Dividend Sentiment, Catering Incentives, and Return Predictability*

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Abstract – Using Internet search volume of dividend-related keywords to measure investor preference for dividends that varies over time and across states, we show that dividend sentiment affects corporate policies and asset prices. Investors search more for dividends when economic conditions are poor, with the peak volume reached during the recent COVID-19 pandemic. Firms initiate or increase dividends when dividend sentiment is stronger, especially in regions with strong dividend sentiment. Shifts in dividend sentiment predict higher investor demand for dividends and higher returns for high dividend stocks. Further, mutual funds that pay high dividends receive more inflows when dividend sentiment is stronger.

JEL classification: G32; G35.

Key words: Dividend catering; investor attention; Internet search volume; dividend sentiment; return predictability.

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1. Introduction

We propose a novel and direct measure of investors' dividend sentiment to examine whether investor demand for dividends affects corporate dividend policies, investor trading behavior, and stock returns. Baker and Wurgler (2004a, 2004b) posit that firms cater to investors' time-varying demand for dividend-paying stocks. Several studies provide empirical support for the catering theory by studying dividend changes (Li and Lie, 2006) and share repurchases (Jiang, Kim, Lie, and Yang, 2013; Kulchania, 2013). The empirical research on dividend catering has typically used a market-based measure to capture catering incentives, i.e. the dividend premium, which is computed using the market-to-book ratios of firms with the differential dividend policy. However, it is criticised for also capturing changes in firm fundamentals, such as growth opportunities and firm risk. Hoberg and Prabhala (2009) show that the observed correlation between the propensity to pay dividends, and the dividend premium can be largely explained by differences in firm risk.

In this study, we develop a test of the catering theory of dividends that does not rely on market-based measures, such as market-to-book ratio, to infer investor preferences. Our key innovation is to use the Internet search volume of dividend-related keywords to measure investors' preference for dividends. The search volume index (*SVI*) allows us to measure dividend sentiment at higher frequency than proxies used in the literature, and is likely to capture broader information on the time-series and cross-sectional (i.e., state-level) variation in investors' preference for dividends (i.e., dividend sentiment). Based on data from Google Trends, *SVI* on the dividend topic reached its historical record in March 2020 during the most recent coronavirus (COVID-19) pandemic and doubled its previous peak reached during the 2007-08 global financial crisis (see Figure 1). Using the new dividend sentiment measure that is independent of those used in the literature, we still find support for predictions from the dividend catering theory.

Our new dividend sentiment measure is based on the assumption that investors would search for dividend-related keywords more often when they are more actively thinking about dividends. Therefore, time variation in Internet search intensity for dividend-related keywords would reflect investors' time-varying preference for dividends. Our key conjecture is that investors' attention to dividends, which would affect investor demand and asset prices, could motivate managers to adjust their payout policy. In particular, we posit that managers would initiate or increase (decrease) dividends when investors search for dividends more (less) using the Google search engine. Further, managerial sensitivity to time-varying investor preferences is likely to be stronger in geographical areas in which investors are known to exhibit a stronger preference for dividends.

Time-varying dividend sentiment could also affect stock returns. When investors' dividend sentiment is stronger, investors' demand for high dividend stocks would increase. If arbitrage costs are high or arbitrageurs are unable to supply sufficient liquidity, the excess demand, in turn, could generate price pressure on high dividend stocks and generate positive abnormal returns in the short run. The mispricing of dividned sentiment also implies that traditional measures such as dividend premium might not fully capture catering incentives.

We find that lower interest rates or less favorable economic conditions are associated with higher subsequent dividend sentiment. This evidence is consistent with dividend income serving as a substitute for interest income for income-seeking investors (Hartzmark and Solomon, 2019). The correlation between our dividend sentiment measure (*SVI*) and the dividend premium is 0.43 and statistically significant at the 1% level. This is consistent with these two measures being economically related. Still, the correlation suggests that our search-based measure does not merely repackage information from the dividend premium and captures a component of investors' dividend sentiment that is not included in the dividend premium. Using the new dividend sentiment measure, we show that when investors' dividend sentiment strengthens (weakens), managers exhibit a stronger propensity to announce dividend initiation or increase (decrease) in the next quarter. In economic terms, a one-standard-deviation increase in investors' dividend sentiment is associated with a 0.2% higher dividend initiation rate in the next quarter. These results are economically significant as this increase is 6.1% of the average dividend initiation rate in our sample.

Next, we examine whether our dividend sentiment measure explains the residual variation in dividend policies after accounting for various firm characteristics and risk measures. We estimate the propensity to pay dividends (*PTP*) using a logit model and find that the dividend sentiment effect is consistent with the catering hypothesis. When dividends attract more (fewer) investors, firms exhibit a higher propensity to pay, initiate, or increase (decrease) dividends. This evidence is incremental over the effects of the known determinants of dividend policies.

We also investigate the extent to which geographical differences in dividend sentiment influence a firm's dividend policy. As local investors' dividend sentiment varies across regions, we conjecture that the effects of dividend sentiment on a firm's dividend policy should be stronger in U.S. states with stronger dividend sentiment. In these states, investors pay more attention to dividends and hold more local stocks (Becker, Ivkovic, and Weisbenner, 2011). To test our prediction, we use each firm's headquarters' state to define its location and use the average state-level *SVI* to measure local investors' dividend sentiment. We find that managers cater to the time-varying dividend sentiment in U.S. states with strong dividend sentiment.

To further rule out an alternative explanation where investors search online for "dividend" after dividend announcements, we also study whether dividend sentiment predicts the number of subsequent dividend announcements made by firms. We find that higher dividend sentiment leads to more subsequent announcements to pay dividends, and the result is concentrated among firms headquartered in states with strong dividend sentiment.

In the next set of tests, we examine the effects of dividend sentiment on mutual fund flows, investor trading behavior and stock returns. We conjecture that investors will exhibit a stronger preference for mutual funds that pay high dividends when dividend sentiment is stronger. Consistent with our conjecture, we find that our Internet search-based dividend sentiment measure is positively associated with subsequent fund inflows among funds that invest in high dividend stocks. In particular, a one-standard-deviation increase in dividend sentiment is associated with a 5.2% increase in the fund flow for high dividend-paying mutual funds in the next quarter.

Using transaction-level investor trading data from TAQ, we find a higher excess buy-sell imbalance among high dividend stocks when investors' dividend sentiment becomes stronger. Similarly, based on aggregate trading volume data from CRSP, we find that a one-standard-deviation increase in *ASVI* is associated with 1.43% more abnormal trading in the next quarter among high dividend stocks relative to other stocks. This evidence is consistent with our conjecture that high dividend sentiment is associated with greater aggregate demand for high dividend stocks.

Examining the impact of time-varying investor demand for dividends, we find that high dividend stocks earn positive abnormal returns in the following month when investors have stronger dividend sentiment. A 10% increase in the *SVI* for the search topic "dividend" is associated with a significantly positive price change of 20 basis points in the following month. The coefficient estimates become statistically insignificant from month 2 onward and turn significantly negative in month 10, a price reversal indicating that dividend sentiment generates short-term mispricing among high dividend stocks. A long-short trading strategy conditional on *ASVI*, which attempts to exploit the demand-induced mispricing generates an annualized risk-adjusted return of 8.6%.

To gather additional support for our key conjecture, in additional tests, we demonstrate that managers cater to the time-varying demand not only for dividends but also for share repurchases. Using the Internet search volume of share buybacks to measure investors' repurchase sentiment, we find that repurchase sentiment is positively associated with changes in the propensity to repurchase shares. A one-standard-deviation increase in investors' repurchase sentiment leads to an economically significant 0.4% increase in the propensity to repurchase shares in the next quarter.

We conduct several additional tests to ensure our findings are robust. First, we conduct the Granger causality test to determine whether a firms' dividend policy is Granger-caused by investors' dividend sentiment or vice versa. We find that investors' dividend sentiment leads to changes in a firms' dividend policy, and not vice versa. Second, we include five commonly used macroeconomic variables in our baseline analysis to account for the business-cycle effects and find that they do not affect our results. Third, we include the Baker and Wurgler (2006) investor sentiment measure as a control variable and find that our results remain qualitatively similar. This evidence suggests that our dividend sentiment measure is distinct from other proxies for investor sentiment. Fourth, we demonstrate that our main results are not driven by the financial crisis or the public availability of Google Trends.

Fifth, our Google search measure does not load significantly on risk factors, which may help explain why the dividend sentiment can still predict firms' dividend policies after controlling for risk loadings (whereas dividend premium cannot). Sixth, investors' dividend sentiment significantly predicts firms' subsequent dividend policies after controlling for firms' lifecycle. Seventh, we also construct two keyword-based measures of dividend sentiment and our baseline results are robust when using this modified dividend sentiment measure. Last, our results are unaltered when we control for news media attention and social media attention.

Taken together, our paper provides a more direct measure of investor demand on dividend by using Internet search volumes, which are easily observable to firm managers and can inform dividend policies. Given the mispricing of investor demand (as shown in our return predictblility tests), it is reasonable to expect that our measure captures dividend sentiment more accurately and provides a better proxy of catering incentives than traditional measures. Using our dividend sentiment measure that is independent of those used in the literature, we find that changes in investors' dividend attitudes affect firms' dividend policies, investor trading behavior, mutual fund flows, and stock prices.

Our results contribute to several strands of the finance literature. First, our findings relate to studies that examine the catering theory of corporate payout. Baker and Wurgler (2004b) and Li and Lie (2006) find that when investors exhibit a stronger preference for dividend-paying firms, managers initiate or increase dividends to capture the dividend premium. Baker, Nagel, and Wurgler (2007) show that individuals prefer to consume dividends. Jiang, Kim, Lie, and Yang (2013) and Kulchania (2013) extend the catering theory to share repurchases and demonstrate that managers cater to investor demand for share buybacks. These studies have typically used dividend premium to measure investor demand for dividends, which has been criticized in the literature. Hoberg and Prabhala (2009) argue that the relation can be explained by differences in firm risk. We contribute to this critical debate in corporate payout policies by developing a novel and direct measure of investors' dividend sentiment that is independent of the market-based measure used in the literature and showing that shifts over time and across states in investors' attitudes about dividends affect payout policies, even after controlling for firm risk.[1]

[1] In untabulated results, we find that our dividend sentiment measure is less related to risk factors and more strongly related to sentiment on bond yields than dividend premium. In contrast to our measure, dividend premium does not predict stock returns, mutual fund flows, or local sentiment for dividends during our sample period. These differences highlight the merits of our search-based measure for catering incentives.

Our paper also relates to research that attempts to identify the factors that drive dividend demand and returns of dividend-paying stocks. Daniel, Garlappi, and Xiao (2021) and Jiang and Sun (2020) find that demand for dividends is higher in low interest-rate environments. Hartzmark and Solomon (2013) show that companies have positive abnormal returns in dividend premium months, and this premium is likely to reflect price pressure from dividend-seeking investors.[2] More recently, Hartzmark and Solomon (2019) employ stock returns between the dividend announcement date and the ex-dividend date as a proxy for the relative demand for dividend-paying stocks. Extending this literature, using a measure of time-varying investor demand for dividends with high frequency and cross-sectional variation, we show that higher dividend sentiment leads to an increase in investors' demand for high dividend stocks. The excess demand generates price pressure on high dividend stocks, and we find higher abnormal returns for high dividend stocks in the short run.

More broadly, our paper is related to the catering theory in corporate settings. Baker, Greenwood, and Wurgler (2009) propose a catering theory of nominal share prices and show that when investors place a premium on low-price firms, managers respond by supplying shares at lower prices through stock splits. Polk and Sapienza (2009) suggest that the stock market might misprice firms based on firms' investment level and that managers cater to mispricing through their investment decisions by inflating stock prices. Aghion and Stein (2008) find that managers either maximize sales growth or improve profit margins, depending on which is preferred by the stock market. Extending this literature, we examine the dividend catering theory using the Internet search volume of dividend-related keywords as a direct measure of dividend sentiment.

[2] Harris, Hartzmark, and Solomon (2015) find that mutual funds purchase dividend-paying stocks before the ex-dividend date to artificially increase their dividend yield.

Beyond the catering literature, our paper provides new evidence on the economic effects of investor attention. An extensive finance literature uses indirect proxies, such as news and headlines (Barber and Odean, 2008), extreme returns (Barber and Odean, 2008), advertising expenses (Grullon, Kanatas, and Weston, 2004), and trading volume (Gervais, Kaniel, and Mingelgrin, 2001), for investor attention. Da, Engelberg, and Gao (2011) propose a measure of investor attention using Google Trends and show that it captures investor attention effectively. In a similar manner, we show that managers initiate or increase dividends when investors pay more attention to dividends.[3]

The rest of the paper is organized in the following manner. Section 2 describes the data, our new sentiment measure, and the validation tests. Section 3 presents our main results. Section 4 provides evidence on dividend sentiment and mutual fund flows. Section 5 provides evidence on dividend sentiment and investor trading. Section 6 presents evidence on stock return predictability. Section 7 provides evidence on share repurchases. Section 8 examines the robustness of our findings. Section 9 concludes with a brief discussion.

2. Data and Sample Construction

We collect data from various sources to test our conjectures. In this section, we describe these data sets and the new dividend sentiment measure.

2.1. Dividend sentiment data

Google provides data on search term frequency via Google Trends starting in January 2004.[4] The search data from Google Trends are normalized and scaled to a range of 0 to 100.[5] We use the search volume index (*SVI*) of dividend-related searches at both the national and the

[3] Graham and Kumar (2006) use investor trades around dividend events to provide evidence of attention-induced trading by groups of investors who like dividends.
[4] Google Trends is available at https://www.google.com/trends/.
[5] Da, Engelberg, and Gao (2011) report that Google accounted for 72.1% of all search queries in the United States. Thus, the search volume data are representative of the search behavior of the general population.

state level in the United States from 2004 to 2016 to capture investors' dividend sentiment.[6] The *SVI* indicates the popularity of a search term relative to all other terms from the same location at the same time. An increase in the *SVI* indicates that individual investors pay more attention to the search than they usually do. The monthly *SVI* for a search term is the number of searches for that term scaled by its time-series average.

Google Trends provides topic searches that are searched with the topic we enter (for instance, "dividend"). We then use the search volume index for dividend-related keywords from Google to capture investors' dividend sentiment (Da, Engelberg, and Gao, 2011, 2015). In particular, the *SVI* is the search volume index for the topic "dividend" from Google Trends and includes searches using different dividend-related words and various text strings.

To study the geographical variation in investors' attitudes about dividends, we collect the monthly Internet search volume from Google Trends for each U.S. state from 2004 to 2016. State-level *SVI*s are not directly comparable when downloaded separately. We deflate the *SVI* of each state by the corresponding national-level *SVI* to ensure both are comparable cross-sectionally and across time.

Similar to the Da, Engelberg, and Gao (2011), our key variable of interest is the change in the *SVI*, that is, the abnormal search volume index (*ASVI*).[7] We define *ASVI* for search term j at time t as

$$ASVI_{j,t} = \log\left(SVI_{j,t}\right) - \log\left(SVI_{j,t-1}\right), \tag{1}$$

[6] It is possible that our measure captures more dividend demand from less sophisticated investors, e.g. retail investors. While sophisticated institutional investors might use professional data platforms and terminals to conduct dividend searches, less sophisticated investors could rely on Internet as the first destination for their searches on dividend.

[7] *ASVI* has the advantage of low-frequency seasonality and time trends are removed.

where $\log(SVI_{j,t})$ and $\log(SVI_{j,t-1})$ represent the natural logarithm of *SVIs* during month t and month t -1, respectively.[8] The time series of *ASVI* starts in February 2004 and measures changes in dividend sentiment. To eliminate seasonality from $ASVI_{j,t}$, we regress $ASVI_{j,t}$ on month dummies and use the residual (Da, Engelberg, and Gao, 2015). Quarterly $ASVI_{j,t}$ is the median value of the monthly $ASVI_{j,t}$ within each quarter.

2.2. Sample construction

We analyze the dividend policy of firms from 2004 to 2016. We use quarterly dividend data rather than annual dividends to increase the number of observations. The Compustat sample for quarter t includes those firms that have the following data (Compustat data items are in parentheses): total assets (44), stock price (12), shares outstanding (61) at the end of each quarter, income before extraordinary items (8), interest expenses (22), dividends per share by ex-date (16), preferred dividends (24), and preferred stock carrying value (55). Firms must also have (a) stockholder's equity (60), (b) liabilities (54), or (c) common equity (59) and preferred stock par value (55). Total assets must be available in quarters t and t - 1. The other items must be available in quarter t.

We also use but do not require, balance-sheet-deferred taxes and investment tax credits (52), income statement deferred taxes (35), purchases of common and preferred stock (93), sales of common and preferred stock (84), and common Treasury stock (98). We exclude firms with book equity below \$250,000 or assets below \$500,000. The Compustat sample includes only firms with a CRSP share code of 10 or 11. The CRSP sample includes NYSE, AMEX, and NASDAQ securities. We exclude utilities (SIC codes 4900 to 4949) and financial firms (SIC codes 6000 to 6999).

[8] When we define *ASVI* as the natural logarithm of the *SVI* during month t minus the average natural logarithm of the *SVI* in month $t-1$ and $t-2$, our results are similar.

Our mutual fund data are from the Center for Research on Security Prices (CRSP) Survivorship Bias-free Mutual Fund Database from 2004 to 2016. Following Spiegel and Zhang (2013), we only include non-specialty domestic equity funds in the final sample (Lipper Objectives EI, EIEI, ELCC, EMN, G, GI, I, LCCE, LCGE, LCVE, LSE, MC, MCCE, MCGE, CMVE, MLCE, MLGE, MLVE, MR, SCCE, SCGE, SCVE, and SG). Our main variable of interest is the net fund flow for fund *i* in quarter *t*:

$$Fund\ Flow = \frac{TNA_{i,t} - TNA_{i,t-1}}{TNA_{i,t-1}} - r_{i,t}, \tag{2}$$

where $TNA_{i,t}$ denotes fund *i*'s total net assets at the end of quarter *t* and $r_{i,t}$ denotes fund *i*'s return in quarter *t* as reported in CRSP. To eliminate the impact of outliers, we winsorize fund flows at the 1st and 99th percentiles. Table A1 in the Appendix provides definitions of all variables on firm and fund characteristics.

We use five commonly used macroeconomic variables to capture the effects of business cycles. Unexpected inflation (*UEI*) is the difference between the current month's inflation and the average of the past 12 realizations. Monthly growth in industrial production (*MP*) is obtained from the Federal Reserve website. Monthly default risk premium (*RP*) is the difference between Moody's Baa-rated and Aaa-rated corporate bond yields. The term spread (*TS*) is the difference between the yields of a constant maturity 10-year Treasury bond and a 3-month Treasury bill. The U.S. monthly unemployment rate (*UNEMP*) is obtained from the website of the Bureau of Labor Statistics. Quarterly macroeconomic variables are obtained by averaging the monthly data within each quarter.

Table 1 reports the summary statistics for our main variables. The average dividend initiation rate is 3.5% during the 2004 to 2016 period. Our dividend sentiment measure, *ASVI*, has significant variation: the 90th percentile value is 0.028, and the 10th percentile is –0.040.

Firm and risk controls are like those previously reported in the literature (Fama and French, 2001; Hoberg and Prabhala, 2009).

2.3. What drives the demand for dividends?

In this section, we analyze the determinants of the demand for dividends.[9] For income-seeking investors, dividend income may act as a substitute to interest income (Hartzmark and Solomon, 2019). If interest rates are low, investors may seek income by investing in dividend-paying stocks. Conversely, if interest rates are high, investors may increase their investments in bonds and reduce their portfolio weight in dividend-paying stocks. Similarly, when economic conditions become unfavorable with increased economic uncertainty, investors might value dividend income more and increase their demand for dividends.

We report the results in Panel A of Table 2. We consider the interest rates of three different bonds: Moody's Aaa-rated and Baa-rated corporate bonds and a 10-year Treasury bond. Consistently, we find that the interest rate is negatively associated with subsequent dividend sentiment in all specifications. In economic terms, a one-standard-deviation decrease in interest rate leads to a 7.8% (0.791*0.098) higher dividend sentiment in the next quarter. This indicates that interest rates and dividends appear to be substitutes to income-seeking investors. Further, unexpected inflation and unemployment rate are significantly and positively associated with subsequent dividend sentiment, while quarterly growth in industrial production is significantly and inversely related to subsequent dividend sentiment. This suggests that when the economic condition is unfavorable, investors prefer the perceived stability of dividends and pay more attention to dividends.[10]

[9] Daniel, Garlappi, and Xiao (2021) find that a low-interest-rate monetary policy increases investors' demand for high-dividend stocks, which is more pronounced among investors who fund consumption using dividend income.
[10] We also use monthly interest rates and dividend sentiment. Results are unchanged (see the online appendix).

In Panel B, we use bond-related search volume data from Google Trends to examine further the determinants of the demand for dividends. When the search volume of bond-related key-words is higher, subsequent dividend sentiment becomes lower. This supports our conjecture that investors treat dividend income as a substitute for interest income.

2.4. Relation between dividend sentiment and the dividend premium

In Panel C of Table 2, we study contemporaneous and lagged relationships between the dividend premium and the seasonally adjusted *SVI*. To examine the dynamic relationship between the dividend premium and dividend sentiment, we regress the current dividend premium on the current, one-, and two-quarter-lagged dividend sentiment. The results show that the coefficients on the current and lagged dividend sentiment are all positive and statistically significant at, at least, the 5% level. This confirms the expected positive relationship between the dividend premium and the dividend sentiment.[11]

2.5. Validation tests: Economic crisis

Before using the dividend sentiment measure in our main empirical tests, we conduct a validation test to ensure that our measure of dividend sentiment is reasonable.

We visually examine the time-series variation of the Internet search volume for the 2004 to 2020 period. Investors are more likely to seek income and prefer dividend-paying stocks when the economy does poorly. Figure 1 shows the natural log of the *SVI* from January 2004 to March 2020. To eliminate seasonality from this measure, we regress it on month dummies and keep the residual. We follow the National Bureau of Economic Research (NBER) and define a recession period from December 2007 to June 2009.[12] We find that individual

[11] Results are similar if we regress the current dividend sentiment on the current, one-, and two-quarter-lagged dividend premium, respectively.
[12] Dates on business cycles are available at http://www.nber.org/cycles/cyclesmain.html.

investors search more on dividends during the financial crisis period than during the pre-crisis period. The search volume spikes in October 2008, shortly after the stock prices of U.S. investment banks sharply drop and two American banks collapse.

Further, *SVI* on the dividend topic reached its historical record in March 2020 during the current coronavirus (COVID-19) crisis. We define the crisis period from the 23rd January 2020 when Wuhan began its lockdown (see Figure 1). As the virus spread globally and the World Health Organization declared this as a global pandemic on 11th March 2020, the Internet search volume for dividends peaked in March 2020. Its raw *SVI* (100) was 127% higher than the pre-crisis average value of 44 (see Figure IA.1 in the online appendix). This evidence validates our conjecture that the Internet search volume captures investors' attention to dividends and represents an appropriate measure of dividend sentiment.

3. Dividend Sentiment and Dividend Policy

3.1. Dividend sentiment and dividend payment decisions: Estimation framework

Baker and Wurgler (2004b) define a firm-quarter observation as a dividend payer if the observation has positive dividends per share by the ex-day. Similarly, we identify a firm-quarter observation as a dividend payer if it has positive dividends per share in the announcement quarter, and a non-dividend payer otherwise.[13] For those firms with missing announcement dates, we use ex-dividend dates instead.

We then define *Payers* and *Old payers* as follows:

$$Payers_t = New\ Payers_t + Old\ Payers_t + List\ Payers_t\ , \tag{3}$$

$$Old\ Payers_t = Payers_{t-1} - New\ Nonpayers_t - Delist\ Payers_t\ . \tag{4}$$

[13] Investors could search for dividends before the payment date after the dividend is announced. For example, suppose that a firm announced a dividend initiation in February 2017 and the payment date was in April 2017. Increased internet searches in the first quarter of 2017 could be a result of the dividend announcement itself, rather than elevated dividend sentiment overall. The median length between declaration dates and payment dates is 30 days for firms in our sample. To ensure that our results are not affected by this issue, we use dividend declaration dates instead of dividend payment dates to identify dividend payer-quarter.

Here, *Payers* is the total number of dividend payers in quarter *t*; *New payers* is the number of firms that initiate dividends among the last quarter's dividend nonpayers; *Old payers* is the number of dividend payers among the last quarter's payers; *List payers* is the number of dividend payers in the current quarter that were not in the sample last quarter; *New nonpayers* is the number of firms that omitted dividends in the current quarter but paid dividends in the previous quarter; and *Delist payers* is the number of last quarter's dividend payers that are not in the sample this quarter.

We then define three measures to capture the dividend payment decisions:

$$Initiate_t = \frac{New\ Payers_t}{Nonpayers_{t-1} - Delist\ Nonpayers_t}, \tag{5}$$

$$Increase_t = \frac{Increase\ Payers_t}{Payers_{t-1} - Delist\ Payers_t}, \text{ and} \tag{6}$$

$$Decrease_t = \frac{Decrease\ Payers_t}{Payers_{t-1} - Delist\ Payers_t}. \tag{7}$$

Here, *Initiate* is the fraction of surviving nonpayers that starts paying dividends.[14] *Increase payers (Decrease payers)* is the number of firms that increase (decrease) their dividends in the current quarter among last quarter's dividend payers. We count a firm-quarter observation as an increase (decrease) payer if the current quarter's dividend per share is higher (lower) than that in the last quarter. *Increase (Decrease)* is the fraction of surviving payers that increase (decrease) their dividends.[15]

Unlike annual dividends, which are typically used in the previous literature (Baker and Wurgler, 2004b; Li and Lie, 2006; Hoberg and Prabhala, 2009), quarterly dividend payments

[14] Baker and Wurgler (2004b) argue that the dividend payout ratio is sensitive to profitability, whereas the decision to initiate dividend is always a policy decision.

[15] We include dividend omissions in our analysis. We find that shifts in investors' dividend attitudes over time do not affect dividend omission decisions of firms. These findings are consistent with those of Hoberg and Prabhala (2009), who provide several reasons on why catering incentives are less likely to apply to dividend omissions.

are seasonal (Verdelhan, 2010). To eliminate seasonality from the dividend payment measure, we regress *Initiate*, *Increase*, and *Decrease* on quarter dummies, respectively, and obtain the residual (Da, Engelberg, and Gao, 2015).

3.2. The propensity to pay dividends: Estimation results

Next, we formally examine whether dividend sentiment predicts firms' dividend policies. If the demand for dividend-paying stocks increases, we expect *ASVI* to have a positive (negative) impact on subsequent dividend initiation or the increase (decrease) ratio. We regress the dividend payment measure on one-quarter-lagged *ASVI*.

Panel A of Table 3 reports the results. The dependent variable in column (1) is the fraction of new dividend payers in quarter *t* as a percentage of surviving nonpayers from *t*-1. The coefficient on *ASVI* is significantly positive at the 1% level. This evidence suggests that *ASVI*, on a stand-alone basis, strongly predicts the next quarter's dividend initiation ratio. The regression coefficient of 0.074 indicates that a one-standard-deviation increase in *ASVI* is associated with a 0.21% (0.029*0.074) higher dividend initiation ratio in the next quarter. These results are economically significant as the increase is 6.1% of the average dividend initiation ratio in our sample (= 0.035).

Column (2) reports the regression estimates for the rate of a dividend increase. The dependent variable is the fraction of payers that increase dividends in quarter *t*. We find that one-quarter-lagged *ASVI* is positively associated with the dividend increase rate. This evidence suggests that firms increase dividends when investors exhibit a stronger dividend sentiment. In economic terms, a one-standard-deviation increase in *ASVI* is associated with a 1.34% (0.029*0.461) increase in the dividend increase rate in the next quarter.

The results in column (3) shows that the dividend decrease rate is negatively associated with *ASVI*. When investors exhibit weaker dividend sentiment, firms are more likely to decrease dividends. The regression coefficient of 0.089 indicates that a one-standard-deviation decrease in *ASVI* is associated with a 0.26% (0.029*0.089) increase in the dividend decrease rate in the next quarter.

Previous studies on dividend catering have used the dividend premium to measure investors' demand for dividends.[16] Next, we examine whether dividend sentiment predicts firms' dividend policies after controlling for the dividend premium. The quarterly dividend premium is defined as the difference between the logs of the value-weighted market-to-book ratio for dividend payers and nonpayers each quarter.[17] We regress *ASVI* on the dividend premium and obtain the residual (*ASVI _DP).*

We repeat the analysis in Panel A using *ASVI _DP* and report the results in Panel B of Table 3. We find that *ASVI _DP* is positively (negatively) associated with dividend initiation and the increase (decrease) ratio. The economic significance remains similar in all specifications. This finding suggests that managers cater to investor demand by initiating or increasing (cutting) dividends when investors search more (less) for dividends on the Internet. These results are consistent with the dividend catering hypothesis and suggest that our dividend sentiment measure captures effects that are incremental over those captured by the dividend premium.

An implicit assumption underlying our tests is that it is feasible for the board of directors of a firm to adjust dividend policy in response to changes in investors' dividend sentiment, given the frequency of board meetings. Vafeas (1999) finds that the median board holds 7 meetings per year, and more than half of the boards in his sample meet between 5 to 9 times

[16] Baker and Wurgler (2004b) use four measures to proxy for investors' demand for dividends. The dividend premium, which is the difference between the average market-to-book ratio of dividend payers and nonpayers; difference in the prices of Citizens Utilities' cash dividend and stock dividend share classes; the average announcement effect of recent dividend initiations; and the difference between the future stock returns of payers and nonpayers. All of them are based on stock market data. Among them, the dividend premium is the most widely used proxy in the literature for investors' demand for dividends.

[17] To eliminate seasonality from quarterly dividend premiums, we regress the ratio on quarter dummies and obtain the residual.

per year. Similarly, Hahn and Lasfer (2007) show that the average number of board meetings from 1998 to 2004 is 8.8, ranging between 4 and 17. Based on these studies, boards meet, at least, quarterly on average. Given that our dividend payment analysis is at a quarterly frequency, it is, therefore, reasonable to expect firms to adjust their dividend policy in the next quarter based on dividend sentiment in the capital market.

Overall, our baseline results indicate that dividend sentiment predicts firms' dividend policies. Managers initiate or increase (decrease) dividends when investors exhibit a stronger (weaker) dividend sentiment. Also, we find that our dividend sentiment measure captures incremental information over the dividend premium proposed by Baker and Wurgler (2004b).

3.3. Regression estimates controlling for firm characteristics and risk

It is possible that the dividend payment measure is related to the cross-sectional differences in firm characteristics associated with dividends. For instance, instead of indicating that managers cater to the stronger sentiment of investors, an increase in the dividend initiation rate may suggest that firms do not need to retain internal cash.

We test for this possibility by including additional firm characteristics in the regression specification. Specifically, we examine whether dividend sentiment helps explain residual variation in dividend policies after controlling for various firm characteristics proposed in the literature. We obtain Fama and MacBeth (1973) estimates using the following logit model with seven control variables:

$$\Pr(Payer_{it}=1)=\log it(a+bNYP_{it}+c\frac{M}{B_{it}}+d\frac{dA}{A_{it}}+e\frac{E}{A_{it}}+fFCF_{it}+gLEV_{it}+hINV_{it})+u_{it}, \quad (8)$$

where size (*NYP)* is the NYSE market capitalization percentile, that is, the percentage of NYSE firms with capitalization equal to or less than the capitalization of firm *i* in quarter *t*. Market-to-book ratio (*M/B)* is book assets (item 44) minus the book value of equity (item 60 + item 52) plus the market value of equity (item 12 * item 61), all divided by book assets (item 44). Asset growth (*dA/A)* is the difference between book assets (item 44) and lagged book assets, divided by lagged book assets. Profitability (*E/A)* is earnings before extraordinary items (item 8) plus interest expense (item 22) plus income statement deferred tax (item 35), divided by book assets (item 44). *Free cash flow* is gross operating income (item 13) minus the sum of depreciation (item 14), taxes paid (item 16), interest expenses (item 15), and dividends paid (item19 + item 21). *Leverage* is defined as the book value of debt (item 9 + item 34), divided by the sum of the book value of debt (item 9 + item 34) and the market value of equity (item 25* item 24). *Investment* is defined as capital expenditures (item 145), divided by total assets (item 6).

Like the test used by Baker and Wurgler (2004b), our test is conducted in three stages. We first estimate a set of Fama-Macbeth logit regressions of the dividend payment on firm characteristics. We obtain the average quarterly prediction errors (actual dividend policy minus predicted policy) from the logit regressions. To eliminate seasonality from the average quarterly prediction errors, following Da, Engelberg, and Gao (2015), we regress the prediction errors on quarterly dummies and obtain the residual. In the final stage, we regress the seasonally adjusted residual of the average quarterly prediction errors on *ASVI*. The propensity to pay (*PTP*) is the difference between the actual percentage of firms that pay dividends in a given quarter and the expected percentage, which is the average predicted probability from the logit model.

Panel A of Table 4 reports the final stage results.[18] The dependent variable in the final stage regression is the change in the propensity to pay (*CPTP*) dividends between quarter *t*-1 and *t*. The coefficient on *ASVI* is significantly positive. This evidence suggests that *ASVI* predicts a firm's propensity to pay dividends in the next quarter. This evidence is consistent with the

[18] We report the first-stage results in the online appendix. Consistent with Fama and French (2001) and Baker and Wurgler (2004b), we find that larger and more profitable firms with substantial free cash flows and high leverage are more likely to pay dividends, whereas firms with more investment opportunities and greater asset growth are less likely to pay dividends.

catering prediction, even after controlling for firm characteristics: managers pay dividends when investors have stronger dividend sentiment.

In any given quarter, the supply of dividends comes from two sources: (1) firms that already pay dividends and (2) firms that newly initiate dividends. Next, we divide the sample into surviving nonpayers in column (2) and surviving payers in columns (3) and (4). The dependent variable in the first-stage regression in column (2) is a binary variable that equals 1 if firm *i* pays dividends in quarter *t* and 0 otherwise. The average quarterly prediction errors in column (2) represent the propensity to initiate dividends (*PTI*). *PTI* is the difference between the actual percentage of previous nonpayers that initiate dividends in a given quarter and the expected percentage, which is the average predicted probability from the logit model.

The dependent variable in the first-stage regression in columns (3) and (4) is a binary variable that equals 1 if firm *i* increases or decreases dividends in quarter *t* and 0 otherwise. The average quarterly prediction errors in columns (3) and (4) represent the propensity to increase or decrease dividends (*PTE/PTD*). The propensity to increase or decrease (*PTE/PTD*) is the difference between the actual percentage of firms that increase or decrease dividends in a given quarter and the expected percentage, which is the average predicted probability from the logit model.

As predicted by the dividend catering hypothesis, *ASVI* is positively associated with the changes in the propensity to initiate (*CPTI*) or increase (*CPTIN*) dividends and negatively associated with the changes in the propensity to decrease dividends (*CPTD*). Specifically, firms are more (less) likely to initiate or increase dividends when investors search more (less) for dividends on the Internet. The regression coefficient of 0.077 in column (2) suggests that a one-standard-deviation increase in *ASVI* is associated with a 0.22% (0.029*0.077) increase in the propensity to initiate dividends in the following quarter. These results remain robust after we control for the effects captured by the dividend premium variable in Panel B of Table 4.

Hoberg and Prabhala (2009) show that firm risk is a significant determinant of the propensity to pay dividends and that the dividend premium becomes an insignificant predictor after accounting for appropriate firm risk variables. Therefore, we also control for risk in the first-stage Fama-Macbeth logit regressions. These tests also proceed in three stages as before. We obtain the Fama and MacBeth (1973) estimates using a logit model with two additional risk controls in the first stage, where *Systematic risk* is the standard deviation of the predicted value from a regression of a firm's daily excess stock returns (raw returns less the risk-free rate) on the market factor (i.e., the value-weighted market return less the risk-free rate). Firm-quarter observations for systematic risk are calculated using firm-specific daily stock returns within a quarter. *Idiosyncratic risk* is the standard deviation of residuals from the above regression used to define systematic risk.[19]

Consistent with the evidence in Hoberg and Prabhala (2009), we find that both systematic risk and idiosyncratic risk measures are negatively associated with the propensity to pay dividends in the first-stage regression (see the online appendix). Next, we report the trend in firms' dividend-paying policies in Figure 2. In particular, we include the time-series plots of firms' propensity to pay dividends and our dividend sentiment measure *ASVI* from 2004 to 2016. Panel A reports firms' propensity to pay dividends after controlling for firm characteristics, while Panel B adjusts for risk in addition to firm characteristics. There is an upward trend in firms' propensity to pay dividends (under both measures), except for the global financial crisis period of 2007-2009. In addition, the risk-adjusted propensity to pay dividends and one-quarter-lagged dividend sentiment measure show a positive correlation (see Panel B of Figure 2), consistent with dividend catering and demonstrating the importance of risk adjustment in catering incentives.

[19] Both risk controls have correlations of less than 0.08 with most of the firm characteristics proposed in the literature, which indicates that multicollinearity is not a significant concern in our analysis.

We report the final stage regression results in Panel C of Table 4. We find that *ASVI* is positively associated with changes in the propensity to pay dividends.[20] A one-standard-deviation increase in *ASVI* leads to a 0.81% (0.029*0.281) increase in the propensity to pay dividends in the next quarter. We then study companies that newly initiate dividends in column (2) and firms that already pay dividends in columns (3) and (4). The coefficient on *ASVI* is significantly positive in columns (2) and (3) and becomes significantly negative in column (4) after controlling for risk. Results are robust after controlling for the dividend premium in Panel D of Table 4. This again confirms that our dividend sentiment measure might capture information not reflected in the market data.[21]

Collectively, these results indicate that investors' dividend sentiment still strongly predicts firms' subsequent dividend policies after controlling for firm characteristics, risk, and the dividend premium. We show that firms exhibit a greater propensity to initiate or increase (decrease) dividends when dividends attract more (fewer) investors.

3.4. State-level dividend sentiment and dividend policy

Next, we examine whether cross-sectional differences in dividend sentiment affect dividend policy. Since dividend sentiment varies across different regions in the United States, we conjecture that the impact of dividend sentiment on dividend policy would be stronger among U.S. states with stronger dividend sentiment. Investors in these states are more likely to exhibit a strong preference for dividend-paying stocks, and they are likely to hold more local stocks (Becker, Ivkovic, and Weisbenner, 2011). Consequently, local corporate managers may

[20] Consistent with Hoberg and Prabhala (2009), we find that the coefficient estimate of the dividend premium variable becomes insignificant once we control for risk.
[21] Daniel, Garlappi, and Xiao (2021) and Jiang and Sun (2020) find that the demand for dividends is higher in low interest-rate environments. In the online appendix, we control for interest rates in the final-stage regression and find that our main results still hold.

be more motivated to cater to time-varying investor demands as catering increases firm value (Manconi and Massa, 2013).

To test our prediction, we perform logit regressions of dividend payment on state-level dividend sentiment and a dummy variable indicating high-dividend-sentiment states. We use a firm's headquarter state to identify its location and use the historical average state-level *SVI* to measure local investors' dividend sentiment. For each quarter, we rank all U.S. states based on the average deflated *SVI* in all past quarters since 2004. *High DS State* is a dummy variable that equals one if firm *i* is located in a top-10 dividend sentiment state and 0 otherwise. We include both firm and time fixed effects and standard errors are clustered at the firm and quarter level.

Table 5 reports the results. The dependent variable is a dummy variable that equals one if firm *i* pays dividends in quarter *t* and 0 otherwise in column (1). The key variable of interest is the *SVI**High DS State*, which is based on state-level *SVI*. We find that the interaction variable carries a positive and statistically significant (at the 5% level) coefficient, which suggests that firms in high-dividend sentiment states have a higher propensity to pay dividends than those in other states when dividend sentiment becomes stronger.

We then restrict the sample to surviving nonpayers in column (2). Consistent with our conjecture, we find that firms in high-dividend sentiment states do exhibit a higher likelihood to initiate dividends than do firms in other states when the demand for dividends is higher. In column (3), we examine dividend increases. The coefficient of the interaction term is also positive, albeit statistically insignificant. Collectively, the results based on state-level dividend sentiment are consistent with our conjecture. We find that in regions with strong dividend sentiment, local corporate managers cater to investors' dividend sentiment.[22]

[22] We also use the state-level dividend premium and examine whether cross-sectional differences in dividend premium affect dividend policy. We find that cross-sectional differences in state-level dividend premium does not significantly affect dividend policy. Results are available on request.

3.5. Does dividend sentiment predict dividend announcements?

Next, we examine whether dividend sentiment affects subsequent dividend announcements. If elevated dividend sentiment increases the demand for dividend-paying stocks, we expect firms to have more subsequent dividend announcements. Dividend announcement dates are obtained from CRSP, and we aggregate the number of dividend declarations for each month and for each quarter. Table 6 reports the results. In panel A (B), we use national-level (state-level) dividend sentiment and regress the number of dividend announcements on the 1-month-lagged (one-quarter-lagged) *SVI*. The dependent variable is the natural log of the number of dividend announcements.

In Panel A of Table 6, we find that 1-, 2-, and 3-month-lagged *SVIs* are all positively associated with subsequent dividend announcements. This is consistent with our conjecture that higher demand for dividend-paying stocks motivates firms to announce more dividends. In economic terms, the number of dividend announcements increases by 1.43% [=0.143*0.1] after 3 months when the *SVI* increases by 10%. Moreover, we show that 4-, 5-, and 6-month-lagged *SVIs* are not significantly associated with subsequent dividend announcements. This evidence indicates that the effect only exists in the short-run for up to 3 months.[23]

In Panel B of Table 6, we perform Fama-Macbeth regression in columns (1) and (2) and an OLS regression in column (3). *High DS State* is a dummy variable that equals one if the state is a top-10 dividend sentiment state and 0 otherwise. In column (1), we find that state-level dividend sentiment is positively associated with the number of dividend announcements in the next quarter. Moreover, we interact the state-level *SVI* with the *High DS State* in column (2) and find that the coefficient on the double interaction variable is significantly positive. This

[23] We also examine whether the number of dividend announcements predicts subsequent Google searches and find that dividend announcements do not lead investors to search more on Google. Results are available on request.

finding suggests that elevated dividend sentiment increases the demand for dividend following dividend announcements in high-dividend sentiment states. Results are similar in column (3) when we use an OLS regression.

Overall, these results based on dividend announcements support our earlier findings related to dividend payment decisions. We find that in regions with strong dividend sentiment, firms announce more dividends when investors' dividend sentiment becomes stronger.

4. Dividend Sentiment and Mutual Fund Flows

In this section, we examine whether the time variation in dividend sentiment predicts mutual fund flows. We conjecture that investors are likely to favor mutual funds that pay high dividends when dividend sentiment is strong. In particular, we test whether our dividend sentiment measure can explain the residual variation in mutual fund flows, after controlling for the known effects of fund size, fund age, fund risk, past fund performance, expense ratio, turnover ratio, fund family size, fund family flow, and segment flow (Sirri and Tufano, 1998; Del Guercio and Tkac, 2002; Kumar, Niessen-Ruenzi, and Spalt, 2015; Kostovetsky, 2016). We lag all these control variables by one quarter. We also control for lagged fund flows up to the previous four quarters. To eliminate the impact of outliers, we winsorize the control variables at the 1st and 99th percentile levels.

We define a mutual fund as a high-dividend fund if the fund name contains "high dividend," "super dividend," "ultra dividend," "rising dividend," or "dividend growth." Our sample contains 206 high-dividend mutual funds. The *abnormal fund flow* is the average fund flow of these high-dividend funds minus the average fund flow of all other conventional funds. The test is conducted in two stages. First, we estimate a set of Fama-Macbeth regressions for mutual fund flow using various fund characteristics. We obtain the average quarterly prediction errors (actual fund flow minus predicted fund flow) from the first-stage regressions. We then regress the residual of average quarterly prediction errors on *ASVI* in the second stage.

Panel A of Table 7 presents the results of the first-stage regression. We estimate Fama-MacBeth (1973) regressions in columns (1) to (4) and standard errors are clustered at the fund level. Consistent with the evidence in Kumar, Niessen-Ruenzi, and Spalt (2015), the first-stage regression estimates indicate that smaller and younger mutual funds with better past fund performance, a lower expense ratio, a larger fund family, and higher family and segment flow have more subsequent fund inflows.

Panel B of Table 7 reports the second-stage results. The dependent variable in columns (1) and (2) is the mutual fund flow of high-dividend funds. We find that *ASVI* is positively associated with subsequent fund inflows. In economic terms, a one-standard-deviation increase in *ASVI* leads to a 5.2% (0.029*1.809) increase in fund flows among high-dividend funds in the next quarter. This evidence confirms our conjecture that investors are more likely to invest in high-dividend mutual funds when dividend sentiment is stronger. Results are unaltered if we control for the dividend premium in column (2) and if the dependent variable is the *abnormal fund flow* in columns (3) and (4).

Overall, the fund flow results indicate that dividend sentiment predicts mutual fund flows even after we account for the known determinants of fund flow. Specifically, high-dividend mutual funds receive more fund inflows when dividend sentiment is stronger. This evidence suggests that our Internet search-based dividend sentiment measure is likely a good indicator of investors' time-varying attitudes toward dividends.[24]

5. Dividend Sentiment and Investor Trading: Direct Link

[24] We also examine whether time variation in dividend premium predicts mutual fund flows. We find that dividend premium is not significantly associated with subsequent fund inflows among funds that invest in high dividend stocks. Results are available on request.

The time-varying investors' demand for dividends triggers trading. We provide this direct link and conjecture that the shift in dividend attitudes positively affects subsequent investor trading. We expect that investors purchase more high dividend stocks when their dividend sentiment becomes stronger and vice versa. In particular, we directly examine whether investors increase aggregate demand for high dividend stocks when dividend sentiment is more elevated. We calculate two measures of abnormal trading using the transaction-level investor trading data from Trade and Quote (TAQ) and aggregate trading volume from CRSP.

To examine the impact of dividend sentiment on investor trading, we measure the aggregated demand for high dividend stocks as the excess buy-sell imbalance (*EBSI*), which is defined as $EBSI_t = LBSI_t - OBSI_t$, where $LBSI_t$ is the month t buy-sell imbalance of a portfolio of high dividend stocks, and $OBSI_t$ is the month t buy-sell imbalance of a portfolio of low dividend stocks (Kumar, 2009).[25] This measure captures the change in investors' preference toward high dividend stocks relative to the change in their preference toward low dividend stocks. We define a stock as a high- (low-) dividend stock if its dividend yield is in the top (bottom) 30th percentile among all CRSP stocks. We then estimate the following regression:

$$EBSI_t = \alpha + \beta_1 ASVI_{t-1} + \beta_2 DIVRET_t + \beta_3 DIVRET_{t-1} + \beta_4 MKTRET_t + \beta_5 MKTRET_{t-1} + \beta_6 EBSI_{t-1} + \beta_7 Controls_{t-1} + \varepsilon_t \quad (9)$$

The dependent variable is the excess buy-sell imbalance (*EBSI*) for high dividend stocks in month t. The independent variables include (1) contemporaneous and one-quarter-lagged returns on high dividend stocks and (2) contemporaneous and one-quarter-lagged market

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[25] Buy-sell imbalance (*BSI*) of portfolio p in month t is defined as $BSI_{pt} = \frac{100}{N_{pt}} \sum_{i=1}^{N_{pt}} BSI_{it}$, where the *BSI* for stock i in month t is defined as $BSI_{it} = \frac{\sum_{j=1}^{D_t} \left(VB_{ijt} - VS_{ijt}\right)}{\sum_{j=1}^{D_t} \left(VB_{ijt} + VS_{ijt}\right)}$. D_t is the number of days in month t, VB_{ijt} (VS_{ijt}) is the buy (sell) volume for stock i on day j in month t. N_{pt} is the number of stocks in portfolio p in month t. Following Kumar and Lee (2006) and Kumar (2009), we use an equally weighted *BSI* measure, which is more appropriate for capturing shifts in investor sentiment than a value-weighted *BSI* measure.

returns. We include lagged *EBSI* to account for potential serial correlation and *RP* (quarterly default risk premium), *TS* (term spread), *UNEMP* (unemployment rate), *UEI* (unexpected inflation), and *MP* (growth in industrial production) to control for business-cycle effects, because investors might have stronger dividend sentiment during economic recessions.

Table 8 reports the results. We use national-level quarterly *ASVI* in columns (1) to (3) and state-level quarterly *ASVI* in columns (4) to (6). In columns (4) to (6), we control for time and state fixed effects and cluster standard errors by state. In columns (1) to (3), we find that *ASVI* is positively associated with subsequent excess buy-sell imbalance for high dividend stocks. This suggests that investors are more likely to purchase high dividend stocks when dividend sentiment is stronger. Results are similar when we use state-level *ASVI* in columns (4) to (6). When dividend sentiment is stronger, the net purchase of high dividend stocks is significantly higher than that of low dividend stocks.

Next, we use aggregate trading volume data from CRSP to examine whether dividend sentiment triggers abnormal trading. Abnormal trading volume is calculated as the stock's CRSP quarterly volume, divided by the previous two quarter's average CRSP trading volume (Ben-Rephael, Da and Israelsen, 2017). Table 9 reports the results. *ASVI* is the state-level abnormal search volume index for the topic "dividend" from Google Trends. *DY30* is a dummy variable that equals one if the dividend yield of the stock is in the top 30th percentile among all CRSP stocks and 0 otherwise. We perform an OLS regression and cluster standard errors by firms and quarters.

The key variable of interest is *ASVI**DY30*. The coefficient on this interaction term is significantly positive in all three specifications, which indicates that for high dividend stocks, stronger dividend sentiment triggers more abnormal trading in the next quarter. In economic terms, a one-standard-deviation increase in *ASVI* is associated with 1.43% more abnormal trading (0.357*0.040) in the next quarter for high dividend stocks relative to other stocks.

Collectively, the results in Tables 8 and 9 show that dividend sentiment motivates investors to increase their aggregate demand for high dividend stocks. The shift in dividend attitudes is positively correlated with subsequent investor trading.

6. Stock Return Predictability

In this section, we examine the impact of the time-varying dividend sentiment on stock returns. We conjecture that investors' dividend sentiment should have a positive effect on the abnormal returns of high dividend stocks in the short run and lead to price reversals in the long run. When investors' dividend sentiment becomes stronger, the excess demand for high dividend stocks generates price pressure on these stocks, and these stocks might be temporarily mispriced. Next, we test whether this short-term return predictability exists and how we exploit the profitability of a trading strategy based on dividend sentiment.

First, we examine whether the price pressure for high dividend stocks is short-lived. To measure the abnormal return performance of high dividend stocks, we use the Fama-French (2015) five-factor model plus the momentum factor as the benchmark to control for the market return, size, the market-to-book ratio, operating profitability, investment, and momentum.[26] We obtain value-weighted portfolios of high dividend, low dividend, and zero dividend stocks from Kenneth R. French's data library.[27] We estimate the abnormal return of each portfolio using 36-month rolling window regressions. After estimating the factor loadings for each factor, we calculate the abnormal return for each portfolio as:

$$AR_{i,t} = \left(r_i - r_f\right) - \hat{\beta}_{mkt,t-1}\left(r_{mkt} - r_f\right) - \hat{\beta}_{SMB,t-1} r_{SMB} - \hat{\beta}_{HML,t-1} r_{HML} - \hat{\beta}_{UMD,t-1} r_{UMD} - \hat{\beta}_{RMW,t-1} r_{RMW} - \hat{\beta}_{CMA,t-1} r_{CMA} \quad (10)$$

[26] Results are similar if we use the Fama-French (1993) three-factor model as a benchmark to control for market return, size, and market-to-book.
[27] Results are similar if we construct equally weighted portfolios. Dividend yield portfolio data can be downloaded at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_port_form_dp.html.

where $AR_{i,t}$ is the abnormal return of portfolio *i* in month *t*. Factor loadings are estimated from month *t*-36 to *t*-1. Next, we estimate the following regression to test if stock returns are predictable in the short run:

$$AR_{portfolio,t+n} = \alpha + \beta_n \ln(SVI_t) + \varepsilon_t,\ n = 0,1,2,3\,.... \qquad (11)$$

where $AR_{portfolio,t+n}$ is the average abnormal return in month $t + n$ of a value-weighted portfolio. The coefficient β_n measures the predictive power of the natural log of the *SVI* with *n* lags.

The coefficient estimates in Table 10 support our conjecture. The β_n coefficients are significantly positive in months 0 and 1 for a high dividend stock portfolio. In economic terms, a 10% increase in the *SVI* for the topic “dividend” is associated with a significantly positive price change of 20 basis points (=2.041*0.1) in month 1. The coefficient estimates are still positive but become insignificant from month 2 onward and turn into significantly negative in month 10. In month 10, a 10% increase in the *SVI* for the topic “dividend” is associated with a significantly negative price change of 19 basis points (=1.909*0.1). This finding indicates that the price pressure for these high dividend stocks is temporary and we document significant long-run return reversals within the year. In contrast to the high dividend stock portfolio, the *SVI* has no power to predict the return of low dividend stock portfolios.

Further, the estimates in the last column show that the return predictability is stronger when we long high dividend stocks and short zero dividend stocks simultaneously. In economic terms, a 10% increase in the *SVI* for the topic “dividend” leads to a significantly positive price change of 36 basis points (=3.562*0.1) in month 1 for this long-short strategy. Figure 3 depicts the estimated coefficient on the natural log of *SVI* from month 0 to 10 and the respective 95% confidence bands. Results are similar when we long high-dividend stocks and short low-dividend stocks simultaneously.

Next, we examine the profitability of a trading strategy that attempts to exploit mispricing induced by dividend sentiment. In particular, we estimate the risk-adjusted performance of long-short trading strategies conditional on the level of *ASVI*. The estimation period is from January 2004 to June 2017. We "long" ("short") the high-yield portfolio and "short" ("long") the low-/zero-yield portfolio in the next month if the *ASVI* in the current month is higher (lower) than the average *ASVI* in all previous months since 2004. The benchmark models contain the following factors: the market excess return (*RMRF*), the size factor (*SMB*), the value factor (*HML*), the momentum factor (*UMD*), the profitability factor (*RMW*), and the investment factor (*CMA*).

Table 11 reports the results. The dependent variable is the return of the long-short portfolio in each month. When we use a value-weighted portfolio, we find that the monthly six-factor alpha estimate of the long-short portfolio for high-/low-yield portfolios (top 20 and bottom 20) is 0.720 (see Panel A, column 2). The long-short alpha translates into an annual risk-adjusted performance of 8.64%. Similarly, the performance of the long-short portfolio for high-/zero-yield portfolios (top 20/zero) in column (4) is statistically and economically significant as well. The long-short alpha (= 0.614) translates into an annual risk-adjusted performance of 7.37%. Our results are similar if we form an equally weighted portfolio, as shown in Panel B.

Overall, the results in this section support the notion that high dividend stocks earn significantly positive abnormal returns in the short run followed by long-run reversal when investors have stronger dividend sentiment. A long-short trading strategy that attempts to exploit the demand-induced mispricing generates an annualized risk-adjusted return of 8.64%. This is consistent with our conjecture that investors' dividend sentiment would create short-term mispricing among these high dividend stocks, and therefore affects firms' catering incentives.[28]

7. Repurchase Sentiment

The catering literature shows that managers cater to the time-varying demand not only for dividends but also for share repurchases (Kulchania, 2013). Jiang, Kim, Lie, and Yang (2013) find that the time-varying demand for share repurchases positively affects firms' repurchase policies. Similarly, we use the search volume index of repurchase-related searches to capture investors' repurchase sentiment directly. Specifically, *ASVI_Rep* is the abnormal search volume index if the search term in Google Trends includes "share buyback," "share repurchase," "stock buyback," or "stock repurchase."[29]

In this section, we examine whether our repurchase sentiment measure predicts firm's share repurchases after we control for firm characteristics and risk. These tests also proceed in three stages. We first estimate a set of Fama-Macbeth logit regressions on share repurchases and firm characteristics and risk. We obtain the average quarterly prediction errors (actual repurchase policy minus predicted policy) from the logit regressions. To eliminate seasonality from the average quarterly prediction errors, we regress the prediction errors on quarter dummies and obtain the residual. In the final stage, we regress the seasonally adjusted residual of average quarterly prediction errors on *ASVI_Rep*.

We report the first and final stage regression results in Table 12. In the first stage, we find that firms with large free cash-flow and profitability, or with low leverage, risk, investment,

[28] In contrast, we find no evidence of return predictability using dividend premium for the current quarter and the following four quarters. We also examine the profitability of a trading strategy by estimating the risk-adjusted performance of long-short trading strategies conditional on the level of dividend premium, and find insignificant risk-adjusted return.
[29] The state-level search volume index for repurchase-related keywords is unavailable. Google Trends does not report valid search volume data when the search volume is very low.

and market-to-book, are more likely to repurchase shares. For the final stage results, we find that *ASVI_Rep* is positively associated with the changes in the propensity to repurchase shares. A one-standard-deviation increase in *ASVI_Rep* leads to a 0.40% (0.133*0.030) increase in the propensity to repurchase shares in the next quarter. This confirms that repurchase sentiment has predictive power in capturing the catering behavior of managers. We then study companies that newly repurchase shares in column (2) and firms that already repurchase shares in columns (3) and (4). The coefficient on *ASVI_Rep* is significantly positive in columns (2) and (3) and becomes significantly negative in column (4). This confirms that investors' repurchase sentiment strongly predicts firms' share repurchase policies.

Collectively, we find that investors' repurchase sentiment strongly predicts firms' subsequent share repurchase policies after controlling for firm characteristics and risk. Managers cater to investors' time-varying demand for share repurchases.

8. Additional Evidence and Robustness Tests

8.1.Granger causality test

One potential concern is that our main results of the relation between dividend sentiment and firms' dividend policy could suffer from potential bias from reverse causality. Reverse causality implies that firms' dividend policies might cause investors to search more for dividends. In the first test, we conduct the Granger causality test to determine whether firms' dividend policies are Granger-caused by investors' dividend sentiment or vice versa. The results reject the null hypothesis that investors' dividend sentiment does not cause firms to initiate dividends and fails to reject the null hypothesis that the initiation of dividends does not cause stronger dividend sentiment afterward. Overall, we find that investors' dividend sentiment leads to changes in firms' dividend policies, not vice versa.

8.2. Macroeconomic and investor sentiment controls

In the next test, we include five commonly used macroeconomic variables in the regression specification to account for potential business-cycle effects. The results are reported in the online appendix. We find that the relation between dividend sentiment and the dividend policy remains similar after controlling for these macroeconomic variables. This evidence suggests that U.S. business cycles cannot fully explain the predictive power of our dividend sentiment measure.

We also test whether other investor sentiment proxies can explain our findings. Specifically, Baker and Wurgler (BW) (2006, 2007) construct an investor sentiment index based on the first principle component of five sentiment proxies, where each of the proxies has been orthogonalized with respect to a set of six macroeconomic indicators.[30] We repeat our baseline analysis in Table 4 with the additional BW sentiment controls and report results in the online appendix. We find that our results remain similar when we control for the BW investor sentiment index. This finding suggests that our dividend sentiment measure does not capture the information contained in other investor sentiment proxies.

8.3. Subsample analysis

To examine whether our baseline results are driven by the financial crisis period and the public availability of Google Trends, we perform subsample tests. We report the results in the online appendix. First, we restrict our sample to the pre-crisis period (prior to December 2007) and find that the results are robust. Second, we exclude the financial crisis period (December 2007 to June 2009), and the results remain unchanged. Third, we use the subperiod starting in June 2006, because the search volume index from Google was publicly available only after

[30] These data are available at http://people.stern.nyu.edu/jwurgler/.

June 2006. Our results are robust: the predictive power of our dividend sentiment measure remains intact even after Google's *SVI* data were made public.

8.4. Risk exposure

We also investigate whether risk explains the difference between our Google search measure and the dividend premium. We find that our dividend sentiment measure is less related to risk factors than dividend premium (results are reported in the online appendix). Further, we investigate whether our baseline results hold after controlling for these risk factors. Specifically, we regress *ASVI* on six risk factors and obtain the residual (*ASVI_Risk*). We still find that dividend sentiment predicts firms' dividend policies after controlling for these risk loadings.

8.5. Lifecycle explanation

To explore whether our baseline results hold after controlling for firms' lifecycle, we follow the prior literature (DeAngelo, DeAngelo, and Stulz, 2006; Denis and Osobov, 2008) and include the proportion of total equity that is generated internally via retained earnings (RE/TE) in the first-stage regression of Table 4. RE/TE (retained earnings over total equity) measures the life cycle stage of a given firm as the extent to which that firm's equity is earned or contributed. In the online appendix, we show that RE/TE has a positive and highly significant impact on the probability of paying dividends in the first stage. Next, we regress the residual from the first-stage regression on *ASVI*. We find that investors' dividend sentiment still strongly predicts firms' subsequent dividend policies after controlling for firms' lifecycle.

8.6. Keyword-based dividend sentiment

The topic search from Google could be confounded by some less relevant dividend keyword searches (deHaan, Lawrence and Litjens, 2020). Hence we examine the robustness of our results by carefully selecting a set of keywords from top dividend searches that are most frequently searched. In particular, we constructed two measures of keyword-based dividend sentiment. The first one is the abnormal search volume index if the search term in Google Trends includes "*dividend*" or "*dividends*". The second one includes more keywords, i.e., it is the abnormal search volume index if the search term in Google Trends includes "*dividend*" or "*dividends*" or "*dividend stocks*" or "*dividend payout*" or "*payout*". In the online appendix, we show that our baseline results are robust when using the modified dividend sentiment measure.[31]

8.7. News media and social media attention

Our Google search measure might be related to media attention (Da, Engelberg, Gao, 2011; Bybee, Kelly, Manela, and Xiu, 2020). In this section, we examine whether our baseline results hold after controlling for three measures of media attention on dividend.

We first control for news media attention proposed by Bybee, Kelly, Manela, and Xiu (2020), who apply textual analysis of business news from 800,000 *Wall Street Journal* articles and estimate a topic model that summarizes business news and quantifies the proportion of news attention allocated to each theme at each point in time. We selected the relevant topic "share payouts" to our paper and downloaded the data from their website.[32] We repeat our baseline analysis in Table 4 and control for the news media attention in the final stage regression. Results are reported in the online appendix. Our dividend sentiment measure still strongly predicts firms' subsequent dividend policies after controlling for the news media attention. The coefficient of the news media attention is insignificant at conventional levels

[31] One potential concern with the keyword-based measure is that the selection of dividend-related keywords is somewhat arbitrary. Using the dividend topic search to proxy for the dividend sentiment, as we do in the paper, could alleviate this concern.
[32] These data are available at http://structureofnews.com/.

across all specifications, which shows that the media attention for payout does not predict firms' subsequent dividend policies.

We are aware that this captures not only dividend-related topics but also topics on share repurchases. Hence we also construct a second measure of dividend media attention ourselves by using data from Dow Jones Factiva, which is an international news database covering a wide range of news from newspapers, newswires, industry publications, websites, and company reports. For each quarter, we calculate our news media attention by using the total number of dividend-related articles (i.e. containing dividend-related keywords in the headline, abstract or content) divided by the total number of published articles in the dataset. Again, we find that our dividend sentiment measure strongly predicts firms' subsequent dividend policies after controlling for the news media attention computed from Factiva. The coefficients of news media attention are insignificant in 3 out of 4 specifications, which indicates that media-based dividend attention does not predict firms' dividend policies in most models.[33]

Further, we constructed social media attention on dividend using data from Twitter. Since 2006, Twitter reports the intensity of tweets on topics across many categories, which reflect the conversations individuals have on Twitter about events, people, and things they discuss. Our social media attention measure is computed as the number of tweets on the dividend topic divided by the total number of tweets for each quarter. Our baseline results still hold after controlling for the social media attention from Twitter. The coefficient of the social media attention is statistically insignificant across all models, which suggests that the dividend-related social media attention does not predict firms' subsequent dividend policies.

[33] Over a quarter of all NYSE stocks are not covered in the press for a typical year (Fang and Peress, 2009). News coverage also does not guarantee investor attention. Hence news coverage might not be a good proxy for dividend-related catering incentives.

9. Summary and Conclusion

This paper investigates how changes in investors' attitudes toward dividends affect corporate dividend policy, investor trading behavior, mutual fund flows, and stock returns. Our empirical tests do not rely on valuation ratios that are typically used in the literature, which may capture changes in growth opportunities and firm risk. Instead, we use the Internet search volume of dividend-related keywords as a measure of investors' preference for dividends (i.e., dividend sentiment). We find that investors search more for dividends when economic conditions are poor (e.g., low interest rates), with the peak volume reached during the recent COVID-19 pandemic.

Using our measure of dividend sentiment, we provide direct evidence to support the view that managers cater to time-varying investor demand for dividends. In particular, we show that managers initiate or increase (decrease) dividends when investors have a stronger (weaker) dividend sentiment. Examining cross-sectional variation in dividend sentiment, we find that firms in regions with strong dividend sentiment announce more dividends and have a higher propensity to pay dividends than do those in other states when investors' dividend sentiment becomes stronger.

Mutual funds that pay high dividends receive more inflows when dividend sentiment is stronger. The shift in dividend attitudes is positively correlated with subsequent investor demand for high dividend stocks: dividend sentiment motivates investors to increase their aggregate demand for dividends. Consequently, high dividend stocks earn positive abnormal returns in the following month followed by long-run reversal when investors have stronger dividend sentiment.

We also show that managers cater to the time-varying demand for share repurchases. Our results are similar when we account for firm characteristics, firm risk estimates, the dividend premium, and a battery of robustness tests. Taken together, these findings contribute to the finance literature that examines the role of investor sentiment in corporate decisions and asset prices. In future work, it would be interesting to study Internet search volume related to other corporate decisions such as security issuance. It may also be useful to investigate whether dividend sentiment can explain the returns of very risky and speculative assets that are likely to have lower demand during periods when investors favor firms that provide “security”.

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Table 1. Summary statistics

This table reports the summary statistics for each variable. *Dividend initiation* expresses the number of new payers at quarter *t* as a percentage of surviving nonpayers from *t* - 1. *Dividend increase* expresses the number of payers that increase dividend payment at quarter *t* as a percentage of surviving payers from *t* - 1. *Dividend decrease* expresses the number of payers that decrease dividend payment at quarter *t* as a percentage of surviving payers from *t* - 1. *SVI* is the search volume index for the topic "dividend" from Google Trends. It includes searches for different text strings and for various dividend-related words. *ASVI* is the abnormal search volume index for the topic "dividend" from Google Trends. *Dividend premium* is the difference between the logs of the value-weighted market-to-book ratio for dividend payers and nonpayers. We regress *ASVI* on the dividend premium and compute the residual (*ASVI_DP*). To eliminate seasonality from our *ASVI* measures (*Dividend premium*), we regress the ratio on month (quarter) dummies and calculate the residual. Market-to-book ratio (*M/B*) is the book assets (item 44) minus book value of equity (item 60 + item 52) plus the market value of equity (item 12 * item 61), all divided by book assets (item 44). Asset growth (*dA/A*) is the difference between book assets (item 44) and lagged book assets, divided by lagged book assets. Profitability (*E/A*) is earnings before extraordinary items (item 8) plus interest expense (item 22) plus income statement deferred tax (item 35), divided by book assets (item 44). Size (*NYP*) is the NYSE market capitalization percentile, that is, the percentage of NYSE firms with capitalization equal to or less than the capitalization of firm *i* in year *t*. *FCF* is the gross operating income (item 13) minus the sum of depreciation (item 14), tax paid (item 16), interest expenses (item 15), and dividends paid (item 19 + item 21). *Leverage* is defined as the book value of debt (item 9 + item 34), divided by the sum of the book value of debt (item 9 + item 34) and the market value of equity (item 25 * item 24). *Investment* is defined as capital expenditure (item 145 in Compustat), divided by total assets (item 6). *Systematic risk* is the standard deviation of the predicted value from a regression of a firm's daily excess stock returns (raw returns less the riskless rate) on the market factor (i.e., the value-weighted market return less the riskless rate). One firm-quarter observation of systematic risk is calculated using firm-specific daily stock returns within a quarter. *Idiosyncratic risk* is the standard deviation of residuals from the above regression used to define systematic risk.

Variables	**Mean**	**10th perc.**	**Median**	**90th perc.**	**SD**
Dividend initiation	0.035	0.017	0.033	0.057	0.015
Dividend increase	0.174	0.126	0.172	0.246	0.044
Dividend decrease	0.044	0.032	0.041	0.059	0.011
SVI	-0.005	-0.164	0.031	0.110	0.108
ASVI	-0.004	-0.040	0.002	0.028	0.029
Dividend premium	0.001	-0.078	0.003	0.074	0.054
ASVI_DP	0.000	-0.030	-0.002	0.032	0.024
M/B	2.021	0.903	1.525	3.618	1.627
dA/A	0.024	-0.073	0.008	0.103	0.137
E/A	-0.003	-0.061	0.013	0.038	0.066
NYP	0.313	0.003	0.210	0.815	0.307
FCF	-0.004	-0.055	0.009	0.034	0.060
Leverage	0.208	0.000	0.178	0.484	0.190
Investment	0.031	0.002	0.016	0.076	0.044
Systematic risk	0.011	0.003	0.009	0.021	0.010
Idiosyncratic risk	0.027	0.011	0.022	0.048	0.024

Table 2. Determinants of dividend sentiment

In Panels A and B, the dependent variable is the seasonally adjusted *SVI*, which is the search volume index for the topic "dividend" from Google Trends. It includes searches for different text strings and for various dividend-related words. In Panel A, we report the relation between dividend sentiment and lagged bond yields and macroeconomic characteristics from 2004 to 2016. *Aaa (Baa)* is Moody's Aaa-rated and Baa-rated corporate bond yields. *Treasury bond* is the yield of a constant maturity 10-year Treasury bond. *UEI* (unexpected inflation) is the current quarter's inflation minus the average of the past 12 realizations. *UNEMP* is the quarterly unemployment rate. *MP* is the quarterly growth in industrial production. In Panel B, we show the relation between dividend sentiment and lagged sentiment on bond yields. The independent variable in all specifications is the search volume index for the corresponding topic from Google Trends. In Panel C, we report the contemporaneous and lead-lag relation between the dividend premium and the seasonally adjusted *SVI.* All standard errors are robust to heteroskedasticity and serial correlation. We consider four lags and use the procedure of Newey and West (1987) to account for serial correlation. ***, **, and * represent the 1%, 5%, and 10% significance levels, respectively.

Panel A. Dividend sentiment and lagged bond yields and macroeconomic characteristics

	(1)	(2)	(3)
Aaa	**-0.098**		
	[7.96]***		
Baa		**-0.082**	
		[7.07]***	
Treasury bond			**-0.080**
			[8.62]***
UEI	**0.020**	**0.006**	**0.022**
	[3.77]***	[0.98]	[3.76]***
UNEMP	**0.019**	**0.027**	**0.007**
	[4.77]***	[5.85]***	[1.72]*
MP	**-4.938**	**-8.761**	**-1.863**
	[2.58]***	[4.49]***	[1.06]
Constant	**0.349**	**0.315**	**0.211**
	[5.40]***	[4.65]***	[3.73]***
N	53	53	53

Panel B. Dividend sentiment and lagged sentiment on bond yields

	(1)	(2)	(3)	(4)
Yield spread	**-0.167**			
	[6.21]***			
Bond		**-0.444**		
		[5.38]***		
Bond yields			**-0.120**	
			[1.82]*	
Yield				**-0.476**
				[4.71]***
Constant	**0.004**	**0.004**	**0.004**	**0.004**
	[0.26]	[0.23]	[0.14]	[0.24]
N	53	53	53	53

Panel C. Contemporaneous and lagged *SVI* on dividend premium

	Dividend premium$_t$	*Dividend premium$_t$*	*Dividend premium$_t$*
SVI_t	**0.204**		
	[2.60]***		
SVI_{t-1}		**0.176**	
		[2.12]**	
SVI_{t-2}			**0.230**
			[2.77]***
Constant	**0.002**	**0.004**	**0.003**
	[0.17]	[0.39]	[0.32]
N	52	51	50

Table 3. Dividend payment and dividend sentiment: baseline results

This table presents OLS regression estimates of dividend initiation, increase, and decrease rates on one-quarter-lagged dividend sentiment. The sample period is from 2004 to 2016. The initiation rate expresses the number of new payers at quarter *t* as a percentage of surviving nonpayers from *t*-1. The increase rate expresses the number of payers that increase dividend payment at quarter *t* as a percentage of surviving payers from *t*-1. The decrease rate expresses the number of payers that decrease dividend payment at quarter *t* as a percentage of surviving payers from *t*-1. *ASVI* is the abnormal search volume index for the topic "dividend" from Google Trends. It includes searches for different text strings and for various dividend-related words. The dividend premium is the difference between the logs of the value-weighted market-to-book ratio for dividend payers and nonpayers. To eliminate seasonality from dividend initiations, dividend increases, dividend decreases, and the dividend premium (*ASVI*), we regress the ratio on quarter (month) dummies and compute the residual. We regress *ASVI* on the dividend premium in Panel B and keep the residual (*ASVI_DP)*. Standard errors are robust to heteroskedasticity and serial correlation. We consider four lags and use the procedure of Newey and West (1987) to account for serial correlation. ***, **, and * represent the 1%, 5%, and 10% significance levels, respectively.

Panel A. Abnormal search volume index

	Initiate	Increase	Decrease
ASVI	**0.074**	**0.461**	**-0.089**
	[2.70]***	[1.82]*	[2.11]**
Constant	**0.001**	**0.004**	**0.001**
	[0.50]	[0.52]	[0.40]
N	51	51	51

Panel B. Residual abnormal search volume index

	Initiate	Increase	Decrease
ASVI _DP	**0.074**	**0.461**	**-0.089**
	[2.72]***	[1.83]*	[2.11]**
Constant	**0.001**	**0.003**	**0.001**
	[0.36]	[0.30]	[0.60]
N	51	51	51

Table 4. Dividend payment and dividend sentiment: firm characteristics and risk

This table reports the final stage results of three-stage regressions of dividend payment on firm characteristics, risk, and dividend sentiment. In Panels A and B (C and D), we first perform a set of Fama-Macbeth logit regression of dividend payment on firm characteristics (firm characteristics and risk). We obtain the average quarterly prediction errors (actual dividend policy minus predicted policy) from the first-stage logit regressions. To eliminate seasonality from the average quarterly prediction errors, we regress the prediction errors on quarter dummies and compute the residual (the propensity to pay, initiate, increase, or decrease dividends). The propensity to pay, initiate, increase, or decrease (*PTP/PTI/PTIN/PTDE*) is the difference between the actual percentage of firms that propensity to pay, initiate, increase, or decrease dividends in a given quarter and the expected percentage, which is the average predicted probability from the logit model. We regress the seasonally adjusted residual of average quarterly prediction error on *ASVI* in the final stage. We also regress *ASVI* on the dividend premium and obtain the residual (*ASVI_DP)*. The dependent variable is the change in the propensity to pay, initiate, increase, or decrease dividends (*CPTP/CPTI/CPTIN/CPTDE*). Table A1 provides definitions of the control variables. Standard errors in the final stage are robust to heteroskedasticity and serial correlation. We consider four lags and use the procedure of Newey and West (1987) to account for serial correlation. ***, **, and * represent the 1%, 5%, and 10% significance levels, respectively.

Panel A. Controlling for firm characteristics in the first-stage regression: Raw *ASVI*

	CPTP	CPTI	CPTIN	CPTDE
ASVI	**0.192**	**0.077**	**0.118**	**-0.090**
	[1.82]*	[2.55]***	[2.11]**	[1.92]*
Constant	**0.002**	**0.000**	**0.000**	**-0.000**
	[0.32]	[0.13]	[0.01]	[0.07]
N	51	51	51	51

Panel B. Controlling for firm characteristics in the first-stage regression: Residual *ASVI*

	CPTP	CPTI	CPTIN	CPTDE
ASVI_DP	**0.192**	**0.077**	**0.117**	**-0.090**
	[1.82]*	[2.57]***	[2.10]**	[1.92]*
Constant	**0.002**	**-0.000**	**-0.000**	**0.000**
	[0.22]	[0.02]	[0.11]	[0.11]
N	51	51	51	51

Panel C. Controlling for firm characteristics and risk in the first-stage regression: Raw *ASVI*

	CPTP	CPTI	CPTIN	CPTDE
ASVI	**0.281**	**0.119**	**0.565**	**-0.108**
	[2.47]***	[2.97]***	[2.48]***	[2.06]**
Constant	**0.002**	**0.000**	**0.003**	**-0.000**
	[0.58]	[0.17]	[0.70]	[0.10]
N	51	51	51	51

Panel D. Controlling for firm characteristics and risk in the first-stage regression: Residual *ASVI*

	CPTP	CPTI	CPTIN	CPTDE
ASVI_DP	**0.282**	**0.122**	**0.563**	**-0.108**
	[2.47]***	[2.97]***	[2.45]***	[2.05]**
Constant	**0.001**	**-0.000**	**0.000**	**0.000**
	[0.18]	[0.45]	[0.10]	[0.09]
N	51	51	51	51

Table 5. Dividend payment and state-level dividend sentiment

This table reports the logit regression estimates of dividend payment on state-level dividend sentiment. *SVI* is the natural log of the state-level search volume index for the topic "dividend" from Google Trends. It includes searches for different text strings and for various dividend-related words. As state-level *SVI*s are not directly comparable when downloaded separately, we deflate the *SVI* of each state by the corresponding national-level *SVI* to ensure they are comparable cross-sectionally and across time. *High DS State* is a dummy variable that equals one if firm *i* is located in a top-10 dividend sentiment state and 0 otherwise. We rank all U.S. states by the deflated mean value of the *SVI* from 2004 to 2016. For each quarter, we rank all states based on the average *SVI* in all previous quarters since 2004 and the top-10 U.S. states are those with the highest deflated average *SVI*. We restrict the sample to surviving nonpayers in column (2). The dependent variable is a dummy variable that equals one if firm *i* pays dividends in quarter *t* and 0 otherwise from columns (1) to (2). The dependent variable in column (3) is a binary variable that equals one if firm *i* increases dividends in quarter *t* and 0 otherwise. Table A1 provides definitions of the control variables. We include both firm and time fixed effects and standard errors are clustered at the firm and quarter level. ***, **, and * represent the 1%, 5%, and 10% significance levels, respectively.

	(1)	(2)	(3)
SVI	**-0.022**	**-0.013**	**-0.004**
	[1.58]	[1.08]	[0.48]
High DS State	**-0.049**	**-0.018**	**-0.005**
	[1.94]*	[2.12]**	[0.56]
*SVI*High DS State*	**0.041**	**0.013**	**0.003**
	[2.08]**	[1.96]**	[0.43]
M/B	**-0.001**	**0.001**	**0.001**
	[0.61]	[1.94]*	[1.18]
dA/A	**-0.013**	**-0.016**	**-0.006**
	[2.42]***	[4.58]***	[1.23]
E/A	**0.035**	**0.039**	**0.043**
	[1.64]	[5.34]***	[3.47]***
NYP	**0.183**	**0.032**	**0.102**
	[3.59]***	[4.06]***	[3.42]***
Systematic risk	**-0.423**	**-0.098**	**-0.547**
	[1.95]*	[1.65]*	[4.29]***
Idiosyncratic risk	**-0.462**	**-0.068**	**-0.008**
	[5.85]***	[3.02]***	[0.22]
FCF	**0.012**	**0.021**	**0.021**
	[0.59]	[4.46]***	[3.08]***
Leverage	**-0.096**	**-0.020**	**-0.029**
	[4.12]***	[3.41]***	[3.66]***
Investment	**0.129**	**0.046**	**0.008**
	[2.51]***	[2.14]**	[0.20]
Firm FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
R^2	0.82	0.41	0.28
N	96,688	66,973	96,688

Table 6. Dividend announcements and dividend sentiment

This table shows the relation between lagged dividend sentiment and subsequent dividend announcements, at the national or state level. In Panel A, the dependent variable is the natural log of the number of dividend announcements each month. *SVI* is the natural log of the national level monthly search volume index for the topic "dividend" from Google Trends. It includes searches for different text strings and for various dividend-related words. In Panel B, the dependent variable is the natural log of the number of dividend announcements each quarter and the *SVI* is at the state level. We perform a Fama-Macbeth regression in columns (1) and (2) and an OLS regression in column (3). *High DS State* is a dummy variable that equals one if the state is a top-10 dividend sentiment state and 0 otherwise. We rank all U.S. states by the deflated mean value of the *SVI* from 2004 to 2016. For each quarter, we rank all states based on the historical average *SVI* in all previous quarters since 2004 and the top-10 U.S. states are those with the highest deflated average *SVI*. All standard errors are robust to heteroskedasticity and serial correlation. We consider two lags and use the procedure of Newey and West (1987) to account for serial correlation in columns (1) and (2), and we cluster standard errors by state in column (3). ***, **, and * represent the 1%, 5%, and 10% significance levels, respectively.

Panel A. Dividend announcements and national level dividend sentiment

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
SVI_{t-1}	**0.116**					
	[1.86]*					
SVI_{t-2}		**0.177**				
		[3.30]***				
SVI_{t-3}			**0.143**			
			[2.29]**			
SVI_{t-4}				**0.041**		
				[0.70]		
SVI_{t-5}					**0.034**	
					[0.64]	
SVI_{t-6}						**-0.018**
						[0.33]
Constant	**6.698**	**6.441**	**6.589**	**7.022**	**7.051**	**7.276**
	[25.21]***	[28.76]***	[25.13]***	[28.42]***	[31.77]***	[31.22]***
N	155	154	153	152	151	150

Panel B. Dividend announcements and state-level dividend sentiment

	FMB	**FMB**	**OLS**
SVI	**0.452**	**-3.500**	**0.140**
	[2.20]**	[1.24]	[0.96]
High DS State		**1.970**	**1.843**
		[40.46]***	[3.29]***
*SVI*High DS State*		**8.938**	**0.445**
		[2.12]**	[2.20]**
Constant	**2.878**	**-0.057**	**-0.073**
	[20.22]***	[2.07]**	[0.33]
Time FE	No	No	Yes
R^2	0.02	0.40	0.24
N	2,480	2,480	2,480

Table 7. Mutual fund flows and dividend sentiment

This table reports estimates from two-stage regressions of mutual fund flow on fund characteristics and dividend sentiment. We first perform a set of Fama-Macbeth regression of mutual fund flow on fund characteristics in columns (1) to (4). The dependent variable is the quarter net fund flow. Our set of control variables includes *fund size, fund age, fund risk, past fund return, the squared past fund return, expense ratio, turnover ratio, fund family size, family flow,* and *segment flow*. We also control for lagged fund flows up to the previous four quarters. Table A1 provides definitions of the control variables. We obtain the average quarterly prediction errors (actual fund flow minus predicted fund flow) from the first-stage regressions. The second stage regresses the residual of average quarterly prediction errors on seasonally adjusted *ASVI*. In column 1 (2) of Panel B, the dependent variable is the mutual fund flows for high-dividend funds before (after) controlling for the dividend premium. In column 3 (4), the dependent variable is the *abnormal mutual fund flows* (the average fund flow of these high-dividend funds minus the average fund flow of all other conventional funds) before (after) controlling for the dividend premium. We define a mutual fund as a high-dividend fund if the fund name contains "high dividend," "super dividend," "ultra dividend," "rising dividend," or "dividend growth." Our sample contains 206 high-dividend mutual funds. Standard errors in the second stage are robust to heteroskedasticity and serial correlation. We consider four lags and use the procedure of Newey and West (1987) to account for serial correlation. ***, **, and * represent the 1%, 5%, and 10% significance levels, respectively.

Panel A: First stage regression estimates

	FMB (1)	**FMB (2)**	**FMB (3)**	**FMB (4)**
Fund size	**-0.012**	**-0.012**	**-0.011**	**-0.011**
	[12.01]***	[11.60]***	[11.38]***	[10.69]***
Fund age	**-0.052**	**-0.051**	**-0.049**	**-0.046**
	[24.61]***	[20.83]***	[18.13]***	[15.81]***
Fund risk	**-0.894**	**-0.860**	**-0.838**	**-0.886**
	[3.20]***	[3.03]***	[2.86]***	[2.95]***
Past fund return	**7.751**	**8.020**	**8.293**	**8.328**
	[12.57]***	[13.17]***	[13.44]***	[13.11]***
Past fund return^2	**138.869**	**139.193**	**144.383**	**142.886**
	[5.60]***	[5.15]***	[5.17]***	[4.68]***
Expense ratio	**-0.926**	**-0.935**	**-0.844**	**-0.779**
	[2.10]**	[2.09]**	[1.91]*	[1.83]*
Turnover ratio	**0.002**	**0.001**	**0.002**	**0.002**
	[0.76]	[0.64]	[1.09]	[0.85]
Fund family size	**0.004**	**0.004**	**0.004**	**0.004**
	[6.80]***	[6.39]***	[6.06]***	[5.61]***
Family flow	**0.033**	**0.032**	**0.027**	**0.027**
	[2.88]***	[2.84]***	[2.73]***	[2.72]***
Segment flow	**0.151**	**0.145**	**0.157**	**0.163**
	[3.73]***	[3.55]***	[3.66]***	[3.59]***
Lagged fund flow$_{t-1}$	**0.149**	**0.146**	**0.142**	**0.138**
	[24.43]***	[24.74]***	[24.71]***	[25.76]***
Lagged fund flow$_{t-2}$		**0.001**	**0.001**	**0.002**
		[2.00]**	[1.92]*	[1.77]*
Lagged fund flow$_{t-3}$			**0.001**	**0.001**
			[2.02]**	[1.79]*
Lagged fund flow$_{t-4}$				**0.001**
				[1.74]*
Constant	**0.130**	**0.129**	**0.122**	**0.116**
	[15.96]***	[15.56]***	[12.58]***	[11.12]***
R^2	0.10	0.10	0.10	0.09
N	409,560	400,220	389,773	376,825

Panel B: Second stage regression estimates – column (4)

	(1)	**(2)**	**(3)**	**(4)**
ASVI	**1.809**		**1.337**	
	[2.91]***		[2.00]**	
ASVI_DP		**1.850**		**1.338**
		[2.98]***		[2.02]**
Constant	**0.015**	**0.001**	**0.042**	**0.032**
	[0.98]	[0.04]	[2.62]***	[1.99]**
N	47	47	47	47

Table 8. Excess buy-sell imbalance and dividend sentiment: TAQ Data

This table reports the results of dividend sentiment and the excess buy-sell imbalance (EBSI). We calculate quarterly excess buy-sell imbalance (EBSI) using TAQ data. The dependent variable in columns (1) to (6) is the excess buy-sell imbalance (EBSI) for high dividend stocks in a given month. This measure captures the change in investors' preference toward high dividend stocks relative to the change in their preference toward low dividend stocks. It is defined as $EBSI_t = LBSI_t - OBSI_t$, where $LBSI_t$ is the month t buy-sell imbalance of a portfolio of high dividend stocks, and $OBSI_t$ is the month t buy-sell imbalance of a portfolio that contains the low dividend stocks. We define the stock as a high- (low-) dividend stock if its dividend yield is in the top (bottom) 30th percentile among all CRSP stocks. We use national-level monthly *ASVI* in columns (1) to (3) and state-level monthly *ASVI* in columns (4) to (6). *RP* (quarterly default risk premium) is the difference between Moody's Baa-rated and Aaa-rated corporate bond yields. *TS* (term spread) is the difference between the yields of a constant maturity 10-year Treasury bond and a 3-month Treasury bill. *UNEMP* is the quarterly unemployment rate. *UEI* (unexpected inflation) is the current quarter's inflation minus the average of the past 12 realizations. *MP* is the quarterly growth in industrial production. *DIVRET* is the mean monthly return on high dividend stocks. *MKTRET* is the monthly market return. In columns (1) to (3), all standard errors are robust to heteroskedasticity and serial correlation. We consider four lags and use the procedure of Newey and West (1987) to account for serial correlation. In columns (4) to (6), we cluster standard errors by state. ***, **, and * represent the 1%, 5%, and 10% significance levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
ASVI	**5.065**	**5.391**	**5.138**	**1.779**	**1.963**	**2.100**
	[1.82]*	[2.04]**	[3.07]***	[2.01]**	[2.15]**	[2.28]**
RP_{t-1}	**0.615**	**0.570**	**0.409**	**0.119**	**9.525**	**11.830**
	[3.42]***	[3.06]***	[3.31]***	[1.09]	[0.68]	[0.84]
TS_{t-1}	**0.670**	**0.606**	**-0.258**	**0.057**	**5.472**	**10.445**
	[0.94]	[0.86]	[0.53]	[0.16]	[0.23]	[0.43]
$UNEMP_{t-1}$	**-0.258**	**-0.207**	**-0.086**	**0.156**	**-9.742**	**-11.686**
	[0.75]	[0.61]	[0.39]	[1.16]	[0.90]	[1.08]
UEI_{t-1}	**0.188**	**0.234**	**0.059**	**-0.005**	**-0.427**	**-0.044**
	[0.87]	[1.06]	[0.37]	[0.04]	[0.19]	[0.02]
MP_{t-1}	**25.857**	**12.834**	**23.070**	**12.080**	**-14.418**	**-11.730**
	[1.10]	[0.54]	[1.01]	[0.54]	[0.14]	[0.12]
$DIVRET_{t-1}$		**2.686**	**-1.023**	**1.036**	**-0.158**	**1.344**
		[0.55]	[0.08]	[0.28]	[0.04]	[0.41]
$DIVRET_t$		**11.170**	**63.480**	**27.245**	**28.723**	**28.024**
		[1.78]*	[4.18]***	[6.61]***	[6.89]***	[6.88]***
$MKTRET_t$			**-48.964**	**-20.987**	**-100.521**	**-117.055**
			[4.31]***	[4.82]***	[0.89]	[1.03]
$MKTRET_{t-1}$			**-1.931**	**-6.107**	**-40.529**	**-67.640**
			[0.19]	[1.31]	[0.37]	[0.60]
$EBSI_{t-1}$			**0.304**	**-0.001**	**-0.009**	**-0.023**
			[3.69]***	[0.05]	[0.42]	[1.25]
Constant	**-2.496**	**-2.355**	**-1.213**	**0.075**	**-26.617**	**-37.049**
	[2.65]***	[2.48]***	[1.95]*	[0.10]	[0.48]	[0.67]
Time FE	No	No	No	No	Yes	Yes
State FE	No	No	No	No	No	Yes
N	159	159	159	6,486	6,486	6,486

Table 9. Aggregate trading volume and dividend sentiment

This table reports the results of dividend sentiment and abnormal trading and we perform an OLS regression. Abnormal trading volume is calculated as the stock's *CRSP* quarterly volume, divided by the previous two quarter's average CRSP trading volume. The dependent variable is the abnormal trading volume in a given quarter. *ASVI* is the state-level abnormal search volume index for the topic "dividend" from Google Trends. It includes searches for different text strings and for various dividend-related words. *DY30* is a dummy variable that equals 1 if the dividend yield of the stock is in the top 30[th] percentile among all CRSP stocks and 0 otherwise. *Bid-ask spread* is the amount by which the asking price exceeds the bid price for the stock in the market. *MKTRET* is the quarterly market return. Table A1 provides definitions of the control variables. We cluster standard errors by firms and quarters. ***, **, and * represent the 1%, 5%, and 10% significance levels, respectively.

	(1)	**(2)**	**(3)**
$ASVI_{t-1}$	**-0.143**	**-0.142**	**-0.119**
	[1.73]*	[1.79]*	[1.31]
DP30	**0.030**	**0.015**	**0.018**
	[2.56]**	[1.57]	[1.20]
$ASVI_{t-1}*DP30$	**0.357**	**0.353**	**0.323**
	[1.97]**	[1.98]**	[2.03]**
$NYSE_{t-1}$	**0.018**	**0.017**	**0.019**
	[0.49]	[0.47]	[0.20]
MB_{t-1}	**0.027**	**0.030**	**0.072**
	[7.37]***	[7.19]***	[8.07]***
AG_{t-1}	**0.258**	**0.252**	**0.187**
	[6.83]***	[6.92]***	[5.04]***
EA_{t-1}	**0.104**	**0.062**	**0.021**
	[0.90]	[0.54]	[0.17]
FCF_{t-1}	**-0.279**	**-0.265**	**-0.191**
	[1.17]	[1.20]	[0.81]
$Leverage_{t-1}$	**0.109**	**0.084**	**-0.004**
	[5.37]***	[5.16]***	[0.08]
$Investment_{t-1}$	**0.071**	**-0.152**	**-0.617**
	[0.39]	[0.70]	[1.89]*
$Systematic\ risk_{t-1}$	**-5.050**	**-5.505**	**-6.639**
	[4.24]***	[4.41]***	[4.33]***
$Idiosyncratic\ risk_{t-1}$	**1.403**	**1.510**	**1.454**
	[1.15]	[1.25]	[1.11]
$Bid\text{-}ask\ spread_{t-1}$	**0.247**	**0.268**	**0.391**
	[2.50]**	[2.66]***	[2.83]***
$MKTRET_{t-1}$	**-0.444**	**-0.515**	**-0.851**
	[0.71]	[0.85]	[1.58]
Constant	**1.037**	**0.973**	**1.018**
	[28.04]***	[29.31]***	[21.16]***
Industry FE	No	Yes	No
Firm FE	No	No	Yes
Time FE	Yes	Yes	Yes
Adjusted R^2	0.02	0.02	0.11
N	39,363	39,363	39,226

Table 10. Dividend sentiment and return predictability

The following results show the predictive power of our Google dividend sentiment measure after controlling for seasonality. We regress portfolios' abnormal returns (in percentage) on the abnormal search volume intensity for the topic "dividend":

$$AR_{portfolio,t+n} = \alpha + \beta_n \times \ln(SVI_t) + \varepsilon_t, \ (n = 0, 1, 2, 3.....).$$

We use the Fama-French five-factor model plus momentum as the benchmark. We then form value-weighted portfolios of high-yield, low-yield, zero-yield, and other stocks. High-yield stocks are defined as stocks within the upper 20th percentile of the dividend yield in each year. Low-yield stocks are defined as stocks in the bottom 20th percentile of the dividend yield in each year. Zero-yield stocks are defined as stocks with a zero dividend yield in each year. We estimate the abnormal return of each portfolio using 36-month rolling window regressions. β_n measures the predictive power of the natural log of *SVI* with *n* lags. Column (1) indicates the month, *n*, where *n* = 0, 1, 2, or 3. Columns (2) to (4) report the regression coefficients on *SVI* (β_n) for the high-yield, low-yield, and zero-yield stock portfolios, respectively. Column 5 reports the coefficient estimates of a portfolio strategy that goes long in high-yield stocks and goes short in low-yield stocks. Column 6 reports the coefficient estimates of a portfolio strategy that goes long in high-yield stocks and goes short in zero-yield stocks. Standard errors (reported in brackets) are adjusted for autocorrelation using the Newey and West (1987) method. *******, ******, and ***** indicate significance at the 1%, 5%, and 10% levels, respectively.

Month	Hi20	Lo20	Zero	Hi-Lo	Hi-zero
0	**2.327**	**-0.945**	**-0.665**	**3.272**	**2.991**
	[2.01]**	[0.92]	[1.096]	[1.68]*	[1.98]**
1	**2.041**	**0.005**	**-1.521**	**2.036**	**3.562**
	[1.98]**	[0.01]	[2.14]**	[1.81]*	[2.73]***
2	**0.942**	**1.334**	**-0.802**	**-0.392**	**1.744**
	[0.73]	[1.29]	[1.30]	[0.19]	[1.09]
3	**0.391**	**1.083**	**0.095**	**-0.692**	**0.296**
	[0.27]	[0.94]	[0.12]	[0.29]	[0.15]
4	**0.812**	**0.529**	**0.210**	**0.283**	**0.602**
	[0.77]	[0.46]	[0.34]	[0.14]	[0.44]
5	**1.608**	**-1.656**	**2.142**	**3.264**	**-0.534**
	[0.98]	[1.35]	[2.02]**	[1.23]	[0.24]
6	**0.195**	**1.823**	**-0.007**	**-1.629**	**0.202**
	[0.19]	[1.78]*	[0.01]	[0.95]	[0.14]
7	**0.476**	**0.981**	**-1.220**	**-0.504**	**1.696**
	[0.43]	[0.95]	[2.25]**	[0.26]	[1.25]
8	**0.576**	**0.662**	**-0.891**	**-0.087**	**1.467**
	[0.49]	[0.51]	[1.65]	[0.04]	[1.01]
9	**-0.760**	**2.163**	**0.236**	**-2.923**	**-0.996**
	[0.48]	[1.69]*	[0.32]	[1.11]	[0.47]
10	**-1.909**	**1.565**	**0.362**	**-3.474**	**-2.271**
	[1.93]*	[2.15]**	[0.83]	[2.29]**	[1.70]*

Table 11. Dividend sentiment and return predictability: long-short trading strategies

This table reports the factor model risk-adjusted performance estimates of long-short trading strategies conditional on *ASVI*. The estimation period is from January 2004 to June 2017. We "long" ("short") the high-yield portfolio and "short" ("long") the low-/zero-yield portfolio in the next month if the *ASVI* in the current month is higher (lower) than the average *ASVI* in all previous months since 2004. High-yield stocks are defined as stocks within the upper 30th or 20th percentile of the dividend yield in each year. Low-yield stocks are defined as stocks in the bottom 30th or 20th percentile of the dividend yield in each year. The dependent variable is the difference in the returns of the long-short portfolios for each month. We form a value-weighted portfolio in Panel A and equally weighted portfolio in Panel B. The factor models contain the following factors: the market excess return (*RMRF*), the size factor (*SMB*), the value factor (*HML*), the momentum factor (*UMD*), the profitability factor (*RMW*), and the investment factor (*CMA*). All standard errors are robust to heteroskedasticity and serial correlation. We consider four lags and use the procedure of Newey and West (1987) to account for serial correlation. ***, **, and * represent the 1%, 5%, and 10% significance levels, respectively.

Panel A: Value-weighted portfolio

	Top/bottom 30	Top/bottom 20	Top 30/zero	Top 20/zero
Alpha	**0.507**	**0.720**	**0.440**	**0.614**
	[2.26]**	[2.32]**	[1.67]*	[1.86]*
RMRF	**-0.123**	**-0.158**	**-0.123**	**-0.156**
	[1.54]	[1.51]	[1.50]	[1.53]
HML	**-0.391**	**-0.453**	**-0.519**	**-0.601**
	[1.99]**	[1.75]*	[2.45]***	[2.27]**
SMB	**0.165**	**0.245**	**0.162**	**0.241**
	[1.65]*	[1.88]*	[1.55]	[1.93]*
RMW	**-0.466**	**-0.488**	**-0.510**	**-0.518**
	[2.51]***	[1.91]*	[2.73]***	[2.33]***
CMA	**0.275**	**0.217**	**0.500**	**0.463**
	[1.27]	[0.80]	[2.33]***	[1.84]*
UMD	**-0.112**	**-0.172**	**-0.079**	**-0.140**
	[1.65]*	[1.99]**	[0.98]	[1.45]
N	149	149	149	149

Panel B: Equally weighted portfolio

	Top/bottom 30	Top/bottom 20	Top 30/zero	Top 20/zero
Alpha	**0.333**	**0.401**	**0.463**	**0.553**
	[2.15]**	[1.99]**	[2.13]**	[2.26]**
RMRF	**-0.061**	**-0.052**	**-0.167**	**-0.166**
	[0.96]	[0.68]	[2.24]**	[2.07]**
HML	**-0.167**	**-0.220**	**-0.431**	**-0.451**
	[1.74]*	[1.75]*	[2.44]***	[2.42]***
SMB	**0.064**	**0.064**	**0.068**	**0.074**
	[0.97]	[0.80]	[0.72]	[0.79]
RMW	**-0.241**	**-0.315**	**-0.465**	**-0.536**
	[1.68]*	[1.65]*	[2.53]***	[2.76]***
CMA	**0.093**	**0.098**	**0.315**	**0.319**
	[0.62]	[0.55]	[1.67]*	[1.69]*
UMD	**-0.121**	**-0.152**	**-0.132**	**-0.150**
	[2.70]***	[2.67]***	[2.17]**	[2.32]**
N	149	149	149	149

Table 12. Share repurchases and repurchase sentiment

This table reports the results from three-stage regressions of share repurchases on firm characteristics, risk, and repurchase sentiment. We first perform a set of Fama-Macbeth logit regression of repurchase payment on firm characteristics and risk. We restrict the sample to surviving non-repurchasers in column (2) and surviving repurchasers in columns (3) and (4). The dependent variable in columns (1) and (2) is a dummy variable that equals 1 if firm *i* repurchases shares in quarter *t* and 0 otherwise. The dependent variable in column (3) ((4)) is a binary variable that equals 1 if firm *i* increases (decreases) share repurchases in quarter *t* and 0 otherwise:

$$\Pr(\mathrm{Re}\,purchaser_{it}=1)=\log it(a+bNYP_{it}+c\frac{M}{B_{it}}+d\frac{dA}{A_{it}}+e\frac{E}{A_{it}}+fFCF_{it}+gLEV_{it}+hINV_{it}+Systematic\,risk+Idiosyncratic\,risk)+u_{it}$$

We obtain the average quarterly prediction errors (actual repurchase policy minus predicted policy) from the first-stage logit regressions. To eliminate seasonality from the average quarterly prediction errors, we regress the prediction errors on quarter dummies and obtain the residual (propensity to repurchase, initiate, increase, or decrease). The propensity to conduct, initiate, increase, or decrease (*PTR/PTI/PTIN/PTDE*) is the difference between the actual percentage of firms that conduct, initiate, increase, or decrease share repurchases in a given quarter and the expected percentage, which is the average predicted probability from the logit model. We regress the seasonally adjusted residual of average quarterly prediction error on *ASVI_Rep* in the final stage. The dependent variable in the final stage is the change in the propensity to conduct, initiate, increase, or decrease share repurchases (*CPTR/CPTI/CPTIN/CPTDE*). *ASVI_Rep* is the abnormal search volume if investors search on "share buyback," "share repurchase," "stock buyback," or "stock repurchase" through Google. Table A1 provides definitions of the control variables. Standard errors in the final stage are robust to heteroskedasticity and serial correlation. We consider four lags and use the procedure of Newey and West (1987) to account for serial correlation. ***, **, and * represent the 1%, 5%, and 10% significance levels, respectively.

Panel A. First-stage regressions

	PTR	*PTI*	*PTIN*	*PTDE*
M/B	**-0.005**	**-0.002**	**0.001**	**0.001**
	[2.94]***	[3.77]***	[0.62]	[1.21]
dA/A	**-0.226**	**-0.040**	**-0.239**	**-0.055**
	[15.86]***	[8.20]***	[7.90]***	[3.18]***
E/A	**0.189**	**0.066**	**0.565**	**0.131**
	[4.64]***	[3.65]***	[3.37]***	[1.18]
NYSE	**0.323**	**0.031**	**0.142**	**0.061**
	[14.76]***	[6.38]***	[10.13]***	[5.06]***
Systematic risk	**-2.201**	**0.024**	**0.514**	**-0.237**
	[4.77]***	[0.20]	[0.56]	[0.54]
Idiosyncratic risk	**-1.533**	**-0.141**	**-2.756**	**-0.887**
	[8.46]***	[3.47]***	[6.30]***	[3.63]***
FCF	**0.431**	**0.031**	**0.163**	**0.050**
	[8.31]***	[1.53]	[1.24]	[0.57]
Leverage	**-0.095**	**-0.006**	**-0.103**	**-0.018**
	[12.80]***	[1.85]*	[6.24]***	[1.58]
Investment	**-0.666**	**-0.058**	**-0.131**	**-0.314**
	[9.59]***	[3.58]***	[1.25]	[3.39]***
Constant	**0.217**	**0.030**	**0.581**	**0.142**
	[18.07]***	[13.80]***	[22.76]***	[7.33]***
N	115,116	71,427	43,671	43,671

Panel B. Final stage regressions: Raw *ASVI*

	CPTR	*CPTI*	*CPTE*	*CPTD*
ASVI_Rep	**0.030**	**0.014**	**0.039**	**-0.107**
	[1.71]*	[2.87]***	[1.99]**	[2.12]**
Constant	**0.001**	**0.000**	**0.001**	**0.001**
	[0.27]	[0.05]	[0.29]	[0.46]
N	51	51	51	51

Figure 1. Search volume index on dividends: the time series

This figure shows the natural logarithm of the search volume index (*SVI)* from January 2004 to March 2020. We follow the National Bureau of Economic Research (NBER) and define the financial crisis period from December 2007 to June 2009 (the financial crisis period is within the first two dashed lines). The outbreak of coronavirus (COVID-19) started on 23 January 2020 when Wuhan began the lockdown (the pandemic period is within the last two dashed lines). *SVI* is seasonally-adjusted and logged search volume index for the topic "dividend" from Google Trends, based on searched from the United States. It includes searches for different text strings and various dividend-related words. To eliminate seasonality from the natural log of the search volume index, we regress it on month dummies and use the residual.

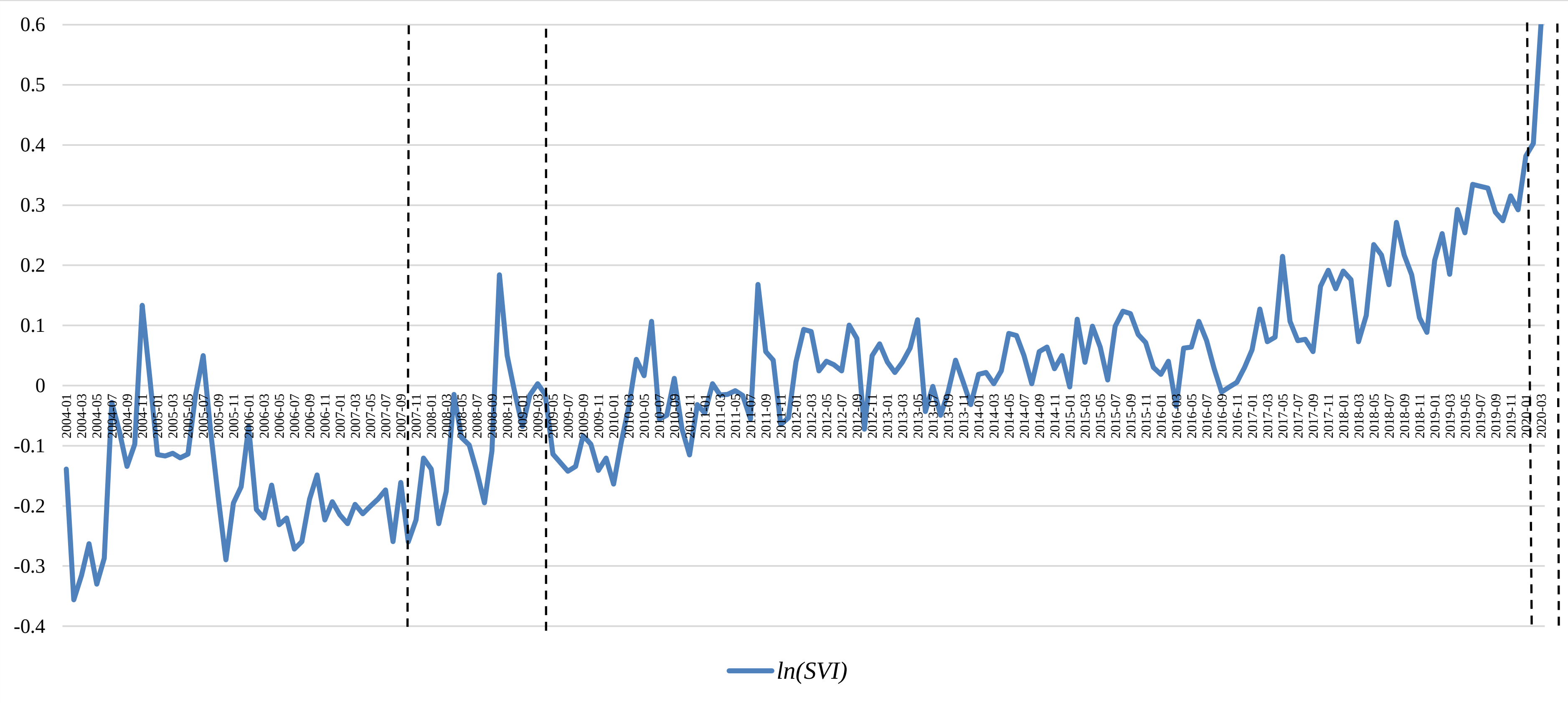
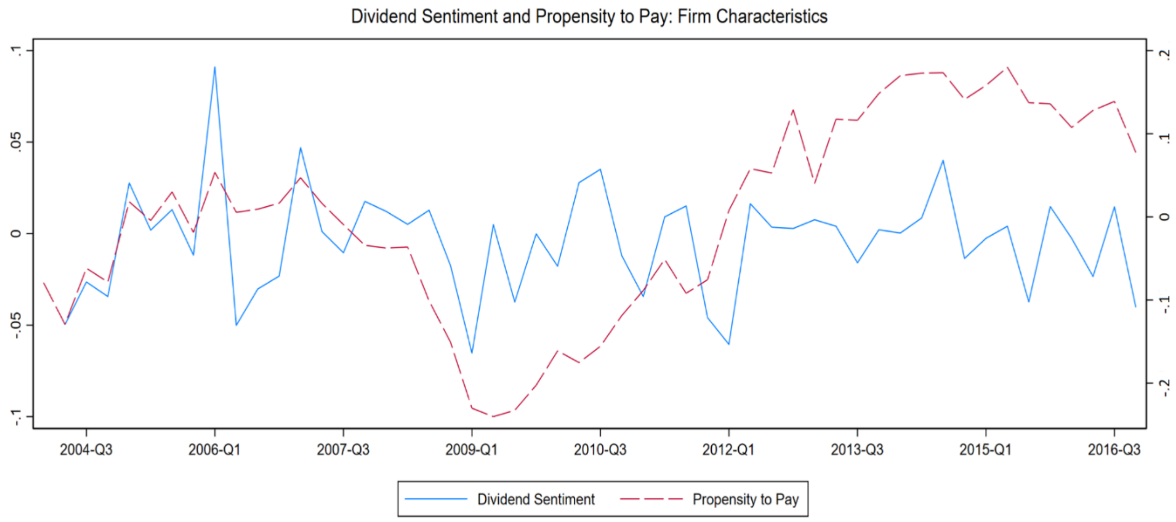


Figure 2. Dividend sentiment and the propensity to pay dividends from 2004 to 2016

This figure shows the relation between our dividend sentiment measure (*ASVI*) and the propensity to pay dividends from 2004 to 2016. The propensity to pay is the difference between the actual percentage of firms that pay dividends in a given quarter and the expected percentage, which is the average predicted probability from the logit model. In Panel A, the logit model includes the same firm characteristic variables, as in Fama and French (2001). In Panel B, the logit model includes additional controls for idiosyncratic and systematic risk. Table A1 provides definitions of these control variables. *ASVI* is the one-quarter-lagged abnormal search volume index for the topic "dividend" from Google Trends. It includes searches for different text strings and for various dividend-related words.

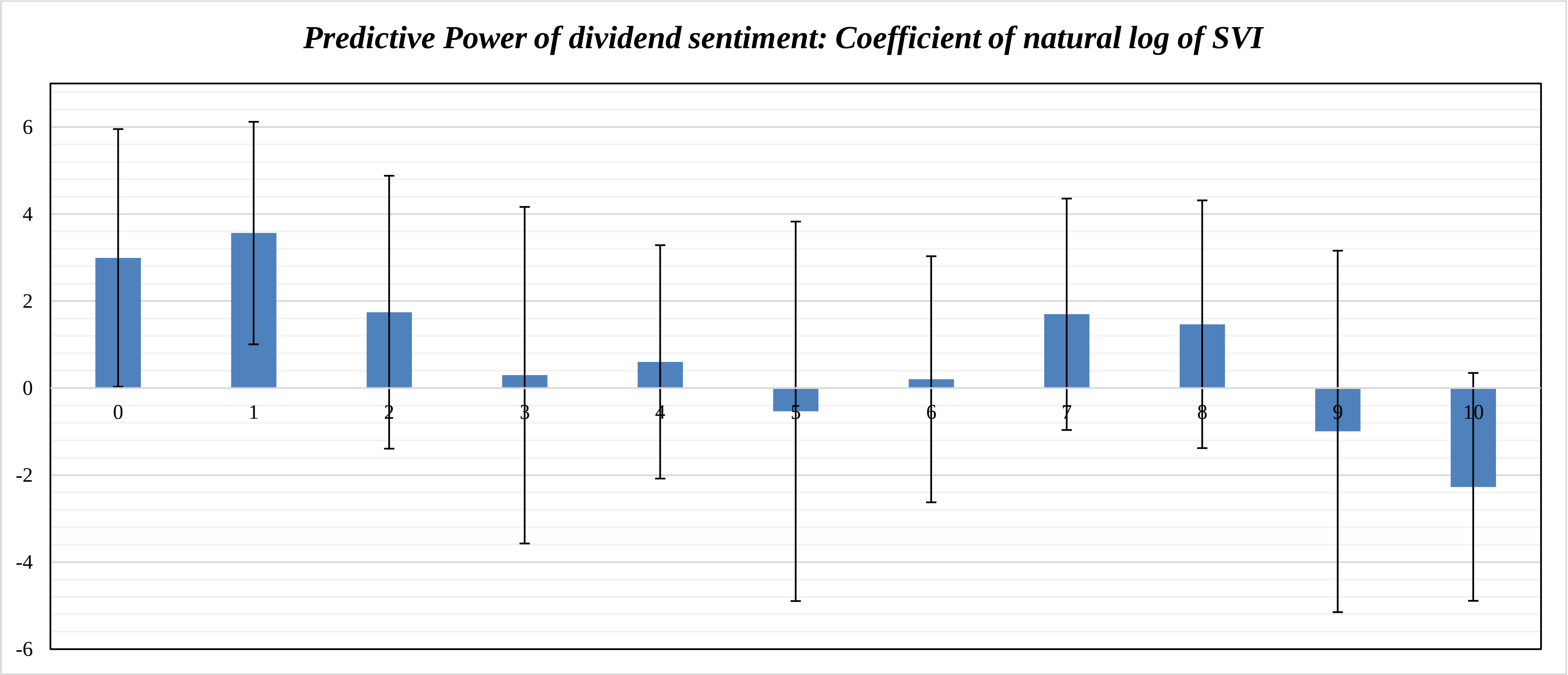
Panel A. The propensity of pay dividends without risk controls



Panel B. The propensity of pay dividends with risk controls

Figure 3. The predictive power of dividend sentiment

This figure plots the estimated coefficients on the natural log of *SVI* in a regression specification as in the last column of Table 10. The estimated coefficient measures the predictive power of the natural log of *SVI* with *n* lags where *n* = 0, 1, 2, … or 10. For each coefficient, the 95% confidence bands are displayed.



Appendix

Table A1. Variable definitions

Panel A. Firm characteristics

Variable	Definition
NYP	NYSE market capitalization percentile, that is, the percentage of NYSE firms with capitalization equal to or less than the capitalization of firm *i* in quarter *t*. *Source:* Compustat
M/B	Book assets (item 44) minus the book value of equity (item 60+item 52) plus the market value of equity (item 12*item 61), all divided by book assets (item 44). *Source:* Compustat
dA/A	The difference between book assets (item 44) and lagged book assets, all divided by lagged book assets. *Source:* Compustat
E/A	Earnings before extraordinary items (item 8) plus interest expense (item 22) plus income statement deferred tax (item 35), all divided by book assets (item 44). *Source:* Compustat
Free cash flow	Gross operating income (item 13) minus the sum of depreciation (item 14), tax paid (item 16), interest expenses (item 15), and dividends paid (item 19 + item 21). *Source:* Compustat
Leverage	Book value of debt (item 9+ item 34), divided by the sum of the book value of debt (item 9 + item 34) and market value of equity (item 25* item 24). *Source:* Compustat
Investment	Capital expenditure (item 145), divided by total assets (item 6). *Source:* Compustat

Panel B. Risk

Systematic risk	The standard deviation of the predicted value from a regression of a firm's daily excess stock returns (raw returns less the riskless rate) on the market factor (i.e., the value-weighted market return less the riskless rate). One firm-quarter observation of systematic risk is calculated using firm-specific daily stock returns within one quarter. *Source:* Center for Research in Securities Prices (CRSP)
Idiosyncratic risk	The standard deviation of residuals from the above regression used to define systematic risk. *Source:* Center for Research in Securities Prices (CRSP)

Panel C. Fund characteristics

Fund flow	Computed as ($TNA_{i,t}$-$TNA_{i,t-1}$)/$TNA_{i,t-1}$-$r_{i,t}$ where $TNA_{i,t}$ denotes fund *i*'s total net assets in quarter *t* and $r_{i,t}$ denotes fund *i*'s return in quarter *t* as reported in CRSP, winsorised at the top 99% and bottom 1%. *Source:* CRSP, Estimated
Abnormal fund flow	The average fund flow of high-dividend funds minus that of all other conventional funds. We define a mutual fund as a high-dividend fund if the fund name contains "high dividend," "super dividend," or "ultra dividend". *Source:* CRSP, Estimated
Fund size	The lagged natural logarithm of a fund's total net assets. Source: CRSP
Fund age	The natural logarithm of a fund's age computed from the date the fund was first offered ((*first_offer_dt* in CRSP). *Source:* CRSP, Estimated
Fund risk	The standard deviation of the fund return using the return observations for the past 3 months. *Source:* CRSP, Estimated
Past fund return	The average fund return in the past 3 months. *Source:* CRSP
Expense ratio	The ratio of the total investment that shareholders pay for the fund's operating expenses, which include 12b-1 fees. *Source:* CRSP
Turnover ratio	The fund turnover ratio *Source:* CRSP
Fund family size	The natural logarithm of the assets of the entire fund family at the start of the quarter. *Source:* CRSP
Family flow	The growth rate of fund *i*'s fund family due to flows in quarter *t*, excluding flows in fund *i*. It is computed as ($TNA_{f,t}$-$TNA_{f,t-1}$)/$TNA_{f,t-1}$-$r_{f,t}$, where $TNA_{f,t}$ denotes fund company *f*'s total net assets less fund *i* in quarter *t* and $r_{f,t}$ denotes fund company *f*'s equal-weighted return in quarter *t*. *Source:* CRSP, Estimated
Segment flow	The growth rate of fund *i*'s market segment (i.e., all other funds with the same CRSP investment objective code) due to flows in quarter *t*, excluding flows in fund *i*. It is computed as ($TNA_{j,t}$-$TNA_{j,t-1}$)/$TNA_{j,t-1}$-$r_{j,t}$, where $TNA_{j,t}$ denotes segment *j*'s total net assets less fund *i* in quarter *t* and $r_{j,t}$ denotes segment *j*'s equal-weighted return in quarter *t*. *Source:* CRSP, Estimated