Predictable Price Pressure

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ABSTRACT

We demonstrate that predictable uninformed cash flows forecast market and individual stock returns. Buying pressure from dividend payments (announced weeks prior) predicts higher value-weighted market returns, four times greater on the top quintile of payment days than the lowest. This effect holds internationally, varies with reinvestment intensity, and increases with high VIX. Selling pressure leads predictable high stock expense firms to have lower returns when selling restrictions lift, by 117 bp in four days. We estimate market-level price multipliers of 1.5 to 2.3. These results suggest price pressure is a widespread result of flows, rather than an anomaly.

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If more people attempt to exchange twenty dollar bills for strawberries at their current price, textbook microeconomic theory suggests that the price of strawberries will rise. By contrast, if more people attempt to exchange twenty dollar bills for hundred dollar bills, except in unusual circumstances, the price of hundred dollar bills (denominated in twenty dollar bills) will not rise. What, then, should the prediction be when more people attempt to convert their twenty dollar bills into shares of Microsoft? Is Microsoft merely a stream of agreed-upon future cash flows, a sequence of hundred dollar bills of well-understood value? Or is it like strawberries, where the simple act of more people arriving to the market trying to buy is enough to influence its price?

At the core of most asset pricing models is the assumption that a stock is like a hundred dollar bill. If an investor wants to trade, and it is clear that he has no private information, he should be able to buy or sell any number of shares at the current price (e.g. Sharpe 1964, Ross 1976, and many others). However, if there is a possibility that a trader wants to purchase or sell a stock because he has private information about its value, then the act of trying to trade should shift prices, as the trade potentially reveals private information. Testing this hypothesis that uninformed trade does not shift prices thus necessitates a situation where traders predictably have money to invest (for reasons unrelated to predicting future returns) and invest this money without an information advantage. If textbook asset pricing models are correct, such a situation would not influence prices. But if trades themselves inherently affect prices, then predictable buying will produce higher returns and predictable selling will produce lower returns. Across a variety of markets and settings, we find that predictable uninformed shifts in demand and supply of stocks lead to predictable price changes.

In order to establish that price pressure is a predictable and natural consequence of increases in buy or sell orders, we study the question in settings that ex ante ought to have the *least* likelihood of observing price effects. First, like Gabaix and Koijen (2020), we primarily consider changes in demand for the deepest and most liquid test assets - the value-weighted market portfolio. Second, like Hartzmark and Solomon (2013) (but unlike Gabaix and Koijen 2020) we consider settings where shifts in demand are *predictable* in both timing and amount. This predictability gives liquidity-providing market participants the best chance to make offsetting trades to prevent price impact.

We begin by studying dividend payments. No new information is revealed on the the payment date, as it occurs weeks after the announcement and the ex-day (the first day a buyer of a stock will not receive the dividend). While most of the dividends received by retail investors are consumed (e.g. Hartzmark and Solomon 2019, Di Maggio, Kermani, and Majlesi 2020, Baker, Nagel, and Wurgler 2006), other investors predictably invest this money into the market. Thus, dividend-related flows are not only uninformed, but ought to be understood as such by market participants. This makes them strong candidates for plausibly exogenous and uninformed shifts in demand.

We find that when daily dividend payouts are higher, daily value-weighted market returns are significantly higher. The magnitude of this effect is considerable - a one standard deviation increase in payout is associated with higher returns of 3.2 basis points (compared to an unconditional mean return of 4.1 b.p.). Value weighted market returns are four times higher in the highest quintile of dividend payment days than in the lowest. This is not due to shifts in the denominator of stock market capitalization. Similar effects are obtained with year-by-month fixed effects, or with a measure of abnormal dividends based on the difference from the longer–term average daily dividend. These effects survive controlling for day-of-the-week effects, turn-of-the-month effects (e.g. Lakonishok and Smidt 1988), Fed announcement days (Lucca and Moench 2015) and other macroeconomic announcement days (Savor and Wilson 2013). Daily value-weighted returns are 12.8 b.p. higher if dividends are in the top 5 days of the past 250, and 4.8 b.p. higher if they are in the top 50 days.

We next show that this result holds on average in 58 international markets. High dividend payouts are associated with high market returns after controlling for worldwide daily patterns in returns and dividends. If a country has higher dividends on a given day relative to other countries, it tends to have higher returns that day.

Consistent with price pressure from uninformed demand, market predictability is related not just to the amount of dividends, but their likelihood of reinvestment. Asset managers typically make their largest payouts in the fourth quarter, most commonly in December, making them less likely to reinvest dividends at such times (as they need to shortly pay out the cash to their own investors). During the fourth quarter, dividend payments do not predict market returns. At the other extreme, during the first quarter, when dividend investment is likely to be highest (as most managers have a long time before needing to pay out again) we find the largest effect. A one standard deviation increase in dividend payments in the first quarter is associated with an increase in the value-weighted market return of 6.4 b.p. Evidence from the overall time series is also consistent with the importance of asset managers. The impact of dividend price pressure has increased since roughly 1990, as mutual funds, ETFs and other asset managers have become a larger component of equity holdings. Consistent with liquidity being important for price pressure, when the VIX index is at its highest quintile, the price impact from dividends that day more than doubles.

Up to this point, we have been agnostic over whether the increase in buy orders will lead to a permanent price impact (as Shleifer (1986) argues occurs with index additions) or a temporary price impact (as Hartzmark and Solomon (2013) show for purchases of stocks by dividend-seeking investors). Using our baseline specification we find no evidence of a reversal over the month after dividend payment, If anything, the data suggests a continuation, consistent with some investors reinvesting dividends with a delay. We test for a longer term reversal by examining the cross-section of industry returns, and how they relate to past price pressure. We take each industry portfolio and regress its daily returns from 13 months ago to one month ago on daily dividends, to measure how sensitive that industry's returns are to past payouts. We find that industries in the highest quartile of exposure to dividend price pressure over the previous year underperform those in the lowest quartile by 28 basis points per month, with a t-statistic of 3.38. This is consistent with some of the price pressure from dividend payment eventually reversing.

The analysis of price pressure so far has considered buying pressure. This is not because there should necessarily be a difference in the influence of selling and buying, but simply due to the clean identification offered by dividend payments. To identify evidence of predictable selling pressure, we examine stock compensation. Some firms predictably have high stock expenses due to paying a significant portion of employee compensation using equity. These employees have incentives to sell this as soon as possible. Many firms allow employees to trade only within a limited window, typically after earnings are announced. This should lead to concentrated selling pressure after earnings announcements for high stock expense firms, but it is predictable and uninformed selling pressure of the sort that the market should easily understand and offset. To demonstrate the expense is easily predictable and not related to news in the current announcement, we focus on stock expenses announced the prior quarter. We find that firms with higher stock expense have more negative returns. Firms in the top 5% of stock expense have returns of more than -117 b.p. (t-statistic of 5.50) in the four days after their earnings announcement.

Finally, we perform a back-of-the-envelope calculation to estimate the multiplier of prices with respect to reinvested dividends, similar to Gabaix and Koijen (2020). This represents the magnitude of a market capitalization increase for a dollar of dividends reinvested (i.e. the inverse of elasticity). We estimate reinvestment rates for different investor groups, and combine this with our results to give a multiplier of 1.5 to 2.3. This is somewhat lower than that in Gabaix and Koijen (2020), showing potentially that the size of the multiplier estimated may be sensitive to methodology and which flows are used for estimation. One particularly important difference is that the flows studied in Gabaix and Koijen (2020) are not anticipated. In this respect, their model predicts that the flows we study should have *smaller* effects than what we find. In other words, despite the fact that our estimated multipliers are lower, they are puzzlingly large under their model.

This paper fits into several strands of literature showing the existence of price pressure. A number of papers have explored reactions to one-off events. When companies are added to an index, this results in a mostly permanent increase in price (Shleifer 1986, Harris and Gurel 1986, Wurgler and Zhuravskaya 2002, Chang, Hong, and Liskovich 2015). A related literature on fire sales explores how flows in mutual funds can induce price pressure from predictable purchases and sales of underlying assets (Coval and Stafford 2007, Lou 2012, Frazzini and Lamont 2008). Ben-David et al. (2020) argue that flows from Morningstar ratings changes induce price pressure to individual stocks and that changes to the ratings systems influenced the dynamics of cross-sectional style returns as well. Also on the individual stock side, there are positive payment date returns for individual stocks that have dividend reinvestment plans (Berkman and Koch 2017) and for stocks owned by a mutual fund when the fund receives a payment (Schmickler 2021). Price pressure is found in events that are both predictable and recurring, as when companies declare a dividend, there are price increases in the lead-up to the ex-day, and negative returns thereafter (Hartzmark and Solomon 2013).

Evidence of price pressure for *entire markets* is harder to find. Closest in this respect is Gabaix and Koijen (2020), who use granular instrumental variables to show how demand shocks to institutions can be used to estimate the multiplier of flows on prices. Parker, Schoar, and Sun (2020) examine the mechanical rebalancing by target date funds and find evidence that these flows influence both the cross-section of stock returns as well as overall market dynamics. Da et al. (2018) finds evidence of market-wide price pressure in Chile for stocks and bonds following a firm's recommendations for pension allocations and Li, Pearson, and Zhang (2020) show that flows based on IPO regulations influence the Chinese market. Our paper complements this work by providing evidence of predictable price pressure through a much simpler identification channel where the argument for the flows being uninformed is strong, and where the flows are predictable in both timing and amount.[1] This reinforces the conclusion that price pressure is evident even at the asset class level, for the largest and most liquid stock market in the world.

This notion has significant implications for financial markets. It provides a parsimonious framework for understanding the large and continued price rises of cryptocurrencies, and for the price rise in "meme" stocks like Gamestop in 2021. It provides simple and intuitive explanations for why order flow matters for currencies, and why the Federal Reserve can influence asset prices in low interest rate environments. It predicts that demographic shifts will affect prices. We discuss these ideas more at the end of the paper.

The results point to the existence of price pressure based only on predictable flows, in both buying and selling directions, at the broad level of the market and for individual firms. This suggests that price pressure should be plausible default assumption in any scenario when considering how changes in buy and sell orders affect prices. This raises the difficult question of understanding why we observe such buying or selling in the first place. The conceptual difficulty of this task, however,

[1] Much of the literature examining price pressure lacks the granularity of data to disentangle information released by announcements from the direct influence of buying or selling on price. Our use of daily data with announcements occurring long before payments means that we can cleanly identify the influence of buying and selling alone.

does not justify assuming away the problem by positing that liquidity is infinite.

I. Framework

For most settings in microeconomics, more buyers attempting to purchase a good at the current price will lead to the prediction of a price rise. The simplest intuitions given to undergraduate microeconomics students typically partition the world into consumers of products who make up the downward-sloping demand curve, and producers who make up the upward-sloping supply curve. The price is given by the intersection of those curves, which varies based on changes to the buyers (shifts in demand) and to the sellers (shifts in supply).

This is not the most common way to think about the supply and demand for a stock, however. Supply is usually described as the total number of shares outstanding, fixed in the short term. This means that the supply curve is a vertical line (see Shleifer (1986) for a discussion of the standard intuition). The (net) demand curve, of buyers minus sellers, is typically assumed to be horizontal.[2]

While there is nothing *incorrect* about this framing, it creates considerable confusion, both conceptually and in how it maps to real life trading. To see this, consider what the phrase "a shift in demand" means in this framework. In the normal case of downward sloping demand, it makes no difference if the demand curve is considered to be transposed *vertically* (i.e. a willingness to pay a higher price for the same quantity) or if it is transposed *horizontally* (i.e. buying a greater quantity at each price), because the final effect is the same. Indeed, the expressions "demand shifts up", "demand shifts to the right", and "demand shifts up and to the right" are generally used as *synonyms*, meaning that most students likely have not considered which version they have in mind.

For horizontal demand, this equivalency is removed. An increase in quantity demanded given the price (a horizontal transposition) has no influence. It leads to an identical line, as unconstrained net demand is infinite at the market price, and is zero at a price of one penny more. However, if a shift in demand is interpreted as a shift in the willingness to pay (a vertical transposition), this leads to a shift in price. These two different predictions lack a distinct vocabulary, making it challenging

[2]Or nearly so. See Gabaix and Koijen (2020) for quantification of the the demand curve slope in various models.

for students to grasp how the model is meant to work.

When this conceptual confusion is cleared up, the formulation yields intuition about market dynamics from a representative agent under the efficient market hypothesis, namely that the market is willing to bear a net demand equal to any quantity at the prevailing market price, with quantity set by the fixed number of shares. But in doing so, it obscures, rather than illuminates, the effect of different traders' beliefs or liquidity needs. The day-to-day buying and selling of stocks is not represented by interactions of supply and demand, but rather it occurs *within* the net demand curve. While it is common to hear popular discussion of increased demand, or a shortage for a financial security, there is no room for such a concept in these models. The framework makes concepts like "price pressure" confusing. Pressure on what? One investor is buying, one investor is selling, and the quantity of shares is fixed. How can the aggregate investor have price pressure?

An alternative conception, and we feel a more useful one, is to consider demand and supply in terms of people bringing trades to market. At a specific moment in time, this maps closely to the concept of the limit order book (aggregated over all trading venues). For most economic applications, the instantaneous elasticity is not the length of time over which price impact is evaluated, so it is worth extending the concept over the relevant horizon, such as a day or a month, etc. There is no real world analogue to this, but the theoretical goal is to capture investors in the current limit order book along with all those who would enter the market when prices shift. In such a scenario, supply is no longer the number of shares outstanding. Rather, it is the number of shares of a stock that would enter as sell orders over the horizon of interest if the price shifted. We feel that this formulation yields significantly more intuition, as the number of shares outstanding is not generally a constraining factor in the number of sell limit orders that can be placed.[3] Similarly, demand is the number of shares that would enter as buy orders under the same circumstances.

Price pressure in this framework is easily understood, as intuitions about elasticity map into orders submitted by traders. When a sufficiently large liquidity-demanding order is placed, it will eat through the limit orders in the book, and eventually will affect the last trade price. The question

[3]Short sellers can generally borrow shares and generate greater numbers of sell limit orders. Even the company itself can also be reduced to a potential seller or purchaser of shares, rather than the main determinant of supply.

is what happens next. If aggregate net demand is perfectly elastic in the standard framework, this is equivalent to saying that this theoretical limit order book over some period of time has *infinite depth at both the bid and the ask.* Put this way, this assumption is far from innocuous. At short horizons we can observe a finite depth of the current limit order book for all securities.

Thus, to motivate perfectly elastic demand, there must be an arbitrage mechanism functioning beyond the current limit order book. The standard assumption is that investors will realize that the price has deviated from fundamentals, and place large trades in the opposite direction to restore the price to its previous level. While this could be the case, perhaps they won't, either due to lacking capital, or thinking the trade isn't worth it, or being uncertain whether the counter-party knows something they don't, or trading in the opposite direction thereby exacerbating rather than correcting the mispricing (e.g. Brunnermeier and Nagel 2004). In any case, the idea of offsetting limit orders to replace price-affecting trades (even if economically intuitive in certain contexts) is an additional assumption layered on top of the mechanics of the limit order book. In other words, price pressure is a general and largely *mechanical* prediction, whereas offsetting trades are an economic prediction arising from particular models of how investors trade.

This is the framework we explore in this paper. We evaluate the above concept - are offsetting trades so plausible that they should be considered the default? Predictable shifts in buy and sell orders are especially well-suited to this task. If large order flows come in by surprise, it may be understandable that traders are caught unaware, and either take longer to respond, or do not know what to infer from the price changes. However, rational actors cannot be predictably surprised by recurring information due to the law of iterated expectations. If the shifts in orders happen on a predictable basis, and other traders *still* do not respond enough to stop them affecting prices, this makes it plausible that some level of price pressure from changes in orders ought to be considered a reasonable null hypothesis, not an aberration requiring additional explanation.

This simple framework allows us to derive a number of testable predictions. First, buy and sell orders should have price pressure. More people attempting to buy a stock (or the market) will lead to price increases, and more people attempting to sell a stock will lead to price decreases. Second, the magnitude of these effects will increase with the desired amount of stock being purchased or sold. Finally, because price pressure is fundamentally about limited liquidity, we predict that the effects of a given amount of buying or selling will be greater in periods of lower liquidity.

II. Data

Stock return data is from the Center for Research in Securities Prices (CRSP), including returns, dividend amounts and payment dates. We limit our return data to ordinary common shares (codes 10 or 11) listed on the NYSE, NASDAQ or AMEX. For dividend amounts we examine ordinary cash dividends. We examine data from 1926 through 2018. Monthly mutual fund holdings comes from CRSP. Stock compensation expenses come from Compustat. International stock returns data comes from Compustat Global. Fama and French industry portfolios are from Ken French's website.

Unless otherwise noted, when we refer to a dividend and its timing it is based on the payment date. For example, when we refer to a dividend date or a dividend yield, we are referring to date or yield based on the payment date. The major exception to this is when we examine mutual fund dividends as there is not payment date information for fund dividends, so the ex-date is used.

III. Results

A. Aggregate Dividend Payments and Market Returns

Our first set of tests examines the impact of aggregate dividend payments on market returns. Aggregate dividend payments represent an interesting source of price pressure because their timing is completely predictable well in advance of the date the payments actually occur. The fact that the payments are known in advance, and result in predictable reinvestment, offers clean identification of whether uninformed flows into the market impact prices.

While there is uncertainty in the timing and amount of dividends that companies will declare, this is resolved when the dividend is announced. Once the dividend is declared, companies have a legal obligation to pay it.[4] Moreover, there is usually some delay, on average 21 days, between the announcement of the dividend and the ex-date (the first day when those who buy the share will not receive the dividend). The ex-date is when any implications of receiving a dividend payment, such as tax consequences, are resolved. We focus on the payment date, which on average occurs 22 days after the ex-date, and so is on average 43 days after the initial announcement. The payment date is the date when cash is disbursed, and lacks economically meaningful news or tax implications.

As a consequence, dividend payment amounts are predictable well before they occur. Market-wide dividend payments also exhibit substantial day-to-day variation due to idiosyncratic differences between individual companies' payment dates, as well as large differences in firm size. Further, while there is some seasonality in dividend payments, over 90% of trading days involve a dividend payment.

An increase in cash must end up somewhere - it can be consumed, left in cash or the money market, or invested into risky securities. We focus on the latter as a potential driver of returns. Hartzmark and Solomon (2019) show that investors of any type, including institutional investors and mutual funds, do not generally reinvest dividends into the securities from which they came. Given the paucity of same-stock reinvestment, this raises the question of whether the remainder of the dividend amounts are invested into other stocks, which may be inducing price pressure.

To consider the broadest and most liquid set of test assets, we take as our main dependent variable the value-weighted market portfolio from CRSP. While the choice of which stock to purchase with a dividend payment might be driven by private information, the predictable reinvestment into the overall market should be easily understood as uninformed.

The final question is the timeline under which people use a dividend payment to purchase securities. Dividend reinvestment likely occurs with different timing for institutional reasons, differences in attention, and differences in strategy. If investors trade once their cash balances update, differences in reinvestment timing could be due to differences in when the cash appears in an account.[5]

[4] Even in the event of corporate bankruptcy before the payment date, shareholders are unsecured creditors for the amount of the dividend.

[5] Attentive investors could trade before the payment date, since cash is only required at settlement. The settlement date, occurs two or three days after the purchase date, depending on when in the sample the trade occurred. Further, an investor could borrow against a future dividend and trade sooner. If such behavior were widespread we would not expect price pressure on the dividend payment date itself, because investment of the payment would occur prior. In

For example, some institutions update balances throughout the day (allowing for trade on t=0 and after), though many banks clear each day's deposits that night (allowing for trade on t=1 and after).[6] Further, not every attentive investor has a strategy that trades every day. In addition, some investors may not be attentive to a dividend payment, and reinvest only when the higher cash balance comes to their attention. We lack details for the myriad of institutions, time periods and strategies involved, so while we predict there will be reinvestment on the payment date and the days immediately following it, we are agnostic as to which specific day should have the largest effect.

Table I examines the effects of daily payment yield on value-weighted market returns. The independent variable is the dividend payment yield on a payment day t, which is the daily total dividend payments, divided by the previous day's total market capitalization. If a dividend payment is invested on the payment date and induces price pressure, the market return on date t would be predicted by the dividend payment on date t, while if it is invested the day after the payment date, the market return on date t would be predicted by the dividend payment on date t-1. In column 1, we consider dividend payments at various lags from zero days to four days. This shows a coefficient on payment yield of 55.76 for day t (t-statistic of 1.74), 60.04 for day t-1 (t-statistic of 2.73). Days t-2 and t-3 are smaller and statistically insignificant, though day t-4 is also larger and marginally significant (t-statistic of 1.89). In terms of magnitudes, a one standard deviation increase in payout yield (.0003176) predicts higher returns of 1.8 b.p. on day t, and 1.9 b.p. on day $t+1$.

Payout yield uses the market level as a denominator, so we wish to make sure that the effects capture variation in dividends, not variation in market level. We deal with this problem in several ways. As a first step, in column 2 we include a year-by-month fixed effect. If the concern is that the price-to-dividend ratio predicts long-term periods when the market has a higher or lower return, a year-by-month fixed effect will control for general differences in such an average. This also controls for specific calendar effects (e.g. the January effect in Rozeff and Kinney Jr (1976) and Thaler (1987)). The inclusion of this fixed effect increases the magnitude and significance of the

unreported results we find no evidence of price pressure in the days before the payment date.

[6]There is likely heterogeneity across institutions as to when in a day a payment appears in an account, even if the payment appears on the same day. Further, we expect that in the early period of our sample there was likely more heterogeneity and longer lags for a payment to clear, though we lack documentation from this period.

coefficients, to 74.85 on day t (t-statistic of 2.26), 71.98 on day t-1 (t-statistic of 3.10), and 66.66 (2.32) on t-4 (with days t-2 and t-3 also being slightly larger, though insignificant).

Given this daily pattern, in columns 3 and 4 we focus on the main variable we will use, the cumulative dividend payment yield on the payment date and the day before.[7] Column 3 finds similar effects to column 1 - dividend payout from day t and day t-1 positively and significantly predicts value-weighted market returns on day t (coefficient of 59.50 and t-statistic of 3.32). When year-by-month fixed effects are added in column 4, the results are again stronger, with coefficients increased to 67.07 and a t-statistic of 3.47. A one standard deviation increase in payout yield over days t and t-1 (.0004711) predicts higher daily returns of 3.2 b.p. on day t.

In columns 4-8, we perform the same tests using the equal-weighted market portfolio. In general, the effects are slightly larger, though in columns 5 and 6 relatively more of the effect is for returns on day t rather than day t+1. When looking at two-day effects combined, in columns 7 and 8, the effects are also somewhat larger. These results, though slightly larger in point estimate, seem to reflect a broadly similar picture to that using the value-weighted market.

While year-by-month fixed effects remove slow-moving trends in the market price, it is possible that the effects are driven by day-to-day fluctuations in the denominator. We employ a number of empirical strategies to ensure that this is not the case. First, in Table II Panel A we examine a measure of dividend payment that does not employ market prices at all. Specifically, we construct an abnormal dividend yield which is dividends on days t and t-1 divided by the average daily dividend paid over the prior year.[8] When market returns are regressed on abnormal dividends, the results are positive and statistically significant at the 1% level, regardless of whether value-weighted (columns 1 and 2) or equal-weighted (columns 3 and 4) returns are used, and regardless of whether year-by-month fixed effects are included. Taking the value-weighted estimate in column 2, a one standard deviation increase in the dividend yield is associated with an increase in expected returns of 2.7

[7]We find the t-4 effect likely reflects delays in receiving the dividend in the early period of our sample, so we mostly focus on the first two days where the predictions are clearest. Running the Column 2 specification using data prior to 1960 yields a coefficient on Mkt Div Pay[t-4] of 79.9 (t-statistic of 1.83), post 1960 this coefficient is 45.73 (t statistic of 1.58), and post 1980 is 32.23 (t-statistic of 0.73).

[8]We calculate this average using the trading days from t-20 to t-272. The average year contains 252 trading days and we skip about a month (20 trading days) to ensure the denominator excludes any recent market information.

b.p., similar to the 3.2 b.p. found from the same specification normalizing by market capitalization.

Figure 1 examines how value-weighted returns vary with this abnormal dividend.[9] We split days into quintiles based on the abnormal dividend and take the average of the value-weighted market returns in each quintile. The graph shows a monotonically increasing relationship between payment yield and returns. The returns in the lowest two quintiles are about 2 basis points. For the next two quintiles this value increases to roughly 4 basis points. The top quintile of abnormal dividends is associated with value-weighted market returns of about 8 basis points.

The graph suggests that the largest effect is concentrated in more extreme dividend payment dates. To test this, and to use a simple rule that is easy to interpret and ex-ante tradable, we examine whether or not a given day's dividend payment is in the top five or fifty days out of the previous 250. We regress market returns on a dummy variable equal to one if the current or prior day falls in the top five or fifty days and equal to zero otherwise. These regressions display the magnitude of the return effect from the regression coefficient, as it represents how different the return on these extreme dividend payment days is relative to the other days.

Column 1 of Table II Panel B shows that with no controls, the top 5 days are associated with higher value-weighted returns by 12.8 b.p., with a t-statistic of 2.99. In column 2, with a year-by-month fixed effect, this increases slightly to 14.3 b.p. In columns 3 and 4, the results are similar when examining equal-weighted returns. In column 5, without adding controls, being in the top 50 days results in higher value-weighted returns of 4.8 b.p. (with a t-statistic of 3.34). Again, adding a year-by-month fixed effect increases the coefficient to 5.9 b.p. with a t-statistic of 3.93. In columns 7 and 8, the effects are slightly smaller, though materially similar, using equal-weighted returns.

Figure 2 demonstrates the cumulative magnitude of these effects. We plot the cumulative returns to a $1 investment in 1926 for a strategy that invests in the value-weighted market portfolio only on days where the dividend payment yield on day t or t-1 is in the top 50 days (red line) compared with the same investment only on days outside the top 50 (blue line). Despite the fact that the blue line has about double the number of days of exposure to the market (and the associated equity

[9] In addition to not being influenced by daily variation in the market price, the abnormal dividend is also largely independent from long run changes to the market dividend yield (e.g., Fama and French 2001).

premium), the high payment day red line cumulated to $254 by the end of the sample, compared to only $20 for the low payment blue line. Panel B shows the same effect, but if a strategy is not invested in the market it earns the risk free rate, rather than the zero earned in Panel A. The high dividend exposure portfolio has final value of $1,849 and the low dividend portfolio $56.

A question that naturally arises is whether the effects represent price pressure in the companies that paid the dividend, or elsewhere in the market. We note that Hartzmark and Solomon (2019) document that, when looking at mutual funds and institutions, dividends are rarely reinvested into the stocks that they came from. If this is the case, we predict that price pressure should not be limited to the firms that actually paid the dividend.[10]

In Panel C of Table II, we consider how the effects are different for the firms paying dividends that day versus other firms, and find the strongest effect for firms that do not pay the dividend. For columns 1-4, when examining non-dividend-payers, the results are similar in magnitude and significance to Table I, regardless of whether the results are value-weighted (columns 1 and 2) or equal-weighted (columns 3 and 4), or whether or not year-by-month fixed effects are included (columns 2 and 4). When the effects of dividend payment is examined for firms that paid the dividends on those days, the results are considerably smaller - around two thirds as large for value-weighted returns (columns 5 and 6), and one-quarter to one-third as large, and statistically insignificant, for equal-weighted returns (columns 7 and 8).

Another potential confounding effect is that returns vary over the week (with the lowest returns on Monday and the highest on Friday), as well as over the month (with the highest returns at the turn-of-the-month, as in Lakonishok and Smidt 1988). If dividend payments are more likely on certain days of the week or periods of the month, payment yield might proxy for such effects.

Table III Panel A examines such effects and finds they are unlikely to account for the results. Columns 1 and 2 include day-of-the-week fixed effects, columns 3 and 4 include turn-of-the-month fixed effects and columns 5 and 6 include both.[11] All of the coefficients are positive and significant,

[10]It is difficult to predict the relative magnitudes of effects for paying and non-paying firms. Even if the majority of money is invested outside paying firms, there are many more non-paying firms. Thus we predict *some* price pressure for non-paying firms, but the relative amount of price pressure for the two groups is ultimately an empirical question.

[11]Following Lakonishok and Smidt 1988, our turn-of-the-month dummy variable is equal to one for the last trading

suggesting that these calendar patterns do not account for our result.

Another predictor of daily market returns is macroeconomic announcements. Perhaps the most attention has been given to Federal Open Market Committee (FOMC) announcements, when Lucca and Moench 2015 argue a large fraction of the equity premium is earned. Savor and Wilson 2013 initially documented this FOMC effect, as well as similar positive returns coinciding with other macroeconomic announcements. If dividend payments coincide with FOMC announcements, or macroeconomic announcements more broadly, such an effect could account for the results.

Table III Panel B examines FOMC announcements. Our FOMC announcement data runs from 1988 through 2019, so the first two columns repeat our baseline analysis over this time period, and show stronger results than for the whole sample.[12] Columns 3 and 4 include dummy variables for FOMC announcement days, and finds coefficients that are roughly unchanged. This suggests that the FOMC announcement effect is largely unrelated to the effects we document.

Table III Panel C extends to further macroeconomic announcements including CPI, PPI, Initial Claims, Employment and GDP. This data runs from 1994-2019, so the first two columns repeat our baseline in this period, and show stronger results than using the whole sample. Columns 3 and 4 include dummy variables for these macroeconomic announcement days, while columns five and six also include FOMC announcements. The results are not meaningfully different across these columns, which suggests that dividend payments are not proxying for the influence of macroeconomic announcements on returns.

B. International Evidence on Dividend Payments and Market Returns

In order to test the robustness of the effect, Table IV switches to an international setting, and considers how daily dividend payments predict market returns across 58 international markets.[13]

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date of the month and the first three trading dates of the month.

[12]Data on all of the macroeconomic announcements are the same as used in Neuhierl and Weber 2019.

[13]These 58 markets are the subset with sufficient data from the 125 markets in Compustat Global. A given market and day is included when it contains at least 100 stocks with prices. The countries in the analysis are: Australia, Austria, Belgium, Bangladesh, Bulgaria, Bermuda, Brazil, the Cayman Islands Chile, China, Croatia, Cyprus, Czechia, Denmark, Egypt, Finland, France, Great Britain, Germany, Greece, Guernsey, Hong Kong, India, Indonesia, Ireland, Israel, Italy, Japan, Jordan, Korea, Kuwait, Luxembourg, Malaysia, Mexico, the Netherlands, Nigeria, New Zealand, Norway, Pakistan, Peru, the Philippines, Poland, Romania, Russia, Saudi Arabia, Singapore,

These tests examine predictable price pressure while abstracting away from a number of possible institutional details that are unique to the US. We again focus on the dividend payment on day t and t-1. While the exact payment mechanisms will vary from country to country, there is nonetheless a reasonable assumption that, payment dates and/or the day after should roughly correspond to the day when investors can use the payment to purchase securities. To the extent that international institutional details lead to mismeasurement of reinvestment, or that the data is less accurate, we expect this to bias against finding a result.

In column 1 of Table IV, with no controls, we find that a higher dividend payment yield is associated with higher returns, with a coefficient of 20.30 and a t-statistic of 2.19. Column 2 adds country-by-year-by-month fixed effects, and the coefficient increases to 30.21 with a t-statistic of 3.59. The economic magnitudes of these effects are somewhat smaller than in the US. A one standard deviation increase in payment (0.000389) predicts higher returns in column 2 by 1.2 b.p.

This panel setting means that we can compare returns across countries on the same day based on the difference in countries' dividend payments. Column 3 adds a day fixed effect, and finds similar magnitudes to column 1, but with a larger t-statistic. Column 4 includes date and country-by-year-by-month fixed effects, and the significance increases again, to a t-statistic of 4.50.

C. Returns based on reinvestment intensity

Prior research and results in Section III.H suggest that retail investors rarely reinvest dividends. Thus, it is likely that the returns we document are largely related to the reinvestment rate of professional investors. We would expect these reinvestment rates to differ based on whether there is an imminent payout to investors. If a fund is about to send cash to investors and receives a dividend from its holdings, it may not be worth it to pay the transaction costs to hold the new shares only for a short time. As a consequence, reinvestment rates are likely to be lower as the fund's own dividend payment draws near. In the US, funds and ETFs are subject to the pass-through rule, whereby to avoid paying corporate income tax at the fund or ETF level, all dividends and realized

Spain, Sri Lanka, South Africa, Sweden, Switzerland, Thailand, Turkey, Taiwan, Ukraine, United Arab Emirates, and Vietnam. Data cover 1986-2017.

capital gains (minus fund expenses) must be distributed to the fund's investors by the end of the year. This leads many funds to wait until the end of the year to pay out most of their dividends.

Figure 3 Panel A graphs the average proportion of fund annual payouts distributed each quarter.[14] Specifically, the sum of mutual fund payouts that quarter is divided by the sum of mutual fund payouts that calendar year and averaged across years. Consistent with the intuition above, the graphs indicate that a significant fraction of mutual fund payouts, nearly two thirds, occur during the fourth quarter. The next panel graphs the payouts by month, and shows that much of this pattern is driven by December payouts, which constitute roughly 60% of the annual payout.

If money managers are less likely to reinvest when they are about to send cash to investors, and if they are responsible for a significant portion of the price effects we observe, then the price effects should diminish prior to these large payouts. In other words, a given dollar of dividends paid to investors will lead to less reinvestment, and less price pressure. Given the pattern in dividend payments, we would expect the lowest reinvestment in the lead up to the large December payouts. This suggests the lowest price effects in Q4 and December in particular. On the other hand, once the next year arrives, given the long time until the December payouts, we expect the most reinvestment at the beginning of the year.

Table V explores whether this is the case. It repeats our baseline analysis, but examines how the coefficient on dividend yield varies by quarter and includes a year-by-month fixed effect to ensure the regressions are not picking up variation in the level of returns in a given calendar month. Column 1 shows that the magnitudes of the coefficients are consistent with the price pressure predictions. The weakest effect is in the fourth quarter when the largest payouts occur. We find insignificant coefficients that are close to zero during this time. Also consistent with the predictions, the largest effect is during the first quarter, which is the farthest away from the large end of year payments.

While the graph of mutual fund dividend payments suggests a strong quarterly pattern, the monthly graph suggests that much of this pattern is specifically due to December, when we would expect minimal reinvestment. To test this, we split the effects of dividend yield into December

[14] Mutual fund data does not have information on payment dates, so this is based on ex-dates. These payouts include both capital gains and dividends combined, though dividend payments alone display a similar pattern.

versus all other months. Consistent with this, we find no significant effect of dividend payment on market returns in December, and the point estimate is actually negative. Further, when excluding December, we find a coefficient of 83, which is nearly 25% larger than the full sample effect (of 67). In months other than December, a one standard deviation increase in the dividends is associated with returns 3.9 b.p. higher, nearly double the unconditional average market return.

In addition to patterns within the year based on payout frequency, there have been large time series shifts in the popularity of investment vehicles like ETFs and mutual funds. Such products seem particularly likely to reinvest dividends, so one might expect the patterns we observe to become more pronounced as these products become more popular. Figure 4 suggests a significant increase in the effect roughly coinciding with the rise of mutual funds and ETFs. The figure shows regression coefficients of the value-weighted market return on the dividend payment yield on day t and t-1, conducted separately for each decade. For example, the data point graphed for 1970 represents the regression coefficient using daily data from 1970-1979. Prior to the 1990s, the dividend payment coefficient was always positive, with a mean of about 50 and a maximum of 83. The three decades post 1990 represent the three largest coefficients in our sample, each with a coefficient greater than 100. These results further support the interpretation of the main results being due to price pressure, as the size of the effect from a dollar of dividends varies predictably with the reinvestment rate. Meanwhile, it also confirms the importance of financial intermediaries like mutual funds, who are responsible for much of the actual dividend reinvestment in the market.

D. Returns based on market liquidity

An additional prediction of price pressure is that its impact should be larger when there is less liquidity. Similar to Nagel (2012), we proxy for liquidity using measures of market volatility based on the VIX index, which uses implied volatility from S&P 500 options markets. The VIX data we examine begins in 1990, so we also use the news VIX index developed in Manela and Moreira (2017) which is available at the beginning of our sample period.

Table VI examines how the impact of dividend payments interacts with levels of the VIX and

News VIX in predicting market returns. We augment our baseline regression by including VIX and also an interaction of VIX with the dividend payment yield. Column 1 examines the coefficient on this interaction term and shows a significant coefficient of about 30. Column 2 shows similar effects after controlling for year-by-month fixed effects. This suggests that in times when VIX is higher, the impact of dividend reinvestment is also higher.

To the extent that large drops in liquidity are primarily concentrated in periods of market stress, we next consider how much of the overall relationship is driven by periods of particularly high VIX. In Columns 3 and 4 we examine a High VIX dummy variable, equal to one if the VIX is in the top quintile, and zero otherwise. Examining the dividend yield coefficients, we see in normal periods the point estimates are slightly above those of the entire period, though marginally significant. This reflects the fact that overall effects are larger in later period where VIX is available. The high VIX coefficients are large and significant, with coefficients of 470 and 390 without and with year-by-month fixed effects respectively, showing the large increase during periods with high VIX.

A potential concern with these results is that they only cover the period from 1990 onwards and thus may be driven by a relatively short sample. In columns 5 through 8 we use the news VIX index to explore the entire sample. All of the major patterns are the same. Columns 7 and 8 show that high news VIX periods coincide with coefficients on the dividend payment roughly double that of the unconditional estimates. These results further support the interpretation of price pressure, with each dollar of dividends having more effect in periods when there is less liquidity.

E. Long Horizon Returns

Returns around dividend payment dates offer sharp tests of the price pressure prediction because of the clean variation provided by daily payments. Nonetheless, these may not reflect the full extent of price pressure, as some investors may reinvest dividends with a delay. Longer horizons also test whether these returns quickly reverse afterwards.

While the effects are not as tightly identified from timing, we consider how daily payment yields predict returns at horizons out to 4 weeks (the payment day and the 19 subsequent trading days).

We repeat the baseline regressions, but include lagged dividend payment amounts for each day in the prior four weeks, and include year-by-month fixed effects.

Figure 5 graphs the results. Each point is the regression coefficient on the payment yield lagged by the x-axis value. The first four points are the days included in Table I and show similar results of strong price pressure occurring the first week after dividend payment.[15]

After the first week, the pattern is noisier and most of the point estimates are not significant. With that said, the effect from days t-5 through t-19 is weakly positive, with an average coefficient of about 7. Taking the point estimates seriously suggests that reinvestment continues at a lower rate in weeks two through four. Such a result may arise if some investors are inattentive about the timing of dividend payments (consistent with the observation in Hartzmark and Solomon (2020) that dividend payments are often not flagged in brokerage platforms). The noisiness of these results makes it difficult to distinguish between additional buying pressure, or a lack of meaningful returns.

Perhaps most interestingly the results show no evidence of a reversal, even in point estimates. Before seeing these results, a plausible hypothesis might be that the price pressure we observe is a short term phenomenon that quickly reverses, thereby having minimal impact on any long term measure. None of the regressions present evidence consistent such a strong short term reversal.

F. Industry Portfolios and Price Pressure Reversals

While the results above suggest that there is no reversal to the price pressure in the following month, it is possible that such reversal only occurs over a longer horizon. Unfortunately, extending our baseline specification to further lags is unlikely to have sufficient power to identify reversals in cumulative returns over long horizons.

To test for longer term reversals, we turn from the aggregate market to the cross section. To do so, we assume that at each time there are certain stocks that are more likely to be purchased with a dividend payment than others. Given an estimate of which stocks received greater naive flows from dividend payments, we test the proposition that these assets had greater exposure to

[15]The results are not identical to Table I because the regressions include lagged dividend payment controls for days t-5 to t-19.

dividend-related price pressure in the cross-section, and so should have lower subsequent returns.

Because of the noisiness of individual stock returns, we take as our test assets 48 value-weighted industry portfolios. We examine an industry's exposure to dividend reinvestment over the course of the prior year. For each industry portfolio, we take daily returns from 13 months ago to one month ago, and regress them on the cumulated payout yields on days t and t-1. This beta is used to create four quartile portfolios of the industry portfolios. The returns are then regressed on a four-factor model Carhart (1997), using excess market returns, SMB, HML and UMD. The alpha on this portfolio is the difference in expected returns in the subsequent month between industries that had a high or low response to dividend payments over the prior year.

Panel A examines an equal-weighted portfolio of value-weighted industry returns. The portfolio is long industries with the highest quartile of exposure to past dividend payments, and is short industries with the lowest exposure (column 1). This portfolio earns an abnormal return of -28.2 basis points per month, with a t-statistic of -3.38. The next four columns show the abnormal returns to the long portfolio from each quartile. Moving from the highest beta quartile (column 2) to the lowest beta quartile (column 5), there is a monotonic increase in the portfolio's alpha. Panel B examines the returns to a value-weighted portfolio of value-weighted industry portfolios (weighting by the industry market cap at the end of the prior month). The returns are similar - buying industries with the most positive betas and shorting industries with lowest betas produces an alpha of -26.2 basis points per month, with a t-statistic of -2.51.

The existence of eventual reversals also is consistent with price pressure, but difficult to reconcile with the short horizon returns reflecting underlying economic news. In such a case, it would not be obvious that the price increases should eventually predict lower returns. While there is some reversal, this test is not able to identify whether the effect totally reverses. We leave the question of whether there is a long term persistent component of demand for future research.

G. Stock Compensation Expense and Predictable Selling Pressure

The role of price pressure is not conceptually limited to the arrival of buy orders, but ought to apply to predictable selling pressure as well. To demonstrate this we switch to the perspective of selling pressure at the individual stock level.

In order to examine a setting where there is a predictable and sizable increase in selling that does not reveal information, we examine stock compensation. Many companies pay considerable stock-based compensation to employees - not only senior executives, but often lower level employees as well. This represents a core component of the way these firms conduct their business, so such firms predictably expense large amounts of stock. To prevent insider trading, companies often implement blackout periods during which employees cannot trade the company's shares. The periods where employees are allowed to trade is generally immediately after the earnings announcement, when presumably all (or most) material information has been disclosed to the market, and insiders are (hopefully) not at an advantage.[16]

For employees receiving a significant portion of compensation through stock grants, standard portfolio theory suggests that they should diversify to other assets to minimize idiosyncratic risk from large holdings in a single firm, and because they already have a considerable exposure to the firm's returns through their labor income (Malmendier and Tate 2005, Cohen 2009). Both effects mean that employees should want to sell shares they receive as quickly as possible, which predicts that the lifting of these blackout periods are when many employees will predictably sell shares. If such sales create predictable price pressure, returns should be negative just after earnings announcements, these returns should be more negative when stock expenses are higher and returns will potentially turn positive thereafter when the price reverts.

We test this by examining returns around earnings announcement dates from 2002 to 2020, by combining information from both Compustat and IBES.[17] The main variable of interest is stock

[16]Bettis, Coles, and Lemmon (2000) report that, as of 2000, 78% of companies had explicit blackout periods. Most policies only allowing trades shortly after earnings announcements. Jagolinzer, Larcker, and Taylor (2011) reports that the mean blackout period is lifted 0.8 calendar days after the earnings announcement, with a 25th percentile of zero days and a 75th percentile of one day.

[17]2002 is the first year with meaningful stock compensation data. There is sparse data in 2001 (results including

expense as a proportion of market capitalization one day before the announcement. Similar to DellaVigna and Pollet (2009), we define "announcement day," which we refer to as t=0, as the first trading day when the announcement can affect prices.[18] We examine characteristic-adjusted returns which take a firm's return and subtracts the returns of a portfolio matched on quintiles of market capitalization, book-to-market and momentum (Daniel et al. 1997).

In Figure 6 Panel A, we examine how returns after the earnings announcement vary with the level of stock expense. We graph a local linear plot of the characteristic adjusted returns from t+1 to t+3 after the announcement on the y-axis (skipping t=0 to avoid reactions to announcement news for now), relative to the level of stock expense on the x-axis. The graph illustrates a strong negative relation between the two. Companies with expenses of about 0.1% of market cap experienced negative returns of about 25 b.p., those with expenses of 0.2% experienced about -80 b.p., those with expenses of 0.3% experienced about -120 b.p., and those with expenses of 0.4% experienced returns of nearly -150 b.p. Consistent with the predictions of price pressure, the negative returns experienced by firms with stock expenses increases with the level of stock expense.

Figure 6 Panel B explores daily variation in the cumulative characteristic-adjusted returns based on the level of stock expense. The graph shows the returns for the announcement day through twenty days after the announcement. By t=3, companies above the 95th percentile in stock expenses experienced abnormal returns of about -120 b.p., firms between the 90th and 95th percentile experienced about -90 b.p. returns and firms between the 80th to 90th percentile experienced -40 b.p. returns. Firms with lower expenses also experience underperformance relative to firms with no stock expenses who experience positive returns (the earnings announcement premium (Frazzini and Lamont 2007)). Looking further into the future there is evidence of a partial reversal. For the two highest groups the extreme underperformance lessens, but is still around -50 b.p. four weeks after the announcement. For the more moderate groups the lines converge after about two weeks.

A potential concern is that these results do not reflect predictable selling pressure, but rather

2001 are similar) and no data prior.

[18]For example, if a company announces earnings before market open, t=0 is defined as that day. If a company announces earnings after market close, t=0 is defined as the next trading day.

capture correlations with earnings announcement news. These returns could reflect fundamental information from the earnings announcement, be it earnings information, information from the amount of stock expensed, or some other information in the report. While fundamental news from an earnings announcement cannot be predicted prior to the announcement, if our measures capture characteristics of how firms generally conduct their business, then most of the information needed to predict price pressure should be available well before the announcement itself.

To demonstrate the extent to which stock expense represents predictable price pressure and to rule out such information effects, in Table VIII we examine this pattern using stale data available before the current earnings announcement. The table shows regressions of characteristic-adjusted returns over different time periods after earnings announcements on dummy variables for the level of stock expense. In Panel A we sort on stock expenses announced in the prior quarter's earnings announcement.[19] If the relevant information was released months beforehand, it becomes difficult to explain returns as any kind of response to the current earnings information.

Column 1 shows returns from t=0 to t+3 for each category of stock expense relative to the omitted group of firms with no stock expenses. Firms with the highest stock expense (above the 95th percentile) had -117 b.p. returns (t-statistic of -5.50), firms with expenses between the 90 and 95th percentile had returns of -77 b.p. (t-statistic of -4.83) and firms in the 80th to 90th percentile experienced returns of -33 b.p. (t-statistic of -2.93). Firms with positive, but lower, stock expenses (below the 80th percentile) still underperformed firms announcing earnings by 18 b.p. (t-statistic of -3.69).

Another potential concern is that the results represent a delayed reaction to earnings news or a behavioral response to information in the announcement that could have been predicted prior (e.g. the post-earnings announcement drift in Bernard and Thomas 1989). To demonstrate the results are not driven by announcement day effects, Column 2 examines returns from t+1 through t+3 thereby skipping the announcement day. We expect t=0 to also reflect price pressure, particularly

[19] For this lagged measure we use annual expense announced the prior quarter. While quarterly stock expense (which we use in the contemporaneous analysis) is the best measure of the likely amount of selling for that particular announcement, the annual stock expense provides a better proxy for the average quarter. Results are substantially similar if we use quarterly stock expense lagged four quarters.

since our t=0 definition often coincides with the calendar date after the announcement, thus results should be smaller beginning at t=1 under a price pressure explanation. To control for a delayed reaction to the response to earnings news, we include as a control the t=0 characteristic-adjusted return, split into positive and negative returns. The results in column 2 are smaller (consistent with missing some selling pressure), but display a similar pattern for firms with significant stock expense.

Next we examine whether there is a reversal. Columns 3 and 4 repeat the analysis for returns on days t+4 to t+10, and t+4 to t+20, respectively. For returns up to t+10, there are significant positive point estimates for firms above the 80th percentile of expense, consistent with some reversal. Extending to t+20 in Column 4, each estimate has a positive estimate, with significant estimates for firms above the 90th percentile of expenses. In each instance the point estimate is below the returns from t=0 to t+3, suggesting a partial reversal of the effect over the next 20 days.

These results use lagged data to demonstrate the extent of expense predictability, but the actual contemporaneous stock expense (which is publicly known for the periods examined) is a better reflection of the amount of stock currently sold. Panel B repeats the analysis using the current expenses. As predicted, there are modest increases in the point estimates. For example, the 95th percentile of expense moves from -117 b.p. (t-statistic of 5.50) using the lagged variable to -127 b.p. (t-statistic of -5.65) when using contemporaneous data. This underscores that the majority of the selling pressure represents a predictable component of certain firm's business strategy that lacks fundamental information, yet induces large price impact.

These results reinforce the flip side of the dividend results - predictable price pressure is not limited to purchases, but also holds for sales. While the sales we examine are announced before the returns we examine, the economic effects we find are large. This is consistent with markets generally not being fully liquid, and so predictable purchases and sales lead to predictable price changes.

H. Price Multipliers

The previous analysis of dividend payments and market returns considered economic magnitudes primarily in terms of the observed variation in the dependent variable - that is, how much larger are market returns with higher dividends. Another important metric of economic magnitude is the multiplier of market price with respect to a dollar of predictable investment. This is the inverse of the price elasticity (the change in quantity demanded as a function of price changes). In order to estimate such a figure, we need an estimate of what fraction of a dollar of dividends is typically reinvested into the market. While data limits the ability to provide exact figures, this section provides a range of such estimates and what they imply for the market's demand elasticity.

One potential (though implausible) benchmark is to assume that all funds are reinvested on either the payment date or the following day. Under this assumption it is possible to read the implied multiplier from our baseline specification in Table I. For this section we will use the coefficient of 67 for two-day dividend payment yield, using the value-weighted market portfolio with year-by-month fixed effects.[20] This implies a multiplier of 0.67, suggesting that a 1% dividend yield reinvestment leads to a change in returns of 0.67%. Table X lists these back-of-the-envelope calculations and the implied multiplier based on the reinvestment rate. The first row presents the estimate of 0.67 assuming that all investors invest all dividends received.

While a useful frame of reference representing the lower bound of multiplier estimates, 100% reinvestment is both intuitively unlikely and inconsistent with the observed behavior of some investors. For example, retail investors consume dividends at a high rate (e.g., Baker, Nagel, and Wurgler 2006; Di Maggio, Kermani, and Majlesi 2020). In order to do so, they cannot be reinvesting them into the market. Further, these investors trade positions on average about once a year (e.g. Odean 1998) and are less likely to trade if they hold positions that pay dividends (Hartzmark and Solomon 2019). Both of these behaviors are associated with lower reinvestment rates.

With that said, it could be that there is a subset of retail investors that reinvest dividends. To examine whether this is likely, we look at the propensity to buy a position (either open a new position or expand an old position) based on receiving a dividend payment in Table IX Panel A. This table uses data from retail investors trading from their own accounts from 1991-1996 (as in Barber and Odean 2000). All days that an investor could have traded are included, regardless of

[20]This examines the immediate reinvestment on the payment day and the day after, but ignores the impact of reinvestment that occurs subsequently.

whether a trade occurs, and the analysis is conducted at the portfolio level.[21] We regress a dummy variable equal to one if a position is purchased that day on a dummy variable for whether a position in the portfolio received a dividend payment on the current or prior day.

The results suggest dividends do not induce a meaningful increase in buying for individual traders. The constant in the first regressions shows the baseline level of trading activity is low, as only 0.18% of potential trading days include a buy trade. The dividend payment dummy variable is significant, and of a similar magnitude of the constant, suggesting that on days when dividends are received the probability of buying doubles to roughly 0.36%. With that said, the economic magnitude of this coefficient suggests that dividend reinvestment is not common, as the overwhelming majority of dividend payment days lack a purchase. Further, the odds of receiving a dividend vary with portfolio characteristics (such as number of holdings, or strategy) which also vary with trading behavior. To partially control for this possibility, column 2 adds an account fixed effect. This explains much of the variation in buying, decreasing the influence of receiving a recent dividend payment to 0.03%. While there may be some increase in buying when a dividend is received, the small economic magnitude of the effects, and the results in the prior literature, suggest that most dividend payments are not quickly reinvested. Thus we think a reasonable approximation of the reinvestment rate by retail investors of single name stock holdings is zero.[22]

The assumption that retail investors do not reinvest dividends will affect the estimated multiplier in Table I. According to the Financial Accounts of the United States release Z.1 from March 2020, retail investors hold 34% of assets. Taking this estimate and assuming that retail investors never reinvest, and all other investors reinvest 100% of dividends, suggests that, in aggregate, 66% of dividends paid are reinvested in the market. Aggregate reinvestment of 66% of the dividend yields an estimate of the multiplier of 1.02 in the second row of Table X.

The remaining 66% of non-retail investors generally represent more professional investors who

[21] This is in contrast to just examining sell days, as is standard in the disposition effect literature. This filter makes sense when examining behavior that is conditional on attention to the portfolio, but not when examining whether or not a dividend received is reinvested. See Hartzmark 2015 for a description of restrictions on this dataset.

[22] We note that this direct evidence is for retail investors in the 1990s, and it is unclear to what extent it holds in other datasets or more recent time periods where internet based trading and lower trading costs may increase such portfolio reinvestment. We have no direct evidence on these issues, so we leave it to future research.

likely reinvest dividends at higher rates. With that said, it is implausible that reinvestment is 100%. For example, if an asset manager needs to increase their cash buffer or send cash to their clients, they likely would not always reinvest a dividend and may instead use it for these needs. Ultimately we think it is an empirical question as to what this rate is.

While the data is fairly limited to calculate such a number, we use data on mutual funds to estimate their reinvestment rate. Mutual funds represent a large class of professional investors (22% of the US equity market in March 2020) that publicly disclose enough information to estimate a reinvestment rate. While the ideal data set would involve information on daily holdings, dividends received and trades, we do not have access to such a dataset.

Instead, the analysis focuses on monthly holdings data from CRSP which reports the positions a mutual fund holds at the end of the month. To calculate the dividends received we take the positions at the end of a given month and use them to measure dividends received the next month. To calculate the fraction of TNA of a fund accounted for by its listed holdings, we sum a variable that lists the proportion of TNA of each position.[23]

When a dividend payment is received, the value of fund TNA increases by the amount of the dividend payment. If that money is used to buy equity securities that get listed in the monthly reports, then the dividend payment will have no impact on the measure of the fund's TNA explained by the holdings data. If the payment is not reinvested, for example if it remains in cash, then the fund's TNA will increase but the value of equity holdings will not. Thus, absent reinvestment, the fund's fraction of TNA measured in listed holdings will decrease by the dividend payment amount.

An additional complexity arises if the ex-dividend date occurs within the same calendar month as the payment. When a stock goes ex-dividend, the price will drop by the dividend amount, absent taxes and frictions (Miller and Modigliani 1961). In this scenario, the TNA in equity holdings drops by the dividend amount on the ex-date, but if the fund engages in full reinvestment, TNA is replenished by the same amount on the payment date, leading to no change in monthly measures if both occur in the same month. Similarly, zero reinvestment would be associated with a decrease by

[23]To ensure that these positions represent actual holdings we limit the sample to holdings with non-missing CUSIP variables. We focus on this variable as it seems the least prone to erroneous entries and data errors.

the dividend amount. In practice, prices on the ex-day drop by less than the amount of the dividend (Elton and Gruber 1970, Hartzmark and Solomon 2013). Full reinvestment with such positive ex-day returns will lead to position values greater than the original holding. Predictions are much less clear though, because the amount of the price drop (and thus the predicted change in TNA under full reinvestment) varies with a number of factors.[24] This means that our predictions are cleanest for payments where the ex-date occurs during an earlier calendar month. Since these observations also represent about two thirds of such payments, we focus on them for our estimates.[25]

To explore reinvestment behavior, we first graph the change in TNA from the prior month relative to the dividend payments received that month in Figure 7. The figures are a bin-scatter plot splitting the data into 20 bins based on the magnitude of the dividend yield (represented by its location on the x-axis). The y-axis shows the average change in percentage holdings in that month for funds in that bin. The red line is the outcome of a regression of the change in TNA on the dividend payment. The figures are value-weighted by the fund's prior month TNA.

Figure 7 Panel A shows the relation with no controls. The first thing to notice is a strong, positive, roughly linear relation. This is consistent with a general reinvestment of dividend payments that are received. Given that the x-axis and y-axis are on the same scale, perfect reinvestment would be represented by a 45 degree line. The line is substantially flatter than this. Thus the figure suggests that mutual funds reinvest dividends, but do so at a rate significantly below 100%. Such results could be explained by differences over certain time periods, or by heterogeneity across mutual funds. Panel B repeats the analysis but plots the data as the residuals after controlling for fixed effects for each fund and time period. The pattern is similar suggesting some reinvestment, but not 100%.

For more precise estimates of reinvestment, we regress the change in a fund's fraction of holdings on the dividend payment received that month. We value-weight by the prior month TNA to get a better estimate of the dollar-weighted reinvestment amount. With full reinvestment, this regression

[24] Differences in ex-day returns are affected by dividend yield, liquidity, recessions, VIX, etc (Hartzmark and Solomon (2013))

[25] We add a number of additional filters to the mutual fund database to attempt to avoid the noise inherent in this data. We focus on funds with a TNA above $10 million in the prior month that report holding at least 10 positions. We focus on funds where the estimate of the fraction of TNA accounted for by holdings is between 50% and 105% in the current and prior month.

should yield a coefficient of one. With zero reinvestment this regression should yield a coefficient of zero. With partial reinvestment, that amount should be captured by the regression coefficient.

Table IX Panel B reports the results of these regressions. The first column includes no controls and shows a regression coefficient of 0.53 with a t-statistic of 4.39. This suggest 53% of dividends received in a given month are reinvested before the end of that month. The next 3 columns include year-by-month fixed effects, fund fixed effects and both together. This yields estimates ranging from 45% to 69% dividend reinvestment.

We take the high (69%) and low (45%) of these estimates for our our back-of-the-envelope calculations of multipliers.[26] In March 2020, mutual funds held 22% of the US equity market and ETFs held 6%. We think a reasonable assumption is that ETFs behave similarly to mutual funds with respect to reinvestment, so we apply our estimates to 28% of the market.[27] Taking the high estimate of 69% reinvestment suggests an aggregate reinvestment rate of 57% (retaining the assumption that retail investors do not reinvest and the rest of the market reinvests at a rate of 100%). This implies a multiplier of 1.17. Taking the low estimate of 45% reinvestment rate from the value-weighted estimate, we find a multiplier estimate of 1.33.

These elasticities are based on the assumption that the remaining investors who are not retail, mutual funds or ETFs reinvest at 100%, which again seems implausibly high. This group includes foreign investors (16%), pensions (11%), business holdings (4%), hedge funds (3%) and other investors (3%). There is clearly variation across these groups, but they largely represent professional investors who also sometimes pay out money to constituents, similar to a mutual fund. Given that we lack the data to estimate the actual reinvestment rate, we think a reasonable approximate assumption of their reinvestment rate is to take the mutual fund rates and apply it to these investors. Taking the estimate of 69% reinvestment for these other investors yields an aggregate reinvestment

[26]Taking this monthly estimate and applying it to our baseline regression coefficient implies that when a dividend is received it is reinvested within two days. While we think it is plausible that mutual funds will reinvest quickly if they are planning to reinvest at all, this is a conjecture the data does not allow an explicit test of. We note that fund managers often are worried underperforming benchmarks (even going as far as to mis-specify benchmarks in order to beat them - see Sensoy (2009)), and thus have an incentive to quickly redeploy capital rather than having an additional performance drag from holding excess cash.

[27]We lack ETF holdings data to directly perform the same calculation for them.

rate of 46% and a multiplier of 1.47, while 45% reinvestment yields a multiplier estimate of 2.26. Thus we think a reasonable back-of-the-envelope multiplier estimate is likely in the 1.5 to 2.3 range.

IV. Discussion

As noted earlier, the existence of price pressure based on predictable flows strengthens the argument for price pressure in general. Any finite limit order book will have price pressure at some point. The extent of such pressure depends on the ability and willingness of liquidity-providing traders to engage in offsetting trades, which should be easier for traders to do with more advance notice of the timing of liquidity-demanding trades. In this sense, finding price pressure for the most liquid assets when flows are predictable makes it more likely that price pressure exists when flows are not predictable and assets are illiquid. In other words, there is a credible basis to believe that price pressure is a plausible null hypothesis *in general.*

The implications of such a null hypothesis are wide-ranging. Most asset pricing models start with fundamental value from risk-adjusted discounted future cash flows. While they sometimes add frictions or behavioral factors to explain deviations from the rational benchmark, the actual buying and selling is usually relegated to the background. However, beginning with price pressure as the default assumption, and taking fundamental value or psychology as inputs into this buying and selling, can help explain pricing anomalies especially in situations where fundamental value is difficult to model or entirely absent.

Perhaps the strongest example of this phenomenon is cryptocurrencies, a setting in which standard finance models struggle to make any meaningful predictions. Economists have long puzzled over why assets like Bitcoin should have non-zero prices, given they have no underlying cash-flows or clear value proposition other than the ability to sell them to other investors (which, in equilibrium, becomes entirely circular, and potentially applies to any asset whatsoever).[28] Informal

[28]Indeed, finance has had a lot more success in modeling the usefulness of tokens, where the digital asset is an input into a real-world project, and the sale is a means of raising funds for such a project. See, for instance Li and Mann (2018), Cong, Li, and Wang (2021), Catalini and Gans (2018), and others. There are relatively fewer models of coins that exist purely as objects of exchange, even though these assets (especially Bitcoin) are not only the original cryptocurrencies, but still the largest by market capitalization.

justifications for Bitcoin often appeal to the idea of it being a "hedge asset," conditional on it already being fairly widely traded (e.g. Dyhrberg 2016). But this sidesteps the question of why it and other cryptocurrencies have a non-zero price in the first place. In a world of price pressure, the somewhat tautological answer is that these assets have a high price because people keep wanting to buy them. Because Bitcoin is in a fixed total supply, with a small and decreasing amount being released through mining, if enough people continue to buy Bitcoin and hold it, this is predicted to keep raising prices. The relative difficulty of shorting bitcoin is also likely important. Price pressure predicts that the combination of ongoing purchases from optimists with little ability to short sell from pessimists will lead to continued price rises.

This characterization highlights both the strengths and weaknesses of price pressure as an asset pricing framework. It is only a partial theory, because it does not take a stand on what is causing the underlying demand.[29] There is also a sense in which price pressure seems almost tautological, in that enough people buying an asset will push up its price. The rejoinder, however, is that starting with price pressure makes it intuitive to take the existing demand for Bitcoin as a basic fact, and something over which it is acceptable to be agnostic as to the cause or likely duration. While it is unable to identify the source of demand, it still makes a simple and powerful prediction. If demand has been broadly increasing for 12 years, for whatever reason, then prices will rise even for an asset that, by design, produces no cash flows or inherent utility. By contrast, worldviews that start with fundamental value tend to predict that not only should the price of Bitcoin be zero, but that it should *always* have been zero, which suggests that going to zero in the future is somewhere between "highly likely" and "inevitable". This makes it difficult to know how to update expectations for each successive year when prices are not zero, and not obviously heading towards zero.

While cryptocurrencies provide the starkest example where predictions based on fundamental value are insufficient, price pressure can also provide a relatively parsimonious explanation for a

[29] Credible contributors seem likely to be some combination of true believers in the project, people desiring to transact outside the formal banking system, and extrapolative traders. While not directly about cryptocurrencies, Van Wesep and Waters (2021) present a model of unstable valuations due to leveraged optimists, with a similar spirit to some of this discussion. But these components of optimism and leverage are largely conceptually orthogonal to the price pressure component.

number of other results where modeling deviations from fundamental value is either complicated, or incomplete. Price pressure readily accounts for market episodes like the "meme stocks" of Gamestop, Nokia and others during early 2021, that experienced large and surprisingly long-lived price increases as a result of attention on internet forums such as Reddit's r/WallStreetBets. Coordinating lots of people to buy in this manner is predicted to increase prices (even if fundamentals are unchanged), and the findings from our dividend reinvestment results suggest that this need not quickly revert.

Price pressure also provides a way of simplifying other results in the literature where standard asset pricing explanations are plausible but somewhat convoluted. In international finance, it has long been known that macroeconomic models have difficulty explaining exchange rate movements at horizons less than a year (Meese and Rogoff 1983, Meese 1990). Evans and Lyons (2002) shows empirically that order flow matters a great deal for exchange rate movements, and explains this using a model where order flow reveals fundamental decentralized economic information such as future interest rate differentials. Relatedly, Jiang, Krishnamurthy, and Lustig (2021) explain the high valuation of the US dollar, and the importance of shifting supply and demand of dollars for exchange rates, by positing a time-varying convenience yield to holding US dollar assets. In both cases, price pressure provides the very simple prediction that order flow inherently matters for prices, regardless of its source, without the need for additional assumptions as to what such price pressure represents. In other words, it is *possible* that such flows derive from fundamental information about the macroeconomy or expressions of convenience yields, but this need not be the case.

A price pressure framework provides a simple explanation of how the Federal Reserve is able to influence prices in low interest rate environments. Namely, quantitative easing matters, because the almost unlimited budget constraint of the Fed means its purchases directly affect prices (and thus yields) in the assets it buys. While there is considerable evidence that quantitative easing has important effects on markets (Hamilton and Wu 2012, Wu and Xia 2016, Gilchrist, López-Salido, and Zakrajšek 2015, Rebucci, Hartley, and Jiménez 2020) the mechanism driving this is less clear. As Bernanke and Reinhart (2004) describe, close to the zero lower bound the Fed can influence prices by either altering investor expectations, by changing the composition of the Fed's balance sheet, or by changing the quantity of the balance sheet. These latter two options function because of price pressure, though they are often described using different terms.[30] While some of the empirical evidence is consistent with either an expectations or a price pressure channel,[31] some episodes illustrate the importance of price pressure. For example, Vissing-Jørgensen (2021) documents that, during Covid-19, rates spiked due to extreme selling pressure from March 9th-18th and then reversed due to buying pressure by the Fed on the subsequent purchase days (not announcement days). Price pressure represents a parsimonious explanation for the Fed's influence on prices, requiring only that the Fed's budget constraint is huge, and a common understanding that the Fed is willing to use it.[32]

Price pressure also makes predictions for where other asset pricing puzzles may be found. To take one example, in a world of price pressure, demographics matter. More baby boomers selling equity for retirement is predicted to lower prices (holding fundamental news constant). This and other related outcomes are intuitive places to look when the underlying question is "what phenomena are likely to drive significant trade in the same direction?" and may not be as obvious if the initial inquiry is instead "what phenomena will influence the macroeconomy or psychology of investors?".

The idea of price pressure does not imply that fundamental value is unimportant for asset pricing, but the explanation for *why* it matters is different from standard theories. Under a price pressure explanation, fundamental value matters when it affects the prices at which traders are willing to place orders. This means that its impact likely varies according to the context. For example, if

[30]For example, Bernanke and Reinhart (2004) describe the influence by stating "changes in relative demands by a large purchaser have the potential to alter relative security prices" if "investors do not treat all securities as perfect substitutes". The disconnect between a macroeconomics literature that assumes different durations of Treasury securities are *not* perfect substitutes, and a finance literature that assumes entirely different companies *are* perfect substitutes, is curious, to say the least. Price pressure also explains why the evidence for purely compositional changes affecting prices may be "contentious" (as Bernanke and Reinhart (2004) characterize it) - without an overall balance sheet expansion, at least one asset has to be sold, which pushes down prices for the asset the Fed previously held.

[31]Empirically, prices of assets that the Fed announces it will buy tend to increase on announcement days (e.g. Rebucci, Hartley, and Jiménez 2020). This is consistent with both expectation based and price pressure based explanations, as announcing future Fed buying may induce other traders to front run those trades.

[32]Price pressure offers an indirect explanation for the Fed's role in asset classes that it does not directly purchase. For example, (Cieslak and Vissing-Jorgensen, 2020) describe the "Fed Put", that monetary interventions will be used to prevent large stock market declines, satirized in popular discourse as the monetary policy of "big line go up." If Fed actions in one market, such as using buying pressure to lower the interest rate, makes equities appear more attractive, perhaps due to reaching for yield (Lian, Ma, and Wang, 2019) or demand for dividends (Hartzmark and Solomon, 2019), this could induce equity buying pressure and increase the price of the market.

investors generally view prices to be anchored to fundamental value and think other investors share this view (as in the beauty contest in Keynes 1936), then willingness to trade, and thereby the price, will reflect beliefs about fundamental value. On the other hand, if investors believe prices are decoupled from fundamentals (such as in the meme stock example above) or that convergence to fundamentals is a long-term phenomenon (e.g. Royal Dutch / Shell (Rosenthal and Young 1990)), than fundamental value is unlikely to drive trading decisions and will be less relevant for prices.[33]

The results in this paper suggest that an important course of future study is to pair the base hypothesis of price pressure together with an understanding of the context-specific shifts in buying or selling pressure in order to better understand asset price movements.

V. Conclusion

In this paper, we show that predictable increases in the number of people buying shares, or the number of people selling shares, leads to predictable changes in price for those shares. Put in such stark terms, such a finding may seem obvious. And yet many of the standard models in finance assume this result does not hold - that investors are simply exchanging twenty dollar bills for hundred dollar bills, and the price for such an exchange is constant regardless of volume. We consider price changes in the largest and most liquid assets (the value-weighted market portfolio), where the flows in question ought to be known to not result from private information, and where the timing and amount of such flows is known in advance. Even with these aspects stacking the deck against the possibility of price pressure, as arbitrageurs should have the best chance at offsetting any mispricing, price pressure is evident.

One interesting question is whether one would expect price pressure to be more pronounced at the individual stock level or at the market level. Academic finance generally predicts that the larger

[33]Deviations from fundamental value also gives rise to longer-term trading strategies based on economic fundamentals. If a stock's price is low relative to its discounted future cash flows, this represents an opportunity for a long-term investor to buy the stock and receive its cash flows. Conversely, if an asset is overpriced, it may be profitable to issue more equity, or to found a new company and sell equity at the overvalued price. These strategies likely provide weaker constraints on prices, because they take considerable time to implement, and have different risks than betting on mispricing correcting itself.

and more liquid the asset, the more likely that the asset behaves in accordance with the efficient markets hypothesis. It is unclear if this is the appropriate null hypothesis though, since while individual stocks may be close substitutes for each other, there are relatively few good substitutes for the market as a whole, an argument made by Samuelson (as reported in Jung and Shiller 2005). Another interesting question is whether the fact that dividend payments are obvious and recurring make them more or less likely to be correctly priced. Again, standard predictions suggest that the easier it is for a rational actor to understand a given setting, the more likely it is for prices to be correct. With that said, mundane daily predictable basis point fluctuations may be the type of setting that people focus less attention on, making it less likely that arbitrageurs engage in offsetting trades, leading to price changes unrelated to information flows (similar to Da, Gurun, and Warachka 2014; Chang et al. 2016). If either of these mechanisms are at work, this suggest further fundamental issues that are generally unable to be accounted for using standard financial models. Directly testing these channels is an important avenue of future research.

One way of interpreting our results is that, for whatever reason, investors have strong views as to which assets they want to hold, and changes in the price of such stocks do not greatly change their willingness to purchase them. The question of *why* this is the case is one of great interest.

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Figure 1. Daily Market Returns Based on Dividend Payments

This graph shows the the daily value-weighted market return (in %) on day t based on the quintile of the abnormal dividend payment on day t and $t-1$. Red bars represent 95% confidence intervals.

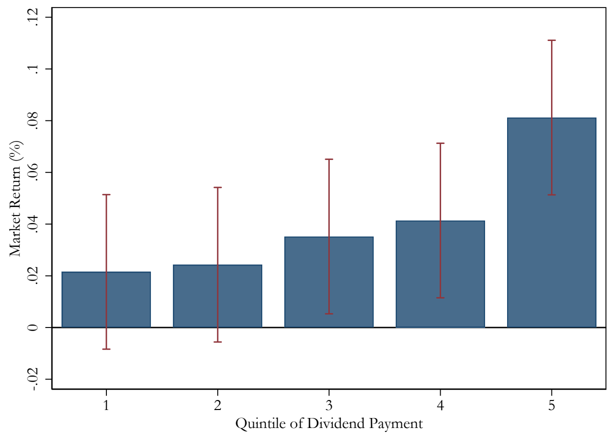
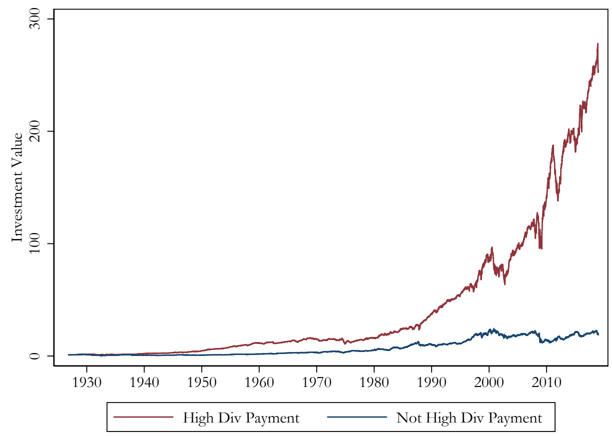


Figure 2. Cumulative Value Weighted Returns from Dividend Payment Strategies
This graph shows the cumulative performance of a $1 investment in the market portfolio based on the dividend payout yield. The maroon line invests in the market if the dividend payment today or yesterday is in the top 50 of the prior 252 days and earns zero returns otherwise. The navy line invests in the market when the dividend payment today or yesterday is not in the top 50 of the prior 252 trading days and earns zero returns otherwise. Panel A presents raw returns. Panel B invests in the risk-free rate when the strategy is not invested in the market.

Panel A: Value of Investment: Stock Market Only



Panel B: Value of Investment: Risk-free rate when not in Stock Market

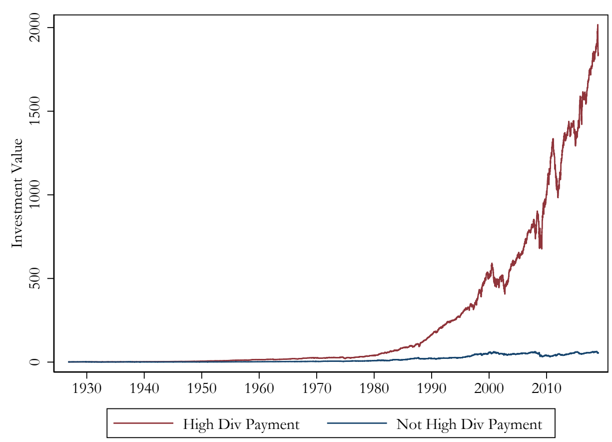
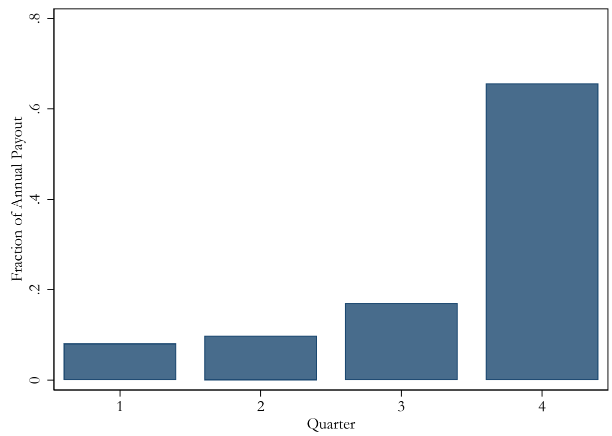


Figure 3. Mutual Fund Distributions

This graph shows the average fraction of the annual total distribution (including dividends and capital gains) by month and by quarter. In Panel A, the sum of all distributions in a given quarter is divided by the sum of all distributions in that calendar year. This value is averaged across years and graphed for each quarter. Thus each bar is the average fraction of distributions paid in a year that occur in a specific quarter. Panel B repeats the exercise using month instead of quarter.

Panel A: Average Distribution by Quarter



Panel B: Average Distribution by Month

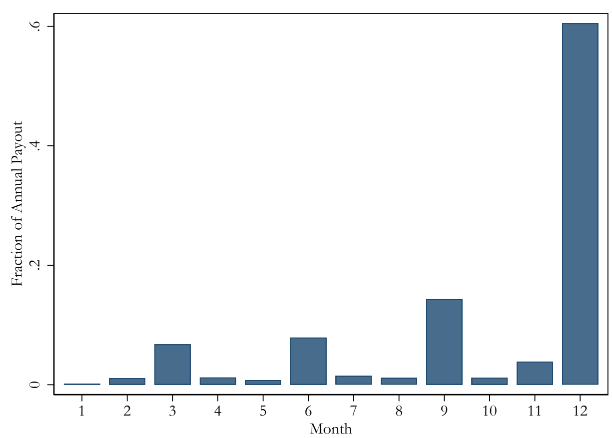


Figure 4. Return Sensitivity to Divided Payment by Decade
This graph shows the coefficient of value weighted market returns regressed on Market Div Pay[t-1,t] conducted separately for each decade. Each data point represents a decade, for example, the data point for 1930 is the regression coefficient when the regression is conducted on all data occurring from 1930 through 1939.

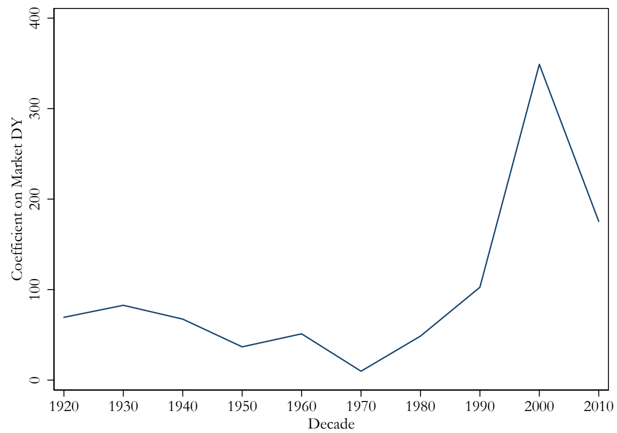


Figure 5. Longer Term Returns Based on Dividend Payment
This graph shows the regression coefficients from value-weighted market returns on the daily payment yield from day t to day t-19. The x-axis indicates the number of days lagged and the y-axis indicates the magnitude of the coefficient on that day. Regressions include year-by-month fixed effects. Gray bars show 90% confidence intervals.

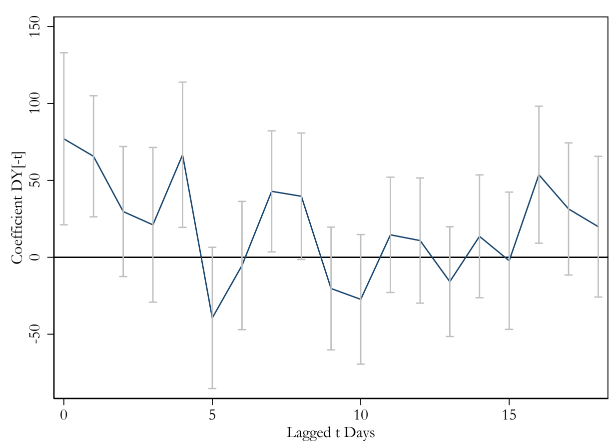
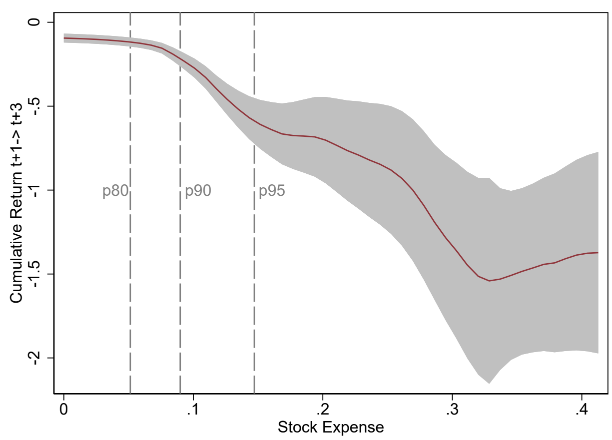


Figure 6. Stock Expense and Returns After Earnings Announcements

These figures show how returns after earnings announcements vary based on the level of stock expense. Panel A show a local linear plot of the cumulative returns from $t+1$ to $t+3$ based on the level of stock expense (winsorized at the 99th percentile). The gray dotted lines show the indicated percentiles of stock expense, among firms with non-zero stock expense. The gray shaded area represents the 95% confidence interval. Panel B shows the cumulative characteristic-adjusted returns from the announcement date (t=0) until 20 days after the announcement. Returns are shown separately based on the percentile of stock expense.

Panel A: Returns by Stock Expense



Panel B: Returns after Announcement

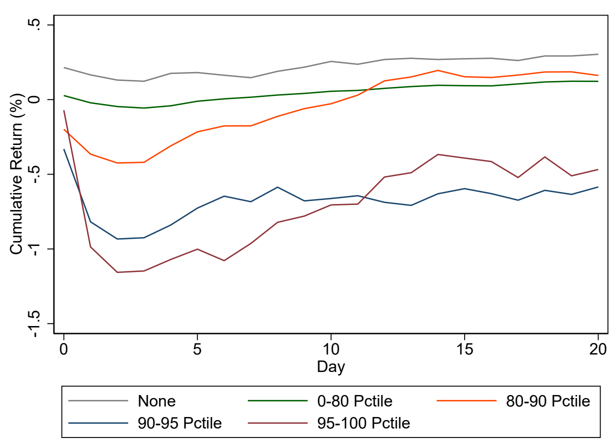
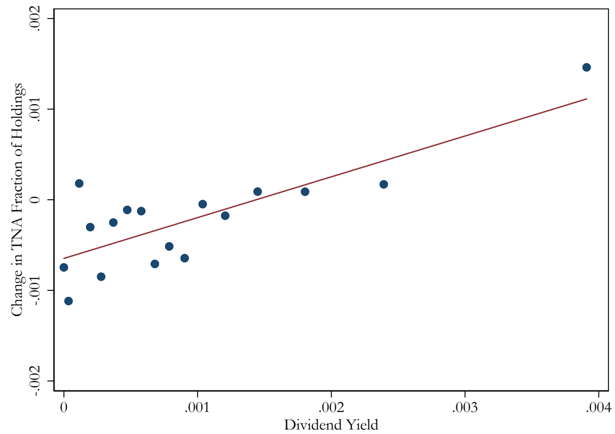


Figure 7. Mutual Fund Reinvestment

This graph shows a bin scatter plot of the change in fraction of TNA covered by holdings (y-axis) relative to the level of dividends received from those holdings (x-axis). Figures are value-weighted by prior month TNA. Panel A does not include controls. Panel B removes a fixed effect for fund and year-by-month. The analysis includes observations with a prior month TNA above $10 million, with at least 10 holdings, and where the fraction of TNA covered by holdings is between 50% and 105% in the current and prior month.

Panel A: No Controls



Panel B: Fund and Year-by-Month Fixed Effects

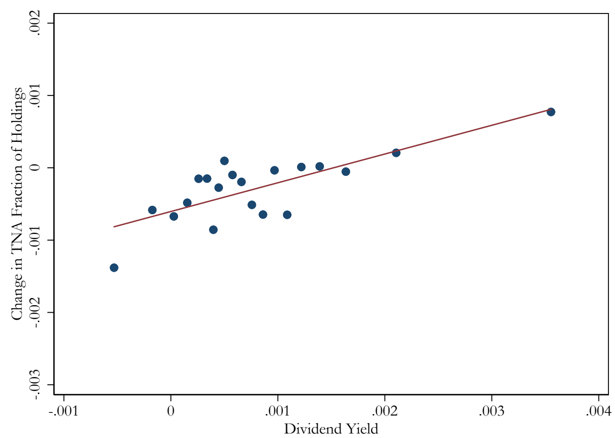


Table I

Market Returns Based on Dividend Payment

This table shows how the market return varies with the dividend payment yield. Market return is measured in percent as either the CRSP value-weighted market index or the CRSP equal-weighted index. Market dividend payment yield is the measured as the cumulative payment yield on day t and t-1 (Market Div Pay[t-1,t]), or the payment yield on the indicated day. Even-numbered columns contain year-by-month fixed effects. t-statistics based on heteroskedasticity-robust standard errors are in parentheses.

	Value Weighted				Equal Weighted			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mkt Div Pay[t-1,t]			59.50***	67.07***			69.18***	72.35***
			(3.32)	(3.47)			(3.48)	(3.50)
Mkt Div Pay[t]	55.76*	74.85**			84.34**	101.9***		
	(1.74)	(2.26)			(2.30)	(2.76)		
Mkt Div Pay[t-1]	60.04***	71.98***			49.58**	58.34**		
	(2.73)	(3.10)			(2.13)	(2.45)		
Mkt Div Pay[t-2]	23.59	35.98			33.93	42.65*		
	(0.98)	(1.43)			(1.44)	(1.76)		
Mkt Div Pay[t-3]	14.56	25.73			29.22	36.40		
	(0.50)	(0.85)			(0.98)	(1.21)		
Mkt Div Pay[t-4]	53.96*	66.66**			67.33**	75.31***		
	(1.89)	(2.32)			(2.28)	(2.60)		
YM FE	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.00105	0.0503	0.000700	0.0498	0.00165	0.0866	0.000964	0.0858
Observations	24534	24534	24537	24537	24534	24534	24537	24537

Table II

Market Returns Based on Dividend Payment: Alternative Dividend Normalizations and Dividend-Paying vs Non-Dividend-Paying Stocks

This table shows how the market return varies with the dividend payment yield using different dividend normalizations and examining stocks by dividend-paying status. In Panel A, the dividend payment yield is measured as the sum of dividends paid on days t and t-1 divided by the average daily dividend payment on days t-20 through t-272. In Panel B, top 5 is a dummy variable equal to one if the payment yield is in the top 5 of the prior 252 trading days and top 50 is a dummy variable equal to one if the payment yield is in the top 50 of the prior 252 trading days. In Panel C, the return is restricted to stocks that did not pay a dividend on days t and t-1 in the first four columns, and those that did pay a dividend on either t or t-1 in the last four columns. Even-numbered columns contain year-by-month fixed effects. t-statistics based on heteroskedasticity-robust standard errors are in parentheses.

Panel A: Abnormal Dividend

	Value Weighted		Equal Weighted	
	(1)	(2)	(3)	(4)
Mkt Abnormal Div[t-1,t]	0.00698***	0.00786***	0.00637***	0.00790***
	(3.39)	(3.58)	(2.89)	(3.43)
YM FE	No	Yes	No	Yes
R^2	0.000499	0.0497	0.000424	0.0857
Observations	24266	24266	24266	24266

Panel B: Top Dividend Payment Days

	Top 5 Days				Top 50 Days			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Top Days	0.128***	0.143***	0.127***	0.134***	0.0482***	0.0593***	0.0414***	0.0535***
	(2.99)	(3.23)	(2.75)	(2.91)	(3.34)	(3.93)	(2.87)	(3.61)
YM FE	No	Yes	No	Yes	No	Yes	No	Yes
Value Weight	Yes	Yes	No	No	Yes	Yes	No	No
Equal Weight	No	No	Yes	Yes	No	No	Yes	Yes
R^2	0.000516	0.0497	0.000514	0.0856	0.000464	0.0497	0.000350	0.0856
Observations	24287	24287	24287	24287	24287	24287	24287	24287

Panel C: Market Returns Restricting To Non-Paying versus Paying Stocks

	No Div Payment				Div Payment			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mkt Div Pay[t-1,t]	57.39***	65.12***	70.20***	74.39***	40.83**	45.91*	24.27	16.09
	(3.16)	(3.34)	(3.46)	(3.52)	(2.06)	(1.94)	(1.20)	(0.62)
YM FE	No	Yes	No	Yes	No	Yes	No	Yes
Value Weight	Yes	Yes	No	No	Yes	Yes	No	No
Equal Weight	No	No	Yes	Yes	No	No	Yes	Yes
R^2	0.000644	0.0494	0.000942	0.0855	0.000142	0.0486	0.0000404	0.0601
Observations	24537	24537	24537	24537	24355	24355	24355	24355

Table III

Market Returns Based on Dividend Payment: Calendar Effects and Macroeconomic Announcements

This table shows how the market return varies with the dividend payment yield controlling for patterns in returns related to calendar events and macroeconomic announcements. The first two columns of Panel A include dummy variables for the day of the week. The next two columns include a turn-of-the-month dummy variable equal to one if it is the last day of the month or the first three days of the month. The final two columns include both dummy variables. Panel B explores FOMC announcements. The announcement data ranges from 1988-2019, so the first two columns show the baseline analysis conducted over this period. The next two columns include dummy variables for days with FOMC announcements. Panel C examines macroeconomic announcements. The announcement dates range from 1994-2019, so the first two columns repeat the baseline analysis for this period. Columns 3 and 4 include dummy variables for CPI, PPI, employment and GDP announcements. Columns 5 and 6 also include dummy variables for FOMC announcements. Market return is measured in percent as the CRSP value-weighted market index. Market payment yield is the measured as the cumulative payment yield on day t and t-1 (Market Div Pay[t-1,t]). Even-numbered columns contain year-by-month fixed effects. t-statistics based on heteroskedasticity-robust standard errors are in parentheses.

Panel A: Day of Week and Turn of Month

	Day of Week		Turn of Month		Both	
	(1)	(2)	(3)	(4)	(5)	(6)
Mkt Div Pay[t-1,t]	74.46***	85.52***	32.01**	35.42**	48.00***	55.71***
	(5.16)	(5.54)	(2.14)	(2.19)	(3.19)	(3.43)
YM FE	No	Yes	No	Yes	No	Yes
R^2	0.00595	0.0552	0.00234	0.0514	0.00743	0.0565
Observations	24537	24537	24537	24537	24537	24537

Panel B: FOMC Announcements (1988-2019)

	(1)	(2)	(3)	(4)
Mkt Div Pay[t-1,t]	161.7***	174.8***	164.5***	179.8***
	(3.08)	(2.94)	(2.93)	(3.02)
FOMC	No	No	Yes	Yes
YM FE	No	Yes	No	Yes
R^2	0.00106	0.0348	0.00350	0.0370
Observations	7812	7812	7812	7812

Panel C: Macroeconomic Announcements (1994-2019)

	(1)	(2)	(3)	(4)	(5)	(6)
Mkt Div Pay[t-1,t]	223.5**	251.1***	228.0**	256.4***	230.8***	264.3***
	(2.25)	(2.67)	(2.56)	(2.71)	(2.60)	(2.80)
Macro	No	No	Yes	Yes	Yes	Yes
FOMC	No	No	No	No	Yes	Yes
YM FE	No	Yes	No	Yes	No	Yes
R^2	0.00101	0.0332	0.00140	0.0336	0.00426	0.0364
Observations	6294	6294	6294	6294	6294	6294

Table IV

International Market Returns Based on Dividend Payment

This table shows how market returns vary based on the dividend payment yield across 58 international markets. Data is in a panel format with data from a market/day combination included when the market reports information for at least 100 stocks. The market return is calculated as the value-weighted averages of those stocks. Market payment yield is measured as the cumulative payment yield on day t and t-1 in that market. Columns 2 and 4 include month-by-market fixed effects. Columns 3 and 4 include date fixed effects. Standard errors are clustered by date and market, with t-statistics in parentheses

	(1)	(2)	(3)	(4)
Mkt Div Pay[t-1,t]	20.30**	30.21***	22.65***	26.89***
	(2.19)	(3.59)	(3.02)	(4.50)
Country YM FE	No	Yes	No	Yes
Date	No	No	Yes	Yes
R^2	0.0000330	0.0611	0.268	0.309
Observations	237185	237070	236775	236660

Table V

Market Returns Based on Dividend Payment by Quarter and Month

This table shows how the market return varies with the dividend payment yield based on the calendar quarter or month. Market return is regressed on Market Div Pay[t-1,t] interacted with time period dummy variables. Columns 1 and 3 include quarter-of-year dummy variables and columns 2 and 4 include dummy variables for whether the calendar month is December, or other months of the year. All columns contain year-by-month fixed effects. *t*-statistics based on heteroskedasticity-robust standard errors are in parentheses.

	Value Weighted		Equal Weighted	
	(1)	(2)	(3)	(4)
Q1*Mkt Div Pay	134.8**		228.8***	
	(2.40)		(3.66)	
Q2*Mkt Div Pay	54.92*		31.60	
	(1.68)		(0.92)	
Q3*Mkt Div Pay	73.78**		53.16*	
	(2.44)		(1.91)	
Q4*Mkt Div Pay	12.01		-6.124	
	(0.35)		(-0.17)	
Not December*Mkt Div Pay		82.91***		89.99***
		(3.89)		(3.96)
December*Mkt Div Pay		-48.92		-56.87
		(-1.25)		(-1.30)
YM FE	Yes	Yes	Yes	Yes
R^2	0.0501	0.0501	0.0872	0.0862
Observations	24537	24537	24537	24537

Table VI

Market Returns Based on Dividend Payment and VIX

This table shows how the market return varies with the dividend payment yield interacted with the VIX and the News VIX. Value-weighted market returns are regressed on the VIX in columns 1-4, or the news VIX in columns 5-6, along with Market Div Pay[t-1,t]. High VIX is a dummy variable equal to one if the VIX or News VIX index is in the top quintile. Columns 2 and 4 include year-by-month fixed effects and Columns 7 and 8 include year fixed effects. t-statistics based on heteroskedasticity-robust standard errors are in parentheses.

	VIX				News VIX			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VIX*Mkt Div Pay	30.08***	24.12***			10.74***	11.53***		
	(3.79)	(2.95)			(2.89)	(3.05)		
Mkt Div Pay	-416.5**	-240.6	76.00	129.0*	-210.1**	-227.0**	28.93*	31.39*
	(-2.47)	(-1.40)	(1.05)	(1.70)	(-2.22)	(-2.36)	(1.75)	(1.86)
High VIX*Mkt Div Pay			469.6***	390.4**			128.9***	133.3***
			(2.88)	(2.25)			(3.77)	(3.88)
YM FE	No	Yes	No	Yes	No	No	No	No
Year FE	No	No	No	No	No	Yes	No	Yes
R^2	0.0191	0.122	0.0109	0.0478	0.00198	0.00690	0.00164	0.00599
Observations	7304	7304	7304	7304	23822	23822	23822	23822

Table VII

Industry Portfolio Returns Sorted on Past Exposure to Dividend Price Pressure

This table shows how monthly Fama French industry portfolio returns vary based on the their past exposure of daily returns to market dividend payments. An industry's value weighted daily return in months $m-13$ through $m-1$ is regressed on the market dividend payment yield on days t and $t-1$, to measure the exposure of that industry's returns to dividend payouts. Industries are sorted into portfolios based on these betas. The first column shows results from a regression of the difference portfolio from the highest quartile of dividend beta industries minus the lowest quartile of dividend payer industries. The next four columns show regressions for each quartile individually. In each case, returns are regression on a four-factor model using excess market returns, SMB, HML and UMD from Ken French's website, as in Carhart (1997). Panel A uses equal-weighting of industries, and Panel B uses value-weighting of industries (using industry market capitalization the prior month). All individual industry portfolios used are the value-weighted industry portfolio.

Panel A: Equal-Weighted Industry Portfolios

	Q4-Q1	Q4	Q3	Q2	Q1
	(1)	(2)	(3)	(4)	(5)
Alpha (%)	-0.282***	-0.0656	-0.0347	0.0972*	0.216***
	(-3.38)	(-1.09)	(-0.70)	(1.91)	(3.53)
Market	-0.0281*	0.975***	1.021***	1.010***	1.003***
	(-1.68)	(80.96)	(103.23)	(98.61)	(81.67)
Size	-0.210***	0.126***	0.209***	0.237***	0.336***
	(-7.94)	(6.64)	(13.34)	(14.65)	(17.32)
Value	-0.0101	0.127***	0.112***	0.0123	0.137***
	(-0.40)	(6.97)	(7.47)	(0.80)	(7.38)
Momentum	0.0400**	-0.0329**	-0.0347***	-0.0154	-0.0729***
	(2.06)	(-2.35)	(-3.03)	(-1.29)	(-5.11)
Observations	1085	1085	1085	1085	1085

Panel B: Value-Weighted Industry Portfolios

	Q4-Q1	Q4	Q3	Q2	Q1
	(1)	(2)	(3)	(4)	(5)
Alpha (%)	-0.262**	-0.0742	-0.0389	0.0816*	0.188***
	(-2.51)	(-1.18)	(-0.81)	(1.75)	(2.93)
Market	-0.0109	0.961***	1.018***	1.020***	0.971***
	(-0.52)	(76.14)	(105.04)	(109.02)	(75.22)
Size	-0.128***	-0.0811***	0.0243	0.0468***	0.0470**
	(-3.86)	(-4.06)	(1.58)	(3.16)	(2.30)
Value	0.319***	0.175***	0.0352**	-0.0491***	-0.144***
	(10.04)	(9.14)	(2.39)	(-3.46)	(-7.36)
Momentum	-0.0386	-0.0409***	-0.00638	-0.00703	-0.00231
	(-1.59)	(-2.79)	(-0.57)	(-0.65)	(-0.15)
Observations	1085	1085	1085	1085	1085

Table VIII

Stock Expense and Post Earnings Announcement Returns

This table shows characteristic-adjusted returns around earnings announcements as a function of the firm's stock expense. The dependent variable is stock returns at various horizons relative to the earnings announcement date (t=0), minus the returns on a portfolio matched on size, book-to-market ratio and momentum (Daniel et al. (1997)). Panel A measures stock expense based on the annual stock expense announced the prior quarter, scaled by market capitalization. Panel B measures stock expense using the quarterly stock expense in the current quarter divided by market capitalization one day before the earnings announcement. Dummy variables are created based on the percentile of stock expense. Values are equal to one if stock expense is in the range indicated in a row, with the omitted group being zero stock expense. Regressions other than column 1 include a control for the t=0 return, allowing for separate effect of positive and negative returns. Standard errors are clustered by date and firm, with t-statistics in parentheses.

Panel A: Prior Quarter Expense

	(1) (t=0, t+3)	(2) (t+1, t+3)	(3) (t+4, t+10)	(4) (t+4, t+20)
Stock Expense >0-80 Pctile	-0.184***	-0.00182	-0.0112	0.0301
	(-3.69)	(-0.05)	(-0.27)	(0.50)
Stock Expense 80-90 Pctile	-0.332***	-0.101	0.238***	0.0965
	(-2.93)	(-1.36)	(2.70)	(0.76)
Stock Expense 90-95 Pctile	-0.774***	-0.236**	0.152	0.477**
	(-4.83)	(-2.04)	(1.19)	(2.37)
Stock Expense 95-100 Pctile	-1.165***	-0.875***	0.455**	0.924**
	(-5.50)	(-5.77)	(2.06)	(2.46)
Constant	0.0987**	-0.0500	0.0819**	0.0465
	(2.24)	(-1.34)	(2.03)	(0.79)
t=0 Return	No	Yes	Yes	Yes
R^2	0.000453	0.000656	0.000289	0.000458
Observations	300456	300473	299789	298274

Panel B: Current Expense

	(1) (t=0, t+3)	(2) (t+1, t+3)	(3) (t+4, t+10)	(4) (t+4,t+20)
Stock Expense >0-80 Pctile	-0.173***	0.00492	-0.0259	0.00993
	(-3.42)	(0.14)	(-0.58)	(0.15)
Stock Expense 80-90 Pctile	-0.543***	-0.123	0.218***	0.359***
	(-5.06)	(-1.64)	(2.59)	(2.89)
Stock Expense 90-95 Pctile	-1.048***	-0.493***	0.151	0.176
	(-6.56)	(-4.24)	(1.19)	(0.76)
Stock Expense 95-100 Pctile	-1.271***	-0.884***	0.222	0.453
	(-5.65)	(-5.81)	(1.02)	(1.31)
Constant	0.123***	-0.0450	0.0973**	0.0619
	(2.73)	(-1.17)	(2.23)	(0.99)
t=0 Return	Yes	Yes	Yes	No
R^2	0.000682	0.000777	0.000233	0.000364
Observations	300456	300473	299789	298274

Table IX

Retail and Mutual Fund Dividend Reinvestment

This table examines how often individual investors and mutual funds reinvest dividends in their portfolio. Panel A considers observations of individual investors at the portfolio level on each day they have holdings, from an anonymous discount brokerage between 1991 and 1996. The dependent variable is a dummy equal to one if the investor made a purchase in any security that day. The independent variable is a dummy equal to one if the investor received a dividend that day or the day before. Column 2 adds account fixed effects, and column 3 adds both account and date fixed effects. Panel B examines monthly mutual fund portfolio changes from CRSP. The dependent variable is the monthly change in the fraction of TNA covered by holdings. The independent variable is the dividend yield those holdings received. Columns 2 and 4 include year-by-month fixed effects and column 4 includes fund fixed effects. Regressions are value-weighted by prior month TNA. The analysis includes observations with a prior month TNA above $10 million, with at least 10 holdings, and where the fraction of TNA covered by holdings is between 50% and 105% in the current and prior month. t-statistics are in parentheses, and are clustered by account and date in Panel A, fund and month in Panel B.

Panel A: Individual Investors

	(1)	(2)	(3)
Div Pay[t-1,t]	0.00176***	0.000307***	0.000370***
	(14.02)	(4.79)	(6.35)
Constant	0.00178***		
	(59.83)		
Account FE	No	Yes	Yes
Date FE	No	No	Yes
R^2	0.0000572	0.0165	0.0168
Observations	46000677	46000623	46000623

Panel B: Mutual Funds

	(1)	(2)	(3)	(4)
Div Received	0.530***	0.446***	0.692***	0.641***
	(4.39)	(3.88)	(4.95)	(4.59)
YM FE	No	Yes	No	Yes
Portno FE	No	No	Yes	Yes
R^2	198141	198139	197716	197714

Table X

Price Multiplier Estimates

This table presents estimates of price multipliers under different assumptions about reinvestment rates. Estimates are based on the coefficient of 67.07 from Table I Panel A Column 2. The first column presents multiplier estimates based on the assumption for aggregate reinvestment rate in Column 2. The multiplier estimate is 67.07 divided by the aggregate reinvestment percentage. The aggregate reinvestment rate is based on the assumptions about reinvestment rates for retail investors (column 3), mutual funds and ETFs (column 4) and all other investors (column 5). The aggregate reinvestment % implied by these numbers is the average of columns 3 through 5, weighted by the proportion of each investor type in the market, which is listed in the column headings and is based on the March 2020 Financial Accounts of the United States release Z.1.

Multiplier	Aggregate Reinvestment %	Retail (34%)	Mutual Funds & ETFs (28%)	Other (38%)
0.67	100%	100%	100%	100%
1.02	66%	0%	100%	100%
1.17	57.3%	0%	69%	100%
1.33	50.6%	0%	45%	100%
1.47	45.5%	0%	69%	69%
2.26	29.7%	0%	45%	45%