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Dividends, trust, and firm value

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Abstract
We find evidence that investors value dividends differently depending on their level of trust. Our tests indicate that investor demand for dividend-paying stocks increases as trust decreases, and that this relationship affects market values. We begin with survey evidence showing that people think accounting fraud is less likely among dividend payers and that people with low trust are more likely to hold dividend-paying stocks. We then empirically exploit accounting fraud discoveries within a mutual fund's portfolio as a shock to trust. In response to these shocks, we show that mutual funds tilt their portfolios toward dividend-paying stocks. This result is not explained by a shift in risk preferences, indicating that these institutional investors are seeking dividends in particular rather than stable firms that just happen to pay dividends. Finally, we provide evidence that dividend payers experience a premium in their market values relative to non-payers when their investor base becomes less trusting.

Keywords Dividends · Trust · Fraud · Mutual funds

JEL classification M41 · G51 · K22 · G40

1 Introduction

Dividends are fundamental to how investors value firms (e.g., Miller and Rock 1985; Fama and French 1998). While prior literature has discovered much about what investors can learn from dividends, it largely focuses on how dividends transmit

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information about firms in a standard agency or signaling framework where investors are rational, capital markets are competitive, and the interesting economics are at the firm level (e.g., Hail et al. 2014; Ham et al. 2020, 2023; Michaely et al. 2021; Ellahie and Kaplan 2021; Kaplan and Pérez-Cavazos 2022). While this literature is productive and insightful, it largely ignores the reality that investors are heterogeneous, as evidenced by the fact that dividend investors tend to cluster in the same stocks (e.g., Hotchkiss and Lawrence 2007). Such heterogeneity may cause investors to interpret dividends differently. One important aspect of this heterogeneity, hitherto unexplored, is the level of trust investors place in firms and their managers. In this paper, we find that low-trust investors have greater demand for dividend-paying stocks, as revealed by their tendency to allocate more of their portfolios to dividend payers. We further find that negative shocks to trust increase the stock market values of dividend payers relative to non-payers.

Trust is known to be an important factor in many areas of economics.[1] We hypothesize that it also plays a role in investor demand for dividends, such that low-trust investors are more likely to invest in dividend payers and value them more highly. The dividend literature is broadly consistent with firms paying dividends to establish trust. Dividends are highly persistent; dividend payers are less likely to manage earnings (e.g., Caskey and Hanlon 2013; Ham et al. 2023); and dividends predict future earnings changes and have implications for earnings persistence (e.g., Skinner and Soltes 2011; Ham et al. 2020). Low-trust investors may have trouble believing a firm's financial statements, either because they do not trust the numbers or because they doubt that the income will ultimately flow to them (e.g., DeAngelo and DeAngelo 2006). If the firm paid dividends, this would address both concerns because dividends provide information that substitutes for earnings (e.g., Ham et al. 2023), and dividends signal to investors that they will not be expropriated by insiders (e.g., Ellahie and Kaplan 2021).

Conceptually, we can think of an investor with low trust as placing a higher probability on managers lying about earnings and misusing money that should be paid out to shareholders (Guiso et al. 2008). Thus, a low-trust investor places a higher probability on each of their investments suffering a big loss due to fraud or expropriation. If investors think fraudulent stocks are less likely to pay dividends than honest stocks, a drop in their trust will induce them to value dividend-paying stocks more (relative to non-payers), resulting in a shift in demand toward dividend payers. For example, suppose an investor thinks dividends would be less likely among fraudulent stocks than honest stocks if fraud existed, but they believe the probability of fraud is zero. In this stark case, dividend payers and non-payers have an equal conditional probability of fraud: zero. Then, suppose the investor has an experience that revises their probability of fraud up to greater than zero. After this revision, dividend payers will have a lower conditional probability of fraud than non-payers, and the expected value of holding dividend payers will increase relative to non-payers.

[1] Examples include Guiso et al. (2006, 2008), Christensen et al. (2019), Pevzner et al. (2015), Guan et al. (2020), Bhagwat and Liu (2020), Knechel et al. (2019), Friedman (2019), Kanagaretnam et al. (2018), Hilary and Huang (2023), Bae et al. (2020), Duarte et al. (2012), Bottazzi et al. (2016), Lins et al. (2017), D'Acunto et al. (2019), Kanagaretnam et al. (2019), and Amiraslani et al. (2022).

Thus, we expect investors experiencing a loss of trust to have greater demand for dividend payers relative to non-payers.[2] This shift in demand will be exacerbated further if, apart from the monetary cost, investors are averse to being cheated.

We begin with survey evidence indicating that people feel that dividend payers are more trustworthy. Prior empirical work shows that dividend payers have a lower probability of committing accounting fraud than non-payers (Caskey and Hanlon 2013). We check whether investor perceptions align with this empirical evidence and find that they do. In a survey conducted by us, respondents rate dividend payers as significantly less likely to commit fraud than the average firm. Furthermore, we find support for the notion that low-trust investors gravitate toward dividend-paying stocks. In data from a preexisting survey where respondents rate their own level of suspicion, we find that less-trusting respondents are more likely to receive dividends even after we control for the respondent's age, gender, and risk aversion. However, because trust and dividends are endogenously determined alongside many other factors, we acknowledge that these results are only suggestive.

Next, we provide better-identified evidence that low-trust investors gravitate toward dividend payers. To isolate the effect of trust on the demand for dividend-paying stocks, we use accounting fraud events as a negative shock to investor trust (Giannetti and Wang 2016).[3] Our test exploits variation in exposure to these shocks by comparing mutual funds that did and did not hold the fraudulent firm in their portfolios at the time of the fraud. We find that funds holding the fraudulent firm (i.e., the treatment group) increase the fraction of dividend payers in their portfolios after the fraud by about 0.6 percentage points ($t=2.80$) relative to funds that were not holding the fraudulent firm (i.e., the control group). This estimate plausibly isolates the accounting fraud's impact on the demand for, rather than the supply of, dividend payers. This is because the test compares treatment and control funds with the same investment style that are likely choosing from the same set of investable stocks.

If dividend-paying firms are also less risky, the preceding result could be capturing a relationship between low trust and a preference for low risk rather than a preference for dividends. We address this potential explanation in three ways. First, in our main regressions in the mutual fund analysis, we control for changes in the riskiness of the fund's portfolio to control for any changes in the fund's risk preferences. Second, we replace the outcome variable in this regression with the variables capturing the change in the portfolio's riskiness. In this test, we fail to detect any shift in risk preferences stemming from exposure to fraud. Instead, we find that funds holding the fraudulent firm make no significant changes to the riskiness of their portfolios relative to funds not holding the fraudulent firm. Third, we conduct a test at the mutual fund-firm-level that allows us to directly control for firm traits. We find that mutual funds with a shock to trust seek dividends in particular rather than old, stable firms

[2] Though there may be an optimal level of trust (i.e., a correct probability of managers lying and expropriating), we refrain from discussing trust in terms of a psychological bias. This is because we cannot observe the probabilities that low- and high-trust investors place on fraud and expropriation. Without this information, we are unable to assess whether either of their probabilities are rational.

[3] Brazel et al. (2015) find that as the perceived prevalence of fraud in the economy increases, investors place greater emphasis on conducting fraud risk assessments.

with less volatile cash flows that just happen to pay dividends. Collectively, these results suggest that the increased preference for dividend-paying stocks is because of their dividend policy rather than their overall riskiness. This finding is in line with prior work that views trust and risk-aversion as distinct—notably Guiso et al. (2008), who model trust and risk aversion as separate constructs; and Ahern et al. (2014), who find that distinct cognitive processes govern risk-aversion and trust.

We next provide evidence that investor trust influences stock prices. We use a similar strategy as in the previous test, except now we show how a shock to the trust of a firm's investor base affects the firm's stock market value in terms of its market-to-book ratio. We use two analyses to triangulate this question. First, we aggregate the mutual fund data to the firm-year level to examine how a firm's valuation is affected, depending on whether or not it pays dividends, when it is held by more mutual funds that have a negative shock to trust. Given our previous results, firms held by more funds experiencing shocks to trust should have higher valuations if they pay dividends and lower valuations if they do not. Consistent with this prediction, we find that firms with more investors hit by shocks to trust have lower valuations when they do not pay dividends (t = -3.25) and higher valuations when they do (t = 4.79 for the difference with non-payers, with the sum of the two coefficients significantly positive at the 1% level).

In our second analysis, we examine how an accounting fraud in a given US state impacts the relative valuation of the state's dividend-paying firms versus its non-paying firms. An accounting fraud is more likely to affect other firms in the same state because they are more likely to share an investor base, given the tendency for investors to hold local stocks (Seasholes and Zhu 2010). In states with accounting frauds, we find that the dividend premium increases by about 4.9% (t = 2.59) in the year following the fraud. This indicates that a fraud-induced drop in trust in a given state leads to a greater value premium for dividend payers versus non-payers. The reported changes in the value premium in both of these tests are plausible to the extent that asset pricing follows a demand system (Koijen and Yogo 2019), where the higher relative demand for dividend payers causes them to have higher relative valuations. They are also plausible under a model of limited investor attention, such as Merton (1987), where a negative shock to trust induces investors to add dividend payers to their investable universe and remove non-payers.

We corroborate the above result of the state-level analysis with an associational test, which shows that US regions with less trust (according to surveys) place a higher relative value on dividend-paying stocks.[4] While we caution that this result may be confounded by other factors, such as differences in corruption (e.g., Smith 2016), it points in the same direction as our finding, where shocks to trust increase the valuation of dividend payers relative to non-payers.

Our paper contributes to the literature on the information investors receive when a firm pays dividends.[5] Prior literature has argued that dividends signal that outsiders are safe from insider expropriation (e.g., Ellahie and Kaplan 2021) or signal

[4] This last result speaks to a growing literature that documents the importance of culture on economic outcomes (Zingales 2015; Ellahie et al. 2017; Na and Yan 2022).

[5] We thank a referee for clarifying how our paper contributes to the dividends literature. Many of the connections to the literature, mentioned below, come from their thoughtful feedback.

positive information about future earnings and cash flows (e.g., Michaely et al. 2021; Ham et al. 2020; Kaplan and Pérez-Cavazos 2022).[6] Our results indicate that there may be heterogeneity in how investors perceive these signals from dividends, with less-trusting investors placing more weight on them relative to other information provided by the firm.

Other papers have explored how various factors increase or decrease the need for dividends in the agency context. For example, Hail et al. (2014) find evidence that dividends are less needed after an improvement in the information environment reduces information asymmetry between managers and investors, and Ellahie and Kaplan (2021) find that dividends are more needed in countries with weak institutions for firms early in their life cycles.[7] The results in these papers suggest that firms use dividends to increase the trust investors place in them. We address trust from a different angle, showing that an investor whose trust is hurt by one firm will change how much they value the dividend policies of other firms. We further provide evidence that heterogeneity in trust can differentially affect dividend and non-dividend payers depending on their investor bases.

In addition to the literature on the information conveyed by dividends, our paper contributes to the literature on dividend clienteles. Dividend investors tend to cluster in the same stocks (e.g., Hotchkiss and Lawrence 2007). Several studies in this literature argue that at least part of the explanation relates to taxes (e.g., Desai and Jin 2011), but this does not explain all of the differences. For example, older investors tend to prefer dividend payers (Becker et al. 2011). We contribute to this literature by showing that less trusting investors are attracted to dividend payers, meaning that heterogeneity in investor trust contributes to the dividend clientele phenomenon.

Finally, we contribute to the literature on financial reporting fraud (see a review by Amiram et al. (2018)). Giannetti and Wang (2016) show that household stock market participation decreases after the revelation of fraud. Our evidence shows that the *type* of investments changes, with frauds pushing investors toward dividend payers.

2 Trust, dividends, and investor behavior

2.1 Dividends and the perceived likelihood of fraud

We begin with a survey in which investors tell us they perceive dividend payers as more trustworthy than the average firm (in the sense of being less likely to commit

[6] There has been a long debate over whether dividends provide incremental news about future earnings and cash flows. Some studies indicate that dividends do provide news (e.g., Brickley 1983; Nissim and Ziv 2001), while others indicate that they contain little or no incremental information (e.g., Watts 1973; Gonedes 1978; Penman 1983; Benartzi et al. 1997; Grullon et al. 2005). Recent work comes down in favor of dividends providing news about future earnings and cash flows, either by using different measures than prior literature (Ham et al. 2020) or by focusing on the second moment rather than the first moment (Michaely et al. 2021).

[7] As another example, Kalcheva and Lins (2007) find that, when external shareholder protection is weak, firm values are higher when controlling managers pay dividends.

fraud). We run a survey on MTurk with 87 respondents.[8] In the survey, we give the participants a series of characteristics and ask them to assess how likely firms with each characteristic are to commit accounting fraud relative to the average firm. For each characteristic, the participants mark their answers on a Likert scale from 1 to 7, where 1 indicates fraud is "much less likely," 7 indicates fraud is "much more likely," and 4 is "neutral" (because it is the midpoint between 1 and 7). One of the characteristics in the series is whether the firm is a dividend payer. We include other characteristics and randomize the list of characteristics presented to participants to mitigate any confounding effects from question order.

We present the results in Table 1. The participants think dividend payers are less likely to commit fraud than the average firm. On average, they rated dividend payers 3.483 on the Likert scale, which is on the "less likely" side of "neutral." Because "neutral" is 4, we test whether the average rating differs significantly from 4 and find that it does at the 1% level. Table 1 shows that paying dividends is the financial variable least associated with fraud. Some characteristics increased the perception of fraud, such as being in the finance industry and beating analyst expectations (with average scores of 4.724 and 4.805, respectively, again significantly different from 4 at the 1% level). The appendix contains the actual questions that generated these findings.

2.2 Trust and the likelihood of receiving dividends

We next provide evidence that investors are more likely to receive dividends when they believe themselves to be less trusting. We use data from CentER Savings Surveys that ask individuals how trusting they are and whether they hold investments that pay dividends.[9] For the regressions used in this analysis, our outcome variable is *Received Dividends*, which is an indicator that equals 1 if the individual says they received dividends in the past year.[10] Our variable of interest is a self-reported measure of trust where the individuals rate themselves on a scale of 1–7, with 1 representing "trusting, credulous" and 7 representing "suspicious." We label this self-reported trust variable *Level of Suspicion* because higher values indicate greater suspicion. As an alternative variable of interest, we also create a dummy variable, *Trust Dummy*, that equals one if the participant rates herself as less than a 4, which means that she is more trusting than suspicious. For both trust variables, we use the individual's self-reported trust from the previous year because the dividends received are reported for

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[8] We use TurkPrime to ensure high-quality survey respondents. Since we want to consider the behavior of investors, we use a filter such that we only survey those who claim to be personally invested in the stock market. Each participant was paid five dollars for accurately providing the random code listed at the end of the survey.

[9] These surveys (now known as the Dutch National Bank Household Survey) were used to collect economic and psychological data from a panel of 2000 Dutch households each year since 1993. This panel "reflects the composition of the Dutch-speaking population." Respondents answer questions at their convenience when their relevant documents (such as their bank balance statement) are accessible.

[10] Dividend information is gathered from responses to the question "Did you, in 'year,' have any income through dividends from shares, stocks, investment accounts or investments funds?" We create a dummy variable, *Received Dividends*, that equals one if the individual responds "Yes.".

Table 1 Perception of Fraud and Firm Characteristics

Firm Characteristic	Likelihood	Number of Observations
Pays dividends	3.483***	87
Reporting earnings higher than analyst expectations	4.805***	87
In the retail industry	3.759*	87
In the finance industry	4.724***	87
In the manufacturing industry	3.552***	87
Reporting a large value of shareholders' equity	4.129	85
Large stock market value	4.034	87
Reporting a high degree of profitability	4.287*	87
Female CEO	2.977***	87

This table presents the results of a survey which has respondents assess the likelihood of fraud in financial reports for given firm characteristics. Respondents are asked to assess the likelihood on a scale of 1 (much less likely than the average firm) to 7 (much more likely than the average firm). These survey questions are presented in the appendix. We ignore answers that indicate "I don't know what this means." We use stars to indicate whether the number is statistically different from 4, the midpoint on the scale. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively

the previous year.[11] Thus, in the regressions, we regress dividends received in a given year on the self-reported trust in that same year. In the regressions, we control for each participant's self-assessed risk tolerance,[12] total assets (converted to deciles),[13] and number of owned stocks.[14] Some specifications also include controls for demographics, including age, number in the household, number of children, and gender.

Our sample is at the individual-year level; it runs from 1997 to 2003 and includes heads of household.[15] We limit the sample to investors by keeping only individuals who report positive holdings in stocks, growth funds, or mutual funds in the past year.[16] In Table 2, Panel A, we present descriptive statistics. About half of the sample receives dividends in any given year. On average, the sample is at about the midpoint of the 1 to 7 scale in terms of *Level of Suspicion* and *Risk Tolerance*. The average *Number of Stocks*

[11] This limits the sample to individuals that have two consecutive years of data.

[12] *Risk Tolerance* is measured similarly to *Level of Suspicion*. *Risk Tolerance* equals subjects' response when asked how much they agree with the statement "I am prepared to take risk to lose money, when there is also a chance to gain money," on a scale of 1 to 7, where 1 represents "totally disagree" and 7 represents "totally agree".

[13] To determine total assets, we sum the self-reported valuations for the main asset categories that appear in every survey from 1997 to 2002. This includes the self-reported valuations of the individual's automobiles, savings account, checking account, etc. Specifically, we sum items 1–4, 6, 7, 8, 11–18, 19Og, 19Hy, and 20–25. For survey years 1997–1999, we also include item 5 to better capture total savings. To mitigate concerns about outliers and to normalize total assets across years, we form total asset deciles for each year.

[14] *Number of Stocks* is the natural logarithm of one plus the number of stocks directly owned by the individual.

[15] After 2003, there is no trust data available. Prior to 1997, the question pertaining to dividends received is different, and in 1996 the question measuring one's trust level is missing.

[16] We also consider a stronger sample restriction by limiting the dataset to individuals that report positive stock holdings. These results are also reported in Table 2.

Table 2 Individual Investors and Dividends

Panel A: Summary statistics

Variable	**N**	**Mean**	**Std. Dev.**
Received Dividends	1,222	0.534	0.499
Level of Suspicion	1,089	4.279	1.212
Trust Dummy	1,089	0.243	0.429
Risk Tolerance	1,109	3.654	1.646
Number of Stocks	1,222	0.619	0.773

Panel B: Estimation results

	Received Dividends					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Level of Suspicion	0.036***	0.041**				
t-stat	(2.77)	(2.21)				
Trust Dummy			−0.082**	−0.136***	−0.071**	−0.132**
t-stat			(−2.24)	(−2.66)	(−1.99)	(−2.53)
Risk Tolerance	0.013	0.005	0.013	0.008	0.022**	0.021
t-stat	(1.25)	(0.33)	(1.23)	(0.53)	(2.07)	(1.36)
Number of Stocks	0.074***	0.074	0.075***	0.074	0.061**	0.051
t-stat	(3.15)	(1.64)	(3.16)	(1.64)	(2.60)	(1.17)
Total Assets Decile	0.094***	0.110***	0.095***	0.111***	0.087***	0.106***
t-stat	(10.69)	(7.15)	(10.95)	(7.48)	(9.63)	(7.94)
Intercept	−0.490***	−0.622***	−0.328***	−0.435**	−0.449*	−0.416
t-stat	(−5.79)	(−4.03)	(−4.50)	(−3.28)	(−2.01)	(−1.25)
N	980	465	980	465	980	465
Demographic controls	N	N	N	N	Y	Y
Sample restricted to stock investors	N	Y	N	Y	N	Y
R-squared	0.1729	0.1759	0.1702	0.1797	0.2135	0.2158

This table shows that individuals who are less trusting are more likely to receive dividends. The sample consists of individual survey data from 1997 to 2003, where the respondents are Dutch heads of household that invested in the previous year. Panel A reports summary statistics. Panel B presents results from a regression at the individual-year level, where the right-hand side contains individual characteristics and the left-hand side is a dummy for whether the individual received dividend payments. The second, fourth, and sixth columns restrict the sample to individual-year observations where the individual had stock investments (for investors without stocks, who are included in the other columns, the dividends come from non-stock investments). The left-hand-side variable is *Received Dividends*, a dummy that equals one if the individual received income from dividends in the past year. Because the survey measures dividends for the past year, we use the previous year's survey to construct the right-hand-side variables; that way, all variables cover the same year. The two variables of interest are *Level of Suspicion* and *Trust Dummy*. *Level of Suspicion* is a survey response ranging from 1 to 7, where 1 indicates that the respondent would describe their personality as trusting/credulous and 7 indicates that the respondent would describe their personality as suspicious. *Trust dummy* equals one if the individual's *Level of Suspicion* is less than 4. All specifications include three controls. *Risk Tolerance* is a survey response ranging from 1 to 7, where 1 indicates a low level of risk tolerance and 7 indicates a high level of risk tolerance. *Number of Stocks* equals ln(1 + number of stocks directly owned by the individual). *Total Asset Decile* is the yearly decile for the individual's total asset value. Our demographic controls, where indicated, include *Age, Age Squared*, *Number in the Household, Number of Children*, and a *Female* indicator. *Age* equals the year of the survey minus the reported year of birth. *Age squared* is in thousands. Standard errors are clustered by individual. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively is 0.619. This last measure is a logarithm; when not in log form, the average number of stocks owned by individuals in the sample is 1.759, with a standard deviation of 4.216.

Figure 1 shows the percentage of sample individuals that receive dividends at each value of *Level of Suspicion*. The graph shows a monotonic increasing relationship between suspicion and dividends. Among the most trusting individuals (*Level of Suspicion* = 1), only about 25% hold investments that pay dividends. The percentage holding dividends increases with each increase in the *Level of Suspicion*, up to about 70% for the least trusting individuals (*Level of Suspicion* = 7).

We next show that the positive relationship between dividends and suspicion holds after including controls. Table 2, Panel B shows the results from the following linear probability model for individual i in year t[17]:

$$Received\ Dividends_{i,t} = \beta_0 + \beta_1 Trust\ Variable_{i,t} + \boldsymbol{\gamma Controls_{i,t}} + \varepsilon_{i,t}$$

where "*Trust Variable*" is either *Level of Suspicion* or *Trust Dummy*. The vector of controls always includes controls for total assets, risk tolerance, and the number of stocks owned.[18] Sometimes it also includes controls for demographic characteristics. Standard errors are clustered by individual, since individuals are likely to give similar survey responses over time.

In Table 2, Panel B, we find evidence consistent with less-trusting investors being more likely to receive dividends. Significant at the 5% level or better, we find that *Received Dividends* is positively associated with *Level of Suspicion* and negatively associated with *Trust Dummy*. Focusing on the *Trust Dummy* results, we estimate that trusting individuals (*Trust Dummy* = 1) are between 7.1 and 13.6 percentage points less likely than suspicious individuals (*Trust Dummy* = 0) to hold investments that pay dividends. These results are consistent with low-trust investors tilting their portfolios toward dividend-paying stocks. We acknowledge, however, that these results are only associations and, therefore, only suggestive. In our main analysis, which we cover next, we turn to a setting that better identifies the impact of trust on the demand for dividend-paying stocks.

3 Trust and mutual fund manager behavior

3.1 The effect of trust on mutual fund investment in dividend-paying stocks

We now turn to our main analysis, in which we design a test to isolate the effect of changes in trust on changes in investor demand for dividend-paying stocks. We use

[17] In this regression, all variables are measured for the same year. To accomplish this, the right-hand-side variables all come from one year's survey, and the left-hand-side variable comes from the next year's survey. This is because the left-hand-side variable comes from a survey question that asks participants if they received dividends in the previous year.

[18] It is important to control for risk tolerance, as trust could be correlated with risk tolerance, and dividend payers may be less risky stocks (Michaely et al. 2021). However, it is important to note that there is evidence that distinct processes govern risk aversion and trust (Ahern et al. 2014). It is also important to control for the number of stocks held by the individual, to control for any mechanical relationship between owning more stocks and holding a stock that receives a dividend.

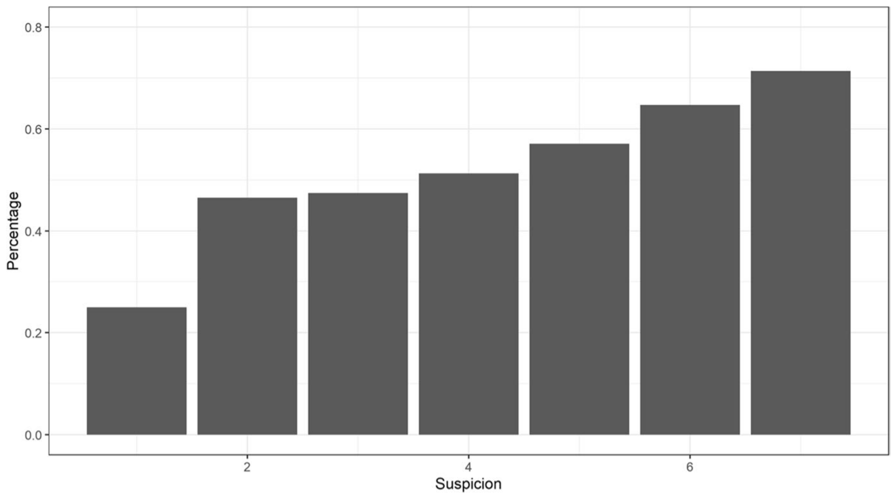


Fig. 1 Dutch Dividend Demand. This figure plots the percentage of survey respondents receiving dividends, broken out by Level of Suspicion, which equals the rating the respondent assigned herself on a scale of 1 to 7, where 1 represents "trusting, credulous" and 7 represents "suspicious." The figure pools together all individual-year observations in our sample from the Dutch survey data

accounting frauds as negative shocks to investor trust (Giannetti and Wang 2016). These shocks presumably affect trust more for investors who hold the stock than for those who have not been exposed to the shocks through their investments (Tversky and Kahneman 1973). This creates variation in the change in trust, which we can exploit to examine the effect of trust on the demand for dividend payers. We focus on mutual funds, whose portfolios are visible, and we compare the investment decisions of funds that do versus do not own stock in the fraudulent firm. We find that the mutual funds that own the fraudulent firm—and therefore have a larger negative shock to trust—tilt their portfolios more towards dividend-paying stocks after the fraud is discovered. This provides evidence that a reduction in investor trust increases their demand for dividend payers.

Our data on accounting fraud discoveries comes from the *Journal of Accounting Research*'s website (Call et al. 2018).[19] The data contains over 1,000 frauds revealed since 1978. After matching the companies in the dataset with Compustat, we are left with 773 frauds revealed from 1978 to 2011.[20] We assume that frauds are discovered and revealed to the public in the year that the SEC starts investigating the fraud.[21] We use these fraud discoveries as our shocks to trust. We measure a mutual fund's

[19] This data can be found at the following website: https://research.chicagobooth.edu/arc/journal-of-accounting-research/online-supplements/volume-56. It is composed of enforcement action data that Gerald Martin collected. The dataset is based on the database developed in Karpoff et al. (2008a, b) and explained in Karpoff et al. (2017).

[20] We use fuzzy matching procedures and hand-matching to match the list of frauds with Compustat data.

[21] We calculate the year of discovery from the data as the beginning date of regulatory proceedings, minus the investigation period.

exposure to these shocks in a given year with the indicator variable *Fraud Investment*, which takes a value of 1 if a fraud was discovered for one of the stocks in the mutual fund's portfolio that year.

Our mutual fund data runs from 1984 to 2011. Our data on mutual fund characteristics comes from the Center for Research in Securities Prices (CRSP) Survivor Bias-Free US Mutual Fund database. Our data on funds' quarterly holdings come from the Thomson Reuters mutual fund holdings database.[22] Our sample consists of US equity mutual funds that are open-ended, diversified, and actively managed.[23] We also exclude very small and very young funds from the sample.[24] CRSP provides information on multiple share classes issued by the same fund. To avoid multiple counting, we aggregate share-class-level data to the portfolio level by taking the value-weighted average of a fund's characteristics across share classes.[25] After requiring non-missing observations for the main fund-level variables,[26] our final sample includes 21,722 mutual fund-year observations.[27] In addition, we obtain data on the stocks held by the mutual fund sample from CRSP. We only consider stocks with share codes 10, 11, 12, and 18 and exchange codes 1, 2, and 3.[28] To determine the prices of each stock, we use the end-of-month prices from CRSP.

[22] We merge these databases using MFLINKS tables, which are available through Wharton Research Data Services (WRDS) and provide a reliable way to merge the Thomson and CRSP databases.

[23] We focus on actively managed diversified equity funds: funds with CRSP objective codes EDYG (Growth), EDYB (Blend), EDYI (Value), EDCM (Mid-Cap), EDCS (Small-Cap), and EDCI (Micro-Cap). We eliminate funds with the CRSP objective code EDCL (S&P 500 Index Objective Funds) to avoid passive funds. We also eliminate index funds by using the CRSP-defined index fund flags and if their names include the words "index," "S&P," "idx," or "passive." Finally, to exclude possible hedge funds, we do not consider funds with the CRSP objective codes EDYH (Long/Short Equity Funds) or EDYS (Dedicated Short Bias Funds). Where the fund has multiple share classes, we use the name and investment objective of the oldest share class for these sample screens. In addition to these sample screens, we eliminate funds holding fewer than ten stocks, again because we want to focus on diversified mutual funds. Furthermore, to focus on US equity mutual funds, we exclude funds with a Thomson objective code of 1, 5, 6, or 7 (International, Municipal Bonds, Bond, or Preferred).

[24] Specifically, we exclude all funds that are less than 36 months old. We also exclude all funds whose total net assets—calculated as the sum of assets across all the fund's share classes—are less than $5 million.

[25] We aggregate monthly returns, turnover, and expenses, weighting each share class by its net assets. Fund age is computed as of the month-end relative to the fund's first offer date. We calculate gross returns before expenses by adding one-twelfth of the fund expense ratio to the net monthly return.

[26] The sample includes mutual funds whether or not they ever experienced a fraud (i.e., we keep mutual funds that always have *Fraud Investment* = 0).

[27] For each fund each year, we use data from the last calendar quarter within the year. We then look at funds' portfolio changes from the last calendar quarter in year t-1 to the last calendar quarter in year t. We look at changes from year to year, rather than from quarter to quarter, to mitigate noise in our estimate of the fraud discovery date. For funds that report multiple times in a given quarter, we keep only the last report of the quarter. To avoid stale data, we do not extrapolate the previous year's holdings to the current year. However, holdings disclosures before the last calendar quarter are carried forward to the calendar year-end.

[28] These share codes represent ordinary common shares that are not further defined (10), need not be further defined (11), are incorporated outside the United States (12), and REITs (Real Estate Investment Trusts) (18). The exchange codes refer to stocks traded in the NYSE (1), American Stock Exchange (2), and Nasdaq Stock Market (3).

To determine the impact of shocks to trust on the demand for dividends, we run regressions with the following functional form:

$$Y_{i,t} = \alpha_{s,t} + \beta Fraud\ Investment_{i,t} + \boldsymbol{\gamma Controls_{i,t}} + \varepsilon_{i,t}.$$

The observations are at the mutual fund-year level. As already discussed, our variable of interest is *Fraud Investment*$_{i,t}$, which takes a value of 1 if a fraud was discovered for one of the stocks in the mutual fund's portfolio that year. We use three measures for the left-hand-side variable, $Y_{i,t}$. The first is Δ *Dividend Share*$_{i,t}$, which equals the change from the last calendar quarter of year *t-1* to the last calendar quarter of year *t* in the fraction of the fund's stocks that are dividend payers. The second and third left-hand-side variables both capture the change in average dividend yield from the last calendar quarter in year t-1 to the last calendar quarter in year t: Δ *Dividend Yield* (*VW*)$_{i,t}$ is the change in the value-weighted average of the dividend yield, where value weights are based on the fund's equity investment values in each company; and Δ *Dividend Yield* (*EW*)$_{i,t}$ is the change in the equal-weighted dividend yield, where the average is equal-weighted across all companies in the fund's portfolio.[29] All three variables are measured excluding the fraud firm from the fund portfolios; that is, the fraud firm is excluded in both years, *t-1* and *t*.[30]

Conceptually, Δ *Dividend Share*$_{i,t}$ is a measure of whether the fund manager increases the number of dividend payers in the portfolio, and both measures of Δ *Dividend Yield*$_{i,t}$ capture whether the fund manager shifts from stocks with low dividend yields to stocks with high dividend yields. Δ *Dividend Share*$_{i,t}$ captures the extensive margin, in the sense that it shows how much mutual funds tilt toward firms paying *any* dividends; and Δ *Dividend Yield*$_{i,t}$ captures both the extensive and intensive margins, in the sense that it also captures whether the mutual funds prefer stocks paying *more* dividends as opposed to less. Table 3, Panel A contains summary statistics for all three of the left-hand-side variables, along with the variable of interest.

We also include fund style-by-year fixed effects to control for any changes in the propensity to pay dividends among the firms in the fund's investable universe.[31] In addition, all specifications include controls related to the fund's performance.[32] In some specifications, we also include controls for the change in the riskiness of the

[29] For constructing both measures of average dividend yield, we calculate the average dividend yield at the end of years *t* and *t-1* and take the difference. Each company's dividend yield at the end of a given year is its annual dividend payout from Compustat that year, divided by its equity market value from CRSP at the end of the year. For the value-weighted average, we weight each company's dividend yield by the value the fund has invested in the company, divided by the total value the fund has invested across all companies for which we have dividend yield data (including firms that do not pay dividends and thus have a yield of 0). For the equal-weighted average, we include all companies with dividend yield data (again including those with a yield of 0) for which the fund owns any stock, and take the equal-weighted average of their dividend yields.

[30] All three left-hand-side variables are winsorized at the 1st and 99th percentiles each year.

[31] When both versions of Δ *Dividend Yield*$_{i,t}$ are on the left-hand side, these fixed effects also control for average changes in the valuation of dividend payers versus non-payers for all funds with the same investment style. This helps remove changes that were not initiated by active investment decisions.

[32] These controls are for the fund's total net assets, expense ratio, turnover ratio, age, net quarterly return, and quarterly fund flows. They are measured in the last calendar quarter of year *t*.

mutual fund's portfolio, in an attempt to control for changes in risk aversion that might be induced by exposure to the fraud. The risk controls include (i) the change in the portfolio's co-movement with the market, (ii) the change in the portfolio's idiosyncratic volatility, (iii) the change in the portfolio's overall volatility, (iv) the change in the portfolio's ability to track its target index, and (v) the intended risk change of a fund's portfolio.[33]

The results for this test are in Table 3, Panel B, and they show evidence that mutual funds tilt their portfolios toward dividend payers when a fraud has been detected in a firm that was part of the fund's portfolio. When the left-hand-side variable is Δ *Dividend Share*$_{i,t}$, we find that funds increase the fraction of stocks that are dividend payers by about 0.6 percentage points compared to funds not invested in the fraud firm. When the left-hand-side variable is Δ *Dividend Yield* $(VW)_{i,t}$ [Δ *Dividend Yield* $(EW)_{i,t}$], we find that funds increase the average dividend yield among their stock investments by about 0.03 [0.04] percentage points compared to funds not invested in the fraud firm. These results are broadly consistent with investors increasing their demand for dividend-paying stocks after they lose some of their trust that earnings numbers are real and will eventually be paid out to shareholders.

In Table 3, Panel C, we evaluate both the parallel trends assumption and the timing of the effect. These tests are the same as in Panel B, except that the right-hand side includes *Fraud Investment*$_{i,t-1}$ and *Fraud Investment*$_{i,t+1}$. These indicator variables are equal to one in the year before (i.e., *t*-1) and the year after (i.e., $t+1$) the fraud year, respectively, for funds that hold the fraudulent firm in year *t*. Regarding the parallel trends assumption, the coefficient on *Fraud Investment*$_{i,t-1}$ is never statistically significant and never positive, indicating that there was no general trend toward holding more dividends before the mutual fund was exposed to the fraud. Regarding the timing of the effect, our evidence suggests

[33] The first four of these risk controls are ex post measures based on the mutual fund's returns over the next 24 months; to control for changes in these risk measures, we use the change from the last calendar quarter in year *t-2* to the last calendar quarter in year *t* to obtain non-overlapping estimation periods. The first ex post risk control is *Δ R2 CAPM*, the change in the R^2 from a regression of market returns on fund returns for the next 24 months; the second is *Δ S.D. Res CAPM*, the change in the standard deviation of residuals from a regression of market returns on fund returns for the next 24 months; the third is *Δ Fund Vol*, the change in the fund volatility for the next 24 months; and the fourth is *Δ Tracking Error*, the change in tracking error volatility (the volatility of the difference between a fund return and the average return of funds in its style) for the next 24 months. The fifth risk control is an ex ante measure of the fund's intended change in risk, *Risk Shifting*, which is the difference between the current holdings return volatility (i.e., what the fund's return volatility would have been had it always held the end-of-year portfolio) and the realized return volatility (i.e., the actual return volatility the fund experienced based on the holdings it had during the year). For calculating *Risk Shifting*, the current holdings return volatility is the standard deviation of the weekly returns of the prior 52-week period based on holdings disclosed in the most recent calendar quarter, and the realized return volatility is the standard deviation of the weekly returns of the prior 52-week period based on the fund's actual reported holdings throughout the year. The difference between current holdings return volatility and realized return volatility is calculated for each quarter in year *t*, averaged across quarters, and multiplied by the square root of 52 to obtain an annual measure. The use of the ex post risk variables, the first four risk variables, is motivated by Brown et al. (1996), Koski and Pontiff (1999), and Elton et al. (2003). The use of the ex ante risk measure, the fifth risk variable, is motivated by Huang et al. (2011).

Table 3 Fraud and Mutual Fund Portfolio Decisions

Panel A: Summary statistics

Variable	**N**	**Mean**	**Std. Dev.**
Δ Dividend Share	21,722	−0.003	0.094
Δ Dividend Yield (VW)	21,722	−0.000	0.007
Δ Dividend Yield (EW)	21,722	−0.000	0.009
Fraud Investment	21,722	0.346	0.476

Panel B: Estimation results

	Δ Dividend Share		**Δ Dividend Yield (VW)**		**Δ Dividend Yield (EW)**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Fraud Investment	0.005**	0.006***	0.0003**	0.0003*	0.0004**	0.0004**
t-stat	(2.42)	(2.80)	(2.06)	(1.93)	(2.20)	(2.36)
N	21,722	17,468	21,722	17,468	21,722	17,468
Performance controls	Y	Y	Y	Y	Y	Y
Risk controls	N	Y	N	Y	N	Y
Style x Year F.E.	Y	Y	Y	Y	Y	Y
R-squared	0.067	0.082	0.178	0.182	0.147	0.152

Panel C: Estimation results with lagged and lead fraud investment

	Δ Dividend Share		**Δ Dividend Yield (VW)**		**Δ Dividend Yield (EW)**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Fraud Investment$_{t-1}$	−0.002	−0.002	−0.0000	−0.0000	−0.0001	−0.0001
t-stat	(−1.17)	(−1.16)	(−0.12)	(−0.33)	(−0.49)	(−0.63)
Fraud Investment	0.005**	0.006***	0.0003**	0.0003*	0.0004**	0.0004**
t-stat	(2.40)	(2.75)	(2.00)	(1.90)	(2.29)	(2.48)
Fraud Investment$_{t+1}$	0.002	0.002	0.0001	0.0001	0.0001	0.0001

Table 3 (continued)

t-stat	(0.96)	(0.90)	(1.36)	(1.10)	(0.78)	(0.42)
N	21,722	17,468	21,722	17,468	21,722	17,468
Performance controls	Y	Y	Y	Y	Y	Y
Risk controls	N	Y	N	Y	N	Y
Style x Year F.E.	Y	Y	Y	Y	Y	Y
R-squared	0.067	0.082	0.178	0.182	0.147	0.152

Panel D: Estimation results with risk variables as dependent variables

	Δ R2 CAPM	**Δ S.D. Res CAPM**	**Δ Fund Vol**	**Δ Tracking Error**	**Risk Shifting**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Fraud Investment	0.000	−0.152	−0.107	0.323	0.001
t-stat	(0.00)	(−0.66)	(−0.26)	(1.31)	(0.57)
N	17,468	17,468	17,468	17,468	17,468
Performance controls	Y	Y	Y	Y	Y
Style x Year F.E.	Y	Y	Y	Y	Y
R-squared	0.515	0.574	0.844	0.490	0.393

This table shows how mutual funds change their investments in dividend stocks when a fraud is discovered at one of their portfolio firms. Observations are at the mutual fund-year level. The variable of interest, *Fraud Investment*, is a dummy variable that takes a value of 1 if a fraud was discovered for one of the stocks in the mutual fund's portfolio that year. There are three left-hand-side variables, all capturing the mutual fund's change in investment in dividend stocks during the year. The first left-hand-side variable is *Δ Dividend Share*, the change in the portfolio share of dividend-paying stocks from the last calendar quarter in year t-1 to the last calendar quarter in year t. The second and third left-hand-side variables both capture the change in average dividend yield from the last calendar quarter in year t-1 to the last calendar quarter in year t: *Δ Dividend Yield (VW)* is the change in the value-weighted average of the dividend yield, where value weights are based on the fund's equity investment values in each company; and *Δ Dividend Yield (EW)* is the change in the equal-weighted dividend yield, where the average is equal-weighted across all companies that appear in the fund's portfolio. For constructing both measures of average dividend yield, each company's dividend yield is its annual dividend payout divided by its equity market value. The fraud firm is removed from the fund portfolios to calculate the left-hand-side variables. The left-hand-side variables are winsorized at the 1st and 99th percentiles each year

Panel A shows descriptive statistics for the variable of interest and the left-hand-side variables. Panel B shows a regression of each left-hand-side variable on the variable of interest. Panel C analyzes trends by adding one-year leads and lags of the variable of interest to the tests in Panel B. In both Panels B and C, all specifications include fund-style-by-year fixed effects and controls for the fund's performance level: total net assets, expense ratio, turnover ratio, age, net quarterly return, and quarterly fund flows.

Table 3 (continued)

These controls are measured in the last calendar quarter of year t. Some specifications also include five risk controls, which are meant to proxy for changes in risk preferences. The first four of these risk controls are ex post measures based on the mutual fund's returns over the next 24 months; to control for changes in these risk measures, we use the change from the last calendar quarter in year t-2 to the last calendar quarter in year t to obtain non-overlapping estimation periods. The first ex post risk control is *Δ R2 CAPM*, the change in the R^2 from a regression of market returns on fund returns for the next 24 months; the second is *Δ S.D. Res CAPM*, the change in the standard deviation of residuals from a regression of market returns on fund returns for the next 24 months; the third is *Δ Fund Vol*, the change in the fund volatility for the next 24 months; and the fourth is *Δ Tracking Error*, the change in tracking error volatility (the volatility of the difference between a fund return and the average return of funds in its style) for the next 24 months. The fifth risk control is an ex ante measure of the fund's intended change in risk, *Risk Shifting*, which is the difference between the current holdings return volatility (i.e., what the fund's return volatility would have been had it always held the end-of-year portfolio) and the realized return volatility (i.e., the actual return volatility the fund experienced based on the holdings it had during the year). For calculating *Risk Shifting*, the current holdings return volatility is the standard deviation of the weekly returns of the prior 52-week period based on holdings disclosed in the most recent calendar quarter, and the realized return volatility is the standard deviation of the weekly returns of the prior 52-week period based on the fund's actual reported holdings throughout the year. The difference between current holdings return volatility and realized return volatility is calculated for each quarter in year t, averaged across quarters, and multiplied by the square root of 52 to obtain an annual measure. Panel D explores whether mutual funds change their risk preferences when exposed to fraud. It reports estimation results that replicate Panel B, but replaces the left-hand-side variables with each of the five risk controls described above (Panel D also omits the risk controls on the right-hand side). Standard errors are clustered by fund style-year. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively that there may be a modest additional move toward dividend payers in the near future after the fraud exposure, because the coefficient on $Fraud\ Investment_{i,t+1}$ is positive. However, the coefficient is never more than half the coefficient on $Fraud\ Investment_{i,t}$, and never statistically significant. This indicates that most of the effect happens immediately after exposure to the fraud.

Finally, Panel D of Table 3 evaluates whether exposure to the fraud increases risk aversion. This test uses the same specification as Panel B, except it removes the risk controls, which proxy for changes in risk aversion, and puts them on the left-hand side, one by one. We fail to detect any increase in risk aversion, as mutual funds exposed to the fraud do not make any detectable decrease in their co-movement with the market (*Δ R2 CAPM*), their idiosyncratic volatility (*Δ S.D. Res CAPM*), their overall volatility (*Δ Fund Vol*), their tracking error (*Δ Tracking Error*), or their risk shifting (*Risk Shifting*). If their risk aversion had increased, we would have expected to see them reduce the riskiness of their portfolios. Thus our evidence uncovers no change in risk aversion, indicating that the main results are due to a drop in trust.

Our inference that there was a change in trust but no change in risk aversion is consistent with prior work that views trust and risk aversion as distinct. For example, Guiso et al. (2008) model trust and risk aversion as two separate constructs, and Ahern et al. (2014) find evidence that distinct cognitive processes govern risk aversion and trust. Under the model provided by Guiso et al. (2008), being low-trust and being risk-averse are conceptually distinct, in that being low-trust means the investor places a high probability on being cheated by a firm's manager, whereas being risk-averse means the investor has a concave utility function. Thus, investors could, in theory, simultaneously be risk-neutral and low-trust, which would translate to having both a linear utility function and a belief that managers are highly likely to cheat. We also note that investors could be averse to being defrauded, apart from any monetary consequences; this could be additional motivation to invest in dividend payers.

3.2 Firm-level characteristics and mutual funds subject to trust shocks

We next analyze which dividend payers have increased demand within mutual funds using a regression of the following general form, for mutual fund *i*, firm *j*, and year *t*:

$$\Delta\ Holdings_{i,j,t} = \beta\ Dividend\ Payer_{j,t} \times Fraud\ Investment_{i,t} + \lambda_{i,t} + \delta_{j,t} + \varepsilon_{i,j,t}.$$

The observations are at the mutual fund-firm-year level. As in the previous section, $Fraud\ Investment_{i,t}$ takes a value of 1 if a fraud was discovered for one of the stocks in the mutual fund's portfolio that year. The left-hand-side variable, $\Delta\ Holdings_{i,j,t}$, is defined as the logarithm of the ratio $(1+\text{shares}_t)/(1+\text{shares}_{t-1})$ held by fund *i* in firm *j*'s stock. $Dividend\ Payer_{j,t}$ is a dummy variable that indicates whether a firm paid dividends in that year. We include fund-by-year fixed effects to absorb time-varying fund characteristics. We also include firm-by-year fixed effects to absorb time-varying firm characteristics. Standard errors are clustered by mutual fund-year. Continuous variables are winsorized at the 1st and 99th percentiles each year. We first run the model as specified above, to document our baseline result for this specification. After that, we interact the model with firm characteristics to examine which dividend payers have increased demand within mutual funds. Summary statistics of the variables employed in this analysis are reported in Table 4, Panel A.

The baseline results are reported in the first column of Table 4, Panel B. The positive and significant coefficient on *Fraud Investment*×*Dividend Payer* of 0.129 (t=3.32) implies that when a mutual fund gets exposed to fraud, it increases its stake in a dividend-paying firm by 12.9% on average. We also run two tests to examine which dividend-paying firms experience the increase in demand from funds experiencing fraud.

First, we test whether other firm characteristics are driving the increase in demand for dividend-paying stocks. It could be that experiencing fraud makes mutual fund managers more risk-averse, and this leads them to invest in established firms with stable cash flows that just happen to pay dividends. To examine this, we not only interact $\textit{Fraud Investment}_{i,t}$ with $\textit{Dividend Payer}_{j,t}$ but also interact it with $\textit{ln\_Firm\_Age}_{j,t}$, $\textit{CFO volatility}_{j,t}$, and $\text{ln\_SIZE}_{j,t}$. $\textit{ln\_Firm\_Age}_{j,t}$ is the natural logarithm of one plus a firm's number of years available in Compustat up to and including year t. $\textit{CFO volatility}_{j,t}$ is the standard deviation of a firm's last five years of cash flows from operations. Cash flow from operations is a firm's operating income after depreciation minus accruals. Accruals are calculated using the balance sheet method. $\text{ln\_SIZE}_{j,t}$ is the natural logarithm of a firm's equity market value. The estimation results are reported in the second column of Table 4, Panel B. We find that dividend payments continue to explain changes in mutual fund portfolios when allowing for firm age, cash flow volatility, and size to explain the effect. The positive and significant coefficient on $\textit{Dividend Payer}_{j,t} \times \textit{Fraud Investment}_{i,t}$ of 0.120 (t=3.15) implies that, even when we control for firm characteristics related to stability, a mutual fund that gets exposed to fraud increases its stake in dividend paying firms by 12%. The coefficients of the other firm-specific variables are not statistically significant. Hence, we conclude that mutual funds with fraud shocks seek dividend-paying stocks rather than stable, established stocks that just happen to pay dividends.

In our second analysis of firm-level characteristics, we examine whether mutual funds seek high dividend payments per se, or whether the funds also account for sustainable funding of the dividend payments. For this analysis, we interact $\textit{Fraud Investment}_{i,t}$ with three dummies that indicate firms with low, mid, or high dividend yields instead of interacting $\textit{Fraud Investment}_{i,t}$ with $\textit{Dividend Payer}_{j,t}$. Low/Mid/High Yield is a dummy that indicates dividend payers in the lowest/second/highest yearly dividend yield tertile, where a firm's dividend yield is its dividend payment divided by its equity market value. Only firms with non-zero dividend payments are used to form the tertiles.[34] Hence, the results are estimated relative to non-payers. The results are reported in the third column of Table 4, Panel B. We find that the effect of trust shocks on the change in mutual fund holdings in dividend-paying firms is concentrated in firms that pay a moderate or high dividend yield. The coefficient on $\textit{Low Yield}_{j,t} \times \textit{Fraud Investment}_{i,t}$ is positive (0.05) but not significant (t=1.35). The coefficient on $\textit{Mid Yield}_{j,t} \times \textit{Fraud Investment}_{i,t}$

[34] The average dividend yield for Low/Mid/High Yield is 0.007/0.018/0.051, respectively.

Table 4 Fraud and Mutual Fund Portfolio Changes

Panel A: Summary statistics			
Variable	**N**	**Mean**	**Std. Dev.**
Δ Holdings	2,047,156	4.197	8.118
Fraud Investment	2,047,156	0.486	0.500
Dividend Payer	2,047,156	0.568	0.495
ln_Firm_Age	2,047,156	2.864	0.833
CFO volatility	1,395,509	0.057	0.045
ln_SIZE	2,047,156	8.013	1.917

Panel B: Estimation results			
	Δ Holdings		
	(1)	**(2)**	**(3)**
Fraud Investment x Dividend Payer	0.129***	0.120***	
t-stat	(3.32)	(3.15)	
Fraud Investment x ln_Firm_Age		0.046	
t-stat		(1.57)	
Fraud Investment x CFO volatility		0.180	
t-stat		(0.73)	
Fraud Investment x ln_SIZE		−0.000	
t-stat		(−0.02)	
Fraud Investment x Low Yield			0.055
t-stat			(1.35)
Fraud Investment x Mid Yield			0.145***
t-stat			(3.12)
Fraud Investment x High Yield			0.212***
t-stat			(4.10)
N	2,047,156	1,395,509	2,047,156
Fund x Year F.E.	Y	Y	Y
Firm x Year F.E.	Y	Y	Y
R-squared	0.461	0.457	0.461

This table shows how mutual funds change their investments in dividend stocks when a fraud is discovered at one of their portfolio firms. Observations are at the mutual fund-firm-year level. Panel A shows summary statistics of the key variables. Panel B shows the estimation results. The variable of interest, *Fraud Investment*, is a dummy variable equal to one if the mutual fund held the fraud firm in the year of the fraud and zero otherwise. The dependent variable in the regressions of Panel B, *Δ Holdings*, is the logarithm of the ratio $(1+\text{shares}_t)/(1+\text{shares}_{t-1})$ held by the mutual fund in the firm's stock. The fraud firm is dropped from the sample to calculate the left-hand-side variable. *Dividend Payer* is a dummy that indicates whether the firm paid dividends that year. *ln_Firm_Age* is the natural logarithm of one plus a firm's number of years available in Compustat up to and including year t. *CFO volatility* is the standard deviation of a firm's last five years of cash flow from operations. Cash flow from operations is a firm's operating income after depreciation minus accruals. Accruals are calculated using the balance sheet method. *ln_SIZE* is the natural logarithm of a firm's equity market value. *Low/Mid/High Yield* is a dummy that indicates dividend payers in the lowest/second/highest yearly dividend yield tertile, where a firm's dividend yield is its dividend payment divided by its equity market value. Only firms with non-zero dividend payments are used to form the tertiles. The continuous variables are winsorized at the 1st and 99th percentiles each quarter. All regressions include fund-year and firm-year fixed effects. Standard errors are clustered by fund-year. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively

($High\ Yield_{j,t} \times Fraud\ Investment_{i,t}$) is 0.145 (0.212) and statistically significant with a t-statistic of 3.12 (4.10). This is consistent with the notion that low dividend yield stocks generate less trust. At the same time, the demand for high dividend yield stocks shows that mutual funds seek higher dividends per se and do not necessarily account for possible dividend cuts in the future. The results hold when looking at extreme deciles instead of tertiles of dividend yield (untabulated).

4 Trust, dividends, and market valuation

We now examine whether the trust level of a firm's investor base differentially affects the firm's market value if the firm does or does not pay dividends. To motivate a prediction that lower trust leads to higher relative values for dividend payers, we can draw upon either of the two asset pricing models. Through the lens of Koijen and Yogo (2019), we can view stock prices as following a characteristics-based demand system. We believe our story fits well with both a key assumption of this model—that investors have heterogeneous beliefs—and the main result of this model—that the optimal portfolio consists of a characteristics-based demand function.[35] The heterogeneous beliefs could include heterogeneity in the investors' belief about how likely managers are to cheat them—which is to say, heterogeneity in investor trust. Furthermore, the characteristics-based demand function could include a stock's dividend payout among the characteristics considered by investors; indeed, Koijen and Yogo (2019) themselves include a dividend characteristic in their specification of the demand function. Consistent with these assumptions, our evidence shows that investors who lose trust increase their demand for dividend payers relative to non-payers. If asset pricing follows a characteristics-based demand system, this greater relative demand should increase the stock prices of dividend payers relative to non-payers.

Through the lens of another model (Merton 1987), we can view investors as being limited to an investable universe of firms based on the total number of firms they can pay attention to at any given time. Firms with fewer investors paying attention to them have fewer investors holding their stock; this means each investor must take on more of the firm's risk, lowering the price the investors are willing to pay for the stock.[36] Under this model, when investors lose trust, their preference for dividend

[35] Koijen and Yogo (2019) assume that investors have heterogenous beliefs and face short-sale constraints, and they assume that returns have a factor structure, with expected returns and factor loadings depending on the assets' own characteristics. From these assumptions, they derive their main result that the optimal portfolio simplifies to characteristics-based demand, where the portfolio weights depend on the assets' characteristics. As we discuss in the main text, our story fits well with both the heterogeneous beliefs assumption and the main result of characteristics-based demand. Regarding the other assumptions, the assumption of short-sale constraints can reasonably be applied to mutual funds; in keeping with this, Koijen and Yogo (2019) illustrate their demand system of asset pricing using 13F data, which includes mutual funds. The assumption that returns have a factor structure follows the empirical asset pricing literature, and we do not believe it is at odds with our story.

[36] In Merton (1987), because each investor only holds stock in the firms they pay attention to, they cannot fully diversify away the idiosyncratic risk of these firms, and they demand a premium for bearing this risk. When fewer investors pay attention to a firm, each investor must take on more of the firm's idiosyncratic risk. This leads the investors to apply a larger discount to the price of the firm's stock.

payers grows, and they allocate their attention more to dividend payers and less to non-payers. As a result, if a dividend payer and a non-payer compete for the same investors' attention, a drop in trust among those investors will cause more of them to pay attention to the dividend payer rather than the non-payer. Such a heterogeneous response will increase the dividend payer's stock price relative to the non-payer.

4.1 Fraud events and firm valuation

In our main tests on the valuation implications of trust and dividends, we again use accounting frauds as negative shocks to trust. We use two sets of analyses to study this question. For the first analysis, we aggregate the mutual fund data to the firm-year level to measure the fraction of a firm's investors experiencing negative shocks to trust because of exposure to fraud. We use this aggregated measure to study how having more investors exposed to fraud affects the stock market values of dividend-paying firms versus non-paying firms. For the second analysis, we examine how accounting fraud in a given US state impacts the stock market values of the state's dividend- and non-dividend-paying firms.

Turning to the first analysis, we expect firms that are held by more funds experiencing shocks to trust will have higher values if they pay dividends and lower values if they do not. For this test, we use the same accounting fraud and mutual fund data as in our previous tests to determine which mutual funds are investing in a given firm and which mutual funds are holding a stock that is committing fraud in a given year. For firm-level data, we use Compustat. Our sample for this test runs from 1985 to 2011, based on the availability of our mutual fund data and our fraud data.

For the first analysis, we conduct a regression of the following model:

$$\begin{aligned} Log(M/B)_{i,t} = {} & \beta_1 DividendPayer_{i,t} + \beta_2 FraudFundInvestment_{i,t-1} \\ & + \beta_3 DividendPayer_{i,t} \times FraudFundInvestment_{i,t-1} \\ & + \boldsymbol{\gamma Controls_{i,t}} + \lambda_i + \delta_t + \varepsilon_{i,t} \end{aligned}$$

The observations are at the firm-year level. The dependent variable is the natural logarithm of the market-to-book ratio, which is calculated by dividing market equity by common equity. *Dividend Payer* is an indicator equal to one if the firm pays dividends in that year. *Fraud Fund Investment*$_{i,t-1}$ is the natural logarithm of one plus the number of funds that both invested in firm i in the previous year and experienced fraud shocks that year. We include firm and year fixed effects. Standard errors are clustered by firm and year. Table 5, Panel A reports the summary statistics of the variables.

Table 5, Panel B reports the estimation results. Consistent with our expectations, non-dividend-paying firms with more funds hit by a trust shock have lower valuations, while dividend-paying firms with more funds hit by a trust shock have higher valuations. The lower valuations for non-dividend payers can be seen from the coefficient on *Fraud Fund Investment*$_{i,t-1}$, which is significantly negative at -0.036 (t = -3.25). The dividend payers have higher valuations than the non-dividend payers, as can be seen from the significantly positive coefficient on

Table 5 Fraud Investment and Firm Valuation

Panel A: Summary statistics

Variable	**N**	**Mean**	**Std. Dev.**
Log(M/B)	71,706	0.611	0.836
Dividend Payer	71,706	0.471	0.499
Fraud Fund Investment	71,706	1.873	1.299

Panel B: Estimation results

	Log(M/B)	
	(1)	**(2)**
Dividend Payer	−0.027	−0.031
t-stat	(−0.88)	(−1.10)
Fraud Fund Investment	−0.036***	−0.039***
t-stat	(−3.25)	(−3.86)
Dividend Payer x Fraud Fund Investment	0.059***	0.052***
t-stat	(4.79)	(4.52)
N	71,706	71,701
Controls	N	Y
Firm F.E.	Y	Y
Year F.E.	Y	Y
R-squared	0.643	0.700

This table documents how the valuation of dividend payers relative to non-dividend payers changes for firms when their investors experience negative shocks to trust from a fraud by one of their investments. Observations are at the firm-year level. Panel A shows summary statistics of the key variables. Panel B shows the estimation results. The left-hand side variable is the logarithm of the firm's market-to-book ratio. *Dividend Payer* is a dummy that indicates whether the firm paid dividends in that year. *Fraud Fund Investment* is the natural logarithm of one plus the number of funds that both invested in the firm in the previous year and experienced fraud shocks that year. In the second column, we include controls for yearly Return on Equity deciles and yearly Leverage deciles. All regressions include firm and year fixed effects. We cluster standard errors by firm and by year. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively

$\textit{Dividend Payer}_{i,t} \times \textit{Fraud Fund Investment}_{i,t-1}$ of 0.059 (t=4.79). Indeed, the dividend payers with more funds hit by a trust shock have higher valuations overall, because the sum of the two coefficients is significantly positive.[37] The inferences are similar when we control for yearly return on equity deciles and yearly leverage deciles. These results indicate that decreasing the trust of a firm's investor base will increase the investors' valuation of the firm's dividends. The results further indicate that a drop in trust that affects some investors more than others will in turn differentially affect firms based on their dividend policies and their investor bases.

In the second analysis, we examine how an accounting fraud in a given US state impacts the relative valuation of the state's dividend-paying firms versus its non-paying firms. Given the tendency for investors to hold local stocks (Seasholes and Zhu 2010), two firms from the same state are more likely to have overlapping investor bases. Thus,

[37] An F-test that tests joint significance of the two coefficients is significant at the 1% level for both column one and column two.

if a firm commits fraud, other firms from the same state will likely experience a drop in investor trust that is greater than the drop experienced by firms from other states. In turn, firms in the same state as the fraud will likely be more affected by an increase in demand for dividend payers, relative to non-payers. In line with this story, we find that dividend payers become more valuable (in terms of market-to-book ratio) relative to non-payers in the same state when another firm in the state commits fraud.[38]

We again use the same accounting fraud data as our test showing that shocks to trust influence demand for dividends. For firm-level data, we again use Compustat. Since our sample of fraud events is from 1978 to 2011, we restrict our firm financial database to the years 1979 to 2012. In doing so, we make it possible for there to have been a fraud in the firm's state in the previous year. Table 6, Panel A shows that about half of the firm-year observations in our sample have a fraud revealed in their state in the previous year. Additionally, our fraud intensity measure, which equals the total number of frauds in the state in the previous year divided by the number of firms in that state, has an average of about 0.4%.

We consider the following regression, with firm-year observations, for firm i in state j in year t:

$$Log(M/B)_{i,t} = \alpha_i + \alpha_t + \beta_1 Dividend\ Payer_{i,t} + \beta_2 Fraud_{j,t-1} + \beta_3 Fraud_{j,t-1} \times Dividend\ Payer_{i,t} + \boldsymbol{\gamma Controls_{i,t}} + \varepsilon_{i,t}.$$

The dependent variable is the logarithm of the market-to-book ratio, calculated by dividing market equity by common equity. *Dividend Payer* is an indicator that turns on if the firm's total dividends (other than stock dividends) that year are positive. The fraud variable is measured for the state where the firm is headquartered, taking on two forms. The first is *Fraud Dummy*, an indicator that turns on if, in the previous year, a fraud was discovered at one of the firms headquartered in the state; the second is *Fraud Intensity*, a continuous variable equal to the previous year's number of frauds discovered in the state divided by the state's total number of firms. The sample for these tests excludes the firms that committed fraud, to avoid confounding our results with the direct market reaction to the news of the fraud. We include firm fixed effects to control for time-invariant firm characteristics that could be related to the market-to-book ratio. We include year fixed effects to account for factors such as market sentiment. We cluster standard errors by firm to account for autocorrelation in the firm's market-to-book ratio, and by year to account for correlated shocks within a year that affect valuation.

The results in Table 6, Panel B provide evidence that a negative shock to trust in the state leads to an increase in market value for dividend payers relative to

[38] This story draws upon our earlier result showing that investors increase their demand for dividends after experiencing a fraud in their portfolios, and that this is directly associated with increases in the values of dividend payers versus non-payers. However, that is not necessarily the only channel by which we could see a result in this test at the state level. Local fraud events could also provide shocks to trust for local investors that are generally greater than for non-local investors (e.g., Giannetti and Wang 2016), possibly because of greater coverage of the fraud in local news outlets. This would also predict our finding that market values increase for dividend payers, relative to non-payers, in the state where the fraud occurred.

Table 6 Fraud Events and Firm Valuation

Panel A: Summary statistics

Variable	**N**	**Mean**	**Std. Dev.**
Dividend Payer	165,324	0.421	0.494
Log(M/B)	166,093	0.615	0.958
Fraud Dummy	166,093	0.525	0.499
Fraud Intensity	166,093	0.004	0.007
GDP Growth	166,093	6.468	3.656

Panel B: Estimation results

	Log(M/B)						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Dividend Payer	0.035*	0.012	0.164***	0.050***	0.025*	0.178***	0.146***
t-stat	(2.03)	(0.69)	(4.01)	(3.29)	(1.75)	(4.41)	(2.96)
Fraud Dummy	−0.021	−0.018	−0.019*				
t-stat	(−1.61)	(−1.44)	(−1.70)				
Fraud Dummy x Dividend Payer	0.056**	0.050**	0.049**				
t-stat	(2.64)	(2.41)	(2.65)				
Fraud Intensity				−1.591**	−1.430**	−1.311**	−0.437
t-stat				(−2.75)	(−2.61)	(−2.44)	(−0.41)
Fraud Intensity x Dividend Payer				3.144***	2.870***	2.512***	2.751*
t-stat				(3.76)	(3.48)	(3.23)	(2.03)
GDP Growth			0.020***			0.020***	0.018***
t-stat			(4.61)			(4.61)	(3.47)
GDP Growth x Dividend Payer			−0.024***			−0.024***	−0.022***
t-stat			(−4.62)			(−4.59)	(−3.33)
N	163,689	163,516	163,516	163,689	163,516	163,516	83,725
Controls	N	Y	Y	N	Y	Y	Y

Table 6 (continued)

Firm F.E.	Y	Y	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y	Y	Y
Only States with Fraud	N	N	N	N	N	N	Y
R-squared	0.574	0.628	0.630	0.574	0.628	0.630	0.636

This table documents how the valuation of dividend payers relative to non-dividend payers changes after fraud events in a state. Observations are at the firm-year level. Panel A shows summary statistics of the key variables. Panel B shows the estimation results. The left-hand side variable is the log of the firm's market-to-book ratio. *Dividend Payer* is a dummy that indicates whether the firm paid dividends that year. *Fraud Dummy* is an indicator that equals one if there was a fraud event in the firm's state in the previous year. *Fraud Intensity* equals the total number of frauds in the firm's state in the previous year divided by the number of firms in that state. *GDP Growth* equals the percentage growth in GDP over the previous year. In the second, third, fifth, sixth and seventh columns, we include controls for the *ROE Decile* and *Leverage Decile*; where *ROE Decile* are deciles formed each fiscal year based on return on equity, defined as income before extraordinary items over common equity; and where *Leverage Deciles* are deciles formed each fiscal year based on leverage, defined as total assets minus common equity over total assets. The final column restricts the sample to states that had a fraud in the previous year. All regressions include firm and year fixed effects. We cluster standard errors by firm and by year. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively non-payers. This can be seen from the positive coefficient on the interaction between *Dividend Payer* and the fraud variables *Fraud Dummy* and *Fraud Intensity*. In the first column, the interaction with *Fraud Dummy* has a coefficient of 0.056 (t = 2.64). This implies that the dividend premium—the market-to-book valuation spread between dividend payers and non-dividend payers—increases by 5.6% for firms in states that had a fraud in the previous year. We also estimate that non-payers in the state see their market-to-book ratios decrease by 2.1% in the year after the fraud (though this estimate is not statistically significant). This is consistent with a negative demand shock for non-payers following a drop in investor trust.[39] An untabulated analysis fails to find evidence of different underlying trends before the year of the fraud in the market-to-book ratios of dividend payers versus non-payers, indicating that the parallel trends assumption is satisfied.[40]

The results are consistent when the fraud variable is *Fraud Intensity*. In the fourth column of Table 6, Panel B, the interaction between *Dividend Payer* and *Fraud Intensity* has a positive coefficient of 3.144 (t = 3.76). The standard deviation of the fraud intensity measure is about 0.0074. This implies that a one standard deviation increase in the fraud intensity measure is associated with a 2.3% increase in the market-to-book ratios of dividend payers relative to non-payers. In this specification, we again find a decrease in values for the non-dividend-paying firms, based on the coefficient on *Fraud Intensity* of -1.591 (t = -2.75).

These results change little when we add controls. In the second and fifth columns of Table 6, Panel B, we add controls for other determinants of firm value. These include the firm's return on equity decile and its leverage decile.[41] After adding these controls, the coefficients of interest are almost the same. In the third and sixth columns, we further add a control for economic conditions. It is plausible that more frauds are revealed during bad economic times. If bad economic times are also associated with a greater dividend premium, then our results may capture the correlation between bad economic times and the dividend premium. Thus, we control for state-level GDP growth rates and an interaction term of this growth rate and *Dividend Payer*.[42] Again, after adding this control in the third and sixth columns, the

[39] Consistent with this, Giannetti and Wang (2016) find that household stock market participation decreases in a fraud state the year following a fraud.

[40] In this test, we regress *Log(M/B)* on *Dividend Payer*; indicators for the year before, the year of, and the year after a fraud occurred at one of the companies in the state; and interactions between these indicators and *Dividend Payer*. The test also includes controls for ROE, leverage, and firm and year fixed effects. The coefficient is insignificant for the interaction between *Dividend Payer* and the indicator for the year before the fraud. The coefficient is positive for *Dividend Payer*'s interactions with both the indicators for the year of and the year after the fraud, indicating that dividend payers see a relative boost in value that begins in the year of the fraud and persists into the year after.

[41] For these two controls, the deciles are formed each fiscal year based on return on equity and leverage. Return on equity is defined as income before extraordinary items divided by common equity. Leverage is defined as total assets minus common equity over total assets.

[42] We download state-level GDP data from the Bureau of Economic Analysis website. In 1997, the BEA moved from SIC industry definitions to NAICS industry definitions. We calculate 1997 growth rates based on SIC industry definitions and then switch to NAICS.

coefficients of interest are almost the same.[43] In the last column of Table 6, Panel B, we restrict our sample to firms that had a fraud event in their state in the previous year. Consistent with columns four through six, fraud intensity is associated with larger market-to-book ratios for dividend payers relative to non-payers. This shows that there is an effect at the intensive margin, in addition to at the extensive margin.

4.2 Valuation of dividend payers based on regional trust

We corroborate the valuation results with an associational test of whether US regions with less trust place higher relative values on dividend-paying stocks. These tests should be interpreted cautiously since the results may be confounded by other factors, such as differences in corruption across regions (e.g., Smith 2016). However, given these caveats, we find that regions with less trust do indeed have dividend payers with higher market-to-book ratios relative to non-payers, consistent with low trust increasing the relative value of dividend payers.

To proxy for the trust level of a firm's investor base, we use the General Social Surveys for the region of the United States that contains the firm's headquarters.[44] Exploiting the regional granularity of the General Social Survey, we separate the United States into nine regions: the Northeast, Mid-Atlantic, Northeast Central, Northwest Central, South Atlantic, Southeast Central, Southwest Central, Mountain, and Pacific. The trust measure we use in this test is *Trusting Fraction*, which is the fraction of respondents in the firm's region that year who believe most people can be trusted. Our test utilizes variation across geographic regions and over time. Figure 2 shows that there is meaningful variation along both dimensions.

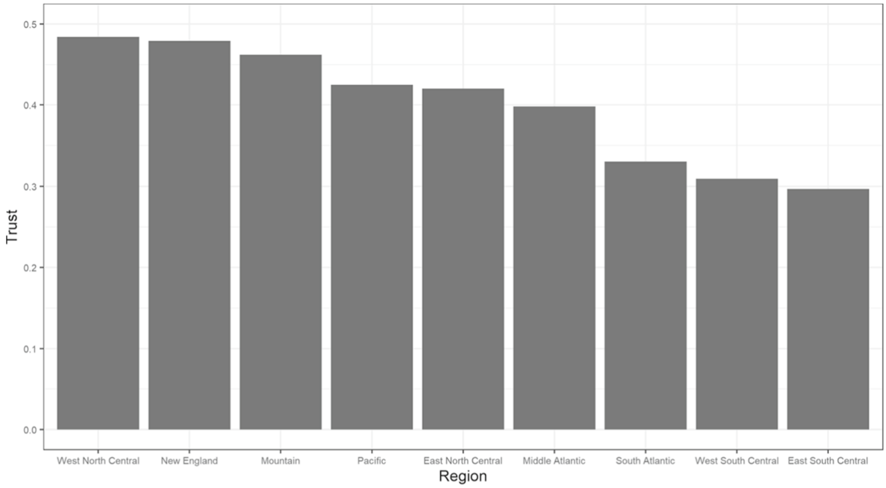
To examine how variation in trust might impact the relative value of dividend payers, we run another regression at the firm-year level that regresses *Log(M/B)* on *Dividend Payer*, *Trusting Fraction*, and the interaction of the two. The results in Table 7 show that the coefficient on the interaction term is significantly negative, meaning that higher-trust regions value dividend payers less than non-dividend payers.[45] This associational result is consistent with our previous results showing that negative shocks

[43] As an aside, we do indeed find that lower state-level GDP growth rates are associated with a larger dividend premium.

[44] To generate a trust measure for the investor base within regions in the United States, we use data from the General Social Survey, which has interviewed Americans since 1972. The survey breaks the United States into nine different regions. We define a firm's investor base as individuals from the region where the firm is headquartered. The survey was administered annually from 1972 to 1994 (with some years missing due to funding issues) and biannually thereafter. The target sample size was 1,500 respondents up until 1993 and almost twice that starting in 1994; it grew to reach 4,500 in 2006. The most recent year we consider is 2016. We assign respondents to a region based on the location of the interview. The trust measure equals the fraction of survey respondents in the corresponding region-year that answer "most people can be trusted" to the question "Generally speaking, would you say that most people can be trusted or that you can't be too careful in dealing with people?" (We ignore answers of "I don't know.") For missing years, we infer a trust value based on interpolation.

[45] We present results for three specifications, all of which cluster standard errors by fiscal year and by firm. The first specification includes year fixed effects, the second adds the controls used in the previous table, and the third adds firm fixed effects. The controls are for return on equity, leverage, the state-level GDP growth rate, and an interaction of the GDP growth rate with *Dividend Payer*.

a: Mean trust by region



b: Mean trust by decade

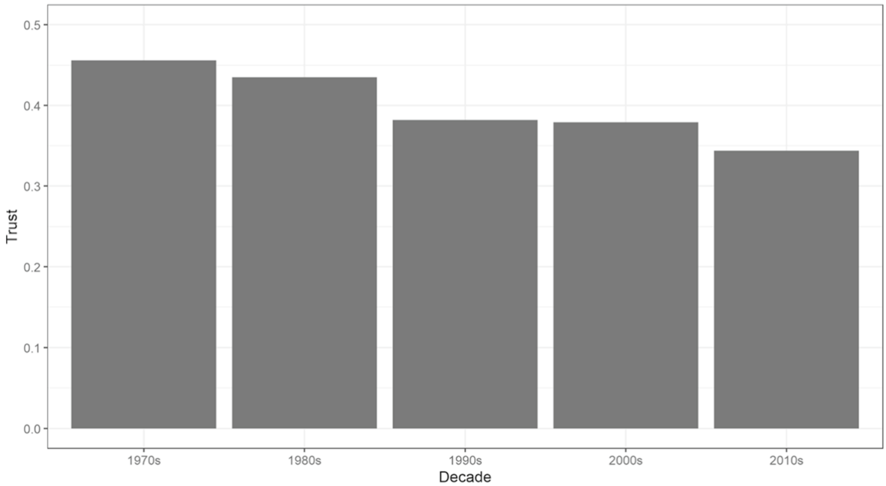


Fig. 2 US Trust Levels. This figure plots mean trust levels from the General Social survey by region (Panel a) and by decade (Panel b). We measure Trust in a specific region-year as the fraction of survey respondents who say "Most people can be trusted" in response to the question "Generally speaking, would you say that most people can be trusted or that you can't be too careful in dealing with people?" To generate trust values for years when the survey is not run, we use interpolation. The region values, presented below, are the average values of annual means across all years. "All regions" is the average of all region values across the entire sample. The unconditional average of respondents that say "Most people can be trusted" without interpolated values is 0.391; with interpolation, it is 0.400

Table 7 Valuation of Dividend-Paying Firms versus Non-Dividend-Paying Firms

	Log(M/B)		
	(1)	(2)	(3)
Trusting Fraction	0.787***	0.836***	0.218*
t-stat	(5.51)	(6.20)	(1.76)
Dividend Payer	0.165**	0.032	0.338***
t-stat	(2.17)	(0.39)	(4.70)
Dividend Payer x Trusting Fraction	−0.930***	−0.903***	−0.464***
t-stat	(−4.41)	(−5.06)	(−3.04)
N	209,933	209,745	208,037
Controls	N	Y	Y
Firm F.E.	N	N	Y
Year F.E.	Y	Y	Y
R-squared	0.1047	0.1523	0.6556

This table shows the relationship between trust, dividends, and valuation across US regions. Observations are at the firm-year level. *Trusting Fraction* is the fraction of respondents in the firm's region-year that are trusting. *Dividend Payer* is a dummy that indicates whether the firm paid dividends that year. Where indicated, we include additional controls. These controls are for return on equity, leverage, and local economic conditions. Specifically, our control for return on equity is *ROE Deciles,* which are formed each fiscal year based on ROE, defined as income before extraordinary items divided by common equity. Our control for leverage is *Leverage Deciles,* which are formed each fiscal year based on leverage, defined as total assets minus common equity over total assets. Our control for local economic conditions is the state-level GDP growth rate and an interaction of the state-level GDP growth rate with the *Dividend Payer* dummy. The left-hand-side variable is the log of the market-to-book ratio. Standard errors are clustered by firm and by fiscal year. All columns include fiscal year fixed effects, and the last column includes firm fixed effects. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively

to trust increase the relative values of dividend payers. If we were to interpret these results as causal—which, we caution, may not be justified—then the interaction term coefficient in the third column has the following interpretation: lowering the fraction of trusting respondents by 10 percentage points increases the market-to-book ratios of dividend payers by 4.6% (t = 3.04) relative to non-payers.[46] Whether or not this causal interpretation is justified, the negative coefficient is consistent with our previous finding that negative shocks to trust increase the relative value of dividend payers.[47]

Thus far, we have focused on the demand for dividends. It is also possible that management will respond to high dividend premiums by issuing dividends (Baker

[46] In untabulated analyses, we find qualitatively similar results when we do similar tests in a cross-country setting.

[47] Another interesting coefficient is the one on Trusting Fraction. Given the results of Guiso et al. (2008) and Giannetti and Wang (2016), one would expect greater stock market participation in regions with higher levels of trust. This trust-participation connection, in combination with local bias and limits to arbitrage, predicts a positive coefficient on Trusting Fraction; that is, one should expect excess demand for stocks headquartered in a more trusting region. The estimation supports this hypothesis; the coefficient on Trusting Fraction is positive and at least marginally significant in all specifications.

and Wurgler 2004). To the extent this occurs, it should weaken the valuation implications of the demand effect, since the most affected firms would likely be the first to start paying dividends when trust drops. We find weak evidence that managers base their dividend decisions on the trust of their investor bases. In unreported results, the relationship between the trust level and the probability of a dividend initiation is only marginally significant (at the 10% level) and economically small (i.e., a 10% drop in trust is associated with a 0.1% increase in the probability of initiating a dividend). We caution against taking this as evidence that managers do not respond to changes in trust when setting dividend policy. First, we think trust and dividends likely form an endogenous system where, even as low trust increases demand for dividends, having more dividends increases trust by showing that earnings are real and managers treat shareholders well. Second, pointing in favor of trust causing managers to adjust their payout policies, prior work shows a positive relationship between a firm's cash holdings and the trust level of the firm's home country (Dudley and Zhang 2016). Overall, the evidence from this test and the previous one indicate that dividend payers experience an increase in their market values relative to non-payers when a drop in trust causes investors to increase their demand for dividend-paying stocks.

5 Conclusion

We find, in surveys, that investors perceive dividend paying firms as less likely to commit accounting fraud than non-dividend paying firms. We expect that decreased trust, or a higher perceived likelihood of fraud, will push investors toward investments that are perceived as less likely to be fraudulent. This leads us to our primary hypothesis: trust levels will be negatively associated with the demand for dividends. We find evidence to support this hypothesis.

First, we show that less trusting households are more likely to receive dividends. Then, for sharper identification, we use accounting frauds as negative shocks to investor trust. We show that mutual funds that are exposed to the fraud (because they hold stock in the fraudulent firm) increase their portfolio allocations to dividend-paying stocks, relative to a control group of unexposed funds. This comparison isolates the change in the demand for dividends from the change in the supply of dividends because both the treatment and control groups are choosing from the same set of investment opportunities. We provide evidence against the notion that the increase in demand for dividend payers is driven by an increase in risk aversion, because we find no evidence that funds exposed to the fraud change the riskiness of their portfolios. This suggests that they are seeking the dividends in and of themselves.

We then provide evidence that low investor trust and the attendant increase in demand for dividend-paying stocks may cause dividend payers to increase in value relative to non-payers. Here, we focus on how changes to the trust of a firm's mutual fund investor base might affect the firm's value if the firm pays dividends relative to if it does not. We find that having more investors hit by frauds causes market-to-book ratios to increase for dividend-paying firms and decrease for non-dividend-paying firms. We also show that dividend payers have higher market-to-book ratios relative to non-payers in the same US state when one of the state's firms committed fraud in the previous year. We then corroborate these tests with an associational test showing that less-trusting regions of the United States have higher relative market-to-book ratios for dividend payers versus non-payers.

Our results indicate that dividends and the information they provide are interpreted and valued differently depending on an investor's level of trust. We already show evidence that a drop in trust among a firm's investors increases the value of dividends for that firm. However, we have not fully explored the implications arising from heterogeneity in investor trust. We think this is a promising area for future research. Another promising direction for future research would be to further explore how drops in trust manifest in investors' utility functions. Our hypothesis is based on trust entering the utility function as the investor's perceived probability of suffering a large loss due to fraud. Another possibility, which would also drive investors toward dividends after a drop in trust, is that investors may have non-standard utility functions whereby they get direct disutility from being cheated or defrauded. This appears consistent with prior evidence that people get disutility from unequal outcomes, especially when they themselves are the ones coming up short (Loewenstein et al. 1989). However, to our knowledge, no prior research explicitly shows that people get direct disutility from being cheated. We encourage future research to investigate this and determine how much of the shift to dividends after a drop in trust is driven by this direct disutility.

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Data Availability Data used in this study are from the publicly available sources stated in the text, except for the survey.

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