2007. Thus, we rely on the earlier lists of DRIP firms from the AAII for this period, which precedes the sample period for our main analysis, 2008–2012. Note that the subset of non-DRIP firms used in this section is classified as non-DRIP firms in 2008.

[27] We do not present the results for the third portfolio of high yield stocks that are hard to arbitrage (III) because of small sample sizes (there are less than 10 events per quarter for the DRIP and non-DRIP subsets of this portfolio).

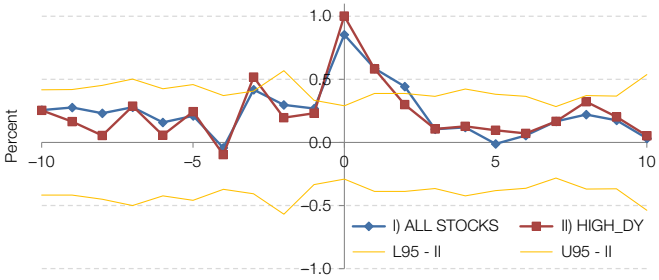
[28] Similar to our other figures, in Figure 4, the confidence interval for portfolio II is conservative for portfolio I.

https://doi.org/10.1017/S0022109017000394 Published online by Cambridge University Press

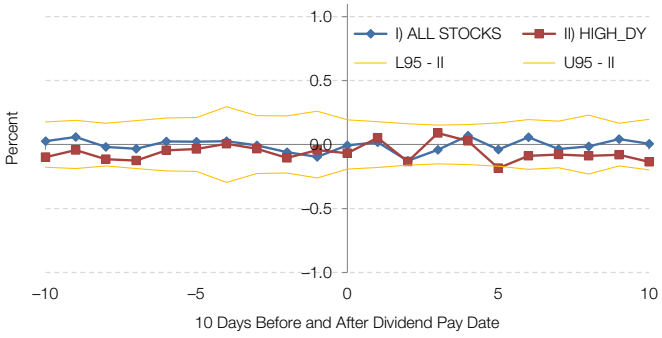
FIGURE 4
Mean Abnormal Short Volume around the Dividend Pay Date

Figure 4 plots the mean daily movements in abnormal short volume (ASV_{itn}) for the subsets of DRIP stocks versus non-DRIP stocks in 2 portfolios each quarter: I) ALL_STOCKS and II) HIGH_DY. There are too few firms in portfolio III (HARD_ARB) with nonzero short volume to obtain reliable results. Abnormal short volume is defined as $ASV_{itn} = (SV/TV)_{itn} - NORMAL(SV/TV)_{in}$, where $(SV/TV)_{itn}$ = short volume as a proportion of total volume for stock i on day t during quarter n and $NORMAL(SV/TV)_{in}$ is the mean $(SV/TV)_{it}$ over days +11 to +30 after the dividend pay date (on day 0). First, every quarter, for each day in the window (−10,+10), we compute the cross-sectional mean of ASV_{itn} across the DRIP stocks or non-DRIP stocks in each portfolio. Second, we compute the time-series mean of these cross-sectional means over the 10 quarters for which we have short sales data, Jan. 2005–June 2007. The standard error of each time-series mean is then used to construct the 95% confidence interval for the DRIP or non-DRIP stocks in portfolio II, for all 21 days in the event window.

Graph A. Abnormal Short Selling for the Subsets of DRIP Stocks in 2 Portfolios



Graph B. Abnormal Short Selling for the Subsets of Non-DRIP Stocks in 2 Portfolios



but their attempt to exploit this price spike is insufficient to eliminate this temporary inflation.

D. The Question of Identification

Since DRIPs are not randomly allocated among firms, there might be a concern about endogeneity regarding the association between DRIPs and the pay date effect documented in this study. We argue that it is unlikely that the pay date effect is caused by anything other than price pressure, which is expected to be substantially greater for stocks with DRIPs. Importantly, there is no new systematic information on the pay date and no tax-induced trading. Still, it is possible that another firm attribute may be a causal factor behind both the presence of DRIPs and the pay date effect. In this light, perhaps the most relevant difference in firm characteristics between DRIP firms and non-DRIP firms relates to liquidity.

https://doi.org/10.1017/S0022109017000394 Published online by Cambridge University Press

Table 3 documents that DRIP firms tend to be larger and more liquid than non-DRIP firms. Thus, to the extent that liquidity may create a spurious correlation between the presence of DRIPs and the pay date effect, we would expect the pay date effect (AR(0)) to be smaller for DRIP firms, not larger. In addition, we explicitly control for differences in liquidity in our analysis and we conduct several tests, which show that, within the sample of DRIP firms, our proxies for increased demand or supply of shares on the pay date display behavior consistent with the price pressure explanation.

VI. Strategies That Trade on This Price Pattern

A. Measuring the Quarterly Performance from 3 Trading Strategies

If the pay date effect reflects a liquidity premium for the temporary increase in demand on the pay date by uninformed traders, then the magnitude of the average pay day effect should be larger during periods when the average cost of liquidity is higher. We measure time-variation in the average pay date effect by analyzing the performance over time of 3 alternative trading strategies that attempt to profit from the price spike on day 0. These strategies prescribe holding the subsets of DRIP stocks in each of our 3 portfolios, I–III, on their respective pay dates.

The three trading strategies are implemented as follows. First, for every day in our sample period from 1996 to 2012, we identify every DRIP stock in each portfolio that pays a dividend on the next day (t).[29] Then, we prescribe buying the subset of all such DRIP stocks in each portfolio that pays dividends on the next day, and holding for 24 hours (i.e., use market-on-close orders to buy at the close on day $t-1$ and sell at the close on day t). In addition, we assume a short position in an exchange traded fund (ETF) that mimics the Standard & Poor's (S&P) 500 index. This strategy earns the *market*-adjusted abnormal return, $AR(0)_{it}$, for each DRIP stock (i) that pays a dividend on any given day (t).

We measure the performance of these 3 trading strategies over time, as follows. First, for every day (t) in the sample period, we compute the average $AR(0)_{it}$ across the subset of DRIP stocks (i) in each portfolio (I–III) that pays a dividend on that given date (t). The resulting mean values, AR(0)_K$_t$, reflect a daily time series of 1-day equal-weighted "abnormal profits" for each trading strategy, K = I–III, for all days (t) where at least 1 DRIP stock in each portfolio pays a dividend. There are some days when no DRIP stocks in a given portfolio (K) pay a dividend. For these days, we assume no trading profits (i.e., AR(0)_K$_t$ = 0).

Figure 5 plots the resulting stream of daily abnormal profits, AR(0)_I$_t$, from applying the first strategy that holds the DRIP stocks in portfolio I on their respective pay dates. On 3,814 (89%) of the 4,284 trading days in the sample period 1996–2012, at least 1 DRIP stock pays a dividend. This strategy produces a mean daily profit (AR(0)_I$_t$) that is positive on 2,273 (60%) of the 3,814 days that produce a trade and averages 0.31% per day across all of these trade days.

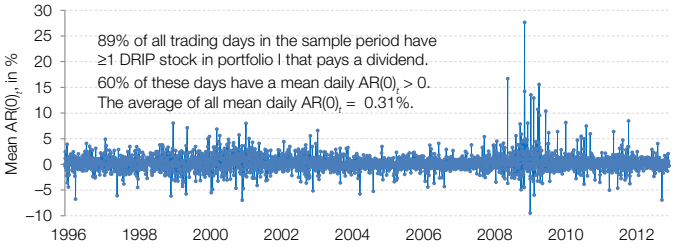
[29] Since our trading strategies prescribe buying only the DRIP stocks in portfolios I–III, it is again appropriate to rely on our accurate lists of DRIP stocks from the AAII for the extended period since 1996.

https://doi.org/10.1017/S0022109017000394 Published online by Cambridge University Press

FIGURE 5

Time Series of Daily Profits, the Mean Market-Adjusted AR(0)_I$_t$, for the Subset of DRIP Stocks in Portfolio I That Pays Dividends on Any Date, *t*

Figure 5 plots the daily time series of equal-weighted abnormal profits, AR(0)_I$_t$, obtained by averaging daily abnormal returns on the dividend pay date, AR(0)$_{it}$, across all stocks in portfolio I that pay a dividend on day *t*. First, daily returns on the dividend pay date for each stock are measured from the close on day −1 to the close on day 0. Second, market-adjusted abnormal returns, AR(0)$_{it}$, are obtained by subtracting the daily return on the S&P 500 index from the daily return for each stock. Third, every day (*t*) in the sample period 1996–2012, we compute the mean of the cross-sectional abnormal returns on the pay date, AR(0)$_{it}$, across the subset of DRIP stocks in portfolio I that pays a dividend on that date. We then plot this time series of daily mean abnormal returns, AR(0)_I$_t$, for all days (*t*) when at least 1 DRIP stock in portfolio I pays a dividend. The results reflect the stream of daily abnormal profits for the first trading strategy that prescribes holding the DRIP stocks in portfolio I on their respective dividend pay dates.



The second and third trading strategies yield similar results. For example, on 2,836 (66%) of all 4,284 trading days, at least 1 DRIP stock in portfolio II pays a dividend, producing a mean daily profit (AR(0)_II$_t$) that is positive on 1,780 (62%) of these trading days and averages 0.49% per day. Likewise, on 1,363 (32%) of all 4,284 trading days, at least 1 DRIP stock in portfolio III pays a dividend, yielding a mean daily profit (AR(0)_III$_t$) that is positive on 899 (66%) of these days and averages 0.86% per day.[30]

Next, for every quarter (*n*) in the sample period, we aggregate the series of daily profits, AR(0)_K$_t$, to obtain the implied stream of cumulative quarterly abnormal profits for each trading strategy, CAR(0)_K$_n$, K = I–III. Figure 6 plots the results for all quarters (*n*), from applying these three trading strategies. For the first portfolio of all DRIP stocks (I), the values of CAR(0)_I$_n$ are positive for 60 of the 68 quarters in the sample period and the average CAR(0)_I$_n$ across all quarters is 17.4%. Likewise, the second portfolio of high yield stocks (II) generates a similar stream of cumulative abnormal profits that are positive for 63 of 68 quarters and result in a somewhat larger mean quarterly CAR(0)_II$_n$ of 21.3%. Finally, the third portfolio of stocks that are hard to arbitrage (III) has a quarterly profit stream that is somewhat more volatile, yet these cumulative abnormal profits are still positive in 62 quarters and average 19.3% per quarter. It is noteworthy that, although each respective trading strategy triggers fewer days each quarter where a trade is made, each successive strategy produces a higher average abnormal return per day traded, resulting in similar CARs over the typical quarter.[31]

[30] In Table D.1 of Internet Appendix D, we estimate the daily alphas from Fama–French 3-factor and 4-factor models and obtain risk-adjusted returns that are similar to these mean daily profits, AR(0)_K$_t$, K = I–III.

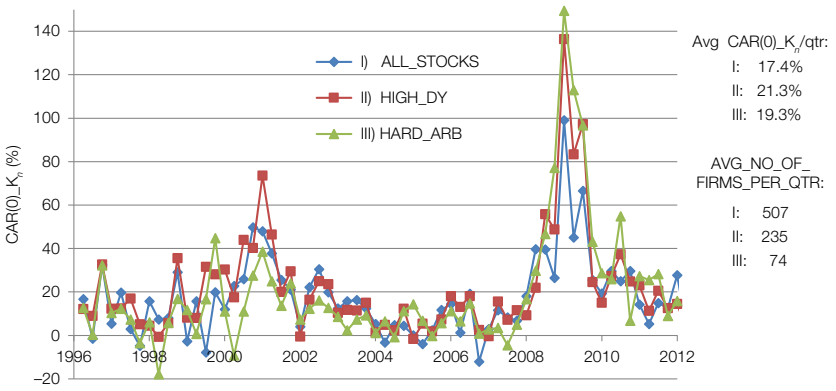
[31] In Figure C.1 of Internet Appendix C, we show that, for portfolios II and III, the price increase tends to occur gradually during the trading hours on day 0. Thus, our prescribed trading strategies will

https://doi.org/10.1017/S0022109017000394 Published online by Cambridge University Press

FIGURE 6

Time Series of Quarterly Profits, the Mean Cumulative Abnormal Return, CAR(0)_K_n, for the Subsets of DRIP Stocks in Portfolios, K = I–III, That Pay Dividends on Any Date, t, during Quarter n

Figure 6 plots the quarterly time series of the CAR(0)_K_n obtained by aggregating the daily cross-sectional mean abnormal returns on the dividend pay date, AR(0)_K_t, across all days during every quarter for which at least 1 DRIP stock in each portfolio (K = I–III) pays a dividend. First, daily returns on the pay date are measured from the close on day −1 to the close on day 0. Second, daily market-adjusted abnormal returns are obtained by subtracting the daily return on the S&P 500 index from the daily return for each stock. Third, every day (t), we compute the mean cross-sectional abnormal return on the pay date, AR(0)$_t$, for the subset of DRIP stocks in each portfolio that pays dividends on that date. Fourth, we compute the quarterly sum of this series of mean daily abnormal returns, AR(0)$_t$, over all days (t) during the quarter (n) for which at least 1 DRIP stock in each portfolio pays a dividend. The results reflect the quarterly aggregate cumulative abnormal return, CAR(0)_K_n, from the three trading strategies that prescribe holding the DRIP stocks in each portfolio (K = I–III) on their respective dividend pay dates during a given quarter (n).



B. Determinants of Time-Series Movements in Cumulative Abnormal Profits

Next, we investigate the price pressure hypothesis by examining several potential economic determinants of these 3 quarterly time series of cumulative abnormal profits. According to the price pressure hypothesis, the pay date effect (AR(0)) represents a liquidity premium that is driven by a temporary increase in uninformed demand for the shares of DRIP stocks on the pay date. This conjecture implies that, over time, the quarterly cumulative profits (CAR(0)_K_n, K = I–III) from these three trading strategies should be larger during periods when there is i) greater demand on the pay date due to higher dividend yields; ii) less liquidity, as indicated by higher spreads for these stocks; or iii) lower aggregate market liquidity. In addition, price pressure on the dividend pay date may be associated with other measures of market stress that might capture dividend demand, such as a recession dummy and the VIX (see Hartzmark and Solomon (2013)), or measures of dividend-related sentiment (see Baker and Wurgler (2004)). Finally, because of the observed increase in the pay date effect through time (see Figure 1), we also include a time trend. This discussion motivates the following time-series

capture the mean AR(0). In addition, we find results similar to Figure 6 when we plot the mean *actual* returns from these trading strategies when we do not subtract the daily market return (see CRET(0)_K_n, plotted in Figure D.1 of Internet Appendix D).

https://doi.org/10.1017/S0022109017000394 Published online by Cambridge University Press

regression model:

$$(7)\quad \text{CAR(0)_K}_n = \beta_0 + \beta_1 \text{RECESSION}_n + \beta_2 \text{TREND}_n + \beta_3 \text{DIV_YIELD_K}_n + \beta_4 \text{SPREAD_K}_n + \beta_5 \text{AGG_LIQ}_n + \beta_6 \text{VIX}_n + \beta_7 \text{DIV_PREM}_n + \varepsilon_n,$$

where CAR(0)_K_n = cumulative mean abnormal profits, CAR(0)_K_n, aggregated across all days during quarter n, where any DRIP stock in portfolio K (K = I–III) pays a dividend;

$\text{RECESSION}_n = 1$ if there is a recession (defined by the National Bureau of Economic Research (NBER)) in quarter n, or 0 otherwise;

TREND_n = time trend that counts the 68 quarters (n) in the sample, 1996–2012;

DIV_YIELD_K_n = mean dividend yield across the DRIP stocks in portfolio K (K = I–III), during quarter n;

SPREAD_K_n = mean closing percentage spread on day −10, 2 weeks before the pay date, for the DRIP stocks in portfolio K (K = I–III), during quarter n;

AGG_LIQ_n = quarterly average of the monthly measures of aggregate market liquidity during quarter n, from Pastor and Stambaugh (2003);

VIX_n = quarterly average of the monthly values of the CBOE VIX Index;

DIV_PREM_n = quarterly average of the monthly aggregate market dividend premium (PDND), from Baker and Wurgler (2006).

Table 7 provides the regression results for the first trading strategy that involves all DRIP stocks, CAR(0)_I_n, for different permutations that include subsets of the variables in equation (6). Consider the coefficients for each independent variable, in turn. First, the coefficient of the recession dummy (β_1) is significantly positive in most permutations of this model. This evidence indicates that the pay date effect tends to be larger during recessions, when there is often a premium placed on dividends. Second, the coefficient of the time trend (β_2) is significantly positive in all permutations, indicating that the magnitude of this price pressure has trended upward over time, as demonstrated in Figure 1. Third, the stream of quarterly profits is positively related to the average dividend yield for the portfolio of all DRIP stocks (i.e., $\beta_3 > 0$). This outcome indicates that a higher average dividend yield is associated with significantly greater demand for shares on the pay date for DRIP stocks, consistent with the price pressure hypothesis. Fourth, the stream of cumulative profits is also positively related to movements in the average spread across all DRIP stocks (i.e., $\beta_4 > 0$), for most permutations. This result indicates that the pay date effect tends to be greater during periods of lower liquidity (i.e., higher average spreads) for the portfolio of DRIP stocks. Fifth, we find similar evidence of a larger pay date effect during periods of lower aggregate liquidity (i.e., $\beta_5 < 0$), which is significant for some permutations of the model. Finally, the VIX and the dividend premium are not significantly related to the stream of quarterly profits for all DRIP stocks (i.e., β_6 and β_7 are not significantly different from 0).

https://doi.org/10.1017/S0022109017000394 Published online by Cambridge University Press

TABLE 7

Determinants of Quarterly Profits from the First Trading Strategy

Table 7 presents estimates for the time-series regression model that analyzes determinants of the quarterly cumulative abnormal profits from our first trading strategy, as follows:

$$(6) \quad \text{CAR(0)_I}_n = \beta_0 + \beta_1 \text{RECESSION}_n + \beta_2 \text{TREND}_n + \beta_3 \text{DIV_YIELD_I}_n + \beta_4 \text{SPREAD_I}_n + \beta_5 \text{AGG_LIQ}_n + \beta_6 \text{VIX}_n + \beta_7 \text{DIV_PREM}_n + \varepsilon_n.$$

The dependent variable, CAR(0)_I_n, is computed in 2 steps. First, for every day (t) in our sample period 1996–2012, we compute the stream of average *daily* profits as the cross-sectional mean market-adjusted AR(0)_I_t across all DRIP stocks in portfolio I (all dividend-paying stocks) that pay dividends on that day. Second, for each quarter (n), we aggregate this stream of *daily* profits, AR(0)_I_t, across all days in which at least 1 DRIP stock in portfolio I pays a dividend, to obtain the cumulative abnormal profit, CAR(0)_I_n, for portfolio I. RECESSION_n is a dummy variable that equals 1 for all quarters during recessions, and 0 otherwise. TREND_n is a deterministic trend that counts the quarters in our sample. DIV_YIELD_I_n is the mean dividend yield in quarter n for the DRIP stocks from portfolio I. SPREAD_I_n is the mean daily closing percentage spread on day −10 prior to the dividend pay dates in quarter n, for the DRIP stocks in portfolio I. AGG_LIQ_n is the aggregate market liquidity measure of Pastor and Stambaugh (2003), averaged across the 3 months during quarter n. VIX_n is the average of the monthly CBOE VIX index values during quarter n. DIV_PREM_n is the quarterly average of the monthly aggregate market dividend premium (PDND), from Baker and Wurgler (2006). The Newey–West (1987) t-ratios appear beneath the parameter estimates. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. [a]The models in the first 3 columns are estimated over the entire 68-quarter sample period 1996–2012. The last column is estimated over the period 1996–2010, due to data limitations on the PDND from Baker and Wurgler (2006).

Variables	Coefficients	1	2	3	4
RECESSION	β_1	11.24	8.14	6.99	4.91
t-ratio		2.8***	2.2**	1.9*	1.2
TREND_n	β_2	0.24	0.29	0.23	0.41
t-ratio		1.9*	2.5**	1.8*	2.1**
DIV_YIELD_K_n	β_3	85.36	74.18	70.30	62.69
t-ratio		4.4***	4.0***	3.7***	3.3***
SPREAD_K_n	β_4	10.48	11.09	8.66	10.43
t-ratio		2.9***	3.2***	1.9*	1.5
AGG_LIQ_n	β_5		−0.97	−0.75	−0.68
t-ratio			−2.6***	−1.9*	−1.5
VIX_n	β_6			0.35	0.41
t-ratio				1.1	0.8
DIV_PREM_n^a	β_7				−0.07
t-ratio					−0.3
Adj. R^2		0.54	0.59	0.60	0.63
Overall F		20.5***	20.5***	17.4***	15.1***

Table D.2 of Internet Appendix D presents analogous results for the successively smaller subsets of DRIP stocks in portfolios II and III. The results are generally consistent with the evidence in Table 7. We conclude that the pay date effect tends to be larger during periods when there is greater temporary demand for these stocks, or when there is less liquidity in these stocks or the overall market, providing further support for the price pressure hypothesis.

VII. Summary and Conclusions

This study analyzes the behavior of stock prices around the dividend pay date. Consistent with the temporary price pressure hypothesis, we find a significant price increase on the pay date, which is followed by a complete reversal. This temporary inflation is concentrated among stocks with DRIPs. It is also exacerbated for finer subsets of DRIP stocks with a higher dividend yield and for high yield DRIP stocks that face greater limits to arbitrage.

These results are corroborated by further cross-sectional and time-series analyses. First, we show that the temporary inflation is larger for DRIP stocks that are subject to greater demand on the pay date, for firms with greater DRIP

https://doi.org/10.1017/S0022109017000394 Published online by Cambridge University Press

participation and a higher dividend yield. Second, we find that the pay date effect is significantly smaller for the subset of events where the DRIP firm issues new shares as an alternative potential means to meet their DRIP obligations. Third, we document that sophisticated investors act on this predictable price pressure by increasing their short selling activity on the pay date for DRIP firms, although the resulting supply response is insufficient to completely attenuate the temporary price pressure.

We propose 3 trading strategies that are designed to take advantage of this predictable price spike on the pay date. These strategies generate a reliable stream of profits over time that is both economically and statistically significant. Time-series variation in this stream of profits is positively related to the average dividend yield and bid–ask spread of the DRIP firms traded, and it is negatively related to aggregate marketwide liquidity. These profits are surprisingly large and consistent over time, given the nature of our proposed trading strategy, which simply exploits a predictable price increase around a recurring noninformation event.

Finally, we suggest that DRIP firms and transfer agents should consider establishing a policy whereby they routinely implement their DRIP by purchasing shares over a period of several days following the pay date, in order to attenuate the price pressure on day 0. Such a policy is likely to be welfare improving from the perspective of the firm's DRIP participants.

References

Asquith, P.; P. Pathak; and J. Ritter. "Short Interest, Institutional Ownership, and Stock Returns." *Journal of Financial Economics*, 78 (2005), 243–276.

Baker, M., and J. Wurgler. "A Catering Theory of Dividends." *Journal of Finance*, 59 (2004), 1125–1165.

Baker, M., and J. Wurgler. "Investor Sentiment and the Cross-Section of Stock Returns." *Journal of Finance*, 61 (2006), 1645–1680.

Beneish, M., and R. Whaley. "Anatomy of the 'S&P Game': The Effect of Changing the Rules." *Journal of Finance*, 51 (1996), 1909–1930.

Berkman, H.; V. Dimitrov; P. C. Jain; P. D. Koch; and S. Tice. "Sell on the News: Differences of Opinion, Short-Sales Constraints, and Returns around Earnings Announcements." *Journal of Financial Economics*, 92 (2009), 376–399.

Blouin, J., and C. B. Cloyd. "Price Pressure from Dividend Reinvestment Activity: Evidence from Closed-End Funds." Working Paper, University of Pennsylvania (2005).

Boehme, R.; B. Danielsen; and S. Sorescu. "Short-Sale Constraints, Differences of Opinion, and Overvaluation." *Journal of Financial and Quantitative Analysis*, 41 (2006), 455–477.

Boehmer, E., and E. Kelley. "Institutional Investors and the Informational Efficiency of Stock Prices." *Review of Financial Studies*, 22 (2009), 3563–3594.

Broadridge and PwC. "How Well Do You Know Your Shareholders?" Available at http://proxypulse.broadridge.com/reports/How-well-do-you-know-your-shareholders.html (2013).

Chen, H.; G. Noronha; and V. Singal. "The Price Response to S&P 500 Index Additions and Deletions: Evidence of Asymmetry and a New Explanation." *Journal of Finance*, 59 (2004), 1901–1930.

Chordia, T.; R. Roll; and A. Subrahmanyam. "Liquidity and Market Efficiency." *Journal of Financial Economics*, 87 (2008), 249–268.

Daniel, K.; M. Grinblatt; S. Titman; and R. Wermers. "Measuring Mutual Fund Performance with Characteristic-Based Benchmarks." *Journal of Finance*, 52 (1997), 1035–1058.

DeAngelo, H.; L. DeAngelo; and D. Skinner. "Corporate Payout Policy." *Foundations and Trends in Finance*, 3 (2009), 95–287.

Dhillon, U.; D. Lasser; and G. Ramirez. "Dividend Reinvestment Plans: An Empirical Analysis." *Review of Quantitative Finance and Accounting*, 2 (1992), 205–213.

Diether, K.; C. Malloy; and A. Sherbina. "Differences of Opinion and the Cross-Section of Stock Returns." *Journal of Finance*, 57 (2002), 2113–2141.

https://doi.org/10.1017/S0022109017000394 Published online by Cambridge University Press

Fama, E. F., and J. D. MacBeth. "Risk, Return, and Equilibrium: Empirical Tests." *Journal of Political Economy*, 81 (1973), 607–636.
Finnerty, J. "New Issue Dividend Reinvestment Plans and the Cost of Capital." *Journal of Business Research*, 18 (1989), 127–139.
Hansen, R.; J. Pinkerton; and A. Keown. "On Dividend Reinvestment Plans: The Adoption Decision and Stockholder Wealth Effects." *Review of Business and Economic Research*, 20 (1985), 1–10.
Harris, L., and E. Gurel. "Price and Volume Effects Associated with Changes in the S&P 500 List: Evidence for the Existence of Price Pressures." *Journal of Finance*, 41 (1986), 815–829.
Hartzmark, S. M., and D. H. Solomon. "The Dividend Month Premium." *Journal of Financial Economics*, 109 (2013), 640–660.
Holthausen, R.; R. Leftwich; and D. Mayers. "Large-Block Transactions, the Speed of Response, and Temporary and Permanent Stock-Price Effects." *Journal of Financial Economics*, 26 (1990), 71–95.
Kaul, A.; V. Mehrotra; and R. Morck. "Demand Curves for Stocks Do Slope Down: New Evidence from an Index Weights Adjustment." *Journal of Finance*, 55 (2000), 893–912.
Keown, A.; J. Pinkerton; and P. Shalini. "Market Reaction to the Formulation of Automatic Dividend Reinvestment Plans." *Review of Economics and Finance*, 26 (1991), 48–58.
McLean, R. D., and J. Pontiff. "Does Academic Research Destroy Stock Return Predictability?" *Journal of Finance*, 71 (2016), 5–32.
Mikkelson, W., and M. Partch. "Valuation Effects of Security Offerings and the Issuance Process." *Journal of Financial Economics*, 15 (1986), 31–60.
Mitchell, M.; T. Pulvino; and E. Stafford. "Limited Arbitrage in Equity Markets." *Journal of Finance*, 62 (2002), 551–584.
Mitchell, M.; T. Pulvino; and E. Stafford. "Price Pressure Around Mergers." *Journal of Finance*, 59 (2004), 31–63.
Nagel, S. "Short Sales, Institutional Investors and the Cross-Section of Stock Returns." *Journal of Financial Economics*, 78 (2005), 277–309.
Newey, W. K., and K. D. West. "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." *Econometrica*, 55 (1987), 703–708.
Ogden, J. P. "A Dividend Payment Effect in Stock Returns." *Financial Review*, 29 (1994), 345–369.
Pastor, L., and R. Stambaugh. "Liquidity Risk and Expected Stock Returns." *Journal of Political Economy*, 111 (2003), 642–685.
Peterson, P. P.; D. R. Peterson; and N. H. Moore. "The Adoption of New-Issue Dividend Reinvestment Plans and Shareholder Wealth." *Financial Review*, 22 (1987), 221–232.
Pettway, R., and R. P. Malone. "Automatic Dividend Reinvestment Plans of Nonfinancial Corporations." *Financial Management*, 2 (1973), 11–18.
Sadka, R., and A. Scherbina. "Analyst Disagreement, Mispricing, and Liquidity." *Journal of Finance*, 62 (2007), 2367–2403.
Schleifer, A. "Do Demand Curves for Stock Slope Down?" *Journal of Finance*, 41 (1986), 579–590.
Scholes, M. "The Market for Corporate Securities: Substitution versus Price Pressure and the Effects of Information on Share Price." *Journal of Business*, 45 (1972), 179–211.
Scholes, M., and M. Wolfson. "Decentralized Investment Banking: The Case of Discount Dividend-Reinvestment and Stock-Purchase Plans." *Journal of Financial Economics*, 23 (1989), 7–35.
Schwert, G. W. "Anomalies and Market Efficiency." In *Handbook of the Economics of Finance*, G. M. Constantinides, M. Harris, and R. Stulz, eds. Amsterdam, The Netherlands: Elsevier Science B.V. (2003), 939–974.
Stambaugh, R.; J. Yu; and Y. Yuan. "The Short of It: Investor Sentiment and Anomalies." *Journal of Financial Economics*, 104 (2012), 288–302.
Wermers, R. "Is Money Really 'Smart'?: New Evidence on the Relation between Mutual Fund Flows, Manager Behavior, and Performance Persistence." Working Paper, University of Maryland (2003).
Yadav, V. "The Settlement Period Effect in Stock Returns around the Dividend Payment Days." Working Paper, INSEAD (2010).

https://doi.org/10.1017/S0022109017000394 Published online by Cambridge University Press