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Cash Induced Demand

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Abstract

I show that cash distributions through cash mergers, dividend payments, and stock buybacks are, in principle, similar to investor fund flows in generating demand for investable assets. Abnormal returns on certain assets can be forecasted because delegated investors predictably reinvest cash returns toward certain holdings. Novel measures of stock-level demand constructed using proportional reinvestments by mutual funds predict abnormal returns and issuances in noncash-paying stocks. These results highlight an alternative and substantial source of price fluctuations in the cross section of equities.

I. Introduction

A large and growing literature in financial economics is interested in identifying demand-driven price pressure as the source of fluctuations in asset prices (Gabaix and Koijen (2020)). While this literature typically uses investor flows into asset managers as the main source of asset demand, in this article, I show cash payouts from public firms form a substantial alternative basis of demand for investable assets. As can be seen in Figure 1, in 2016 alone, publicly listed companies distributed almost $1 trillion through dividends and stock buybacks. In contrast, investment flows to delegated mutual funds are much lower – the total annual investor capital flow to mutual funds added up to no more than $400 billion in that time. In accordance with the demand view of price fluctuations, these large aggregate cash payouts to investors, under limited arbitrage, should drive substantial predictability in asset prices (see, e.g., Shleifer and Vishny (1992), (1997) and Greenwood (2005)).

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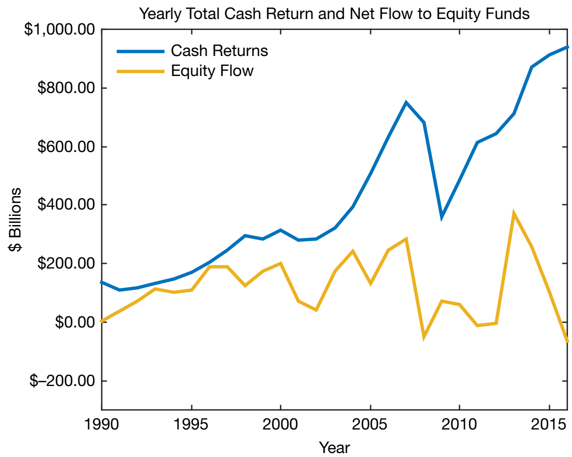
FIGURE 1

Annual Total Capital Return by All Stocks and Net Investor Flow to Equity Funds

Figure 1 plots the annual aggregate capital return (buyback and dividend payments) in the CRSP universe of common stocks traded on the NYSE, Nasdaq, and AMEX, and net fund flow into the CRSP universe of equity funds. Buyback is the product of an adjusted decline in shares and quarter-start prices. Dividend payment is dividend yield (the difference between total and price returns) multiplied by market capitalization at the start of the quarter. Equity flow is calculated from CRSP as the difference between the quarter-end TNA and the quarter-start TNA adjusted by fund returns. The units are in $ billions.



I examine the 3 types of events through which portfolios face potentially large cash distributions that need reinvestment: cash-financed mergers, dividend payments, and asset buyback programs. By exposing the details of these cash programs, I show the mechanical reinvestment of cash returns into assets is, in principle, similar to investor flows into delegated asset managers.

This examination of cash distributions as a source of asset price fluctuations contributes in several ways to the finance literature. First, the use of cash distributions from established holdings may alleviate some of the identification concerns of the relationship between investor flows and prices. The largest firms make the vast majority of total cash distributions, and economic factors that drive such large cash returns are likely different from other factors involved in excess stock returns, especially when I limit the analysis to stocks that do not pay dividends or conduct buybacks. Moreover, many reinvestment programs involved in distributions are automatic and individually small, easing concerns of endogenous cash-management decisions in mutual fund portfolios with large variable investor flows.[1]

Second, I present additional evidence on the dynamics of demand-driven predictability. The typical return pattern in investor flow-driven price pressure is a positive run-up in the prices of the stocks experiencing investor flows, and then a longer-term reversal. Wardlaw (2020) criticizes the reversal pattern as characteristic of the momentum and size factors that are embedded in the measure's construction. The price pressure measurement constructed from cash distributions is likely not

[1]Mutual fund investors can elect to participate in automatic reinvestment programs. In Appendix A2 of the Supplementary Material, I estimate that 84.7% of measured mutual fund distributions are automatically reinvested in the fund portfolio.

subject to the same criticism because the measure itself does not load positively on past returns nor does it pick up stocks characterized by the small size.[2] This cash-induced demand measurement is associated with positive return predictability – amounting to \$4.83 in immediate price appreciation per dollar of cash return. Yet unlike investor flow-driven price impact, this expected price pressure of dividends and buybacks is not associated with significant reversals. In fact, the stocks that are most exposed to payout cash flows also tend to issue equity more than the exposed stocks. This persistent issuance pattern indicates that cash reinvestments through the equity market relax financing constraints in the cross section of equities, or generate price effects that are actively arbitraged by firms, or both.

Ultimately, the cash-induced demand I document offers a substantial alternative source of cash inflow driven investments and effectively serves as a tool for external validation and an out-of-sample test of the demand-driven fluctuation hypothesis.

The article is organized as follows: First, I use mergers as a clean laboratory to examine the timing of purchase decisions and subsequent price fluctuations that are associated with cash returns from assets. During a cash merger, a target is delisted and its shares are exchanged for cash. I show the investors who receive these cash windfalls tend to reinvest in other assets almost immediately after the distribution; that is, if investors engage in any cash management around these events, cash distributions end up affecting the timing of their reinvestment decisions. The shareholders of the merged targets substantially increase their purchases of other stocks (more than nonshareholders) only after the cash payment date.

Institutional investors holding the delisted stock increase their daily net trading activity by roughly 2.80% (4.39%) in the 10 trading days after the 100 (30) largest cash mergers. This effect is notably absent for stock-financed mergers, and therefore likely is not driven by changes in investor expectations or discretionary investment management related to the completion of the merger.

The reinvestment decisions are followed by a pattern of excess returns that is consistent with price predictability. A stock purchased by cash-return-deploying investors on average accumulates contemporaneous returns of 85 basis points (t = 5.45). These returns do partially revert: the same stocks experience excess returns of −52 basis points (t = −2.76) in the next 60 trading days, and −68 basis points (t = −2.39) in the 60 trading days after. These results are robust to controlling for a set of common characteristics, as well as to alternative measures of reinvestment demand.

Further comparison of the pricing of these stocks against the pricing of stocks purchased by noncash-deploying investors yields similar patterns. The targets of cash-redeploying demand can be predicted using the net stock purchases from the same investors at a period significantly prior to the cash distribution, suggesting the redeployment demand loads on investor styles and mandates. Overall, these results indicate the following: reinvestments are likely mechanical results of cash returns, they target a specific cross section of equities, and event-time price impacts are associated with these targets.

[2]The CID measure used in the main text has a −17.05% correlation with past 12-month returns and a 2.77% correlation with a stock's log market cap.

Given this evidence on the timing and the mechanism of reinvestment from cash mergers in hand, the second half of this article examines cash returns from dividend and share repurchase programs. Unlike cash mergers, dividends and share buybacks involve smaller individual payments. Over a quarter, however, these payments aggregate into a diversified portfolio operated, in principle, according to the same investment demand mechanism as cash mergers and investor inflows. I draw on mutual fund holdings to analyze the reinvestment and return predictability associated with these channels of cash deployment.

Assuming mechanical reinvestment, I construct a measure of expected cash-induced demand.[3] I show this measure predicts abnormal returns: a high level of expected price pressure is associated with high excess returns for nonpayout stocks. Regression analysis indicates a price-to-reinvestment demand elasticity of roughly \$4.83 of price appreciation to \$1.00 in cash distributions. In contrast to the evidence from investor flow-driven price pressure, this measure does not predict substantial reversals subsequent to the abnormal returns, potentially because of the persistence of the cash-induced demand inflows. These results are compatible with the inelastic demand hypothesis of Gabaix and Koijen (2020).

Section II first reviews the relevant literature. Section III describes the data used for this study and various institutional details. Section IV examines investor demand for stocks surrounding cash-merger payments. Section V then applies the redeployment mechanism to study payout exposure and the returns of nonpayout stocks. Section VI concludes.

II. Relevant Literature

The most popular method for identifying a source of demand-driven price fluctuations is to aggregate the cash-flows from investor deposits and redemptions in mutual funds onto assets that form potential targets of the induced trades (see, e.g., Warther (1995), Coval and Stafford (2007), Frazzini and Lamont (2008), Edmans, Goldstein, and Jiang (2012), Kahn, Kogan, and Serafeim (2012), and Lou (2012)). This method makes two implicit assumptions: i) The investment of cash from inflows and the liquidation of assets from outflows are largely mechanical and predictably reflect the ex ante snapshots of mutual fund holdings, and ii) the identified targets of this investment demand have characteristics that are at least partially orthogonal to the factors that affect investor flows.

However, the validity of these conditions for identifying the price impact of investor flows is limited. For instance, the discretionary cash management by fund managers will alleviate the price impact of mechanical purchases and liquidation of assets (Chernenko and Sunderam (2019), Choi, Hoseinzade, Shind, and Tehraniane (2020)). Additionally, challenging the second assumption, the factors that drive

[3] Whereas the cash-redeployment mechanism likely operates in mutual funds as well as nonmutual fund holdings, mutual fund portfolios have the advantage of capturing investment mandates and style constraints. Institutional holdings may be composed of multiple portfolios, each with a separate mandate and a different group of ultimate investors. Additionally, using mutual fund portfolios facilitates comparisons to investor flow measures. However, an alternative measure of cash induced demand, constructed using institutional holdings, has 70.7% correlation with that used in the article and gives qualitatively similar results.

investor capital flows are likely related to existing factors that affect asset prices.[4] Lastly, the flow-driven pressure measurements may be correlated with other well-known factors that affect stock returns through their construction (Wardlaw, 2020), making the validation of the demand fluctuation hypothesis limited.

Given the limitations, it is relevant for the finance literature to examine the demand for equity in contexts other than investor capital flow. However, few available alternatives in the finance literature offer an economically significant and comparable source of cross-sectional demand variation in the equity markets. Index inclusions and exclusions (Harris and Gurel (1986), Shleifer (1986), Kaul, Mehrotra, and Morck (2002), and Greenwood (2005)) are limited to event studies and, in principle, would not influence the prices of assets not subject to these actions. Because of the importance of cross-sectional demand to the fluctuations in equity asset prices (Gabaix and Koijen (2020)), I examine payout cash as an alternative to mutual fund investor flows as a source of investment demand.

This article is also part of a growing literature that investigates the treatment of dividends and returns by investors. See, for example, Hartzmark and Solomon (2019) and Di Maggio, Kermani, and Majlesi (2020). This research broadly finds investors treat dividend returns differently than price returns. Hartzmark and Solomon (2019) call the phenomenon the dividend disconnect and document that nondividend-paying stocks experience abnormal returns following large dividend payments. In Swedish household data, Di Maggio et al. (2020) find individuals are more likely to consume dividend income than capital appreciation. I find exposure to dividend and buyback programs is a persistent and variable characteristic of asset-manager portfolios that relates to asset allocation. Stocks exposed to this source of investor demand are a predictable cross section of equity assets.

Payout policy is central to corporate finance. A well-developed literature focuses on payouts from the perspective of the firm. Managers initiate stock repurchases (stock issuance) when they believe their firms are undervalued (overvalued), when manager–investor incentive misalignment exists, or simply when they wish to substitute these repurchases for dividend payments. See the literature developed by Miller and Modigliani (1961), Bhattacharya (1979), Vermaelen (1981), Ikenberry, Lakonishok, and Vermaelen (1995), Loughran and Ritter (1995), Baker and Wurgler (2000), Jagannathan, Stephens, and Weisbach (2000), Graham and Harvey (2002), Grullon and Michaely (2002), Kahle (2002), Stephens and Weisbach (2002), Cook, Krigman, and Leach (2004), Massa, Rehman, and Vermaelen (2007), Hong, Wang, and Yu (2008), Greenwood and Hanson (2012), and Dittmar and Field (2015).

One potential issue with measures of payout exposure is that individual firms time stock repurchases. However, when aggregated at the portfolio level, investor exposure to repurchase dollars is extremely persistent. In other words, when repurchasing dollars from public firms are grouped into a large, diversified portfolio, the cash flow is smooth and predictable. I focus on the use of this cash flow and its effect on stocks that do not conduct payouts.

[4]For instance, return-chasing affects investor flows, whereas momentum predictability in assets is the phenomenon whereby past returns forecast future returns. Mutual funds also typically load up on specific types of styles (see Brown and Goetzmann (1997), Barberis and Shleifer (2003), and Boyer (2011)).

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III. Data and Institutional Details of Cash Mergers, Dividends, and Buybacks

My analysis relies on two data sets that capture trading by institutional investors. The first is the set of trades in individual institutional client accounts from ANcerno (also known as Abel Noser Corp) (see, e.g., Puckett and Yan (2011) and Hu, Jo, Wang, and Xie (2018) for a more detailed description of the data set.). The second is the standard quarterly holdings by mutual fund and institutional portfolios from CDA/Spectrum.

The ANcerno data provide trading disclosures from a large range of institutional clients between Q1 1999 and Q3 2011, after which ANcerno stopped releasing data disaggregated by individual client portfolios. These clients provide the individual trades of their account managers for transaction-cost analysis. According to Hu et al. (2018), investment managers and pension-plan sponsors are the primary clients that released these trade records. The mutual fund and institutional portfolio data come from standard regulatory disclosure forms required by the Securities and Exchange Commission and collected by CDA/Spectrum. This set of funds is matched to the CRSP data set of fund characteristics for the period between 1990 and 2016. Stock return and firm characteristic data come from CRSP and Compustat, respectively. The universe of stocks consists of common U.S. equity, traded on the NYSE, Nasdaq, and AMEX, with market capitalization greater than the bottom 10% of the NYSE.

I first analyze the activities of institutional investors around cash merger events. After a merger announcement, the involved parties apply to regulators for approval. In the case of approval, payment to investors and the closing of a deal occur shortly after. Initial merger announcement-day returns are widely studied in the empirical literature (see, e.g., Mitchell, Pulvino, and Stafford (2004)). The final payment in a cash merger will affect the level of cash holdings while staying invariant to the total value of a portfolio. The largest cash-financed merger in my sample period exchanged over $50 billion in stock for cash within a single day. As a point of reference, the average daily volume of the Nasdaq composite was slightly over $100 billion in the same period. I use the largest of these payment events to identify the effect of cash payments in driving investor demand.

Unlike cash mergers, dividend payments are minuscule at daily intervals, while they aggregate over time to represent a significant source of cash injection. Dividends also do not change the total value of an investor portfolio; a portfolio that holds a stock on its ex-dividend date receives an allocation equal in value to the distributed amount. This allocation offsets the reduction in the value of asset holdings (stock prices adjust to the ex-dividend price). The dividend clearing date is after the ex-dividend date. Despite the lag in clearing, the investor has immediately credited the value of the cash dividend.

Finally, in a share buyback, firms also give cash to investors, although these events involve investor discretionary choice. Over 95% of share buybacks occur through open-market operations. A firm first announces its intention to conduct a repurchase program, focusing largely on the size and term of the program. Firms typically have considerable discretion in the actual purchase. Open-market repurchases occur over years. Investors have no public information regarding their precise timing and generally observe only the ex post changes in a firm's shares outstanding. While only some funds may elect to sell in a stock buyback, a firm's buyback of stocks will ultimately and certainly transfer cash to the investors who had held the stock prior to the buyback.

The expected cash flow to each portfolio from a buyback operation can be calculated without knowing which investors will participate. The percentage decline in aggregate mutual fund holdings matches roughly one-to-one with the percentage reduction in the shares outstanding of firms during a quarter, and I use this expected decline in the average fund portfolio holdings in Section V to calculate the price pressure on other assets.

IV. Cash-Financed Mergers

The standard CRSP data set records the delisting distributions of cash-financed mergers. This record identifies the dates when outstanding stocks retire. These cash mergers are described by delisting code (233) and distribution codes (32XX) in the daily stock header file. From Q1 1999 to Q3 2011, there were 386 cash mergers where a common U.S. stock was delisted for over $1 billion. Table 1 describes summary statistics for the largest 20 of these mergers by the value of stocks retired.

A. Purchasing Pattern Around Cash Mergers

Figure 2 shows net trading activities by ANcerno investors around the three largest cash-financed merger events in the sample period: the purchase of

TABLE 1

Top Cash Mergers and Their Characteristics

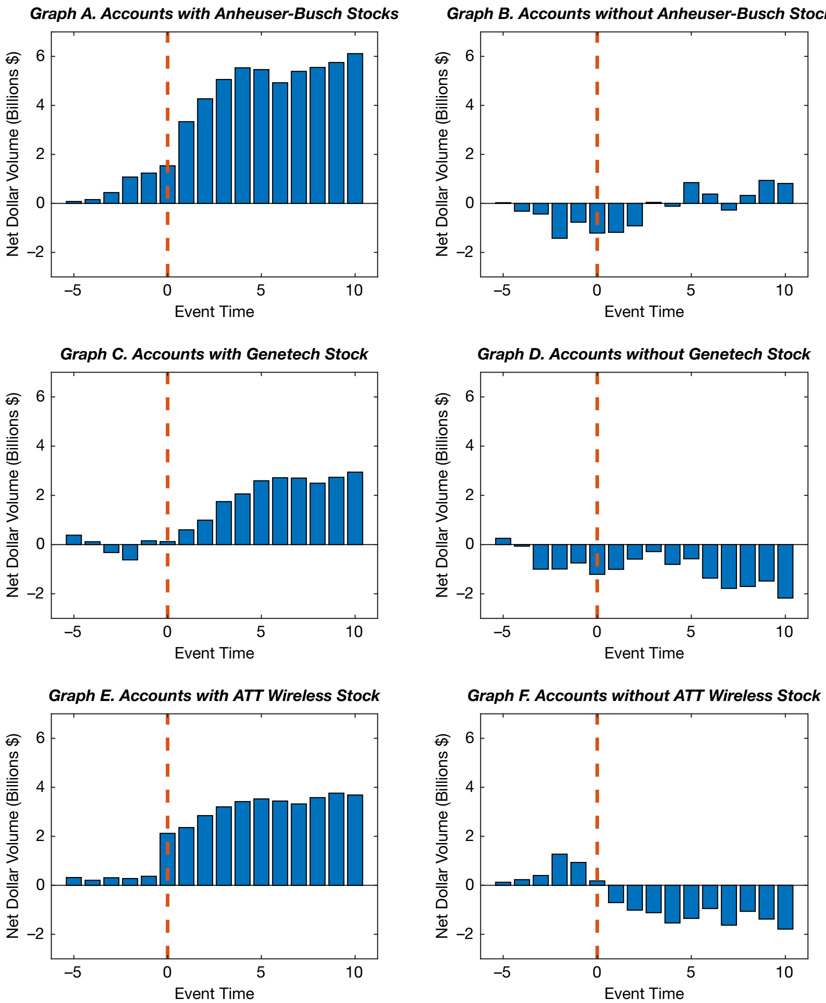
Table 1 tabulates the largest 20 cash mergers, in terms of the value of stocks retired, over Q1 1999 to Q3 2011. These mergers correspond to the delisting code (233) and distribution codes (32XX) in the CRSP header files. The total value of stocks delisted is usually different from the merger deal size due to prior minority shares held by the acquirer in the cash target. No. of ANcerno Accts is the number of client accounts observable in ANcerno that had (and had not) accumulated shares of the cash merger target before the merger payment date.

Cash Merger Target	Total Value of Stocks Delisted	Payment Date	No. of ANcerno Accts with Target	No. of ANcerno Accts Without Target
Genentech	$100,115,275,000	3/26/2009	552	13,196
Anheuser Busch	$50,614,830,000	11/17/2008	342	14,038
AT&T Wireless	$40,943,370,000	10/26/2004	286	6,244
TXU	$31,934,776,000	10/10/2007	406	15,477
First DATA	$25,637,054,000	9/24/2007	366	15,283
Alltel	$24,630,678,000	11/16/2007	209	15,994
Cox Communications	$21,069,585,000	12/8/2004	457	6,514
HCA Inc.	$20,899,800,000	11/17/2006	521	11,999
Bestfoods	$20,255,602,000	10/4/2000	108	3,214
Hilton Hotels	$18,543,810,000	10/24/2007	242	15,877
Clear Channel	$17,923,824,000	7/30/2008	202	14,563
Wrigley William Jr	$17,493,120,000	10/6/2008	206	15,991
Harrahs Entertainment	$16,882,020,000	1/25/2008	182	19,340
Kerr Mcgee	$16,031,982,000	8/10/2006	199	11,131
Rohm & Haas	$15,420,314,000	4/1/2009	162	13,528
Kinder Morgan	$14,434,133,000	5/30/2007	126	17,375
Medimmune	$13,796,576,000	6/18/2007	453	17,737
Electronic Data Sys	$12,631,350,000	8/25/2008	194	13,966
Georgia Pacific	$12,496,224,000	12/22/2005	188	8,400
Lyondell Chemical	$12,174,048,000	12/20/2007	143	19,059

FIGURE 2

Three Largest Cash Mergers Between Q1 1999 and Q3 2011

Figure 2 plots the cumulative net dollar trading volume of all stocks (not including the target and the acquirer during a cash merger) by ANcerno accounts from 5 trading days before to 10 days after the payment date (dashed red line) for the three largest cash mergers completed between Q1 1999 and Q3 2011. I designate an account (CLIENTMGRCODE) in ANcerno as holding a stock if it had, in net, purchased this stock between the account's first observation date and the payment date of the merger. Graphs A, C, and E depict net dollar volume by accounts holding this target stock. Graphs B, D, and F depict the total net trading by the rest of the investor accounts.



i) Anheuser-Busch (AB) by InBev on Nov. 17, 2008; ii) Genentech by Roche on Mar. 26, 2009, and iii) AT&T Wireless by Cingular on Oct. 26, 2004. I separate institutional accounts into two groups according to their prior accumulation of the target stock. The Graphs A, C, and E show the net dollar volume from client accounts that accumulated the target stock prior to the cash payment date. Graphs

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TABLE 2

Trading Activity Around Mergers by ANcerno Portfolios

Table 2 presents the regression of net trading by investors following the delisting event. ABNORMAL_DOLLAR_VOLUME$_{j,t,e}$ for investor j at t trading day into merger event e is the abnormal net dollar volume (on all stocks except for the target and acquirer) originating from j on the [−10, 10) tth trading day. The abnormal dollar volume is calculated by dividing the total net dollar volume on that day by the total cumulative gross dollar volume from the [−30, −10) days around the payment event. Investor portfolios must have had at least $1 million in gross volume in the [−30, −10) days to be in the sample. HELD_TARGET$_{j,e}$ indicates whether investor j held the target of the merger prior to the distribution event. POST_EVENT$_{t,e}$ indicates the trading event time in the [0, 10) days of the distribution. Regressions are conducted separately for the top 10, 30, and 100 cash (columns 1–3) and stock-financed (columns 4–6) mergers. The t-statistics are clustered by each merger event. Coefficients significant at the 10%, 5%, and 1% levels are marked with *, **, and ***, respectively.

	ABNORMAL_DOLLAR_VOLUME$_{t,e}$					
	Cash Mergers			Stock Mergers		
	Top 10	Top 30	Top 100	Top 10	Top 30	Top 100
HELD_TARGET$_{j,e}$	0.0492***	0.0525***	0.0597***	0.0335***	0.0288***	0.0350***
	(5.195)	(6.244)	(6.850)	(4.898)	(4.452)	(4.888)
POST_EVENT$_{t,e}$	−0.00467*	0.00347*	0.000858	0.000250	−0.00173	−0.00284**
	(−1.658)	(1.873)	(0.835)	(0.0730)	(−0.869)	(−2.471)
HELD_TARGET$_{j,e}$ × POST_EVENT$_{t,e}$	0.0604***	0.0439***	0.0280***	−0.00893	0.00367	0.00693*
	(5.637)	(5.964)	(5.996)	(−1.194)	(0.704)	(1.932)
N	488,120	1,419,200	4,654,380	417,000	1,210,780	4,060,000
Adj. R^2	0.001	0.000	0.000	0.000	0.000	0.000

B, D, and F display the dollar volume from client accounts that did not accumulate any shares.[5]

Each graph describes the aggregate trading by the respective groups of ANcerno accounts in the 5 trading days before and the 10 trading days after a cash payment event. In all 3 cases, institutional investors purchased large dollar volumes of other stocks on or after the merger payment date. Institutional accounts in ANcerno purchased a total of $7.6 billion in the 5 trading days after the Anheuser-Busch merger and $8.2 billion over the entire measured horizon (over the −5 to +10 trading-day period). These net dollar volumes are linked to prior ownership of AB stocks. Over 77% of the total cumulative volume came from accounts that were identified as receiving payments from the merger (left graph); only a minority comes from other accounts (right graph). The second (Genentech) and the third (AT&T Wireless) largest cash-financed acquisitions repeat the same event time pattern. In all three cases, the identified stockholders of the respective acquisition targets actively acquired stocks over the remaining investor accounts.

Figure 2 represents a simple summary of the ANcerno investor, but this visible pattern around cash merger payments may be driven by both selection and the payment. Panel A of Table 2 presents a formal test of cash reinvestment using a difference-in-difference panel setup. This panel assesses whether cash payments from cash mergers affect the trading behavior of asset manager accounts.

In order to ensure the treated and control investors have similar ex ante trading patterns, I filter the data to include only accounts with at least $1 million in gross volume during the 30 to 10 trading days prior to the payment date. The

[5]ANcerno reports trades by institutional accounts but not their contemporaneous holdings. I measure the accumulation of a stock by examining the entire trading history of each client. Specifically, I sum all the split-adjusted shares of a stock bought and sold by a client account from the first recorded trade until the most recent trade. If, for a single stock, an account sells more shares than it had bought before the time of that trade, the accumulation is set to 0.

left-hand-side variable, $\text{ABNORMAL\_DOLLAR\_VOLUME}_{j,t,e}$, is the daily dollar volumes from investor j in the tth $[-10, 10)$ trading days around the merger event e, normalized by the investor's average gross daily trading volume in the 30 to 10 trading days prior (of course, excluding activities related to the target and the acquirer). $\text{POST\_EVENT}_{t,e}$ indicates a post-distribution day and captures the pre–post difference.

The ideal treatment for disentangling the payment-induced demand is an investor's exact holdings of the cash merger target. As those data are not available, however, the treatment variable, $\text{HELD\_TARGET}_{j,e}$, is an indicator for whether investor j had ever bought shares of the target stock before the payment date. Therefore, $\text{HELD\_TARGET}_{j,e}$ accounts for the treatment group.

The regression coefficients in Table 2 show that an investor holding the target stock would increase its net dollar trading volume in the days after the cash-financed merger payment. After the payment of the 10 largest cash mergers in my sample, a target-holding investor increased its *net* dollar volume by 6.04% ($t = 5.637$) of its average *gross* volume from the 30 to the 11 days before a merger event. This effect declines as I include smaller cash mergers. I find a treatment effect of 4.39% ($t = 5.964$) for the panel of top 30 mergers and 2.80% ($t = 5.996$) for the top 100 mergers.

These results show cash injection in mergers has an economically significant impact on individual investor demand for stocks. Importantly, this effect is absent for stock-financed mergers in columns 4–6. Stock-financed mergers do not affect investors' net trading behavior to any great degree. Therefore, changing investor expectations of a merger completion is unlikely to drive my results. If there is any cash management by the investors who receive cash, such management does not prevent reinvestment activities from occurring in the data. In summary, these results indicate the timing of cash returns drives investment demand.

B. Pricing Effect of Cash Merger Induced Demand

Given that cash-receiving investors demand assets, the targets of these purchases presumably experience price pressure. I thus examine the pricing patterns of the associated stocks using both ex post (INDUCED_BUY) and ex ante (CASH_MERGER_PRESSURE) measures of potential demand-driven price pressure.

For an ex post measure of demand, I construct INDUCED_BUY, which indicates whether cash-redeploying investors increased their holdings of stock i in the $[0, 30)$ trading days after a merger. Specifically, $\text{INDUCED\_BUY}_{i,e}$ is 1 if the total net purchase of stock i by the investors who held the target stock during event e is positive, and 0 otherwise.[6]

In Table 3, I compare this group of demand-affected stocks with all other stocks in the CRSP universe in Panel A and with stocks purchased by investors who did not hold the target in Panel B. I regress cross-sectional returns on INDUCED_BUY using the standard Fama–MacBeth (1973) methodology. The left-hand-side

[6]INDUCED_BUY splits the CRSP universe of stocks. Fifty-three percent of stocks by value experienced induced buying during the top 100 cash merger payment events. Additionally, this indicator forms 65% of stocks by value out of all stocks bought by both cash-redeploying and noncash-redeploying investors in the ANcerno database.

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TABLE 3

Abnormal Returns Associated with Investor Purchases

Panel A (B) of Table 3 shows the Fama–MacBeth regressions of cumulative excess returns over the daily risk-free rate around the top 100 cash mergers for stocks in the whole CRSP universe (purchased in net by ANcerno investors). $\text{INDUCED\_BUY}_{i,e}$ is an indicator for whether ANcerno stockholders of the merger target increased their net holding of stock *i* in the [0, 30) trading days around the merger payment date. Columns 1 and 2 regress contemporaneous excess returns on $\text{INDUCED\_BUY}_{i,e}$ and controls. Columns 3 and 4 regress excess returns in the following 60 trading days. Columns 5 and 6 regress excess returns during the 90 to 150 days after the merger payment. Columns 7 and 8 document the entire reversal between the 30 and 150 trading days. OLS *t*-statistics are reported in parentheses.

	Event-Time Fama–MacBeth Regressions							
	Excess Return [0, 30)		Excess Return [30, 90)		Excess Return [90, 150)		Excess Return [30, 150)	
Panel A. Entire CRSP Universe								
$\text{INDUCED\_BUY}_{i,e}$	0.847%	0.927%	−0.518%	−0.259%	−0.679%	−0.372%	−1.303%	−0.720%
	(5.45)	(5.95)	(−2.76)	(−1.30)	(−2.39)	(−2.42)	(−3.54)	(−2.53)
$\log(\text{ME})_{i,e}$		−0.083%		−0.117%		−0.545%		−0.749%
		(−0.86)		(−0.82)		(−2.38)		(−2.19)
$\text{BOOK\_TO\_MARKET}_{i,e}$		−0.092%		−0.378%		−1.181%		−2.086%
		(−0.54)		(−1.37)		(−3.87)		(−3.10)
$\text{RET12}_{i,e}$		−0.852%		−0.744%		−0.704%		−1.71%
		(−1.07)		(−0.92)		(−0.72)		(−1.16)
Avg.N	2,474	2,474	2,474	2,474	2,474	2,474	2,474	2,474
Avg.R^2	0.18%	3.06%	0.08%	2.62%	0.06%	2.93%	0.06%	2.82%
Panel B. Purchased by ANcerno Investors								
$\text{INDUCED\_BUY}_{i,e}$	0.512%	0.583%	−0.312%	−0.155%	−0.698%	−0.522%	−0.943%	−0.602%
	(3.26)	(3.97)	(−1.69)	(−0.78)	(−3.03)	(−3.30)	(−3.70)	(−2.08)
$\log(\text{ME})_{i,e}$		−0.020%		−0.149%		−0.682%		−0.841%
		(−0.176)		(−1.03)		(−2.88)		(−2.70)
$\text{BOOK\_TO\_MARKET}_{i,e}$		−0.241%		−0.751%		−2.474%		−4.02%
		(−0.72)		(−1.49)		(−4.02)		(−3.26)
$\text{RET12}_{i,e}$		−1.030%		−1.130%		−0.805%		−2.44%
		(−1.23)		(−1.40)		(−0.82)		(−1.64)
Avg.N	1,969	1,969	1,969	1,969	1,969	1,969	1,969	1,969
Avg.R^2	0.15%	3.62%	0.04%	3.09%	0.05%	2.99%	0.04%	3.39%

variables are cumulative excess returns over the daily risk-free rate during the [0 to 30), [30 to 90), and [90 to 150) trading days after a payment event for the largest 100 merger events. Whereas INDUCED_BUY may select on the buying activity of the cash-redeploying investors, in principle, this selection effect will be diminished by Panel B's comparison with all the other stocks being purchased in net by nontarget-holding ANcerno investors during each event.[7]

Consistent with short-term temporary shocks to prices, INDUCED_BUY is not only correlated with contemporaneous excess returns, but also forecasts reversals at longer horizons. This correlation is demonstrated for stocks in the CRSP universe (Panel A of Table 3) and in the universe of stocks purchased by all ANcerno investors (Panel B). Although the comparison of stocks in the CRSP universe is useful in that it shows the reinvestment demand drives price pressure in all stocks, it may also hardwire in selection of stocks by institutional purchases. Therefore, Panel B's estimates provide more conservative bounds on the price impact associated with this cash-driven demand pressure.

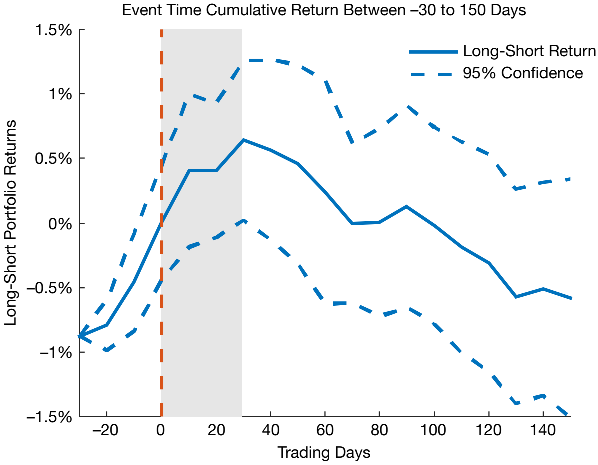
A stock associated with this payout-driven pressure experiences an average of 0.847% ($t = 5.45$) in excess returns over all the other stocks in the CRSP universe in

[7]I thank the referee for this helpful recommendation.

FIGURE 3

Event-Time Cumulative Abnormal Returns During the Top 100 Cash Mergers

Figure 3 plots the long–short event-time cumulative abnormal returns (CAR) of equal-weighted longing (shorting) stocks with (without) INDUCED_BUY. The *y*-axis, Long–Short Return, is the cumulative abnormal return of a portfolio consisting of equal-weighted long positions in INDUCED_BUY stocks and equal-weighted short positions in non-INDUCED_BUY stocks normalized to 0% at the event date. The blue solid line is the average cumulative abnormal returns for the top 100 cash mergers, the blue dashed lines are the 95% confidence intervals, and the red dashed lines indicate the cash-payment date. The gray shaded region indicates [0,30) trading days around the merger completion.



the first 30 trading days after the payment of a merger. In the next 60 days, it experiences a reversal of −0.518% ($t = -2.76$), and a further −0.679% ($t = -2.39$) in the 60 trading days after. Compared with the stocks purchased by other ANcerno investors, which diminishes the selection effect of having been purchased by an institutional investor, INDUCED_BUY stocks experience 0.512% ($t = 3.06$) in excess returns in the first 30 trading days, and a reversal of −0.312% ($t = -1.69$) and −0.698% ($t = -3.03$) in the following 60-day period. This pattern of abnormal returns and reversals remains similar once I include controls for size, book-to-market ratio, and past returns.

Figure 3 records the cumulative excess returns of a portfolio that longs stocks with induced buying and shorts the rest of the cross section from 30 trading days prior to 150 days after the merger payment. Figure 3 mirrors the regression results and demonstrates a pattern of excess contemporaneous (and some prior) abnormal returns and a long subsequent reversal, consistent with nonfundamental price pressure. This pattern is similar to other ranges of top cash mergers (see Appendix A1 of the Supplementary Material).

As additional evidence that price pressures due to cash mergers are not due to ex post selection, I construct a measure of expected demand from cash-merger reinvestments using mutual fund portfolios. This measure mirrors flow induced price pressure (FIPP) of Lou (2012) and the cash-induced demand (CID) of Section V. For each cash merger event *e*, $\text{CASH\_MERGER\_PRESSURE}_{i,e}$ is the aggregate weights of each stock *i* under the assumption of proportional reinvestment by mutual fund portfolios (because the ex ante holdings of ANcerno portfolios are not available). In other words, $\text{CASH\_MERGER\_PRESSURE}_{i,e}$ for each stock

i is the sum of cash merger payments to each mutual portfolio apportioned by i's respective portfolio weights, divided by the total value of i held by all observed portfolios at the last quarter-end (t) prior to event e:

$$\text{(1)}\quad \text{CASH\_MERGER\_PRESSURE}_{i,e} = \sum_j \frac{\text{SHARES\_HELD}_{i,j,e}}{\sum_j \text{SHARES\_HELD}_{i,j,e}} \text{CASH\_MERGER\_WEIGHT}_{j,e}.$$

CASH_MERGER_WEIGHT$_{j,e}$ is the weight of the target of the cash merger in each fund portfolio j in the quarter-end holding disclosure prior to a merger event.

CASH_MERGER_PRESSURE can be interpreted as the percentage increase in the holding of stock i by the aggregate mutual fund portfolio due to cash returns from the merger. A 1% increase in CASH_MERGER_PRESSURE for a stock indicates that, assuming proportional reinvestment, mutual fund portfolios will increase their holdings of that stock by 1% after a cash-merger event.

Panel A of Table 4 reports summary statistics for CASH_MERGER_WEIGHT and CASH_MERGER_PRESSURE. I also observe predictability that coincides with short-term abnormal returns and long-term reversals (although nonsignificant), taking fund portfolios as the representative portfolio. Note in Panel B of Table 4 that during the first 30 trading days of a cash-merger event, a 1-standard-deviation

TABLE 4

Abnormal Returns Associated with Investor Purchases

Panel A of Table 4 shows summary statistics of mutual fund holdings of cash-merger targets and the reinvestment price pressure. CASH_MERGER_WEIGHT$_{j,e}$ is a mutual fund (j)'s holding weight of the cash financed merger target if it had held the target prior to a merger event e. CASH_MERGER_PRESSURE$_{i,e}$ is the predicted price pressure for stock i from all visible mutual fund holdings calculated by assuming proportional reinvestment of cash-merger distribution dollars. Panel B shows Fama–MacBeth regressions of cumulative excess returns over the daily risk-free rate around the top 100 cash mergers for a measure of predicted price pressure. CASH_MERGER_PRESSURE$_{i,e}$ is the aggregate investment into each stock i under the assumption of proportional reinvestment by mutual fund portfolios. Columns 1 and 2 regress contemporaneous excess returns on CASH_MERGER_PRESSURE$_{i,e}$ and controls. Columns 3 and 4 regress excess returns in the following 60 trading days. Columns 5 and 6 regress excess returns during the 90 to 150 days after the merger payment. Columns 7 and 8 document the entire reversal between the 30 and 150 trading days. OLS t-statistics are reported in parentheses.

Panel A. Summary Statistics of Cash Merger Variables

	Mean (%)	Std. Dev. (%)	Q1 (%)	Median (%)	Q3 (%)	N
CASH_MERGER_WEIGHT$_{j,e}$ (Top 10)	1.040	1.549	0.185	0.432	1.190	1,799
CASH_MERGER_WEIGHT$_{j,e}$ (Top 30)	0.763	1.256	0.128	0.272	0.857	4,023
CASH_MERGER_WEIGHT$_{j,e}$ (Top 100)	0.595	1.030	0.066	0.196	0.651	9,839
CASH_MERGER_PRESSURE$_{i,e}$ (Top 10)	0.0494	0.148	0.0024	0.012	0.107	21,474
CASH_MERGER_PRESSURE$_{i,e}$ (Top 30)	0.0311	0.102	0.00067	0.005	0.023	62,855
CASH_MERGER_PRESSURE$_{i,e}$ (Top 100)	0.0245	0.078	0.00074	0.004	0.019	209,510

Panel B. Predictability Regressions

	Event-Time Fama–MacBeth Regressions							
	Excess Return [0, 30)		Excess Return [30, 90)		Excess Return [90, 150)		Excess Return [30, 150)	
CASH_MERGER_PRESSURE$_{i,e}$	0.297%	0.288%	−0.140%	−0.183%	−0.180%	−0.001%	−0.242%	−0.121%
	(2.32)	(2.43)	(−0.66)	(−0.97)	(−0.54)	(0.00)	(−0.54)	(−0.36)
log(ME)$_{i,e}$		−0.125%		−0.138%		−0.634%		−0.860%
		(−1.27)		(−1.00)		(−2.90)		(−2.72)
BOOK_TO_MARKET$_{i,e}$		−0.402%		−1.050%		−2.22%		−4.152%
		(−1.35)		(−2.59)		(−3.99)		(−3.64)
RET12$_{i,e}$		−0.960%		−0.880%		−0.941%		−2.16%
		(−1.13)		(−1.06)		(−0.99)		(−1.41)
Avg.N	2,101	2,101	2,101	2,101	2,101	2,101	2,101	2,101
Avg.R^2	0.21%	3.42%	0.10%	3.17%	0.22%	3.04%	0.017%	3.58%

change in this variable is associated with a 0.297% ($t = 2.31$) change in returns. These returns revert on average in the next two 60-day trading periods by −0.14% ($t = -0.66$) and −0.180% ($t = -0.54$), respectively.

C. Purchased Stock Characteristics

After establishing that merger-driven cash returns drive demand and price pressure for investable assets, I turn to the characteristics of the stocks that were purchased by these cash-deploying asset managers. The primary purpose is to understand whether cash-driven stock purchases can be predicted by an investor's prior holdings and style mandates.

Since the exact holdings of investment accounts in ANcerno are not available, I approximate established investor holdings using indicators of net purchases over each investor's history. Specifically, for each stock around a cash merger event, I measure whether such a stock was purchased in net by ANcerno accounts that are to receive cash merger dollars for redeployment. The variables PRIOR_QTR_BUY and PRIOR_YEAR_BUY are indicators of prior net accumulation of a stock in all ANcerno portfolios including the cash-merger target. I then regress the INDUCED_BUY variable on these two variables and various controls. The stock by event panel in this section consists of the universe of CRSP stocks by each of the largest 100 merger events and the universe of only stocks that were in net purchased by all ANcerno investors by each event. The regression in Table 5 is:

TABLE 5

Characteristics of Stocks that Experience Cash Merger-Induced Demand

Table 5 shows the panel regression of stocks bought by target stockholders around the 100 largest cash mergers on stock characteristics. The left-hand-side variable, $\text{INDUCED\_BUY}_{i,e}$, indicates whether ANcerno institutional investors holding the target of the merger bought stock i in the 30 trading days on and after the payment date of the merger event e. The main right-hand-side variable of interest, $\text{PRIOR\_QTR\_BUY}_{i,e}$, indicates whether such investors also had bought stock i in net during the past [−63, −30) trading days. Similarly, $\text{PRIOR\_YEAR\_BUY}_{i,e}$ indicates whether these investors bought stock i in net during the past [−252, −30) trading days to represent the prior year. $\text{BOOK\_TO\_MARKET}_{i,e}$ is the book-to-market ratio. $\log(\text{ME})_{i,e}$ is log market capitalization. $\text{RET12}_{i,e}$ is past-12-month returns of asset i. $\text{INST\_OWN}_{i,e}$ is the percentage of the stock held by institutional managers normalized by its standard deviation during each merger event. $\text{SP500\_MEMBERSHIP}_{i,e}$ indicates whether the stock was a member of the S&P500 at the time of merger payment. The t-statistics are clustered by each merger event.

	$\text{INDUCED\_BUY}_{i,e}$							
	All CRSP Stocks				Only Stocks Purchased by ANcerno Investors			
$\text{PRIOR\_QTR\_BUY}_{i,e}$	0.132 (11.69)	0.118 (13.93)			0.0859 (10.04)	0.0838 (10.96)		
$\text{PRIOR\_YEAR\_BUY}_{i,e}$			0.0708 (6.438)	0.0669 (7.173)			0.0346 (4.322)	0.0347 (4.183)
$\text{INST\_OWN}_{i,e}$		0.0193 (7.446)		0.0223 (8.310)		−0.00244 (−0.746)		−0.00115 (−0.342)
$\text{SP500\_MEMBERSHIP}_{i,e}$		−0.0744 (−7.621)		−0.0807 (−8.062)		−0.0225 (−2.703)		−0.0268 (−3.110)
$\log(\text{ME})_{i,e}$		0.0324 (5.543)		0.0369 (5.818)		0.0110 (2.192)		0.0137 (2.518)
$\text{BOOK\_TO\_MARKET}_{i,e}$		−0.0189 (−11.83)		−0.0194 (−11.63)		−0.0111 (−3.159)		−0.0112 (−3.114)
$\text{RET12}_{i,e}$		0.00235 (0.836)		0.00186 (0.632)		0.00645 (2.029)		0.00624 (1.873)
N	247,398	247,292	247,398	247,292	190,989	190,924	190,989	190,924
Adj. R^2	0.082	0.092	0.070	0.083	0.044	0.045	0.037	0.038

$$(2)\quad \text{INDUCED\_BUY}_{i,e} = \alpha + \beta \cdot \text{PRIOR\_PERIOD\_BUY}_{i,e} + \sum \gamma \cdot \text{Controls}_{i,e} + \epsilon_{i,e}.$$

Table 5 shows as evidence of mechanical reinvestment toward existing assets that I can predict stocks that were purchased using cash-merger dollars during the [0, 30) trading days after the cash payment using prior net trades by these same investors. The left-hand side of the equation, $\text{INDUCED\_BUY}_{i,e}$, describes whether stockholders who received the cash merger payments bought stock i in net over the [0,30) trading days around the payment event e. The primary right-hand-side variable of interest, PRIOR_YEAR_BUY, indicates whether such investors also bought stock i in net during the past [−252, −30) trading days. Similarly, PRIOR_QTR_BUY indicates whether these investors bought stock i in net during the past [−63, −30) trading days (prior quarter).

Controls include standard characteristics such as log market equity, book-to-market ratio, and past-12-month returns. I also include additional ownership characteristics such as an S&P 500 membership dummy and the percentage of stocks held by 13F institutions to gauge whether such purchases are associated with institutional and index holdings.

Columns 1–4 of Table 5 show the ANcerno accounts that receive cash merger dollars purchase the same assets as the ones they purchased in the past quarter (in columns 1 and 2) and in the past year (in columns 3 and 4). The fact that these same investors bought a stock in the [−63, −30) trading days prior to the merger increases the probability that the stock was purchased in the [0, 30) trading days by 26.0% from its unconditional mean of 50.8%. A net purchase of stock in the [−252, −30) trading days prior to the merger increases the probability by 13.9%.

Columns 5–8 of Table 5 repeat the regressions in columns 1–4, but only for stocks that were purchased in net by all ANcerno accounts. By limiting the data to only stocks bought by all ANcerno investors, this comparison shows the stocks that were purchased using cash merger dollars can be differentiated using the likely prior holdings of the merger-target-holding investor. The difference between the stocks purchased by cash redeploying investors and those purchased by other ANcerno accounts indicates a measurable gap between such investors' respective target portfolios.

Overall, these cash-merger event studies test whether the transfer of cash from firms drives investor demand for other assets. The recipients of this cash flow substantially increase their purchasing activities in the trading days after the closure of a cash measure compared to other investors. These cash mergers also introduce a price effect in the cross section of equities. In the short term after a cash merger deal, the stocks purchased by cash-redeploying investors appreciate in price. Additionally, the targets purchased using cash merger dollars can be predicted using an investor's history of trades. Such patterns are consistent with investment under mandate and style constraints.

V. Cash Induced Demand

The evidence from cash mergers indicates one channel through which cash returns affect the pricing of other stocks. Unlike cash mergers, where the event horizons are clear-cut, the cash return from a single firm at any given date is small. Over horizons such as a quarter or a year, such cash returns aggregate to a larger and more consistent source of investable cash for diversified portfolios-well exceeding other sources of investor demand.

Figure 1 plots the aggregate cash return from common stocks traded on the NYSE, Nasdaq, and AMEX exchanges benchmarked against inflows to equity mutual funds. We can see that between 2010 and 2016 dividend and buyback payouts aggregated to several times the size of retail investor flow into equity funds, indicating cash returns are large aggregate drivers of demand for investable assets.

A. Abnormal Excess Returns Predictability

I now use mutual funds as my representative investors to construct measures of induced demand from cash returns and compare this channel of return predictability with that from investor flows.[8] Because cash payouts do not change the total net asset value of a managed portfolio, this demand measure should not, in principle, capture informed trading. A manager who purchases assets using dividend dollars with the belief that these assets are undervalued could have simply reallocated his portfolio toward these assets in general, notwithstanding these dividend payment programs. Furthermore, I use the pro-rata buyback yield (the percent decrease in shares outstanding of a stock apportioned to each investor's portfolio by their holdings) to avoid the information conveyed by an investor's buyback participation.

Mirroring the construction of Flow Implied Price Pressure (FIPP) in Lou (2012), Cash-Induced Demand (CID) from capital returns for stock i in quarter t is calculated as

$$(3) \qquad \text{CID}_{i,t} = \sum_j \frac{\text{SHARES\_HELD}_{i,j,t-1}}{\sum_j \text{SHARES\_HELD}_{i,j,t-1}} \text{CAP\_FLOW}_{j,t},$$

where $\text{SHARES\_HELD}_{i,j,t-1}$ is the number of shares in stock i held by mutual fund j at $t-1$ and $\text{CAP\_FLOW}_{j,t}$ is the expected cash flow, as a percent of net assets, from payout programs experienced by portfolio j from $t-1$ to t:

$$(4) \qquad \text{CAP\_FLOW}_{j,t} = \underbrace{\sum_i \text{WEIGHT}_{i,j,t-1} \cdot \text{DIVIDENDS}_{i,t}}_{\text{DIVFL\bar{O}W}_{j,t}} + \underbrace{\sum_i \text{WEIGHT}_{i,j,t-1} \cdot |\text{BUYBACK}_{i,t}|}_{\text{BUYFL\bar{O}W}_{j,t}}.$$

[8]These measures of price pressure assume proportional reinvestment into current holdings. Appendix A2 of the Supplementary Material shows most dollars paid to mutual funds tend to stay within the fund. Appendix A7 of the Supplementary Material examines the effect of passive and active mutual funds separately using the active share measures (see Cremers and Petajisto (2009), Petajisto (2013)).

Here, DIVIDEND and |BUYBACK| are, respectively, the dividend and pro-rata buyback yields.[9] With CAP_FLOW, I implicitly assume no overlap exists between the stocks that are sold in a buyback program and those paying dividend returns.[10]

CID is the aggregation of cash returns apportioned by ex ante portfolio weights and can be interpreted as the percentage increase in the holdings of a stock by the aggregate mutual fund portfolio. A 1% CID indicates that, assuming proportional reinvestment, mutual fund portfolios will increase their holdings of stock i by 1% using the cash flows from dividend and buyback payments. An alternative way to write CID is

$$(5)\qquad \mathrm{CID}_{i,t} = \frac{\sum_j \left(\mathrm{CAP\_FLOW}_{j,t} \cdot \mathrm{TNA}_{j,t-1} \cdot \mathrm{WEIGHT}_{i,j,t-1}\right)}{\sum_j \left(\mathrm{PRICE}_{i,t-1} \cdot \mathrm{SHARES\_HELD}_{i,j,t-1}\right)}.$$

That is, $\mathrm{CID}_{i,t}$ for each stock i is the sum of all dollar cash payments to every mutual fund portfolio j apportioned by i's respective portfolio weights, divided by the total value of i held by all observed portfolios.

Table 6 provides summary statistics on CID[11] and FIPP (Lou (2012)), both of which aggregate mutual fund flows by assuming proportional investment. The CID measure has the advantage that it is not skewed toward extreme outliers. Noticeably, the cross-sectional spread between high- and low-CID stocks is much narrower than the spread in FIPP.

I conduct return predictability tests using this cash-induced demand variable. In these tests, I restrict the sample of public common stocks traded on the NYSE, Nasdaq, and AMEX exchanges in two ways: i) I exclude stocks with dividend payments or buybacks in the past year and ii) I exclude stocks with market capitalizations lower than the bottom decile of NYSE firms and the bottom decile of stocks ranked on mutual fund ownership to minimize micro-capitalization and liquidity issues. The final firms in the sample have not explicitly produced cash returns and are large enough to abstract from microstructure-related concerns.[12] This filter also addresses concerns that high payouts by the firms in question drive their own respective high measurements of induced demand. The remaining sample

[9]See Appendix A9 of the Supplementary Material for their construction.

[10]See Appendix A3 of the Supplementary Material for Fama–MacBeth and Appendix A4 of the Supplementary Material for calendar portfolio results using demand measurements based on dividends and buybacks separately. Their summary statistics are reported in Table A6 of the Supplementary Material.

[11]The CID measurements capture styles and mandates, which may not be the same for FIPP. I regress the purchasing patterns of flow portfolios on prior holdings in Appendix A8 of the Supplementary Material.

[12]In Appendix A5 of the Supplementary Material, I relax the first restriction on stocks – which filters out firms with significant cash returns – to demonstrate the identified pricing phenomenon is generalizable, albeit weaker, in the entire cross section of stock returns. The weaker effect may arise from the fact that the measured CID in the general cross section naturally corresponds to the level of a stock's cash payout. By focusing on nonpayout stocks, we eliminate the endogenous choice element of a firm's payout decisions on its stock's pricing.

TABLE 6

Flow and Cash Returns Aggregated

Table 6 reports summary statistics on quarterly cash-induced demand, $\text{CID}_{i,t}$. $\text{FIPP}_{i,t}$, investor flow-induced price pressure, serves as a benchmark. Only stocks that have not had a cash return program are included.

Assuming proportional reinvestment to initial fund values, flows, and capital returns are aggregated to the stock level in this table. Specifically, investor flow-induced price pressure to stock i is calculated as

$$\text{FIPP}_{i,t} = \sum_j \frac{\text{SHARES\_HELD}_{i,j,t-1}}{\sum_j \text{SHARES\_HELD}_{i,j,t-1}} \text{INV\_FLOW}_{j,t}.$$

The flow-induced price pressure is simply the weighted-average percentage flow into each mutual fund scaled by the proportional share held of a stock by each fund. Treating capital returns as inflow and assuming proportional reinvestment, cash-induced demand can be effectively calculated as

$$\text{CID}_{i,t} = \sum_j \frac{\text{SHARES\_HELD}_{i,j,t-1}}{\sum_j \text{SHARES\_HELD}_{i,j,t-1}} \text{CAP\_FLOW}_{j,t},$$

where $\text{CAP\_FLOW}_{j,t}$ is the amount of cash flow from capital returns experienced by portfolio j from $t-1$ to t:

$$\text{CAP\_FLOW}_{j,t} = \sum_i \text{WEIGHT}_{i,j,t-1} \cdot (|\text{BUYBACK}_{i,t}| + \text{DIVIDEND}_{i,t}).$$

CID and FIPP can be interpreted as a percentage increase in the aggregate mutual holdings of stock i as driven by cash returns and investor flows, respectively.

	Mean (%)	Std. Dev. (%)	Q1 (%)	Median (%)	Q3 (%)	$\rho_{t,t-1}$	$\rho_{t,t-4}$	N
$\text{FIPP}_{i,t}$ (1990–2016)	2.53	9.84	−1.50	0.82	4.09	0.260	0.088	87,373
$\text{FIPP}_{i,t}$ (1990–2002)	4.06	12.13	−1.05	1.97	6.16	0.227	0.047	51,922
$\text{FIPP}_{i,t}$ (2003–2016)	0.28	3.82	−1.86	−0.23	1.81	0.228	0.098	35,451
$\text{CID}_{i,t}$ (1990–2016)	0.46	0.23	0.29	0.44	0.60	0.695	0.529	87,373
$\text{CID}_{i,t}$ (1990–2002)	0.37	0.20	0.22	0.34	0.48	0.570	0.384	51,922
$\text{CID}_{i,t}$ (2003–2016)	0.59	0.20	0.45	0.57	0.71	0.661	0.484	35,451

includes 87,373 stock-quarter observations that serve as a clean laboratory for testing the effect of cash-induced demand.

CID is associated with significant excess returns at the one-quarter and 1-year horizons. Table 7 provides Fama–MacBeth regression analysis of returns on CID and various common characteristics. A 1-standard-deviation increase in CID predicts a 1.11% ($t = 2.12$) increase in excess returns in the following quarter and an average increase of 0.97% ($t = 2.50$) per quarter over the following year. The predictability is 1.22% ($t = 2.71$) and 1.03% ($t = 3.09$) respectively once contemporaneous FIPP and other controls are added.

CID and FIPP capture the percentage increase in holdings due to demand as opposed to measures that are normalized by volume, such as the MFFLOW of Edmans et al. (2012). The fact that these measures are proportional increases also allows for direct comparison to the inelastic-asset-demand hypothesis of Gabaix and Koijen (2020). These regression coefficients on CID reflect a much more inelastic demand curve than that of FIPP and are consistent with the estimates of a \$5 price impact to \$1 of inflow from Gabaix and Koijen (2020).

One–standard-deviation of CID in a stock is 0.23% of the stock's shares held by mutual funds. The regression coefficient for this 1-standard-deviation (0.23%) of CID in column 1 of Table 7 is 1.11%, indicating a 1% (and naturally \$1) increase in the holdings of a stock from investor cash reinvestments leads to a 4.83% (\$4.83) increase in the price of the asset. The estimated price impact of FIPP is 3.05% for 1-standard-deviation of 9.84% in investor flows, which is characteristic of a much more elastic demand curve. The reason may be that investor flows tend to be volatile and potentially mean reverting (as mentioned in Gabaix and Koijen (2020)), while cash payouts from public firms are demonstrably persistent.

TABLE 7

Cash-Induced Demand (Fama–MacBeth)

Table 7 records Fama–MacBeth regression coefficients of average quarter excess returns on $\text{CID}_{i,t-1}$ and various controls. Columns 1–3 records the 1 quarter excess return, while columns 4–6 record the average quarterly excess returns over a year.

Assuming proportional reinvestment to initial fund values, capital returns are aggregated to the stock level in this table. Specifically, cash-induced demand for stock i is calculated as

$$\text{CID}_{i,t} = \sum_j \frac{\text{SHARES\_HELD}_{i,j,t-1}}{\sum_j \text{SHARES\_HELD}_{i,j,t-1}} \text{CAP\_FLOW}_{j,t}.$$

$\log(\text{ME})_{i,t-1}$ is the log market capitalization. $\text{BOOK\_TO\_MARKET}_{i,t-1}$ is the book-to-market ratio. $\text{RET12}_{i,t-1}$ is the prior 12-month return. $\text{ISSUE}_{i,t-1}$ is the percentage increase in shares outstanding over the past 5 years. FIPP is the contemporaneous flow-induced price pressure to the period of excess returns. Only nondividend-paying stocks that have not had any capital returns over the past year are used in the regression. Stocks with market capitalizations lower than the bottom decile of NYSE and stocks at the bottom decile of percentage mutual fund holdings are filtered. All the regressor variables are standardized by their unconditional standard deviation. The t-statistics in the first 3 columns are Newey–West with a single lag. The t-statistics in the next 3 columns are Newey–West with 4-lags to account for overlapping returns. Bold font indicates statistical significance at the 95% level.

	1 Quarter Excess Returns			Quarterly Excess Returns Over Year		
$\text{CID}_{i,t-1}$	**1.111%**	**1.336%**	**1.222%**	**0.971%**	**0.961%**	**1.03%**
	(2.12)	**(2.69)**	**(2.71)**	**(2.50)**	**(2.71)**	**(3.09)**
$\log(\text{ME})_{i,t-1}$		−0.336%	−0.187%		−0.212%	−0.150%
		(−1.18)	(−0.72)		(−0.98)	(−0.76)
$\text{BOOK\_TO\_MARKET}_{i,t-1}$		−0.217%	−0.233%		−0.189%	−0.146%
		(−0.86)	(−0.96)		(−0.96)	(−0.82)
$\text{RET12}_{i,t-1}$		0.447%	0.275%		−0.038%	−0.203%
		(0.77)	(0.48)		(−0.07)	(−0.40)
$\text{ISSUE}_{i,t-1}$		**−0.738%**	**−0.719%**		**−0.630%**	**−0.636%**
		(−4.43)	**(−4.34)**		**(−4.10)**	**(−4.12)**
$\text{FIPP}_{i,t-1\to t-1+k}$			**3.053%**			**2.030%**
			(8.20)			**(5.01)**
Avg.N	803	797	797	803	797	797
Avg.R^2	1.33%	3.69%	4.22%	1.26%	3.33%	4.24%

The Fama–MacBeth regressions reflect a particular calendar-time strategy. I sort this cross section of stocks into calendar-time portfolios using CID. Overlapping quintile portfolios are held for multiple quarters following Jegadeesh and Titman (1993). As shown in Table 8, the top-quintile portfolio rebalanced quarterly and held for a single quarter experiences a monthly 4-factor adjusted excess return of 0.57% (t = 3.91), whereas the lowest-quintile portfolio experiences excess return of −0.54% (t = −2.86). A strategy shorting the lowest-quintile portfolio and holding the highest quintile experiences a monthly return of 1.11% (t = 4.71). CID continues to forecast excess returns in overlapping portfolios for multiple horizons.

At the 1-year holding horizon, the top-quintile portfolio has a risk-adjusted alpha of 0.40% (t = 2.93) each month, whereas the bottom-quintile portfolio obtains −0.40% (t = −2.32). The long–short strategy at this horizon generates an excess return alpha of 0.80% (t = 3.71) per month.

Demand-driven fluctuations, in principle, should affect assets on which significant limits to arbitrage exist. Table 9 further divides the universe of nonpayout stocks into calendar-time portfolios sorted to high (above-median) and low (median or below-median) institutional ownership of shares outstanding. While institutional ownership of shares outstanding may capture multiple factors that characterize stocks, one interpretation of high institutional ownership is that arbitrage capital

TABLE 8
Cash-Induced Demand, Calendar-Time Portfolio Returns

Table 8 records monthly excess returns of calendar-time strategies based on cash-induced demand. Specifically, cash-induced demand for stock *i* is calculated as

$$\mathrm{CID}_{i,t} = \sum_j \frac{\mathrm{SHARES\_HELD}_{i,j,t-1}}{\sum_j \mathrm{SHARES\_HELD}_{i,j,t-1}} \mathrm{CAP\_FLOW}_{j,t}.$$

Nondividend-paying stocks that have not had any capital returns over the past year are sorted into quintile portfolios, and the table reports the *monthly* returns of overlapping portfolio strategies that hold each portfolio for 1 (left) to 4 (right) quarters. Stocks with market capitalizations lower than the bottom decile of NYSE and stocks at the bottom decile of percentage mutual fund holdings are filtered. The sample period of returns is from Jan. 1990 to Dec. 2016. Bold font indicates statistical significance at the 95% level.

		Q1 Holding Period				Q1–Q4 Holding Period			
		Raw Rx	CAPM	3-Factors	4-Factors	Raw Rx	CAPM	3-Factors	4-Factors
CID	1	0.35% (0.69)	**−0.69%** **(−2.19)**	**−0.46%** **(−2.47)**	**−0.54%** **(−2.86)**	0.42% (0.84)	**−0.63%** **(−2.12)**	**−0.39%** **(−2.31)**	**−0.40%** **(−2.32)**
	2	0.59% (1.27)	−0.42% (−1.66)	−0.24% (−1.49)	−0.26% (−1.62)	0.55% (1.23)	−0.44% (−1.84)	**−0.26%** **(−2.05)**	**−0.27%** **(−2.07)**
	3	0.57% (1.39)	−0.35% (−1.64)	−0.21% (−1.35)	−0.26% (−1.58)	0.57% (1.45)	−0.34% (−1.84)	−0.21% (−1.68)	−0.19% (−1.46)
	4	0.62% (1.42)	−0.30% (−1.58)	−0.22% (−1.30)	−0.06% (−0.36)	**0.80%** **(2.13)**	−0.08% (−0.44)	0.02% (0.12)	0.13% (0.95)
	5	**1.19%** **(3.74)**	**0.45%** **(3.07)**	**0.49%** **(3.34)**	**0.57%** **(3.91)**	**1.06%** **(3.33)**	**0.32%** **(2.22)**	**0.36%** **(2.62)**	**0.40%** **(2.93)**
	LS 5–1	**0.84%** **(2.47)**	**1.14%** **(3.52)**	**0.95%** **(4.00)**	**1.11%** **(4.71)**	**0.64%** **(2.08)**	**0.94%** **(3.27)**	**0.75%** **(3.51)**	**0.80%** **(3.71)**

TABLE 9
Calendar-Time Portfolio and Institutional Ownership

Table 9 records monthly returns of calendar-time strategies based on cash-induced demand and percentage institutional ownership. Nondividend-paying stocks that have not had any capital returns over the past year are sorted into 2 halves by institutional ownership and then into quintile portfolios based on CID. The table reports the *monthly* returns of calendar-time strategies that hold each portfolio for 1 quarter for the universe of stocks that are above the median (left) and below the median (right) in the percentage of institutional ownership. Stocks with market capitalization lower than the bottom decile of the NYSE and stocks in the bottom decile of percentage mutual fund holdings are filtered. The sample period of returns is from Jan. 1990 to Dec. 2016. Bold font indicates statistical significance at the 95% level.

		High Institutional Ownership (Q1)				Low Institutional Ownership (Q1)			
		Raw Rx	CAPM	3-Factors	4-Factors	Raw Rx	CAPM	3-Factors	4-Factors
CID	1	0.54% (1.08)	−0.48% (−1.52)	−0.25% (−1.22)	−0.36% (−1.74)	0.12% (0.21)	**−0.98%** **(−2.55)**	**−0.71%** **(−2.68)**	**−0.65%** **(−2.43)**
	2	0.56% (1.26)	−0.39% (−1.55)	−0.22% (−1.23)	−0.25% (−1.38)	0.42% (0.81)	**−0.65%** **(−1.97)**	−0.44% (−1.82)	**−0.51%** **(−2.09)**
	3	0.52% (1.28)	**−0.41%** **(1.99)**	−0.30% (−1.68)	−0.30% (−1.68)	0.28% 0.68%	**−0.64%** **(−2.46)**	**−0.52%** **(−2.62)**	**−0.55%** **(−2.72)**
	4	0.73% (1.89)	−0.16% (−0.83)	−0.06% (−0.40)	0.03% (0.22)	**1.06%** **(2.43)**	0.15% (0.55)	0.19% (0.86)	0.38% (1.72)
	5	**0.74%** **(2.17)**	−0.05% (−0.29)	−0.03% (−0.19)	0.07% (0.44)	**1.41%** **(4.04)**	**0.70%** **(3.19)**	**0.75%** **(3.65)**	**0.82%** **(3.92)**
	LS 5–1	0.20% (0.61)	0.43% (1.35)	0.22% (0.89)	0.43% (1.77)	**1.30%** **(3.17)**	**1.68%** **(4.36)**	**1.46%** **(4.46)**	**1.47%** **(4.41)**

may be available to correct price deviations. Stocks with low institutional ownership are likely characterized by limits to arbitrage. At each calendar quarter, I sort stocks into two halves based on their quarter-end institutional ownership, prior to sorting further into quintile CID portfolio.

Table 9 indicates the cross-sectional dispersion between high-CID and low-CID portfolios is the strongest for stocks that had low prior institutional ownership. High-institutional-ownership stocks, with the largest potential arbitrage capital, have a relatively low cross section price dispersion due to CID. The highest-quintile portfolio earns an average of 0.43% (t = 1.77) 4-factor alpha per month above the lowest-quintile portfolio. When there are presumably significant limits to arbitrage, as in the low-institutional-ownership stocks, CID demand generates a 4-factor alpha of 1.47% (t = 4.41) per month between the highest- and the lowest-quintile portfolio. These results suggest limits to arbitrage facilitate the price impact of demand fluctuations.

The abnormal return associated with CID persists; I do not find evidence of reversals in the calendar-time sorted portfolios. This lack of short-term reversal is in contrast to the expected price pressures from the mutual-fund-flows literature but is similar to the returns of stocks that were recently included in an index.[13] As Gabaix and Koijen (2020) argue, demand sources of fluctuations do not necessarily require reversals, as long as that demand is not mean reverting. Similar to membership in stock index, exposure to cash-induced demand through fund portfolios tends to be persistent. Cash-payout programs by individual firms last years if not decades. While stocks with high degrees of mutual-fund-flow pressure would experience fire-sale or purchases for a single quarter, stocks sorted into the highest quintile of CID would likely experience continual levels of demand from cash-redeploying investors. The payout reinvestment mechanism is an alternate but potentially more substantial source of demand to that in the existing literature.

B. Future Issuance, Repurchasing, and Dividend Payment Characteristics

Next, I explore the characteristics of the nonpayout firms that experience high levels of cash-induced demand. Beyond the basic size and value characteristics, I investigate these stocks' future payout and issuance policies to understand how firms respond to the pricing and demand related to cash payouts. Consistent with opportunistic behavior and a relaxation of financing constraints, I find the nonpayout firms most exposed to CID are more likely to issue equity than other nonpayout companies. Furthermore, I find these firms do not substantially increase their cash returns to shareholders at measurable horizons.

First, to start this analysis, Panel A of Table 10 describes the basic size characteristics of firms in the calendar-time portfolios constructed in the previous section. The columns record the average market equity and the book-to-market ratios of these cross sections in 1990, 2003, and 2016, respectively. In this cross section of noncash-returning firms, high exposure to cash-induced demand tends to be associated with a larger size and higher book-to-market value stocks.

Since investment decisions and stock returns capture investors' expectations of a firm's future activities, it is possible that the excess returns documented in the previous section reflect changes to the firm's long-term payout policies. Panel B of Table 10 focuses on the future payout and issuance policies of these nonpayout

[13]Price effects from investor flows begin to revert after their measurement date (Frazzini and Lamont (2008)), whereas those of index inclusions tend to be more persistent (Shleifer (1986)).

TABLE 10

Cash Induced Demand, Calendar-Time Portfolio Characteristics

Table 10 examines the characteristics related to size and future capital returns for stocks sorted on cash-induced demand. Panel A records the average market-equity size in $ billion and the average book-to-market ratios for portfolios sorted on $\mathrm{CID}_{i,t}$ for selected periods of the sample. Panel B records the average share buyback and change in dividends paid quarterly by the firms in these quintile portfolios over the next 12 years. The sample covers 1990–2016. The *t*-statistics are Newey–West corrected with *N* lags to account for overlapping observations.

Panel A. Characteristics of CID Portfolios

	Q1 1990		Q1 2003		Q1 2016	
CID	MARKET_EQUITY	BOOK_TO_MARKET RATIO	MARKET_EQUITY	BOOK_TO_MARKET RATIO	MARKET_EQUITY	BOOK_TO_MARKET RATIO
1	0.245	0.270	0.434	0.425	0.839	0.286
2	0.171	0.489	0.556	0.543	1.103	0.294
3	0.092	0.568	0.618	0.703	1.243	0.392
4	0.148	0.597	0.631	0.805	1.176	0.603
5	0.298	0.691	1.480	0.780	2.431	0.758

Panel B. Changes in Characteristics

The portfolio initiation periods are 1990–2013, 1990–2010, and 1990–2004 for the 12-, 24-, and 48-quarter averages, respectively. That is,

$$N\text{Quarter } \Delta\text{BUYBACK} = \frac{1}{N}\sum_{i=1}^{N}\text{BUYBACK}_{i,t+i} - \frac{1}{20}\sum_{i=1}^{20}\text{BUYBACK}_{i,t-i},$$

$$N\text{Quarter } \Delta\text{DIVIDEND} = \frac{1}{N}\sum_{i=1}^{N}\text{DIVIDEND}_{i,t+i} - \frac{1}{20}\sum_{i=1}^{20}\text{DIVIDEND}_{i,t-i},$$

and

$$N\text{Quarter } \Delta\text{ISSUANCE} = \frac{1}{N}\sum_{i=1}^{N}\text{ISSUANCE}_{i,t+i} - \frac{1}{20}\sum_{i=1}^{20}\text{ISSUANCE}_{i,t-i}.$$

	12-Quarter Average			24-Quarter Average			48-Quarter Average		
CID	ΔBUYBACK	ΔISSUANCE	ΔDIVIDEND	ΔBUYBACK	ΔISSUANCE	ΔDIVIDEND	ΔBUYBACK	ΔISSUANCE	ΔDIVIDEND
1	0.156%	−1.573%	0.018%	0.203%	−1.711%	0.029%	0.282%	−1.834%	0.054%
	(13.88)	(−11.52)	(6.02)	(17.82)	(−10.37)	(3.34)	(23.44)	(−16.86)	(3.34)
2	0.178%	−1.672%	0.022%	0.226%	−1.826%	0.032%	0.291%	−1.614%	0.062%
	(13.53)	(−11.07)	(3.85)	(16.11)	(−7.16)	(3.43)	(15.58)	(−11.93)	(3.52)
3	0.193%	−1.273%	0.036%	0.236%	−1.406%	0.048%	0.296%	−1.244%	0.070%
	(10.98)	(−9.05)	(4.36)	(11.37)	(−9.56)	(3.34)	(11.55)	(−13.48)	(4.37)
4	0.210%	−0.960%	0.048%	0.256%	−0.932%	0.063%	0.306%	−1.113%	0.086%
	(11.28)	(−7.30)	(4.60)	(11.20)	(−5.61)	(5.63)	(12.49)	(−12.55)	(7.95)
5	0.238%	−0.887%	0.062%	0.286%	−0.878%	0.088%	0.296%	−0.650%	0.118%
	(7.51)	(−3.82)	(7.45)	(8.01)	(−3.64)	(10.82)	(11.09)	(−4.82)	(8.92)
LS 5–1	0.082%	0.686%	0.044%	0.083%	0.833%	0.059%	0.014%	1.184%	0.064%
	(3.35)	(2.85)	(5.62)	(2.65)	(4.10)	(14.73)	(0.75)	(13.89)	(8.82)

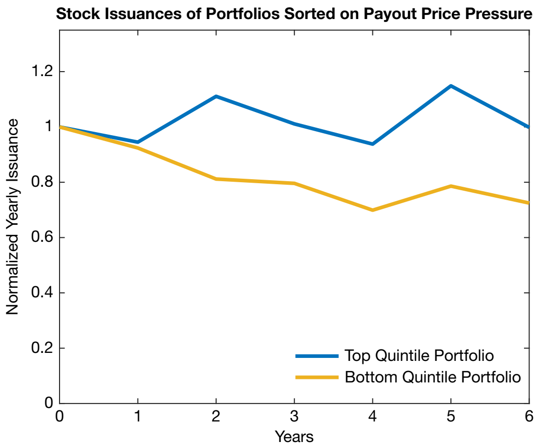
stocks purchased by investors. It describes the forward cash return and issuance policies of firms in each portfolio at the medium 3-year to the potential long-term 6- and 12-year horizons. Because the targets of these stock purchases are high growth-characteristic firms without any recent cash payouts, firms sorted on CID generally have high levels of gross issuances. However, regardless of the horizon that is examined, there is little difference in cross-sectional increases in future payout policy between these portfolios. Despite experiencing a cumulative return difference of more than 12% in a 12-month holding-period window, the highest- and lowest-quintile CID portfolios had a spread of 0.082% on average in the change of their repurchasing activities and a spread of 0.044% in the change in dividend yields over 3 years. Over the 12-year horizon, the increase in buybacks essentially disappears. These measures suggest the abnormal returns for high- versus low-CID portfolios are not due to changing beliefs regarding cash payouts.

Instead, consistent with opportunistic behavior, I find that firms that are strongly associated with cash redeployment tend to have greater levels of gross

FIGURE 4

Equity Issuance by Calendar-Time Portfolios

Figure 4 plots dollar equity issuance patterns of the average stocks in calendar-time portfolios normalized at the total issuance in the first year. The blue and yellow lines are the yearly equity issuance of an average stock in the top- and bottom-quintile portfolios over the next 6-year horizon.



issuance over time. The change in the quarterly issuance of a stock in the top-quintile portfolio sorted on CID is 0.686% higher than that of the bottom-quintile portfolio. Over the 3-year horizon (0.833% at the 6-year and 1.184% at the 12-year horizon).

The issuance levels for both the long and short portfolios are plotted in Figure 4. Due to their initial characteristics, both the long and the short legs start with positive gross issuances (normalized at 1 in the beginning period), which decline over time, but the decline in the short leg is much more dramatic than the long leg. Stocks most associated with CID have significantly more persistent levels of issuance than the stocks in the bottom quintile.

Table 11 presents regression analysis to help us understand the average correlation between CID and changes in buyback, issuance, and dividend activities. Once I control for characteristics such as size, past issuance, and past returns, I find a firm's payout activities increase only marginally with its exposure to cash returns. A 1-standard-deviation increase in the CID measure is associated with a 2-basis-point increase in average buyback activity for a stock over the next 6 years and with a 4-basis-point increase in dividend payment activity. The CID measure, however, is correlated with future issuances at significant levels. A 1-standard-deviation increase in CID implies a 71-basis-point increase in issuances per quarter over 24 quarters. In economic terms, exposure through CID is associated with economically meaningful increases in future issuance, but only minor increases in cash returns.[14]

The evidence here shows that nonpayout firms experiencing this spillover channel of induced price pressure increase their future payout activities only

[14]The results for Fama–Macbeth regressions using other horizons are reported in Appendix A10 of the Supplementary Material.

TABLE 11

Future Payout and Issuance Predictions

Table 11 records Fama–MacBeth regression coefficients of changes in quarterly buyback, dividend payments, and issuances over 24-quarter horizons on $\text{CID}_{i,t-1}$ and various controls. The regressors are normalized so that their standard deviations are 1. ΔBUYBACK is the difference between the average 24-quarter future buybacks and the average buyback from the past 5 years:

$$24\text{Quarter } \Delta\text{BUYBACK} = \frac{1}{24}\sum_{i=1}^{24}\text{BUYBACK}_{i,t+i} - \frac{1}{20}\sum_{i=1}^{20}\text{BUYBACK}_{i,t-i}.$$

ΔDIVIDEND and ΔISSUANCE are calculated in the same way. The *t*-statistics are Newey–West corrected with 24-lags to account for overlapping observations.

Future quarterly average buybacks, dividends, and issuances regressed on various characteristics.

	24-Quarter ΔBUYBACK		24-Quarter ΔDIVIDEND		24-Quarter ΔISSUANCE	
$\text{CID}_{i,t-1}$	0.054%	0.018%	0.040%	0.036%	0.423%	0.712%
	(2.38)	(1.45)	(7.47)	(5.89)	(4.47)	(6.88)
$\log(\text{ME})_{i,t-1}$		0.049%		−0.001%		−0.342%
		(3.68)		(−0.48)		(−7.68)
$\text{BOOK\_TO\_MARKET}_{i,t-1}$		0.010%		0.011%		0.201%
		(2.67)		(2.20)		(−1.12)
$\text{RET12}_{i,t-1}$		−0.024%		0.006%		−0.169%
		(−0.08)		(1.53)		(−0.85)
$\text{ISSUE}_{i,t-1}$		−0.152%		−0.055%		3.220%
		(−4.92)		(−0.11)		(23.75)
$\text{FIPP}_{i,t-1}$		−0.011%		0.006%		0.043%
		(−2.32)		(2.13)		(0.32)
Avg.*N*	432	430	432	430	432	430
Avg.R^2	1.30%	10.29%	1.12%	1.77%	0.25%	24.49%

marginally. Rather, the same firms experiencing demand from cash payout programs persistently issue equity more than firms that are less exposed to such cash-induced demands. The empirical facts documented here suggest that equity issuances are opportunistic response to demand-driven price fluctuations.

VI. Conclusion

This article identifies a substantial source of inflow-driven demand fluctuations in the financial markets. Cash returns made by public firms through cash mergers, dividend payments, and buyback programs represent demands that exceed the aggregate cash flows from investors into mutual funds. These cash-driven asset demands alleviate some of the weaknesses in the identification of investor-driven demand that I often see in the finance literature. The reinvestment of cash payouts, compared with cash from investor flows, is likely more automatic and less subject to endogenous cash management in professional portfolios. Furthermore, stocks exposed to cash-induced demand have different characteristics than stocks exposed to the flow-driven demand that tends to coincide with the typical momentum and size factors.

The documented price pressures do not revert for dividend or buyback programs and are associated with significant stock issuances over longer horizons. The extent and the persistence of this asset demand through cash returns potentially drive large variations in returns. The price predictability documented here complements the empirical foundations of the demand-driven asset fluctuation hypothesis.

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109022001454.

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