Empirical Essays in Corporate Finance

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To my family and friends

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Chapter One

Introduction

From the beginning of research on payout policy, academicians strive to understand why dividends persist, whether dividend policy affects firm value, and what are the determinants of dividend payouts. Miller and Modigliani substantiated their claim of a dividend policy irrelevance to the firm valuation by equating the paid out dividends value to the appreciated stock price in case of retaining the dividends (Miller and Modigliani, 1961). Their cornerstone work convincingly demonstrated that an investment decision of a firm but not its dividend policy determine firm value.

In an effort to justify the existence of dividends, the subsequent research developed by loosening the perfect market restrictions underlying the Miller and Modigliani theory. In particular, lifting the assumption of perfectly symmetric information has given a rise to a number of payout theories. The most prominent among them are the dividend signaling and the free cash flow hypotheses. Both theories rest on the assumption of a separation of corporate ownership and control and, as a result, a conflict between shareholders and managers, which has been acknowledged as early as in the Adam Smith's "The Wealth of Nations" (1887). Signaling theories explain the existence of dividends with a mitigation of informational asymmetries between owners and managers due to unexpected changes in dividend payouts. The first mention of the informational content of dividends is being found in Modigliani and Miller (1959). Subsequent studies elaborated on this idea and developed formal signaling models. Dividends in these models are viewed as a costly signal which is used to credibly convey managers' expectations of future cash flows (Bhattacharya, 1979; John and Williams, 1985; Miller and Rock, 1985). The free cash flow problem laid out by Jensen (1986) refers to an imprudent behavior of managers investing free cash flows in negative net present value projects. Among other disciplining mechanisms, dividends may decrease the free cash flow available for financing managerial decisions that deteriorate firm value.

A conceptually different explanation of dividends has been made possible due to the Kahneman and Tversky's investigation of a human economic behavior which laid a foundation of a new research paradigm. Their prospect theory (Kahneman and Tversky, 1979), as well as the theory of self-control (Thaler and Shefrin, 1981), have been applied by Shefrin and Statman (1984) to explain the existence of dividends. In contrast to the standard financial theory, the authors demonstrate that dividend and capital gains are not perfect substitutes. The other unconventional studies look into the determinants of the level of dividend payouts. They examine the impact of local demographic and cultural characteristics on corporate dividend policy (Graham and Kumar, 2006; Becker et al., 2011; Ucar, 2015). This literature, however, is scarce, and a continued search of socio-demographic explanations can deepen our knowledge on the factors of dividend payouts.

The objective of this thesis is threefold. First, we[1] strive to understand whether managers pay attention to the specific thresholds when setting dividend payouts. We show empirically that managers indeed try to set dividends per share such that they exceed those from the previous quarter. However, they do not systematically beat analysts' forecasts. Second, I ask the question whether this observed managers' behavior is fully rational. Specifically, I look into the wealth effects of meeting or missing the dividend threshold targets. In doing so I pay special attention to confounding events and learn about the marginal information content of earnings and dividend surprises. My results demonstrate that only earnings news and not dividend news make market participants reconsider their stock price valuations. Thus, this study is in line with the Miller and Modigliani's vision on the firm value determinants. Lastly, I uncover a novel link between a firm's geographic dispersion and its payout policy. I argue that a firm's geographic

[1] Chapter 2 of this dissertation is based on a joint work, whereas Chapters 3 and 4 are based on single-authored working papers. Co-authorship is indicated by the use of corresponding personal pronouns throughout the introduction and the remaining chapters of this dissertation.

dispersion is related to investor awareness of a firm; and that the latter in turn is related to a firm's payout policy. My empirical results are consistent with these arguments. The findings of my dissertation should be of particular interest to professional money managers, as well as for corporate financial officers and corporate boards setting the firm's dividend policy.

This dissertation is comprised of three self-contained chapters. Each chapter represents a working paper with an identical title. In the following I summarize research questions, peculiarities in the data and research methods, and key results of each chapter.

Chapter 2.[2]

It is well known that managers manage earnings in order to report profits that exceed those reported in the previous quarter and profits that exceed analyst forecasts. This pattern is consistent with the notion that managers care about investor expectations in general and analyst forecasts in particular when making earnings announcements. In this paper we analyze whether a similar pattern can be detected for dividend announcements.

Our hypotheses are based on the assumption that managers care about the market's reaction to dividend announcements. There is ample empirical evidence that they do. Asquith and Mullins (1986) conclude from the results of an empirical analysis that "dividends are habitforming. If the market does not receive its expected dosage, the stock price will suffer withdrawal symptoms" (p. 35).

[2]This chapter is based on a joint work with Erik Theissen.

Our results provide clear evidence that managers avoid dividend cuts. Small decreases are significantly less likely than small increases. We do not find a similar pattern for dividends relative to analyst forecasts. In fact, dividends that fall short by one cent of the consensus forecast are more frequent than dividends that slightly exceed the forecast. Our results thus support the notion that the relevant threshold for dividends is the previous dividend, not the analyst forecast.

Chapter 3.[3]

Results obtained in the previous chapter indicate that managers of the public companies in the U.S. do not set their payout policy such as to beat stock analysts' dividend expectations. This evidence seems to be at odds with the underlying theory of the dividend information content. According to the information content hypothesis, new dividend information should be reflected in stock prices. Negative surprises to the market should therefore be accompanied with negative stock price changes. In theory, a negative market reaction should discipline managers to avoid falling short of the market expectations.

Despite a long tradition of estimating the wealth effects of dividends, test results are still inconclusive. Most of the earlier efforts in empirical research were in favor of a dividend policy effect on stock prices (see Fama et al. (1969); Pettit (1972, 1976); Charest (1978); Aharony and Swary (1980); Woolridge (1983), and Andres et al. (2013) among others). Watts (1973) refutes this premise. Gonedes (1978) and more recently Amihud and Li (2006) also

[3]This chapter is based on a single-authored working paper.

fail to support the hypothesis. In light of these conflicting findings, I revisit the topic of the information content of dividends.

The major problem in empirical tests of the dividends information content hypothesis is an inability to observe unexpected changes in dividends. Thus, distinct dividend expectation models may be accountable for the mixed results on the validity of the information hypothesis. The existing literature predominantly estimates stock market effects using dividend decreases and increases as a measure of the unexpected dividend change. This approach implicitly assumes constant dividends as a model of market expectations. A serious drawback of this naïve model is that an absolute dividend change contains some anticipated component. The model does not allow for updates in market beliefs in a period between subsequent dividend announcements, which clearly contradicts observable adjustments in analysts' estimates and recommendations. I contribute to the discussion using an underexploited identification strategy approximating market expectations with analysts' dividend expectations available from I/B/E/S. In this chapter, I critically discuss a usage of analysts' expectations as a model of market expectations.

Another empirical issue with a test of the dividend information hypothesis is that dividend announcements are often accompanied by earnings announcements. Therefore, an identification strategy that omits this factor risks falsely attributing an earnings information effect to that of the dividend. I provide a number of tests that aim to isolate potential contemporaneous earnings effects on stock prices.

This study finds that, in a panel of U.S. companies in the period from 2002 to 2012, stock market participants do not price dividend information. I demonstrate that the market neither appreciates nor depreciates the stock value of firms that exceed analysts' dividend expectations or fail to do so. I show that earnings, on the contrary, have a significant firm valuation effect.

Chapter 4.[4]

In the next study I investigate the effect of investor awareness on corporate payout policy. The existing literature suggests that firms may use dividends and repurchases to increase retail investor attention to the firm (Brav et al., 2005; Drake et al., 2012). One way for an investor to become aware of a firm is by being in the geographic area of the firm. Theoretically, investors may encounter the firm's branch during their daily routines, whether using services or products of the firm, being employed by the company, from local news, or by word of mouth.

There are a number of reasons to hypothesize that investor awareness of the firm increases with the firm's geographic dispersion. Local bias is a well-established phenomenon which describes a tendency of both institutional and retail investors to allocate their capital into stocks of well-known and geographically proximate companies (see Coval and Moskowitz (1999, 2001); Baik et al. (2010) for evidence on institutional investors' local bias; see Grinblatt and Keloharju (2002); Huberman (2001); Bodnaruk (2009); Ivkovic and Weisbenner (2005); Seasholes and Zhu (2010) for evidence on individual investors' local bias). One possible explanation for local bias is famil-

[4]This chapter is based on a single-authored working paper.

iarity. This phenomenon is described in Huberman (2001) and Keloharju et al. (2012). Huberman (2001) documents a tendency of investors to hold stock of providers of local telephone services. Keloharju et al. (2012) investigate investment behavior of car buyers from Finland. They conclude that a patronage behavior of investors makes them buy stocks of firms whose products they have experienced.

Evidence from the local bias and familiarity literature thus suggests that, compared to widely dispersed firms, firms with low geographic dispersion exhibit lower investor awareness. In order to gain investor attention, these firms may adopt higher payout strategies. I contribute to the literature by addressing the following research questions: First, do firms with high (low) geographic dispersion have lower (higher) payouts? Second, can the reached level of investor awareness explain the established relationship, if any?

To answer the first question, I obtain 10-K filings submitted by firms annually to the United States Securities and Exchange Commission. These filings provide necessary data on the firm geographic locations. Using U.S. states as the location definition, I observe a highly statistically significant and economically relevant relation between a firm's geographic dispersion and dividends, controlling for firm size, investment opportunities, CEO options, leverage, free cash flows, and several geography related proxies for severeness of agency problems. This relation also holds for repurchases. An increase in the firm economic presence by three states is associated with a 7% decrease in the dividend yield or an 8% decrease in the repurchase yield.

In the subsequent analyses, I explain the channel of the uncovered geography effect. I conduct a number of tests to confirm that using information on a firm's geographic location is a reasonable method to proxy for investor awareness. I hypothesize that if geographic dispersion is a good proxy of awareness then it should be manifested in the Internet searches of a firm. I extract data on Google Search Volume Index (SVI) of a firm name across U.S. states. An analysis of these data reveals that in 95% of firm-year observations, companies have a higher Google search volume from the states where they are economically present than from other states. This and other pieces of evidence suggest that key explanatory variables, which I construct using geographic firm characteristics, are informative about the degree of investors' firm awareness.

Also, I use this evidence combined with the fact that retail firms are more visible to investors than non-retail firms, everything else being equal. My main hypothesis suggests that visibility of a firm negatively relates to its payout levels. The results from the sample split analysis are consistent with the awareness explanation of dividends; the effect of investor awareness on dividends is more pronounced in the retail firms subsample than in the non-retail firms subsample.

In the remaining robustness checks I use other geography-based measures of investor awareness. I also employ several proxies to control for the agency costs and the dividend clientèle explanations of dividends. Furthermore, I discover that small firms are more prone to the awareness effect on payout policy, compared to the large firms. This evidence is in line with an expectation that smaller firms should profit more from an increase in the state economic presence than firms that are already large and enjoy a relatively high investor recognition.

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Chapter Two

To Meet or Beat Analysts' Dividend Forecasts

2.1 Introduction

It is well known that managers care about investor expectations in general and analyst forecasts in particular when making earnings announcements. Burgstahler and Dichev (1997) and Degeorge et al. (1999) find that there are significantly more reports of small positive than of small negative earnings, significantly more reports of small earnings increases than of small decreases, and significantly more reports of earnings that slightly exceed the consensus analyst forecast than of earnings that slightly fall short of the consensus forecast.[1] This pattern is consistent with the notion that managers manage earnings in order to report (1) positive profits, (2) profits that exceed those reported in the previous quarter, and (3) profits that exceed analyst forecasts. Almeida et al. (2016) find that firms that are just about to miss the analysts' earnings per share forecast are significantly more likely to initiate repurchases that increases earnings per share. Bartov et al. (2002) provide evidence that firms that meet or beat analysts' expectations are rewarded by higher subsequent stock returns, even in cases where the "meeting or beating" has been achieved by earnings management.

In this paper we analyze whether a similar pattern can be detected for dividend announcements. Using a broad sample of dividend announcements made by listed U.S. corporations in the period 2003—2014 we test (1) whether there are more small dividend increases than small decreases, and (2) whether there are more dividend announcements that slightly exceed analysts' dividend forecasts than announcements that slightly fall short of analyst forecasts.

Several papers have demonstrated that there are indeed more dividend in-

[1] Brown and Pinello (2007) find that upward earnings management is less pronounced for annual than for quarterly earnings. They attribute their finding to the fact that annual reports are subject to independent audits. They also find, however, that managers use downward expectations management as a substitute for earnings management. Daniel et al. (2008) argue that target dividend levels may also serve as an earnings threshold. Covenants in debt contract may put a limit on the percentage of current earnings that can be paid out as dividends. Consequently, managers may have an incentive to report higher earnings in order to be able to pay out a target dividend. In their empirical analysis the authors find evidence consistent with this hypothesis. There are other patterns in reported earnings besides those alluded to here. For example, Carslaw (1988) and Thomas (1989) find that managers tend to round earnings figures. Baker et al. (2016) find that this result extends to dividends. Both dividend levels and dividend changes tend to cluster on round numbers.

creases than decreases (e.g. Charest (1978), Handjinicolaou and Kalay (1984), Eades et al. (1985), Lang and Litzenberger (1989), Bajaj and Vijh (1990), Dhillon and Johnson (1994), Yoon and Starks (1995), Grullon et al. (2002), Allen and Michaely (2003)). Baker et al. (2016) show explicitly that there are more *small* dividend increases than decreases. The main contribution of our paper is the test of the second hypothesis. To the best of our knowledge this is the first paper that tests whether managers set dividends to meet or beat analysts' forecasts.[2]

Our hypotheses are based on the assumption that managers care about the market's reaction to dividend announcements. There is ample empirical evidence that they do. Based on the surveys he conducted, Lintner (1956) concluded that managers believe that "the market puts a premium on stability or gradual growth in rate" (p. 99) and that therefore "most managements sought to avoid making changes in their dividend rates that might have to be reversed within a year or so" (p. 99). More recently Brav et al. (2005) surveyed 384 financial executives and report that the overwhelming majority (88.1%) of the respondents believe that there are negative consequences to cutting dividends. 93.8% (out of 166 respondents from dividend-paying firms) report that they try to avoid reducing dividends per share, and 89.6% state that they try to maintain a smooth dividend stream. 77.9% indicate that

[2]The paper that comes closest in this respect is Woolridge (1983). He relates dividend announcements to the forecasts made by Value Line, an investment advisory firm, and finds that positive forecast errors far outnumber negative forecast errors. However, Woolridge's sample is very small (225 firms), and he reports (p. 1610) that Value Line tended to underestimate dividends. Specifically, Value Line predicted an unchanged dividend in the majority of the cases under investigation even though the sample period was one of generally increasing dividends. Most importantly, Woolridge (1983) does not analyze whether managers deliberately set dividends such as to meet or beat analysts' forecasts.

they are reluctant to "make dividend changes that might have to be reversed in the future" (p. 494). Asquith and Mullins (1986) conclude from the results of an empirical analysis that "dividends are habit-forming. If the market does not receive its expected dosage, the stock price will suffer withdrawal symptoms" (p. 35).

These findings suggest that managers care about dividend announcements because they anticipate that the announcement will affect the share price. Consistent with this view, numerous studies have confirmed that share prices increase upon the announcement of a dividend increase and decrease upon the announcement of a dividend cut (e.g. Fama et al. (1969), Pettit (1972), Charest (1978), Woolridge (1983), Handjinicolaou and Kalay (1984), Eades et al. (1985), Asquith and Mullins (1986), Lang and Litzenberger (1989), Bajaj and Vijh (1990), Dhillon and Johnson (1994), Yoon and Starks (1995), Lie (2000), Grullon et al. (2002), Dhillon et al. (2003)).[3] Several theories provide reasons *why* dividend changes may trigger share price reactions. The most prominent among them are models of dividend signaling (Bhattacharya (1979), John and Williams (1985), Miller and Rock (1985), Baker et al. (2016)) and the free cash flow hypothesis (Easterbrook (1984), Jensen (1986)).

Earnings and dividend announcements are often made jointly. In these cases it is necessary to differentiate between the information content of the earnings and the dividend announcement. Several papers have attempted to disentangle the two effects (e.g. by only considering cases in which the

[3] In contrast to the bulk of the literature some papers have concluded that the information content of dividends is trivial (e.g. Watts (1973), Gonedes (1978)). Amihud and Li (2006) provide evidence that the information content of dividends has declined over time.

announcements were made on different dates). The results are somewhat ambiguous. Some authors have concluded that dividends do not contain information beyond that reflected in earnings figures (e.g. Gonedes (1978)). On the other side Aharony and Swary (1980) find that "changes in quarterly cash dividends provide useful information beyond that provided by corresponding quarterly earnings numbers" (p. 11), a result which is confirmed by Leftwich and Zmijewski (1994). Andres et al. (2013) find similar results in the German equity market.

Our results provide clear evidence that managers avoid dividend cuts. Small decreases are significantly less likely than small increases. We do not find a similar patterns for dividends relative to analyst forecasts. In fact, dividends that fall short by one cent of the consensus forecast are more frequent than dividends that slightly exceed the forecast. Our results thus support the notion that the relevant threshold for dividends is the previous dividend, not the analyst forecast.

The remainder of the paper is organized as follows. In Section 2.2 we describe our sample and present descriptive statistics. The empirical results are contained in Section 2.3, Section 2.4 describes the robustness checks we have implemented and Section 2.5 concludes.

2.2 Data and Descriptive Statistics

Our analysis requires data on actual dividend announcements, analysts' dividend forecasts, and firm fundamentals. Our sample period starts in 2003[4] and ends in 2014. It comprises all U.S. stocks for which data on analysts' dividend forecasts is available in I/B/E/S. Data on fundamentals is taken from Compustat. We obtain the dividend data from I/B/E/S. I/B/E/S contains data on mean and median analyst dividend forecasts which is updated monthly. We only consider forecasts of the next quarterly dividend and only retain the last forecast published prior to the actual dividend announcement. We delete cases in which the actual dividends and the forecasts are reported in different currencies, and cases in which the forecast interval reported in I/B/E/S extends until after the actual dividend announcement. The intersection of the analyst data and the actual dividend announcement data yields 65,207 firm-quarter observations.[5] Dividend initiations and omissions are included in the sample. We refer to this sample as the full sample.

Many firms either pay no dividend at all, or have a track record of keeping the dividend constant throughout the quarters of a fiscal year. In both cases dividends are easy to forecast. To check the robustness of our results we therefore repeat the entire analysis using a restricted sample that only con-

[4]Data on analysts' dividend forecasts is available from 2002 onwards. However, the number of forecasts in 2002 is very low. We therefore decided to start the sample in 2003.

[5]To identify special dividends, we follow De Angelo et al. (2000). From the CRSP database we obtain all dividend distributions for the firms in our sample using ncusip as an identifier. Then we count how often special dividends (distribution codes 1262 and 1272 as in De Angelo et al. (2000)) were declared by the sample firms. We identify 600 cases. We match the dividend declaration dates with those from our I/B/E/S sample. 570 of the declaration dates do not appear in the I/B/E/S sample. This leaves us with 30 special dividend announcements that are included in our full sample. For the restricted sample, to be described below, this number reduces to 8.

tains dividend changes (i.e. observations in which the dividend in quarter t is different from the dividend in quarter t-1). Further, some firms pay a dividend only once a year or pay the same dividend in all but one quarters of the year (e.g. sequences such as 0,0,5,0 or 3,3,5,3). In these cases (a total of 591 firm-years) we delete the quarter after the differing dividend payment from the sample because the dividend change in that quarter is easy to predict. The restricted sample contains 22,838 observations.

The variables of interest for our analysis are (1) dividend changes and percentage dividend changes and (2) dividend forecast errors and percentage dividend forecast errors. A dividend change is simply the difference, measured in USD, between the actual and the previous dividend. The percentage dividend change is the dividend change expressed as a percentage of the most recent quarterly dividend. The dividend forecast error is the difference between the actual dividend and a summary statistic of the analyst forecasts. In the main analysis we use the median analyst forecast. As a robustness check we also use the mean forecast. The percentage dividend forecast error is the forecast error expressed as a percentage of the mean or median forecast. In cases in which the mean or median forecast is zero, the percentage forecast error is not defined and we set the value to "missing". We winsorize all variables at the 1% and 99% percentile.

Table 2.2.1—Table 2.2.3 provide descriptive statistics for the two samples described above. Table 2.2.1 provides information on the distribution of dividend changes across years in the full sample (see Table 2.2.1, Panel A) and in the restricted sample (see Table 2.2.1, Panel B). The annual number of obser-

vations in the full sample ranges between 1,817 (in 2003) and 6,879 (in 2013). In almost 75% of the cases the dividend is unchanged. Increases (18.9% of the observations) are much more frequent than decreases (6.4%). This relation holds in every year with the exception of the crisis year 2009. Conditional on a change in the dividend, the percentage increase is smaller, at 18.8%,[6] than the average percentage decrease (-39.1% including dividend omissions). This pattern holds for all years. The annual number of observations in the restricted sample ranges between 468 in 2003 and 1,632 in 2013. As in the full sample dividend increases occur much more frequently than decreases.

Table 2.2.2 reports the number of analysts that have reported dividend forecasts to the I/B/E/S database. This number increases throughout the sample period. The table also reveals, however, that there is a large number of firms for which only one forecast is available. The values for the first quartile indicate that in every single year of the sample period for more than 25% of the firms only one analyst dividend forecast is available. To check the robustness of our results we repeat all analyses after excluding observations with only one analyst forecast (see Section 2.4).

Table 2.2.3 reports summary statistics on analysts' forecast errors. As noted above, the forecast error is defined as the actual dividend minus the median forecast. The fact that the median forecast error is always zero (and, in the full sample, even the third quartile forecast error is zero) indicates that analysts are often able to forecast the correct dividend exactly. The mean fore-

[6] Note that dividend initiations are not included in the calculation of the percentage dividend increase because the percentage increase is not defined for initiations.

Table 2.2.1: Distribution of Dividend Changes

This table shows the distribution of dividend decreases and increases. Dividend initiations are not included. The percentage dividend change is defined as the signed difference between the current and the previous quarterly dividend, expressed as a percentage of the previous quarterly dividend.

Year	Obs. decreases	Avg. percentage decrease, %	Obs. no change	Obs. increases	Avg. percentage increase, %
		Panel A. Full sample			
2003	97	-38.31	1,339	381	18.2
2004	173	-29.75	2,259	773	22.3
2005	164	-27.90	1,863	687	19.0
2006	140	-31.01	2,131	716	17.7
2007	224	-34.92	3,081	991	17.2
2008	322	-41.99	2,898	844	16.2
2009	567	-53.38	3,093	519	13.7
2010	357	-41.23	4,433	686	17.4
2011	350	-40.13	5,045	1,016	20.7
2012	339	-40.39	5,327	1,116	20.2
2013	424	-48.47	5,180	1,275	23.8
2014	282	-41.24	5,131	1,217	19.4
Total	3,439	-39.1	40,441	10,221	18.8
		Panel B. Restricted sample			
2003	87	-38.67	0	381	18.2
2004	130	-29.10	0	773	22.3
2005	139	-29.04	0	687	19.0
2006	116	-32.96	0	716	17.7
2007	188	-34.86	0	991	17.2
2008	272	-43.59	0	844	16.2
2009	523	-56.20	0	519	13.7
2010	266	-39.69	0	685	17.4
2011	262	-40.87	0	1,016	20.7
2012	268	-39.89	0	1,116	20.2
2013	357	-51.19	0	1,275	23.8
2014	242	-42.98	0	1,217	19.4
Total	2,850	-39.9	0	10,220	18.8

cast error is predominantly positive. Exceptions only occur in 2008 and 2009. Thus, the average dividend is slightly higher than the average forecast. This is consistent with our hypothesis that managers try to avoid falling short of analyst expectations, either by raising the dividend above the forecast or by successfully "managing downwards" the expectations of analysts.

Table 2.2.4 addresses the question whether analysts, on average, beat a naïve forecast which simply uses the previous dividend to forecast the next div-

Table 2.2.2: Temporal Distribution of the Number of Analysts

This table shows the number of analysts providing dividend forecasts.

Year	Obs.	Mean	Std.	Min	Max	p25	p50	p75
				Panel A. Full sample				
2003	2,602	1.80	1.35	1	11	1	1	2
2004	3,834	2.17	1.71	1	13	1	2	3
2005	3,346	2.23	1.78	1	14	1	2	3
2006	3,826	2.25	1.70	1	12	1	2	3
2007	5,079	2.23	1.60	1	13	1	2	3
2008	4,671	2.47	1.77	1	12	1	2	3
2009	5,181	2.49	1.94	1	17	1	2	3
2010	6,505	2.66	2.40	1	23	1	2	3
2011	7,196	2.97	2.87	1	25	1	2	4
2012	7,589	3.15	2.98	1	23	1	2	4
2013	7,694	3.25	2.98	1	23	1	2	4
2014	7,684	3.35	2.94	1	22	1	2	4
Total	65,207	2.73	2.46	1	25	1	2	3
				Panel B. Restricted sample				
2003	1,253	1.66	1.23	1	11	1	1	2
2004	1,530	1.95	1.56	1	11	1	1	2
2005	1,454	2.02	1.56	1	12	1	1	2
2006	1,669	2.12	1.59	1	12	1	2	3
2007	1,956	2.14	1.58	1	13	1	2	3
2008	1,707	2.33	1.72	1	11	1	2	3
2009	2,031	2.34	1.93	1	14	1	2	3
2010	1,961	2.41	2.06	1	16	1	2	3
2011	2,032	3.00	2.80	1	24	1	2	4
2012	2,165	3.25	2.93	1	23	1	2	4
2013	2,412	3.46	3.07	1	23	1	3	5
2014	2,489	3.45	2.95	1	22	1	2	5
Total	22,659	2.61	2.36	1	24	1	2	3

Table 2.2.3: Percentile Distribution of Dividend Forecast Errors

This table shows the distribution of dividend forecast errors. Dividend forecast errors are defined as the actual minus the median forecasted dividend. Variables are winsorized at the 1st and 99th percentile.

Year	Obs.	Mean	Std.	p05	p25	p50	p75	p95
				Panel A. Full sample				
2003	2,602	0.0012	0.0428	-0.03	-0.0025	0	0	0.03
2004	3,834	0.0017	0.0339	-0.02	0	0	0	0.03
2005	3,346	0.0014	0.0358	-0.02	0	0	0	0.03
2006	3,826	0.0012	0.0356	-0.02	0	0	0	0.03
2007	5,079	0.0000	0.0335	-0.02	0	0	0	0.02
2008	4,671	-0.0008	0.0326	-0.02	0	0	0	0.02
2009	5,181	-0.0003	0.0314	-0.02	0	0	0	0.01
2010	6,505	0.0008	0.0263	-0.01	0	0	0	0.01
2011	7,196	0.0018	0.0266	-0.01	0	0	0	0.02
2012	7,589	0.0022	0.0276	-0.01	0	0	0	0.02
2013	7,694	0.0027	0.0346	-0.01	0	0	0	0.03
2014	7,684	0.0025	0.0310	-0.01	0	0	0	0.03
Total	65,207	0.0012	0.0326	-0.02	0	0	0	0.02
				Panel B. Restricted sample				
2003	1,253	0.0033	0.0495	-0.05	-0.002	0	0.004	0.07
2004	1,532	0.0067	0.0447	-0.03	0	0	0.01	0.07
2005	1,458	0.0049	0.0457	-0.03	0	0	0.01	0.06
2006	1,671	0.0056	0.0458	-0.03	0	0	0.01	0.06
2007	1,962	0.0042	0.0436	-0.03	0	0	0.01	0.06
2008	1,723	-0.0010	0.0472	-0.08	-0.002	0	0	0.04
2009	2,044	-0.0015	0.0442	-0.07	0	0	0	0.04
2010	1,981	0.0037	0.0410	-0.02	0	0	0	0.05
2011	2,063	0.0079	0.0449	-0.02	0	0	0	0.07
2012	2,191	0.0079	0.0443	-0.02	0	0	0.01	0.08
2013	2,447	0.0091	0.0553	-0.05	0	0	0.01	0.13
2014	2,513	0.0080	0.0481	-0.02	0	0	0.01	0.09
Total	22,838	0.0049	0.0462	-0.04	0	0	0.01	0.07

idend. The figures reveal that the analyst forecasts are significantly more accurate than the naïve forecast. This result is consistent with the evidence provided in Bilinski and Bradshaw (2015). These authors analyze analyst dividend forecasts for firms in 16 countries and conclude that the analyst forecasts are more accurate than other estimates such as forecasts based on time-series models.

Table 2.2.4: Comparison of Mean Analyst and Naïve Forecast Errors

This table provides the mean analyst and naïve dividend forecast errors and t-test results. Panel A compares absolute forecast errors, Panel B percentage forecast errors. The analyst dividend forecast error is defined as the actual minus the median forecasted dividend. The percentage analyst dividend forecast error is the forecast error expressed as a percentage of the median forecast. The naïve forecast error is the current quarter dividend minus the previous quarter dividend. The percentage naïve forecast error is defined as the naïve forecast error expressed as a percentage of the previous quarter dividend. The number of observations is lower in Panel B (percentage forecast errors) than in Panel A (absolute forecast errors) because the percentage forecast error (percentage naïve forecast error) is not defined when the median forecast (previous quarter dividend) is zero. The last column reports t-tests for differences in means. *** indicates significance at the 1% level. All variables are winsorized at the 1st and 99th percentile.

	Obs.	Analyst forecast errors	Naïve forecast errors	t-stat
		Panel A. Forecast errors, USD		
Full sample	56,792	0.0015	0.0028	(6.13)***
Restricted sample	13,776	0.0089	0.0277	(10.91)***
		Panel B. Forecast errors, %		
Full sample	44,228	0.9344	2.3274	(15.50)***
Restricted sample	12,748	3.7071	20.7988	(21.25)***

2.3 Results

We hypothesize that (1) managers avoid dividend decreases and that they (2) avoid falling short of the consensus analyst forecast. Hypothesis 1 implies that there should be less small dividend decreases than there are small dividend increases. Similarly, hypothesis 2 implies that there are less small negative forecast errors (i.e. cases in which the actual dividend is slightly lower than the consensus forecast) than small positive forecast errors.

We present the results using histograms of dividend changes (hypothesis 1) and forecast errors (hypothesis 2). In these histograms we exclude observations with zero dividend changes and zero forecast errors, respectively. Because we are interested in *small* dividend changes and forecast errors we only show absolute dividend changes and forecast errors ranging from -10 cents to + 10 cents and relative dividend changes and forecast errors ranging from -10% to +10%, respectively. In each figure Panel A contains a histogram for the full sample, while Panel B contains the corresponding histogram for the restricted sample.

In their paper on earnings management Degeorge et al. (1999) propose a test of the null hypothesis that the distributions of earnings changes and earnings surprises are continuous at the threshold level of zero. In principle this test can be applied to dividend changes and forecast errors. However, while earnings per share can reasonably be assumed to be continuous, dividends per share are not distributed continuously because they are deliberately set, and usually are set to full cents. We therefore apply the Degeorge et al. (1999) test only to percentage dividend changes and percentage forecast errors.[7] The test results are displayed in the histograms (see Figure 2.3.2 and

[7] For details see the appendix in Degeorge et al. (1999). To perform the test we group the data into 20 1% bins. Note that we exclude zero percentage dividend changes and forecast errors from the sample because we want to test whether there are more small positive values than small

Figure 2.3.4, respectively).

Table 2.3.1 presents summary statistics and additional statistical tests corresponding to each of the histograms. Specifically, the table shows the mean, the median, the skewness, and the ratio of positive to negative dividend changes and forecast errors. It further reports test statistics for tests of the null hypothesis that the mean is zero and the null hypothesis that positive and negative dividend changes and forecast errors are equally likely. Columns 1—5 of the table report results for the complete sample (winsorized at the 1st and 99th percentile), while columns 6—10 report results for a trimmed sample that only contains absolute dividend changes and forecast errors between -10 cents and +10 cents and percentage dividend changes and forecast errors between -10% and +10%, respectively. Thus, columns 6—10 are based on the same data as the histograms (but remember that zero dividend changes and zero forecast errors are excluded from the histograms, while they are included in the summary statistics presented in Table 2.3.1).

We start with the results for absolute dividend changes (see Figure 2.3.1). Small dividend increases are far more frequent than small decreases. A one cent dividend increase is about twice as likely as a one cent decrease. These results hold both for the full sample (Panel A) and for the restricted sample (Panel B). When we move from absolute dividend changes to percentage changes (Figure 2.3.2), we obtain very similar results. Small percentage increases are far more frequent than small percentage decreases. Moreover, the test statistic of the Degeorge et al. (1999) discontinuity test is positive

negative values. If we include the zeros, the test clearly indicates a discontinuity at zero.

for both samples and significant for the restricted sample, supporting the evidence that there are more small dividend increases than decreases. The histograms thus provide clear support for hypothesis 1. Our conclusion on hypothesis 1 is further supported by the summary statistics presented in Table 2.3.1. In all four samples (full and restricted, complete and trimmed samples) the mean dividend change is significantly larger than zero. Dividend increases far outnumber decreases. The null hypothesis that positive and negative dividend changes are equally likely is clearly rejected.

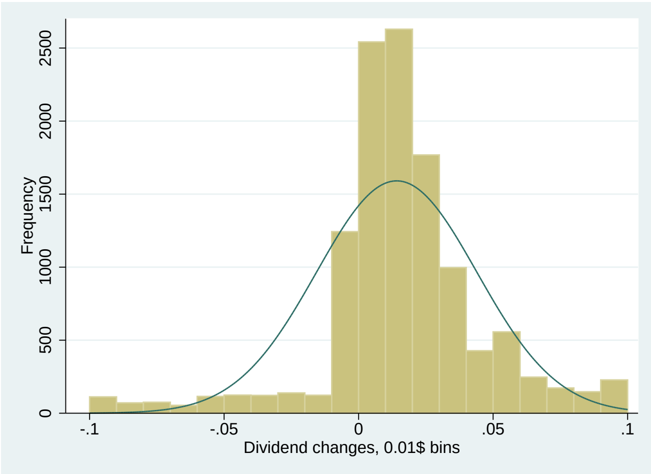
We obtain a much more differentiated picture when we consider absolute dividend forecast errors (Figure 2.3.3). The most frequent category is small (1 cent or less) negative forecast errors.[8] Negative forecast errors larger than one cent are rare. We get a different picture on the right-hand side of the figure. While small (one cent or less) positive forecast errors are much less frequent than similar-sized negative forecast errors, larger positive forecast errors are more frequent than larger negative forecast errors. Again, the full sample and the restricted sample produce similar results. The summary statistics shown in Table 2.3.1 reveal that, in the full sample, the numbers of positive and negative observations are almost equal while in the restricted sample there are more positive than negative forecast errors.

[8]Remember that zero forecast errors are excluded from the histograms. Remember also that the forecast error is defined as the actual dividend minus the consensus forecast. A negative forecast error thus implies that the actual dividend falls short of analyst expectations.

Figure 2.3.1: Histograms of Absolute Dividend Changes from the Interval [-0.10$,0$) and (0$,+0.10$] in 0.01$ Bins

Variables are winsorized at the 1st and 99th percentile. The solid black line shows an appropriately scaled normal density with the same mean and standard deviation as the data.

Panel A. Full sample



Panel B. Restricted sample

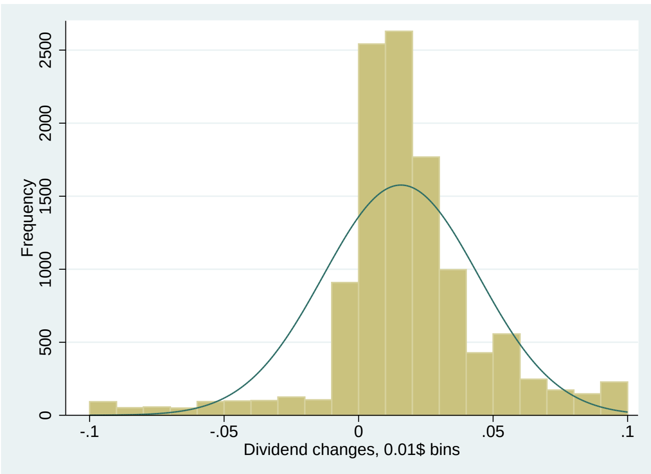
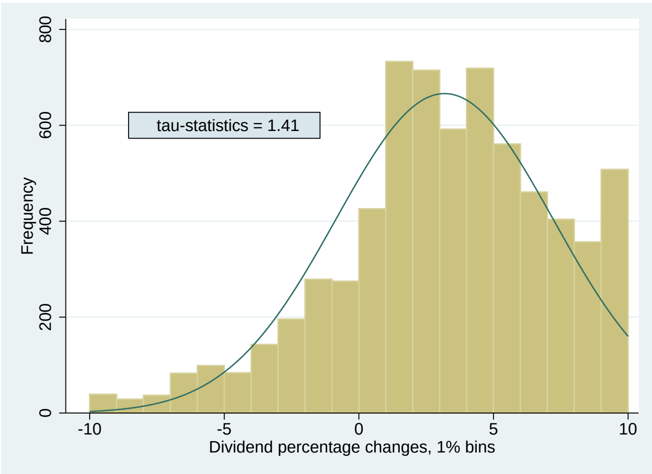


Figure 2.3.2: Histograms of Percentage Dividend Changes from the Interval [-0.10%,0%) and (0%,+0.10%] in 1% Bins

Variables are winsorized at the 1st and 99th percentile. The tau-statistics shown in the boxes are the t-like test statistics borrowed from Degeorge et al. (1999) which follow a standard normal distribution. The tau-statistics are obtained using 1 percent bins, 10 bins to the left and 10 bins to the right of the zero threshold. The solid black line shows an appropriately scaled normal density with the same mean and standard deviation as the data.

Panel A. Full sample



Panel B. Restricted sample

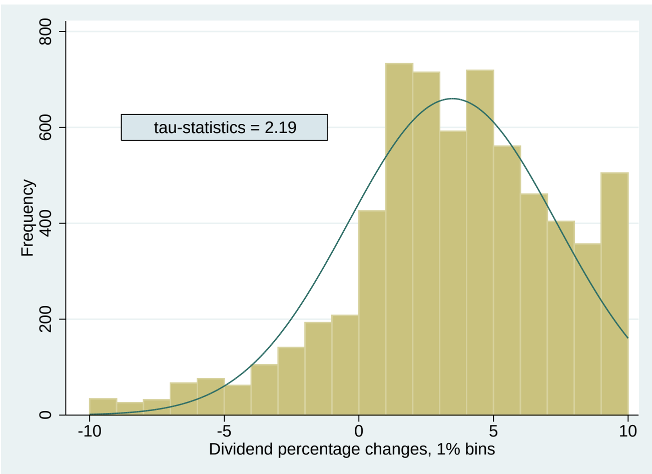
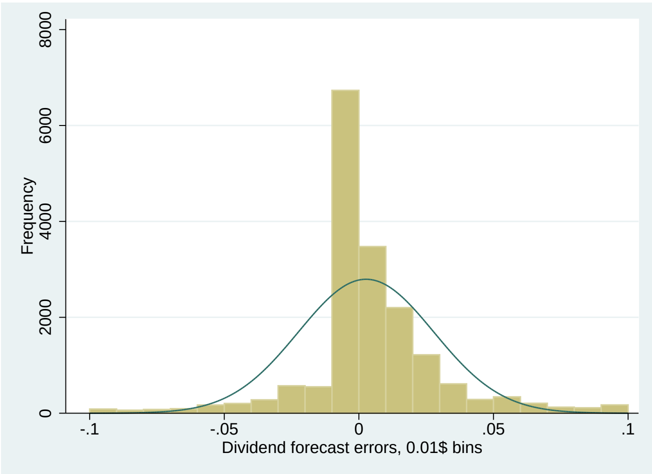


Figure 2.3.3: Histograms of Absolute Dividend Forecast Errors Based on Median Analysts' Forecasts from the Interval [-0.10$,0$) and (0$,+0.10$] in 0.01$ Bins

Variables are winsorized at the 1st and 99th percentile. The solid black line shows an appropriately scaled normal density with the same mean and standard deviation as the data.

Panel A. Full sample



Panel B. Restricted sample

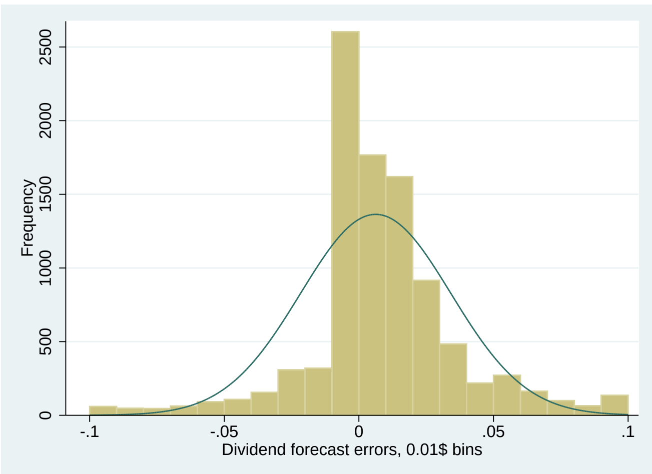
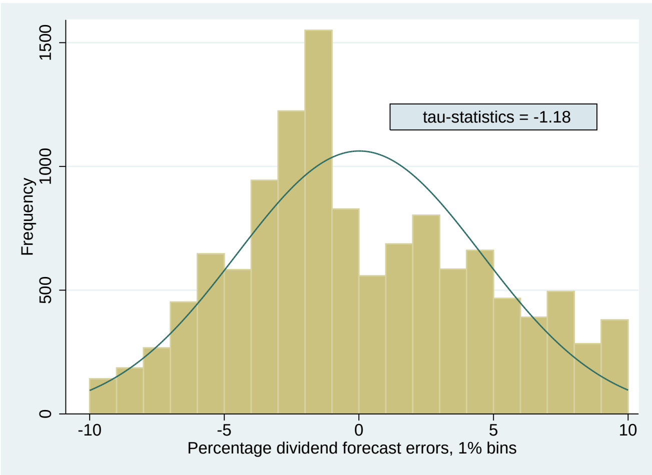


Figure 2.3.4: Histograms of Percentage Dividend Forecast Errors Based on Median Analysts' Forecasts from the Interval [-10%,0%) and (0%,+10%] in 1% Bins

Variables are winsorized at the 1st and 99th percentile. The tau-statistics shown in the boxes are the t-like test statistics borrowed from Degeorge et al. (1999) which follow a standard normal distribution. The tau-statistics are obtained using 1 percent bins, 10 bins to the left and 10 bins to the right of the zero threshold. The solid black line shows an appropriately scaled normal density with the same mean and standard deviation as the data.

Panel A. Full sample



Panel B. Restricted sample

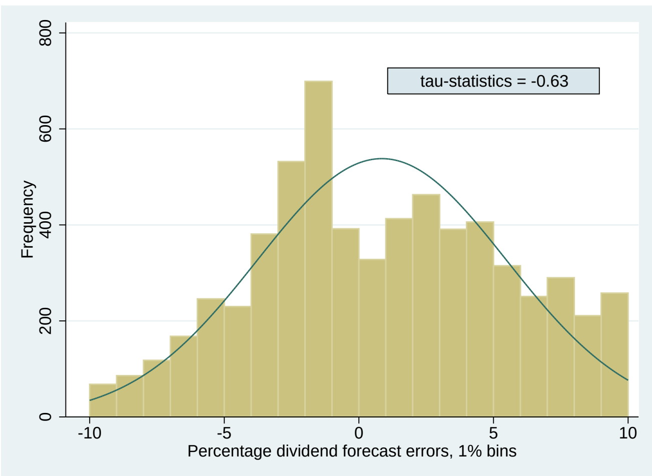


Table 2.3.1: Distributional Properties of Dividend Changes and Forecast Errors

This table presents the distributional properties of both absolute and percentage dividend changes and dividend forecast errors. It shows the mean, the median, the number of positive vs. negative values, and the skewness. It further shows (in parentheses) test statistics for tests of the mean against zero and for the test of the null hypothesis that positive and negative values are equally likely. Columns 1—5 present figures for the full sample (winsorized at the 1% and 99% quantile); columns 6—10 — for a trimmed sample that only contains small (less than 10 cents and less than 10%, respectively) dividend changes and forecast errors. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	Full sample (winsorized at 1% and 99%)					Trimmed sample (-10 cents to +10 cents; -10% to +10%)				
	Mean t-statistic (1)	Median (2)	Ratio pos/neg. z-statistic (3)	Skewness (4)	Obs. (5)	Mean t-statistic (6)	Median (7)	Ratio pos/neg. z-statistic (8)	Skewness (9)	Obs. (10)
Absolute Dividend Changes										
Full sample	0.0029 (12.02)***	0	10,997:3,438 (125.83)***	-0.34	56,215	0.0032 (47.75)***	0	9,716:2,178 (69.12)***	1.13	53,674
Restricted sample	0.0137 (14.50)***	0.01	10,997:2,849 (69.25)***	-0.42	13,846	0.0157 (58.15)***	0.01	9,716:1,685 (75.21)***	-0.39	11,401
Percentage Dividend Changes										
Full sample	0.96 (11.33)***	0	10,220:3,439 (58.02)***	-0.35	55,439	0.44 (52.00)***	3.57	5,431:1,258 (51.02)***	2.57	48,469
Restricted sample	5.65 (16.54)***	5.88	10,220:2,850 (64.47)***	-0.34	13,070	3.48 (71.50)***	0	5,431:938 (56.30)***	-0.60	6,369
Absolute Dividend Forecast Errors										
Full sample	0.0013 (10.82)***	0	9,766:9,764 (0.01)	1.39	65,207	0.0007 (14.03)***	0	8,763:8,840 (0.58)	0.81	63,280
Restricted sample	0.0052 (16.73)***	0	6,577:4,422 (20.55)***	1.10	22,838	0.0028 (21.56)***	0	5,743:3,806 (19.82)***	0.54	21,388
Percentage Dividend Forecast Errors										
Full sample	0.32 (3.39)***	0	9,219:9,764 (3.96)***	-0.04	50,295	0.01 (0.47)	0	5,175:6,643 (13.50)***	0.53	43,130
Restricted sample	2.38 (11.47)***	0	6,201:4,422 (17.26)***	0.16	19,016	0.37 (14.61)	0	3,227:2,807 (5.41)***	0.55	14,427

Turning to percentage forecast errors, visual inspection of the histograms (Figure 2.3.4) suggests that positive forecast errors below 5% are less frequent than similarly sized negative forecast errors, while the reverse holds for forecast errors above 5%. This is consistent with the results, discussed above, for absolute forecast errors.[9] As evidenced by the statistics shown in Table 2.3.1, the first effect dominates in the full sample (i.e. there are significantly more negative than positive forecast errors in the full sample), while the second effect dominates in the restricted sample. The test statistics of the Degeorge et al. (1999) discontinuity test for the percentage forecast errors are insignificantly negative in both the full and the restricted sample. Taken together, these results do not allow us to conclude that managers deliberately set dividends to meet analyst forecasts.

While our results provide clear support for hypothesis 1, they are much less supportive of hypothesis 2. This finding is surprising against the backdrop of the results that previous studies have documented for earnings announcements. To shed more light on the issue, we have merged our data set with data on earnings announcements and analysts' earnings forecasts. For all firm-quarter observations in our sample for which data was available we calculated the percentage earnings forecast error. It is defined as the difference between actual earnings and the median analyst earnings forecast, expressed as a percentage of the forecast. We then classify all observations into three groups, "misses", "matches", and "beats". Following Brown (1997),

[9] When comparing the histograms of absolute and percentage forecast errors, it should be kept in mind that the horizontal scales are different — depending on the dividend level a one cent dividend forecast error will often translate into a much larger percentage value.

a match is defined as a case in which the actual earnings figure is within +/- 10% of the forecasts. Misses and beats are defined correspondingly. For each observation we further record whether the actual dividend was equal to the median analyst forecast, ["match"], larger than the forecast, ["beat"], or smaller than the forecast, ["miss"]. We then cross-tabulate the two groupings separately for the full sample and the restricted sample. The results are shown in Table 2.3.2.

In the full sample (Panel A of Table 2.3.2) cases in which actual earnings exceed forecasted earnings by more than the 10% threshold we apply are much more common than cases in which earnings fall short of the forecast (28.7% as compared to 17.8%). This does not apply to dividends. Here, "misses" and "beats" are equally likely (15.3% as compared to 15.7%). This pattern is consistent with the notion that managers try to beat analysts' earnings forecasts but do not try to beat their dividend forecasts. The results for the restricted sample (Panel B of Table 2.3.2) differ from those for the full sample. Here, the percentage of "beats" is larger than the percentage of "misses" both for the earnings announcements (28.2% as compared to 18.4%) and for the dividend announcements (30.0% as compared to 19.3%). These results thus do not provide unanimous support for the conjecture that managers disregard analysts' dividend forecasts.

Table 2.3.2: Joint Distribution of Earnings and Dividend Forecast Errors

The sample for the analysis in Panel A (Panel B) was created by merging the full sample (restricted sample) with I/B/E/S same quarter data on analysts' median earnings forecasts and quarterly earnings per share. We identify "misses" of dividend forecasts if the quarterly dividend per share is smaller than the median analyst dividend forecast. We identify "matches" of dividend forecasts if the quarterly dividend per share is equal to the median analyst dividend forecast. We identify "beats" of dividend forecasts if the quarterly dividend per share is greater than the median analyst dividend forecast. "Misses" of earnings forecasts are identified if percentage earnings forecast errors are lower than minus ten percent. "Matches" of earnings forecasts are identified if percentage earnings forecast errors are higher than minus ten percent and lower than ten percent. "Beats" of earnings forecast errors are identified if percentage earnings forecast errors are higher than ten percent. Percentage earnings forecast errors are the ratio of quarterly earnings per share minus the median analyst earnings per share forecast to the median analyst earnings per share forecast, expressed in percent.

Panel A. Full sample merged with earnings data

		Earnings announcements							
		misses		match		beats		Total	
Dividend announcements	misses	1,851	3.12%	4,876	8.21%	2,352	3.96%	9,079	15.29%
	match	7,324	12.33%	21,411	36.05%	12,248	20.62%	40,983	69.00%
	beats	1,373	2.31%	5,492	9.25%	2,471	4.16%	9,336	15.72%
	Total	10,548	17.76%	31,779	53.50%	17,071	28.74%	59,398	100.00%

Panel B. Restricted sample merged with earnings data

		Earnings announcements							
		misses		match		beats		Total	
Dividend announcements	misses	955	4.55%	2,052	9.77%	1,049	5.00%	4,056	19.32%
	match	1,995	9.50%	5,473	26.07%	3,183	15.16%	10,651	50.73%
	beats	905	4.31%	3,691	17.58%	1,693	8.06%	6,289	29.95%
	Total	3,855	18.36%	11,216	53.42%	5,925	28.22%	20,996	100.00%

2.4 Robustness Checks

We have conducted a number of robustness checks. First, we have repeated the analysis using the mean analyst forecast instead of the median forecast to calculate the dividend forecast errors. Second, we restricted the sample to cases with at least two analyst forecasts. Third, we repeated the analysis after excluding observations from the crisis years 2008 and 2009 from the sample. In all three cases the results were qualitatively similar to those reported in the previous section. We therefore omit the results from the paper.

Analysts start submitting forecast of the quarter t dividend in quarter t-1 and then may update their forecast throughout quarter t. I/B/E/S aggregates analysts' forecasts at a monthly level. Therefore, there is data available on forecasts made one, two, three and four months before a dividend announcement. In the main analysis we used the last update published prior to the dividend announcement. To check the robustness of our findings we repeat the analysis using the forecasts available two, three and four months before the announcement. The results are similar to those presented above and are thus omitted from the paper.

2.5 Conclusion

It is a well established empirical fact that managers care about investor expectations and analyst forecasts when making earnings announcements. They manage earnings in order to report positive profits, profits in excess of those reported in the previous quarter and profits that exceed analyst forecasts. We analyze whether a similar pattern can be detected for dividend announcements. Using a large sample of dividend announcements made by listed U.S. corporations we test whether there are more small dividend increases than small decreases, and whether there are more dividend announcements that slightly exceed analysts' dividend forecasts than announcements that slightly fall short of analyst forecasts.

We find clear support for the first hypothesis but not for the second hypothesis. Small dividend increases are significantly more likely than small decreases. A similar pattern does not hold for dividends relative to analyst forecasts. Rather, we find that dividends that fall short by one cent of the consensus forecast are *more* frequent than dividends that slightly exceed the forecast. Our results are consistent with the view that the relevant threshold for dividends is the previous dividend, not the analyst forecast. It is an interesting direction for future research to analyze why this is the case.

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Chapter Three

The Marginal Information Content of Dividends and Earnings

3.1 Introduction

Value effects of dividend payouts have received a great deal of attention in corporate finance. A paper by Miller and Modigliani (Miller and Modigliani, 1961) drew a dividing line in this strand of the literature. Whereas previous studies seemed to agree on the existence of wealth effects of dividend announcements, Miller and Modigliani showed in a theoretical setting that this relationship is spurious and, given earnings, dividends cannot independently affect stock valuations. This seminal paper caused previously obtained results to be reconsidered and called for a more thorough examination of dividend and earnings firm value effects. My paper adds to the literature on the information content of dividends by employing an empirical investigation of analysts' dividend expectations in the U.S. from the I/B/E/S database, hitherto unexplored in this setting.

Disputes persist concerning dividend changes' responsibility for firm value change, as well as regarding an underlying explanatory theory. On the one hand, the present value theory suggests firm value is related to a discounted flow of future expected dividends (see Damodaran (2012) or an earlier textbook by Williams (1938), see Preinreich (1932); Clendenin and Cleave (1954); Gordon (1959) for research papers). Therefore, any unexpected dividend change should be accompanied by a corresponding change in stock market valuations of the firms to which this valuation method is being applied. On the other hand, according to Miller and Modigliani (1961), a firm's dividends and more generally its financing policy are irrelevant for the firm's value. The authors argue that what matters instead is a firm's ability to earn money and the risk it bears. In other words, earnings is a key parameter that is responsible for investors' appraisal of a firm, whereas dividends are not. Therefore, stock prices should not adjust to changes in a firm payout. Even if any firm value effects around dividend policy changes are empirically observed, then these indicate updated beliefs of market participants on noise-free earnings. This conclusion from Modigliani and Miller (1959) rests on the assumption that dividends have a potential to signal to the market the real unobservable earnings.

Despite a subsequent critique of the model's assumptions and implications, Miller and Modigliani sent an important message that conclusive results achieved by any empirical investigation of a payout policy's effect on stock prices, if any, is contingent on the consideration of firm earnings. I provide a number of tests that aim to isolate potential contemporaneous earnings effects on stock prices. In particular, I attempt to answer the question of whether dividends have an effect on a stock price independent of that of earnings. I contribute to the discussion using an underexploited identification strategy approximating market expectations with analysts' dividend expectations available from I/B/E/S.

Despite a long tradition of estimating the wealth effects of dividends, test results are still inconclusive. Most of the earlier efforts in empirical research were in favor of a dividend policy effect on stock prices (Fama et al., 1969; Pettit, 1972, 1976; Charest, 1978; Aharony and Swary, 1980; Woolridge, 1983; Handjinicolaou and Kalay, 1984; Eades et al., 1985; Asquith and Mullins, 1986; Lang and Litzenberger, 1989; Bajaj and Vijh, 1990; Dhillon and Johnson, 1994; Leftwich and Zmijewski, 1994; Yoon and Starks, 1995; Grullon et al., 2002; Andres et al., 2013). Watts (1973) refutes this premise. Gonedes (1978) and Amihud and Li (2006) also fail to support the hypothesis. In light of these conflicting findings, I revisit the topic of the information content of dividends.

The major problem in empirical tests of the dividends information content hypothesis is an inability to observe unexpected changes in dividends.[1] This was recognized as early as in the 1980s in Easterbrook (1984), where the author asserts: "These [consequences of dividends] are hard to evaluate, for it is hard to obtain a measure of unanticipated changes in the level of dividends, and only unanticipated changes could change the prices of shares." Thus, distinct dividend expectation models may be accountable for the mixed results on the validity of the information hypothesis. The existing literature, including the references listed above, estimates stock market effects using dividend decreases and increases as a measure of the unexpected dividend change.[2] This approach implicitly assumes constant dividends as a model of market expectations. A serious drawback of this naïve model is that an absolute dividend change contains some anticipated component. The model does not allow for updates in market beliefs in a period between subsequent dividend announcements, which clearly contradicts observable adjustments in analysts' estimates and recommendations.

In this paper I show that I/B/E/S analysts' consensus dividend forecasts represent a superior model of future dividends than naïve forecasts and encourage its implementation as a proxy for market expectations.[3] To the best

[1]Another empirical issue with a test of the dividend information hypothesis briefly mentioned above is that dividend announcements are often accompanied by earnings announcements. Therefore, an identification strategy that omits this factor risks falsely attributing an earnings information effect to that of the dividend.

[2]Another widely-used proxy for unexpected dividends is derived from Lintner's partial adjustment model in which a dividend change is a function of current earnings and lagged dividends (see Lintner (1956) and its modifications as in Fama and Babiak (1968)). The naïve model is found to offer a weaker description of dividends behavior than the Lintner model (Fama and Babiak, 1968).

[3]Brown and Rozeff (1978); Fried and Givoly (1982) use analysts' *earnings* estimates from

of my knowledge, the only paper that uses analysts' expectations from the I/B/E/S database in the dividends context, although on the German market, is by Andres et al. (2013). In drawing parallels to this study, though, attention should be paid to the existence of a different information and institutional environment in Germany, where dividends are paid once a year.[4] A large sample of analysts' dividend forecasts is available with the I/B/E/S database starting from 2002, which may explain why this intuitive proxy for market expectations has not been extensively used in prior research on dividends. Thus, using the reliable proxy for unexpected dividend changes that recently became available and controlling for earnings capacity to convey information allows me to contribute to the debate on the information content of dividends.

Moreover, my paper relates to the literature on valuation models used by stock market analysts. Contrary to the previously mentioned research which develops stock valuation models, researchers in this field study which of the theoretical models are being implemented for business purposes. Barker (1999) conducts a survey of UK fund managers and analysts and finds that price to earnings and dividend yield multiples are the most used valuation models in practice, whereas dividend discount models are disregarded by finance professionals. Still, most of the existing studies in this area show that the price-earnings ratio is dominant in pricing stock assets (Arnold and

Value Line and *Earnings Forecaster* to show that these better portray earnings than time-series models.

[4] Woolridge (1983) approximates market dividend expectations with analysts' forecasts from Value Line, an investment advisory firm. However, this sample is limited to only 367 observations. Most importantly, this study does not control for the earnings surprise.

Moizer, 1984; Previts et al., 1994; Bradshaw, 2002; Demirakos et al., 2004). Although my paper does not study which valuation methods correctly estimate firm value, it provides an empirical analysis suitable to answer the question of whether the dividend discount model is prevalent in stock valuation among stock market professionals.

A quick glance at the data reveals that dividend news does not cause investors to reconsider their stock valuations. In the samples where dividends and earnings announcements occur on the same day, the market goes together with a sign of earnings news even when dividend news is differently signed. Cumulative abnormal returns around dividend news sufficiently isolated in time from earnings news are not signed in line with expectations and are not statistically significant. Although these results are robust to the choice of test statistic, definition of a news event, and across subsamples, they do not consider share repurchases and thus may not be generalizable to the broader payout policy.

The rest of the paper is organized as follows. In Section 3.2 I describe my sample selection and the construction of key variables. Section 3.3 provides relevant descriptive statistics. Section 3.4 includes tests of the marginal informational content of dividends and earnings. Finally, Section 3.5 draws conclusions.

3.2 Data Selection and Variables

For the purpose of this analysis, I define two measures to classify dividend and earnings announcements as a negative, positive or no news event, namely, absolute and relative forecast errors. To group observations into these subsamples, I first compute dividend forecast errors (DFERR), that is, a signed difference between an actual value of dividend per share (DPS) and its mean analyst estimate. I identify positive (negative) dividend news, for the positive (negative) domain of analysts' forecast errors when dividend forecast errors (DFERR) are greater (smaller) than or equal to the median of positive (negative) analysts' dividend forecast errors (median DFERR). Analysts' dividend forecast errors below the median values of positive forecast errors and above the median values of negative forecast errors are classified as no dividend news observations. Analogously, I compute earnings forecast errors (EFERR) and identify negative, positive, and no earnings news (ENEWS negative, ENEWS positive, ENEWS zero).

The second measure used to partition the sample into negative news, no news, and positive news subsamples is relative forecast errors. Its calculation is similar to that of the absolute forecast error described above except that I scale dividend and earnings prediction errors (DFERR and EFERR) by price. In order to avoid picking up the effect of leaking information, I choose the stock price ten business days before an announcement date.[5] I iden-

[5]In the earnings management literature, forecast errors are deflated by the beginning of quarter *t* stock price (Brown and Caylor (2005), Bartov et al. (2002)), scaled by the stock price ten days before the announcement (Berkman and Truong (2009)), or by actual quarterly earnings.

tify positive (negative) dividend news, DNEWS positive (DNEWS negative), for the positive (negative) domain of analysts' prediction errors when the scaled dividend forecast errors (SDFERR) are greater (smaller) than or equal to the median of scaled positive (negative) analysts' dividend forecast errors (median SDFERR). Scaled analysts' dividend prediction errors below the median values of scaled positive forecast errors and above the median values of scaled negative forecast errors are classified as no dividend news observations (DNEWS zero). Analogously, I compute earnings forecast errors (EFERR), scaled earnings forecast errors (SEFERR) and next identify negative, positive, or no earnings surprise (ENEWS negative, ENEWS positive, ENEWS zero).[6] Using relative forecast errors allows me to account for the economic significance of a news event. Additionally, I use the absolute forecast error definition as a robustness check.

To construct my main variables, I use data from several sources. Data on analysts' expectations of quarterly dividends and earnings and their actual values are obtained from the I/B/E/S Summary U.S. forecasts file, and stock price data from the quarterly files of the CRSP-Compustat Merged. I source firm financial data from Compustat.

A universe of I/B/E/S analysts' estimates contains 686,297 firm-quarter-dividend and firm-quarter-earnings forecasts made for the next quarter. Due to the fact that analysts may stop and resume covering some firms, the data is frag-

[6]In this paper I use terms "news" and "surprise" interchangeably. Another way to define earnings surprises used in the earnings literature is to compare the forecast error to some reference point, for example, 10 percent bandwidth. Unlike the earnings literature, I consider both dividend and earnings surprises, and applying the same bandwidth to dividends would leave me with an insufficient number of observations. I therefore use a median threshold.

mented. The sampling period starts in January 2002 because of the first appearance of the dividend forecasts in that year, and extends to December 2012. Every month up to the forecast period end, I/B/E/S updates analysts' estimates. Among these monthly updates I select only the final ones prior to the earnings or dividend announcements. This way I exclude another 450,190 data points and I am left with 236,107 observations. I drop observations with no historical CUSIPs available. I further require data on realised dividend per share (DPS) and earnings per share (EPS) to be available, as well as their announcement dates. The last filter is needed to identify confounding earnings and dividend events, as described below.

For the main analysis, I collapse my I/B/E/S sample to firm-quarter observations where dividends and earnings disclosures are bundled simultaneously in a single announcement. This leaves me with 37,722 same day dividend and earnings announcements for 3,308 individual firms. To obtain relative forecast errors from this sample, I further need to scale them by stock prices on the tenth business day before an announcement. The latter is obtained from the CRSP-Compustat Merged database. Scaling reduces the sample to 37,395 observations for 3,247 individual firms due to missing stock price information in Compustat records (see Table 3.2.1). Some firms have stock price information around a disclosure, but not precisely on the tenth business day before an announcement. In these cases, I take the share price from the most recent day previous to the tenth day before an announcement when the security had a valid price. Four iterations are sufficient to find stock prices for all 114 observations, for which no data are found on the tenth business day preceding an announcement.

Subsequently, I obtain cumulative abnormal returns (CARs). Abnormal stock returns are computed based on one-factor market model residuals estimated by ordinary least squares from day -252 to day -2 with CRSP equally-weighted index returns. Since I require a minimum of 250 days of return data, the actual number of observations available for further analysis (see rows *CARs* in Table 3.2.1) is smaller than the initial number of dividend and earnings news events (see rows *Obs.* in Table 3.2.1).

I use three parametric and two non-parametric tests to test significance of CARs. I perform the Patell test, the cross-sectional and the standardized cross-sectional tests. For the non-parametric, the generalized sign test (Cowan test) and the rank tests (Corrado test) are carried out. Event windows are selected to account for leaking information.[7]

For an additional analysis, I also obtain subsamples with non-concurring earnings and dividend news. To be included in these subsamples, dividend and earnings announcements should occur with a time lag of at least one day and should constitute a positive or negative news event, according to the forecast error definition described above. A different subsample of non-concurring earnings and dividend news consists of dividend news that is

[7] Acker and Duck (2009) raise a concern with regards to the time-stamp errors in earnings announcements. They found a significant percent of I/B/E/S earnings announcement dates to be later than the true date when compared to the hand-collected data. This mislabelling may bias parameter estimates towards zero and lead to the significant returns before an earnings announcement to be falsely attributed to the information leakage. I obtain significant CARs around earnings announcements. This might be due to the fact that, according to the authors, Thomson Reuters has verified and corrected their earnings time stamps for European firms and at the publication date of their paper were about to start the same project for the U.S. firms.

neither preceded by earnings announcements less than three days before, nor followed by earnings announcements less than three days after.[8] This way I am able to isolate a market response to dividends in an event study setting. The three days before a dividend announcement restriction precludes an earnings spillover effect. The three days after a dividend announcement restriction helps to ensure that there is no leaking earnings information yet which can be priced. I use two subsamples with negative and positive dividend news obtained using absolute forecast errors. I do not scale prediction errors in order to avoid a further thinning of the sample due to the missing stock price information.

Also for the subsamples with non-concurring events, I obtain CARs. Here I estimate one-factor market model residuals with ordinary least squares for an estimation window of 250 days starting two days before an announcement. Since I require a minimum of 250 days of return data for parameter estimation, I am not able to generate CARs for some events. Table 3.2.2 demonstrates how many observations are included in the samples with non-concurring news events and used for an analysis in Section 3.4.1.

Analysts' dividend expectations is a more precise proxy for the market expectations than the naïve model commonly employed in the literature. A major drawback of the naïve model is that it does not account for updates in the market beliefs since the previous quarter dividend distributions. This is demonstrated in Table 3.2.3, where I compare forecast errors when a naïve

[8] Ofer and Siegel (1987) use a twelve-day window. Dhillon et al. (2003) use 2 days prior to and 5 days after dividend announcements.

model is applied, as well as analysts' point estimates. To obtain forecast errors for the naïve model using I/B/E/S, I need to assign actual dividends to quarters. For that I merge the I/B/E/S quarterly file with an annual file, which contains a calendar month of a firm's fiscal year. From Table 3.2.3, Panel A, we learn that analysts' forecast errors are smaller than those obtained with a naïve model. The t-test from the same table, Panel B confirms that mean forecast errors of a naïve model and analysts' forecasts are statistically significantly different.

Moreover, stock market analysts' estimates and recommendations form, to a great extent, opinions of other market participants. It is largely their recommendations that are used by less sophisticated investors to assess companies' future earnings and dividend streams and price stocks accordingly; it is their estimates that support trading by institutional investors (Malmendier and Shanthikumar, 2014).

Still, from the earnings forecasting literature, we know that analysts are generally overoptimistic, which is explained by cognitive biases or by their incentives to generate trading volume to support affiliated investment banking or mutual fund activities (Firth et al., 2013). Moreover, management guidance may have meetable and beatable forecasts as a consequence (Matsumoto, 2002; Richardson et al., 2004; Cotter et al., 2006). It follows that true market expectations might deviate from those of analysts.

If analysts exhibit biases with dividend estimates as with those of earnings, this might have certain implications for the validity of analysts' expectations as a model of market expectations. In this case analysts' dividend projections may be a biased estimate of market expectations in two directions predicted in the earnings literature. On the one hand, analysts may issue downward biased forecasts, which are easy to meet or beat. Then, in the case of a negative forecast error (a negative absolute difference between a realized and a forecasted dividend value), the absolute value of the true forecast error is larger than the absolute value of the empirically observed one. This way, the size of the empirically observed negative analysts' forecast error will, on average, underestimate the true stock market forecast error (that is, the true negative forecast error is more negative than the observed one). On the other hand, one may follow the trade generation logic and conjecture that analysts publish DPS estimates larger than their true expectations. In this case, the true positive forecast error is greater than the empirically observed one. It follows that the empirically observed positive analysts' forecast error will, on average, underestimate the true stock market forecast error.

This potentially significant concern about the validity of the proposed market expectations model, if any applies, is not very pronounced in my sample. As evident from Table 3.2.3, I find that the dividend forecast error is of an economically insignificant positive value for the whole sample and it is equal to 0.002 USD when restricting the sample with contemporaneous dividend and earnings announcements to non-zero dividend forecast errors (DFERR is winsorized at the upper and lower 1% levels). Therefore, if same biases apply to analysts' dividends forecasts, then in my sample analysts are neither systematically providing too positive forecasts, nor do they systematically adjust forecasts for managers to easily beat.

Moreover, it has been shown in the earnings literature that the market is able to factor in the biases that analysts may have when pricing the stocks. For example, Jegadeesh and Kim (2010) show that the market reaction is stronger for stock downgrades than upgrades in a sample of analysts' recommendation revisions from 1993 to 2006. Moreover, in their recent study, Hilary and Hsu (2013) demonstrate that analysts are consistent in their forecast errors so that investors may reliably adjust their forecasts by a certain number of cents.

3.3 Descriptive Statistics

In this section I describe statistical properties of the four subsamples tabulated and used in the main analysis. Table 3.3.1 provides relevant statistics. Mean dividend forecast errors (DFERR) range from -0.34 USD in the portfolio with both negative dividend and earnings surprises to 0.30 USD in the portfolio with negative earnings and positive dividend surprises, as shown in Table 3.3.1. The median dividend forecast errors are more moderate, being equal to only -0.02 USD and 0.03 USD for the negative and positive dividend surprise subsamples, respectively. Mean absolute dividend forecast errors are smaller than those for earnings in all four portfolios.

To understand how economically significant these prediction errors are, I scale the forecast errors by the stock price on the tenth day before an announcement. Table 3.3.1 shows that median values of both scaled dividend and earnings forecast errors (SDFERR and SEFERR) are of low magnitudes,

Table 3.2.1: Samples Formation with Contemporaneous Dividend and Earnings Announcements

This table describes main procedures in the construction of the subsamples with dividends and earnings announcements occurring on the same day. *Rel. FERR* and *Abs. FERR* stand for absolute and relative forecast errors, which are used to partition dividend and earnings announcements into negative, positive, or no news subsamples. Minus and plus signs indicate negative (actual dividends lower than prognoses) and positive (actual dividends higher than prognoses) news respectively. *Obs.* refers to the total number of observations available after filters described in the text. *CARs* stands for the subsamples of simultaneous dividend and earnings announcements for which there is sufficient stock price information to compute cumulative abnormal returns.

Rel. FERR	DNEWS(-) ENEWS(-)	DNEWS(-) No ENEWS	DNEWS(-) ENEWS(+)	Total DNEWS(-)
Obs.	633	1,536	835	3,004
CARs	595	1,489	807	2,891
Abs. FERR	DNEWS(-) ENEWS(-)	DNEWS(-) No ENEWS	DNEWS(-) ENEWS(+)	Total DNEWS(-)
Obs.	449	839	581	1,869
CARs	421	808	561	1,790
Rel. FERR	No DNEWS ENEWS(-)	No DNEWS No ENEWS	No DNEWS ENEWS(+)	Total No DNEWS
Obs.	4,622	17,276	9,266	31,164
CARs	4,493	17,008	9,039	30,540
Abs. FERR	No DNEWS ENEWS(-)	No DNEWS No ENEWS	No DNEWS ENEWS(+)	Total No DNEWS
Obs.	5,665	16,569	10,572	32,806
CARs	5,523	16,245	10,363	32,131
Rel. FERR	DNEWS(+) ENEWS(-)	DNEWS(+) No ENEWS	DNEWS(+) ENEWS(+)	Total DNEWS(+)
Obs.	463	1,784	977	3,224
CARs	445	1,753	935	3,133
Abs. FERR	DNEWS(+) ENEWS(-)	DNEWS(+) No ENEWS	DNEWS(+) ENEWS(+)	Total DNEWS(+)
Obs.	426	1,304	990	2,720
CARs	409	1,281	956	2,646
Rel. FERR	Total ENEWS(-)	Total No ENEWS	Total ENEWS(+)	Total
Obs.	5,718	20,596	11,078	37,392
CARs	5,497	20,250	10,781	36,564
Abs. FERR	Total ENEWS(-)	Total No ENEWS	Total ENEWS(+)	Total
Obs.	6,540	18,712	12,143	37,395
CARs	6,353	18,334	11,880	36,567

Table 3.2.2: Samples Formation with Non-Contemporaneous Dividend and Earnings Announcements

This table describes main procedures in the construction of the subsamples with dividends and earnings announcements occurring on different days. *FERR* stands for the forecast error definition, which is used to partition dividend and earnings announcements into negative and positive news subsamples. Minus and plus signs indicate negative (actual dividends lower than prognoses) and positive (actual dividends higher than prognoses) news respectively. *Obs.* refers to the total number of observations available after filters described in the text. *CARs* stands for the subsamples of simultaneous dividend and earnings announcements for which there is sufficient stock price information to compute cumulative abnormal returns.

Panel 1A. Earnings after dividends			
FERR	ENEWS(-)	ENEWS(+)	Total
Obs.	1,281	1,580	2,861
CARs	1,203	1,496	2,699
Panel 1B. Earnings after dividends in at least three days			
FERR	ENEWS(-)	ENEWS(+)	Total
Obs.	1,278	1,577	2,855
CARs	1,200	1,493	2,693
Panel 2A. Dividends after earnings			
FERR	DNEWS(-)	DNEWS(+)	Total
Obs.	918	1044	1,962
CARs	799	933	1,732
Panel 2B. Dividends after earnings in at least three days			
FERR	DNEWS(-)	DNEWS(+)	Total
Obs.	370	405	775
CARs	313	342	655
Panel 3. Dividends after and before earnings at at least three days lag			
FERR	DNEWS(-)	DNEWS(+)	Total
Obs.	351	363	714
CARs	212	238	450

Table 3.2.3: Comparison of Mean Analyst and Naïve Forecast Errors

Panel A provides descriptive statistics on the size of forecast errors with the naïve model and by analysts (both mean and median analysts' forecasts are considered). A naïve forecast error is defined as a current quarter dividend minus a previous quarter dividend. Analysts' forecast errors are defined as a mean (third column) and median (fourth column) analyst forecast minus the actual dividend. The last column reports t-tests for differences in means. * indicates t-test is significant at the 10% level. All variables are winsorized at the 1st and 99th percentile.

Panel A. Forecast errors descriptive statistics			
		Forecast errors	
	Naïve	Analyst (mean)	Analyst (median)
Obs.	56,765	66,339	66,339
Mean	0.003	0.001	0.001
Median	0	0	0
Std.	0.057	0.034	0.032
Min	-0.320	-0.180	-0.160
Max	0.318	0.200	0.200
Panel B. Mean-comparison test of the forecast errors			
Naïve-Analyst (mean)		0.0016	
t-stat		7.28***	
Naïve-Analyst (median)		0.0014	
t-stat		6.50***	

being in absolute terms smaller than 1% in all four subsamples. Scaled earnings forecast errors are greater in mean values, with a wider range than dividends: scaled dividend forecast errors range in absolute terms from 0.78% to 3.74%, whereas earnings range from 1.20% to 10.51%.

Table 3.3.2 provides descriptive statistics for the subsamples from Panels 1A—2B in Table 3.2.2. These statistics are instructive on how dividend and earnings announcements are distributed over time. As expected, and similar to Aharony and Swary (1980), these tend to be dividend announcements that are made after earnings announcements rather than vice versa. Dividends follow earnings news quite closely, in about 2 days (5 days a mean value) in the whole sample (see Table 3.3.2, Panel 2A). In Panel 2B, in order to investigate value effects of dividends, I exclude dividend news that happens less than three days after earnings because it is potentially more severely affected by the spillover effects of earnings news. The median number of days that separate a dividend announcement from a preceding earnings announcement amounts to 6 days. From Panel 1A we learn that earnings usually follow much later after dividends, with a median value of 86 days (a mean value of 81 days), which is close to the length of one quarter. Statistics from Panel 1B, which excludes cases where earnings were announced almost right after dividends, are close to those from Panel 1A for the reason that there are few such cases and the resulting subsample is not very different from the initial one.

Table 3.3.1: Descriptive Statistics of Forecast Errors in Four Subsamples

This table provides descriptive statistics relevant for an event study with four portfolios using an announcement day surprise definition. It reports magnitudes of forecast errors and the number of observations in four portfolios for which scaling prices are available.

		Rel. EFERR negative				**Rel. EFERR positive**			
		DFERR	EFERR	SDFERR	SEFERR	DFERR	EFERR	SDFERR	SEFERR
Rel. DFERR negative	Obs.	633				835			
	Mean	-0.34	-0.52	-2.07%	-10.51%	-0.17	0.18	-1.09%	1.75%
	Median	-0.02	-0.11	-0.13%	-0.62%	-0.02	0.08	-0.08%	0.36%
	Std.deviation	3.83	4.82	0.14	0.88	1.94	0.48	0.08	0.11
	Min, %	-74.000	-119.680	-2.453	-19.057	-54.000	0.010	-1.716	0.001
	Max, %	-0.002	-0.010	0.000	-0.002	-0.002	7.860	0.000	2.623
Rel. DFERR positive	Obs.	463				977			
	Mean	0.30	-0.31	3.74%	-2.42%	0.16	0.20	0.78%	1.20%
	Median	0.03	-0.11	0.13%	-0.52%	0.03	0.09	0.10%	0.32%
	Std.deviation	3.28	0.98	0.55	0.10	1.00	0.76	0.06	0.07
	Min, %	-0.02	-14.11	0.00	-1.58	-0.080	-0.120	0.000	0.001
	Max, %	68.700	0.260	11.684	-0.002	26.420	20.330	1.702	1.438

Table 3.3.2: Time Lag Between Non-Concurring Earnings and Dividend News

This table provides statistics on a number of days outstanding from a dividend to an earnings announcement (Panel 1) and from an earnings to a dividend announcement (Panel 2), which constitutes a positive or negative news event. Absolute forecast errors are used to classify an event as a positive or negative news. Panel 1A provides statistics for earnings following dividend announcements by no more than 92 days. Panel 1B provides statistics for earnings following dividend announcements by no fewer than 3 days and no more than 92 days. Panel 2A stands for the cases where dividends follow earnings by no more than 92 days. Panel 2B stands for the cases where dividends follow earnings by no fewer than 3 days and no more than 92 days.

Panel 1A. Earnings after dividends					
Obs.	Mean	Median	Std.	Min	Max
2,861	80.8	86	13.3	1	92
Panel 1B. Earnings after dividends in at least three days					
Obs.	Mean	Median	Std.	Min	Max
2,855	81.0	86	12.8	10	92
Panel 2A. Dividends after earnings					
Obs.	Mean	Median	Std.	Min	Max
1,962	5.1	2	9.4	1	91
Panel 2B. Dividends after earnings in at least three days					
Obs.	Mean	Median	Std.	Min	Max
775	10.8	6	13.1	4	91

3.4 Results

3.4.1 Univariate Analysis of Price Reaction to Dividend Announcements

I first approach the question of the information content of dividends in that I measure cumulative abnormal returns around dividend announcements

(CARs). For that purpose, I consider dividend declarations that may coincide with the earnings announcements but do not necessarily do so. I obtain samples with negative and positive dividend news from the I/B/E/S database using absolute and relative dividend forecast errors (for a reference to these samples' construction see Table 3.2.1, boxes *Total DNEWS(-)/DNEWS(+)*). If dividends were to drive stock market returns, then in the panel of dividend news (see Table 3.4.1) we should find significant CARs for both positive and negative announcements. Moreover, given that negative dividend surprises should make rational market participants adjust prices downwards, we would expect to find negative CARs.

Contrary to predictions, I obtain positive returns across both specifications of negative dividend news and across all event windows. Also, tests do not uniformly indicate a significance of stock market abnormal returns. In Panel A, Table 3.4.1, CARs(-1,1) are not significant for negative or positive dividend announcements based on three out of five tests. In Panel B of the same table, negative dividend news is not accompanied by any statistically significant changes in stock price for the three-day event window according to all five tests.

Table 3.4.1: Cumulative Abnormal Returns Around Positive and Negative Dividend Announcements

This table provides cumulative abnormal returns for five event windows as well as extensive tests statistics. In Panel A absolute forecast errors are used to partition the sample into positive and negative dividend announcements. In Panel B relative forecast errors are applied to obtain positive and negative dividend announcements. The second columns in each window show the number of events with positive and negative compounded abnormal returns. The third columns show mean cumulative abnormal returns in the first and median cumulative abnormal returns in the second row. The following tests are shown: the generalized sign test, the Patell test, the standardized cross-sectional (or Boehmer, Musumesi and Poulsen) test, the cross-sectional standard deviation and the rank tests. P-values are in parentheses. The generalized sign test significance levels are given in the second columns. The symbols (,<,≪, or),>,≫, show the direction and generic one-tail significance of the generalized sign test at the 0.10, 0.05, 0.01 and 0.001 levels, respectively.

Panel A. Dividend news using absolute forecast errors

	Total DNEWS(-)						Total DNEWS(+)					
Event window	**Obs.**	**CAR**	**Patell**	**BMP**	**CSectErr**	**Corrado**	**Obs.**	**CAR**	**Patell**	**BMP**	**CSectErr**	**Corrado**
(-1,0)	1,790	0.27%	2.586	1.427	1.831	1.102	2,646	0.07%	0.966	0.532	0.678	0.973
	911:879)		(0.0097)	(0.1535)	(0.0672)	(0.2716)	1325:1321		(0.3339)	(0.5944)	(0.4979)	(0.3313)
(-1,+1)	1,790	0.37%	2.256	1.074	1.663	0.469	2,646	0.24%	3.606	1.808	1.692	1.408
	913:877)		(0.0241)	(0.2827)	(0.0963)	(0.6394)	1356:1290>		(0.0003)	(0.0706)	(0.0906)	(0.1601)
(-1,+3)	1,790	0.31%	0.847	0.469	1.332	-0.406	2,646	0.26%	1.813	1.050	1.355	-0.241
	907:883		(0.3971)	(0.6392)	(0.1827)	(0.6848)	1311:1335		(0.0699)	(0.2938)	(0.1755)	(0.8097)
(-1,+5)	1,790	0.30%	1.065	0.675	1.257	-0.176	2,646	0.23%	1.092	0.713	1.235	-1.093
	914:876)		(0.2870)	(0.5000)	(0.2098)	(0.8607)	1309:1337		(0.2749)	(0.4760)	(0.2168)	(0.2755)
(-1,+14)	1,790	0.17%	0.134	0.111	0.615	-0.047	2,646	0.22%	1.659	1.374	0.907	-0.256
	893:897		(0.8935)	(0.9119)	(0.5386)	(0.9629)	1301:1345		(0.0971)	(0.1694)	(0.3645)	(0.7984)

Panel B. Dividend news using relative forecast errors

	Total DNEWS(-)						Total DNEWS(+)					
Event window	**Obs.**	**CAR**	**Patell**	**BMP**	**CSectErr**	**Corrado**	**Obs.**	**CAR**	**Patell**	**BMP**	**CSectErr**	**Corrado**
(-1,0)	2,891	0.18%	2.273	1.322	1.715	0.510	3,133	0.12%	2.398	1.345	1.315	1.918
	1442:1449		(0.0230)	(0.1860)	(0.0864)	(0.6103)	1584:1549>		(0.0165)	(0.1786)	(0.1884)	(0.0561)
(-1,+1)	2,891	0.19%	1.245	0.616	1.179	-0.205	3,133	0.28%	4.494	2.279	2.158	1.894
	1444:1447		(0.2131)	(0.5381)	(0.2383)	(0.8379)	1608:1525≫		(<.0001)	(0.0226)	(0.0309)	(0.0592)
(-1,+3)	2,891	0.17%	0.866	0.491	0.997	-0.380	3,133	0.33%	2.992	1.753	1.904	0.632
	1446:1445		(0.3864)	(0.6231)	(0.3190)	(0.7039)	1569:1564		(0.0028)	(0.0795)	(0.0569)	(0.5277)
(-1,+5)	2,891	0.14%	0.851	0.542	0.756	-0.235	3,133	0.26%	1.932	1.279	1.567	-0.266
	1461:1430)		(0.3950)	(0.5877)	(0.4494)	(0.8143)	1562:1571		(0.0534)	(0.2007)	(0.1171)	(0.7904)
(-1,+14)	2,891	0.06%	0.652	0.528	0.257	-0.441	3,133	0.24%	2.076	1.746	1.103	0.078
	1431:1460		(0.5144)	(0.5977)	(0.7975)	(0.6594)	1546:1587		(0.0379)	(0.0809)	(0.2699)	(0.9382)

The next set of results helps reconcile whether concurrent dividend *and* earnings announcements rather than dividends alone explain stock price changes[9]. To be classified as concurrent, dividend and earnings announcements should happen on the same day. Table 3.4.2 shows CARs over five event windows with 0 being the combined dividend-earnings on announcement day. Portfolios of unexpected dividend and earnings changes are formed using relative forecast errors. The left-hand side portfolios and the right-hand side portfolios have negative and positive earnings surprises respectively. The two upper portfolios and the lower portfolios have negative and positive dividend surprises respectively.

The tabulated event study results are highly statistically significant, indicating that a combined dividend-earnings announcement indeed constitutes a market value relevant event. The signs of the CARs in the case of conflicting signals allow us to speculate on their marginal power. In particular, the CARs are signed as the dividend surprise only if the dividend signal is supported by the same sign earnings signal: in the case of negative dividend surprises abnormal returns are significantly negative only if earnings surprises are negative as well and positive only if earnings surprises are positive. In cases where two signals are not aligned, the market moves together with the earnings surprise sign.[10] I also consider subsamples in which one of the an-

[9]For the construction of these samples refer to Table 3.2.1, boxes with negatively and/or positively signed dividend and earnings news

[10]As a robustness check, I repeated an event study using market-adjusted and comparison-period abnormal returns, with CRSP equally weighted as a market index. Obtained CARs for the portfolio with positive dividend and negative earnings news are significantly negative. Events from the portfolio with negative dividend and positive earnings surprises were accompanied by significantly positive abnormal returns, which justifies earnings surprises driving market returns, unlike dividend surprises.

nouncements contains no market surprise. The tests indicate insignificant results for the cases with zero earnings surprises, even when the dividend surprise is positively or negatively signed (results not tabulated). The structure of Table 3.4.3 is identical to Table 3.4.2, except that I use absolute forecast errors to partition observations into subsamples with differently signed news. The results found from this table qualitatively confirm those obtained with relative forecast errors. This demonstrates again that in the absence of an earnings surprise, dividend news does not move the market.

Table 3.4.2: Cumulative Abnormal Returns Around Contemporaneous Earnings and Dividend Announcements Using Relative Forecast Errors

This table provides cumulative abnormal returns for five event windows as well as extensive tests statistics. The upper-left portfolio includes both negative dividend and earnings news. The lower-left portfolio is comprised of positive dividend and negative earnings news. The upper-right portfolio includes observations with negative dividend and positive earnings news. The lower-right portfolio includes observations with both positive dividend and earnings news. The second columns in each window show the number of events with positive and negative compounded abnormal returns. The third columns show mean cumulative abnormal returns in the first and median cumulative abnormal returns in the second row. The following tests are shown: the generalized sign test, the Patell test, the standardized cross-sectional (or Boehmer, Musumesi and Poulsen) test, the cross-sectional standard deviation and the rank tests. P-values are in parentheses. The generalized sign test significance levels are given in the second columns. The symbols (,<,≪, or),>,≫, show the direction and generic one-tail significance of the generalized sign test at the 0.10, 0.05, 0.01 and 0.001 levels, respectively.

DNEWS(-), ENEWS(-)

Event window	Obs.	CAR	Patell	BMP	CSectErr	Corrado
(-1,0)	595	-1.27%	-9.927	-5.301	-3.704	-4.377
	239:356		(<.0001)	(<.0001)	(0.0002)	(<.0001)
(-1,+1)	595	-2.53%	-18.070	-6.781	-4.236	-7.436
	200:395		(<.0001)	(<.0001)	(<.0001)	(<.0001)
(-1,+3)	595	-2.76%	-14.917	-6.499	-4.482	-6.102
	205:390		(<.0001)	(<.0001)	(<.0001)	(<.0001)
(-1,+5)	595	-3.19%	-13.260	-6.765	-5.439	-5.927
	202:393		(<.0001)	(<.0001)	(<.0001)	(<.0001)
(-1,+14)	595	-3.72%	-8.801	-6.740	-5.888	-5.023
	208:387		(<.0001)	(<.0001)	(<.0001)	(<.0001)

DNEWS(-), ENEWS(+)

Event window	Obs.	CAR	Patell	BMP	CSectErr	Corrado
(-1,0)	807	1.49%	13.083	8.036	6.913	5.631
	494:313		(<.0001)	(<.0001)	(<.0001)	(<.0001)
(-1,+1)	807	2.50%	18.989	11.021	9.833	8.258
	536:271		(<.0001)	(<.0001)	(<.0001)	(<.0001)
(-1,+3)	807	2.45%	14.725	9.778	8.414	6.334
	516:291		(<.0001)	(<.0001)	(<.0001)	(<.0001)
(-1,+5)	807	2.61%	13.293	9.789	8.185	6.015
	523:284		(<.0001)	(<.0001)	(<.0001)	(<.0001)
(-1,+14)	807	2.82%	9.186	7.963	6.850	4.813
	483:324		(<.0001)	(<.0001)	(<.0001)	(<.0001)

DNEWS(+), ENEWS(-)

Event window	Obs.	CAR	Patell	BMP	CSectErr	Corrado
(-1,0)	445	-1.06%	-9.224	-5.260	-2.925	-3.828
	172:273		(<.0001)	(<.0001)	(0.0035)	(0.0002)
(-1,+1)	445	-2.17%	-15.970	-7.566	-4.295	-7.083
	157:288		(<.0001)	(<.0001)	(<.0001)	(<.0001)
(-1,+3)	445	-1.94%	-13.081	-6.900	-2.293	-6.363
	146:299		(<.0001)	(<.0001)	(0.0219)	(<.0001)
(-1,+5)	445	-2.26%	-11.118	-6.932	-3.551	-6.207
	155:290		(<.0001)	(<.0001)	(0.0004)	(<.0001)
(-1,+14)	445	-2.17%	-6.502	-5.292	-3.072	-4.064
	166:279		(<.0001)	(<.0001)	(0.0021)	(<.0001)

DNEWS(+), ENEWS(+)

Event window	Obs.	CAR	Patell	BMP	CSectErr	Corrado
(-1,0)	935	1.23%	14.792	8.329	6.788	6.688
	559:376		(<.0001)	(<.0001)	(<.0001)	(<.0001)
(-1,+1)	935	2.23%	22.196	11.687	8.150	9.229
	620:315		(<.0001)	(<.0001)	(<.0001)	(<.0001)
(-1,+3)	935	2.41%	18.021	11.009	7.581	7.814
	597:338		(<.0001)	(<.0001)	(<.0001)	(<.0001)
(-1,+5)	935	2.39%	14.393	9.782	6.204	6.294
	589:346		(<.0001)	(<.0001)	(<.0001)	(<.0001)
(-1,+14)	935	2.47%	10.298	8.964	4.549	4.510
	566:369		(<.0001)	(<.0001)	(<.0001)	(<.0001)

Table 3.4.3: Cumulative Abnormal Returns Around Contemporaneous Earnings and Dividend Announcements Using Absolute Forecast Errors

This table provides cumulative abnormal returns for five event windows as well as extensive tests statistics. The upper-left portfolio includes both negative dividend and earnings news. The lower-left portfolio is comprised of positive dividend and negative earnings news. The upper-right portfolio includes observations with negative dividend and positive earnings news. The lower-right portfolio includes observations with both positive dividend and earnings news. The second columns in each window show the number of events with positive and negative compounded abnormal returns. The third columns show mean cumulative abnormal returns in the first and median cumulative abnormal returns in the second row. The following tests are shown: the generalized sign test, the Patell test, the standardized cross-sectional (or Boehmer, Musumesi and Poulsen) test, the cross-sectional standard deviation and the rank tests. P-values are in parentheses. The generalized sign test significance levels are given in the second columns. The symbols (,<,≪, or),>,≫, show the direction and generic one-tail significance of the generalized sign test at the 0.10, 0.05, 0.01 and 0.001 levels, respectively.

		DNEWS(-), ENEWS(-)							DNEWS(-), ENEWS(+)				
Event window	**Obs.**	**CAR**	**Patell**	**BMP**	**CSectErr**	**Corrado**	**Event window**	**Obs.**	**CAR**	**Patell**	**BMP**	**CSectErr**	**Corrado**
(-1,0)	421	-1.03%	-8.073	-4.306	-2.511	-3.899	(-1,0)	561	1.54%	12.154	7.134	5.887	5.943
	164:257		(<.0001)	(<.0001)	(0.0121)	(0.0001)		355:206		(<.0001)	(<.0001)	(<.0001)	(<.0001)
(-1,+1)	421	-1.68%	-12.817	-6.347	-2.333	-6.867	(-1,+1)	561	2.36%	15.835	8.869	7.959	7.583
	136:285		(<.0001)	(<.0001)	(0.0196)	(<.0001)		367:194		(<.0001)	(<.0001)	(<.0001)	(<.0001)
(-1,+3)	421	-1.89%	-10.473	-6.283	-2.732	-5.560	(-1,+3)	561	2.27%	11.622	7.490	6.675	5.714
	143:278		(<.0001)	(<.0001)	(0.0063)	(<.0001)		358:203		(<.0001)	(<.0001)	(<.0001)	(<.0001)
(-1,+5)	421	-2.30%	-9.192	-6.134	-3.647	-5.006	(-1,+5)	561	2.41%	10.114	7.200	6.284	5.165
	143:278		(<.0001)	(<.0001)	(0.0003)	(<.0001)		355:206		(<.0001)	(<.0001)	(<.0001)	(<.0001)
(-1,+14)	421	-2.59%	-6.515	-5.525	-3.998	-3.892	(-1,+14)	561	2.46%	6.529	5.502	5.094	4.219
	149:272		(<.0001)	(<.0001)	(<.0001)	(0.0001)		331:230		(<.0001)	(<.0001)	(<.0001)	(<.0001)
		DNEWS(+), ENEWS(-)							DNEWS(+), ENEWS(+)				
Event window	**Obs.**	**CAR**	**Patell**	**BMP**	**CSectErr**	**Corrado**	**Event window**	**Obs.**	**CAR**	**Patell**	**BMP**	**CSectErr**	**Corrado**
(-1,0)	409	-1.28%	-13.227	-6.796	-3.328	-5.452	(-1,0)	956	1.02%	14.229	8.332	6.941	6.174
	143:266		(<.0001)	(<.0001)	(0.0009)	(<.0001)		566:390		(<.0001)	(<.0001)	(<.0001)	(<.0001)
(-1,+1)	409	-1.99%	-16.964	-8.341	-3.900	-7.655	(-1,+1)	956	1.83%	20.914	10.940	7.668	8.624
	132:277		(<.0001)	(<.0001)	(0.0001)	(<.0001)		607:349		(<.0001)	(<.0001)	(<.0001)	(<.0001)
(-1,+3)	409	-1.82%	-14.044	-7.530	-2.034	-6.865	(-1,+3)	956	1.98%	16.510	10.015	7.104	6.484
	130:279		(<.0001)	(<.0001)	(0.0420)	(<.0001)		591:365		(<.0001)	(<.0001)	(<.0001)	(<.0001)
(-1,+5)	409	-2.12%	-11.930	-7.399	-3.278	-6.363	(-1,+5)	956	2.02%	13.360	9.005	5.775	4.995
	134:275		(<.0001)	(<.0001)	(0.0011)	(<.0001)		586:370		(<.0001)	(<.0001)	(<.0001)	(<.0001)
(-1,+14)	409	-1.76%	-6.429	-5.239	-2.511	-3.491	(-1,+14)	956	2.04%	9.353	7.907	4.022	3.854
	146:263		(<.0001)	(<.0001)	(0.0121)	(0.0006)		575:381		(<.0001)	(<.0001)	(<.0001)	(0.0001)

With the third set of double sort results we can demonstrate whether an earnings effect survives a neutralization of a dividend factor. Table 3.4.4 contains the results of a double sort on dividend surprises followed by earnings surprises. Observations are first grouped into quintiles based on the size of scaled (negative or positive) dividend forecast errors. Next, I create decile portfolios based on the earnings surprise magnitude within each of these dividend quintiles. Finally, a dividend neutral top decile earnings portfolio is constructed by combining the five top decile earnings portfolios from within each dividend quintile (and similarly for the other nine earnings decile portfolios). E1 stands for the earnings decile with values of the lowest magnitude. E10 stands for the earnings decile with values of the highest magnitude.

Panels A and B from Table 3.4.4 show an effect of positive earnings news after the neutralization of a dividend factor. CARs are significant across all three event windows. As one would expect, and as also evident from Table 3.4.4, abnormal returns are higher in the top earnings decile portfolios compared to the lowest portfolios. A difference in CARs between the top five portfolios and the lowest five portfolios is about 8.48 percentage points for the five-day event window in Panel A and 7.38 percentage points for the same event window in Panel B. Similar observations apply to Panel C, where portfolios with the most negative earnings surprises generate negative returns at considerably larger magnitudes than portfolios with a moderate size of earnings surprise. Also in Panel D, the top five earnings decile portfolios are different from the lowest ones. Earnings are almost uniformly significant at the 1% level after a dividend neutralization of a double sort. The only exceptions are the largest earnings surprises in deciles nine and ten, which produce the lowest in size and nonsignificant returns. Overall, the earnings effect turns out to be robust to the neutralization of dividends. Hence, positive earnings news generates positive returns irrespective of the size and the sign of the dividend surprise; furthermore, negative earnings news causes plummeting returns independent of the dividend surprise.

Table 3.4.4: Double Sorted Results. Dividend Neutral Earnings Portfolios

This table documents mean CARs obtained for dividend neutral earnings portfolios. Observations are grouped using scaled forecast errors. Panels A and B present CARs on positive earnings news after dividend factor neutralization. Panels C and D contain the same results for negative earnings news after dividend factor neutralization. *E1* stands for the decile with values of the lowest magnitude. E10 stands for the decile with values of the highest magnitude. *High—Low* is computed as the simple difference between the sum of the five highest portfolios from E6 to E10 and the sum of the five lowest portfolios from E1 to E5. Based on the Patell test, *, **, *** indicate p-values significance at the 10%, 5%, and 1% levels, respectively.

	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	High—Low
Panel A. CARs from double sort on negative scaled dividend forecast errors and positive scaled earnings forecast errors											
(-1,0)	0.73%**	-0.02%	0.97%***	1.36%***	1.63%***	1.74%***	1.43%***	2.35%***	1.18%***	3.52%***	5.55%
(-1,+1)	1.46%***	0.26%*	1.85%***	2.30%***	2.87%***	2.97%***	2.65%***	3.63%***	2.30%***	4.70%***	7.51%
(-1,+3)	1.10%**	0.34%*	1.84%***	1.82%***	2.94%***	2.83%***	2.97%***	3.00%***	3.37%***	4.35%***	8.48%
Panel B. CARs from double sort on positive scaled dividend forecast errors and positive scaled dividend earnings errors											
	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	High-Low
(-1,0)	1.20%***	0.20%**	1.55%***	1.02%***	1.22%***	0.66%***	0.64%***	1.36%***	2.17%***	2.27%***	1.91%
(-1,+1)	2.00%***	0.34%***	2.44%***	1.97%***	1.62%***	1.22%***	2.48%***	3.02%***	3.40%***	3.82%***	5.57%
(-1,+3)	1.95%***	0.92%***	2.27%***	1.82%***	1.41%***	1.68%***	2.83%***	2.63%***	3.68%***	4.93%***	7.38%
Panel C. CARs from double sort on negative scaled dividend forecast errors and negative scaled earnings forecast errors											
	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	High-Low
(-1,0)	-1.39%***	-0.69%***	-1.21%***	-1.06%***	0.25%	-1.38%**	-0.77%	-0.07%	-2.78%	-3.35% ***	-4.25%
(-1,+1)	-2.50%***	-2.35%***	-1.89%***	-2.12%***	-1.17%***	-2.96%***	-2.18%***	0.87%***	-5.70%	-4.87% ***	-4.81%
(-1,+3)	-2.46%***	-2.29%***	-1.43%***	-2.36%***	-1.17%***	-3.70%***	-2.59%***	0.53%***	-6.41%	-5.29% ***	-7.75%
Panel D. CARs from double sort on positive scaled dividend forecast errors and negative scaled earnings forecast errors											
	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	High-Low
(-1,0)	-1.10%***	-0.91%*	-2.31%***	-1.53%***	-0.97%***	-1.86%***	-1.38%***	-1.47%**	0.72%	0.07%	2.9%
(-1,+1)	-1.26%***	-2.28%***	-4.01%***	-3.58%***	-1.90%***	-3.41%***	-2.50%***	-3.10%***	-0.30%	0.53%*	3.19%
(-1,+3)	-1.22%***	-2.00%***	-4.68%***	-3.85%***	-1.51%***	-3.79%***	-2.90% ***	-3.85%***	0.31%	3.89%	4.48%

The battery of results above is insightful for judging which firm financial information is relevant for firm valuation. The signs of abnormal returns seem to be driven by the sign of the earnings signal. Still, they are not sufficient to completely disregard the informativeness of the dividend signal. The next set of results presented in Table 3.4.5 and Table 3.4.6 serves as a clean test of whether unexpected changes in dividends are relevant for the stock market valuation.

To construct samples from Table 3.4.5, I use my analysis of a time lag between earnings and dividend events (for details see Table 3.2.2, Panels 1A—2B). In Panel 2A, Table 3.4.5, I compute CARs around a dividend news event with a distance of at least one day from an earnings announcement. Negative dividend events are accompanied by statistically significant negative CARs in four of the five event windows. However, with these results it should be taken into consideration that dividends often follow earnings in two days and results may be contaminated by an earnings effect. Accounting at least in part for this potential problem, I compute CARs for only that negative dividend news which is not preceded by earnings news for at least three days. Dividend news events are shown in Panel 2B to lose their significance. At the same time, CARs around earnings news are significant at the 1% significance level, also when computed for the subsample where earnings are more than three days from a dividend announcement (see Panel 1A and Panel 1B in Table 3.4.5).

For the analysis in Table 3.4.6, I use dividend announcements separated from earnings announcements (for details on this sample formation see Table 3.2.2, Panel 3). To be included in this sample, there must be no earnings announcements within a three-day announcement window centered around a dividend declaration event. As Table 3.4.6 indicates, only negative dividend news events from three event windows exhibit significant CARs; in all other negative and positive dividend news events CARs are not significantly different from zero. Overall, the results obtained do not support the notion that any changes in dividends unexpected by the market affect firm value. The combined evidence from the four sets of tests shows that dividend changes do not signal changes in the firm value to the market.

3.4.2 Multivariate Analysis of Price Reaction to Dividend Surprises

Since forecast errors may be correlated with other explanatory variables of abnormal returns (e.g., high forecast errors negatively correlated with firm information transparency), univariate analysis may not be sufficient to provide conclusive results. Therefore, in order to answer the question of whether meeting and beating dividend or earnings expectations has firm value consequences, I also model regressions controlling for firm specific characteristics. I include firm size, firm age, investment opportunities, and leverage as control variables. The results are provided in Table 3.4.7.

DFERRSIZE and *EFERRSIZE* in Table 3.4.7 stand for the size of dividend and earnings prediction errors, computed as the simple difference between the actual value and its mean analysts' estimate, including analysts' perfect fore-

Table 3.4.5: Cumulative Abnormal Returns Around Non-Concurring Earnings and Dividend News Events

This table provides cumulative abnormal returns around non-concurring earnings and dividend news events. Absolute forecast errors are used to classify events as containing positive or negative news. The first row of the *Obs.* columns shows the total number of events with negative (*ENEWS(-)*/*DNEWS(-)*) and positive (*ENEWS(+)*/*DNEWS(+)*) news. The second row presents the number of positive and negative *CARs* in the indicated event window to the left and to the right of the semicolon respectively. The *CAR* columns show mean cumulative abnormal returns and *p*-values of the standardized cross-sectional test in parentheses.

Panel 1A. Earnings news after dividend news					
ENEWS(-)			**ENEWS(+)**		
Event window	**Obs.**	**CAR**	**Event window**	**Obs.**	**CAR**
(-1,0)	1,203	-1.18%	(-1,0)	1,496	1.21%
	506:697	(<.001)		852:644	(<.001)
(-1,+1)	1,203	-2.93%	(-1,+1)	1,496	2.41%
	395:808	(<.001)		925:571	(<.001)
(-1,+3)	1,203	-3.27%	(-1,+3)	1,496	2.54%
	400:803	(<.001)		928:568	(<.001)
(-1,+5)	1,203	-3.06%	(-1,+5)	1,496	2.63%
	421:782	(<.001)		925:571	(<.001)
(-1,+14)	1,203	-2.75%	(-1,+14)	1,496	2.28%
	462:741	(<.001)		851:645	(<.001)
Panel 1B. Earnings news after dividend news in at least three days					
ENEWS(-)			**ENEWS(+)**		
Event window	**Obs.**	**CAR**	**Event window**	**Obs.**	**CAR**
(-1,0)	1,200	-1.18%	(-1,0)	1,493	1.21%
	504:696	(<.001)		849:644	(<.001)
(-1,+1)	1,200	-2.93%	(-1,+1)	1,493	2.41%
	395:805	(<.001)		924:569	(<.001)
(-1,+3)	1,200	-3.26%	(-1,+3)	1,493	2.55%
	400:800	(<.001)		927:566	(<.001)
(-1,+5)	1,200	-3.05%	(-1,+5)	1,493	2.64%
	421:779	(<.001)		924:569	(<.001)
(-1,+14)	1,200	-2.73%	(-1,+14)	1,493	2.30%
	461:739	(<.001)		850:643	(<.001)
Panel 2A. Dividend news after earnings news					
DNEWS(-)			**DNEWS(+)**		
Event window	**Obs.**	**CAR**	**Event window**	**Obs.**	**CAR**
(-1,0)	799	-0.41%	(-1,0)	933	-0.03%
	363:436	(0.035)		466:467	(0.408)
(-1,+1)	799	-0.51%	(-1,+1)	933	-0.01%
	375:424	(0.066)		454:479	(0.425)
(-1,+3)	799	-0.53%	(-1,+3)	933	-0.18%
	388:411	(0.048)		433:500	(0.135)
(-1,+5)	799	-0.25%	(-1,+5)	933	-0.26%
	413:386	(0.208)		442:491	(0.048)
(-1,+14)	799	-0.63%	(-1,+14)	933	0.10%
	400:399	(0.057)		447:486	(0.227)

Table 3.4.5 continued here

Panel 2B. Dividend news after earnings news in at least three days					
DNEWS(-)			**DNEWS(+)**		
Event window	**Obs.**	**CAR**	**Event window**	**Obs.**	**CAR**
(-1,0)	313	-0.45%	(-1,0)	342	0.12%
	144:169	(0.138)		164:178	(0.350)
(-1,+1)	313	-0.46%	(-1,+1)	342	0.14%
	148:165	(0.253)		164:178	(0.250)
(-1,+3)	313	-0.87%	(-1,+3)	342	0.01%
	150:1673	(0.046)		144:198	(0.117)
(-1,+5)	313	-0.27%	(-1,+5)	342	-0.03%
	164:149	(0.185)		163:179	(0.053)
(-1,+14)	313	-0.62%	(-1,+14)	342	0.09%
	162:151	(0.047)		152:190	(0.034)

sight cases when forecast errors equal zero. *DFERRSIGN* is a dummy variable equal to 1 for positive and zero for negative dividend forecast errors. *EFERRSIGN* is a dummy variable equal to 1 for positive and zero for negative earnings forecasts. Since in Models 3 and 4 I examine the effect of the sign of the forecast errors, I eliminate zero forecast error observations, which leaves me 7,127 firm-quarters. I also control for firm size, firm age, investment opportunities, and leverage. Since firm size is highly positively correlated with firm age, I use these variables interchangeably.[11] Firm size has been used in the literature as a control for the density of the informational environment of the firm (Amihud and Li, 2006). This means that investors accumulate

[11] I check formally for multicollinearity in my regression models. I do not find that my predictor variables are strongly correlated with each other. Thus, in Model 4 the variance inflation factor ranges from 1.00 to 1.04 for the coefficients on *dividend forecast errors size*, *earnings forecast errors size*, *dividend forecast error sign*, *earnings forecast errors sign*, and *firm age*. The variance inflation factor for *leverage* and *investment opportunities* coefficients is slightly higher and equals 2.4, which might be because the derivation of both variables includes the total market value of equity. Overall low values of the variance inflation factor indicate that estimated coefficients are not increased by much due to the inclusion of any predictor in the model.

Table 3.4.6: Cumulative Abnormal Returns Around Isolated Dividend Announcements

This table provides cumulative abnormal returns around dividend announcements. To be included in the sample, a dividend event must be isolated from an earnings event by at least three days. Dividend news is identified using absolute dividend forecast errors. The first row of the *Obs.* columns shows the total number of events with negative (*DNEWS(-)*) and positive (*DNEWS(+)*) dividend announcements. The second row presents the number of positive and negative *CARs* in the indicated event window to the left and to the right of the semicolon correspondingly. The *CAR* columns show mean cumulative abnormal returns and *p*-values in parentheses. The latter are the one-tailed *p*-values evaluating the null against the alternative that the mean is less than zero for negative dividend announcements and greater than zero for positive dividend announcements.

DNEWS(-)			DNEWS(+)		
Event window	**Obs.**	**CAR**	**Event window**	**Obs.**	**CAR**
(-1,0)	212	-0.70%	(-1,0)	238	0.04%
	112:100	(0.059)		130:107	(0.446)
(-1,+1)	212	-0.63%	(-1,+1)	238	-0.08%
	115:97	(0.094)		131:106	(0.596)
(-1,+3)	212	-0.91%	(-1,+3)	238	-0.28%
	107:105	(0.058)		133:104	(0.773)
(-1,+5)	212	-0.30%	(-1,+5)	238	-0.23%
	99:113	(0.309)		127:110	(0.692)
(-1,+14)	212	-0.97%	(-1,+14)	238	-0.77%
	99:113	(0.192)		137:100	(0.848)

more information about the older firm than the younger one by the time of an announcement. One therefore expects a weaker price reaction for a large, old firm and a negative sign on the *firm size*, *firm age* coefficients. *Firm size* is the logarithm of the sum of the total liabilities and the total market value of common shares outstanding at the quarter-end for single issue companies or the sum of all issue-level market values, including trading and non-trading issues, for multiple issue companies. *Firm age* is the number of years since the firm's first appearance in CRSP. In accordance with the literature, I also include investment opportunities and leverage as control variables (see, e.g., Andres et al. (2013)). The *investment opportunities* variable is approximated with the ratio of total market value of equity to total assets. *Leverage* is obtained as the ratio of total liabilities to the sum of the total liabilities and the total market value of common shares outstanding at the quarter-end for single issue companies or the sum of all issue-level market values, including trading and non-trading issues, for multiple issue companies.

As evident from Table 3.4.7, no statistically significant linear dependence between mean CARs and dividend news to the market can be found. Meanwhile, earnings related variables enter all four model specifications with significant coefficients. Models 1 and 2 predict that a dollar change in earnings forecast errors is associated with a change in CARs of 0.001 and 0.002 percentage points respectively. At the same time, declaring higher earnings than expected generates on average 0.04 percentage points higher returns (Models 3 and 4). The regression results allow us to conclude that it is the new information on earnings, rather than that on dividends, which causes market participants to review their price targets.

3.5 Conclusion

In this paper, I reexamine the information content of dividends. I empirically test whether dividends provide incremental information over and above that conveyed by earnings. My approach differs from that of the relevant literature in that I employ I/B/E/S analysts' forecasts as a more precise proxy for market expectations than the conventionally used previous quarter div-

Table 3.4.7: Regression Coefficients of Cumulative Abnormal Returns on the Forecast Errors and Control Variables

This table provides the results of estimating OLS regressions, where the dependent variable is CARs around contemporaneous announcements of dividends and earnings from the event window (-1,1). Explanatory variables are the size and the sign of earnings and dividend forecast errors. *DFERRSIZE* and *EFERRSIZE* stand for the size of dividend and earnings absolute forecast errors. Forecast errors are identified as the simple difference between the actual value and its mean analysts' estimate. *DFERRSIGN* is a dummy variable equal to 1 for positive and zero for negative dividend forecast errors. *EFERRSIGN* is a dummy variable equal to 1 for positive and zero for negative earnings forecasts. A set of control variables is obtained from the Compustat database. *Firm size* is defined as the log of the sum of the total liabilities and the total market value of common shares outstanding at the quarter-end for single issue companies or the sum of all issue-level market values, including trading and non-trading issues, for multiple issue companies. *Firm age* is the number of years since the firm's first appearance in CRSP. *Investment opportunities* is defined as the ratio of market value of equity to the book value of assets. *Leverage* is measured as the ratio of total liabilities to the sum of the total liabilities and the total market value of common shares outstanding at the quarter-end for single issue companies or the sum of all issue-level market values, including trading and non-trading issues, for multiple issue companies. The associated *p*-values are reported in parentheses.

	CARs(-1,1)			
	Model 1	**Model 2**	**Model 3**	**Model 4**
DFERRSIZE	-0.0004	-0.0004	-0.0003	-0.0003
	(0.298)	(0.303)	(0.311)	(0.288)
EFERRSIZE	0.001	0.001	0.002	0.002
	(0.000)	(0.000)	(0.000)	(0.000)
DFERRSIGN			-0.001	-0.001
			(0.535)	(0.441)
EFERRSIGN			0.038	0.037
			(0.000)	(0.000)
Firm size	0.00001		-0.002	
	(0.974)		(0.000)	
Firm age		-0.0001		-0.0001
		(0.026)		(0.002)
Inv.opportunities	0.002	0.002	0.002	0.002
	(0.000)	(0.000)	(0.054)	(0.183)
Leverage	-0.001	-0.002	0.003	-0.002
	(0.592)	(0.441)	(0.513)	(0.716)
Constant	0.003	0.002	-0.007	-0.02
	(0.923)	(0.285)	(0.133)	(0.000)
No. of obs	26,720	26,720	7,127	7,127
R-squared	0.003	0.004	0.08	0.08
F-statistic	18.46	19.46	92.57	90.92

idends. By combining price-reaction and expectations data in an event study and by means of a regression analysis, I examine whether unexpected changes in dividend policy explain changes in firm valuation. The specification of my event studies, in which I use analysts' dividend projections, sheds light on the discussion in the research literature on whether analysts prominently base their stock valuation models on dividends.

This study finds that, in a panel of U.S. companies in the period from 2002 to 2012, stock market participants did not price dividend information. In this paper, I show that the market neither appreciates nor depreciates the stock value of firms that exceed analysts' dividend expectations or fail to do so. I show that earnings, on the contrary, had a significant firm valuation effect. The absence of significant stock price effects from dividend surprises may indicate that dividend discount models have not been the prevailing asset valuation models among U.S. stock market professionals in the past decade.

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Chapter Four

Investor Awareness and Firm Payout Policy

4.1 Introduction

High investor awareness has been described in the literature as an important factor of the cost of capital and stock liquidity. In this paper I confirm and apply the fact that high geographic dispersion of the firm is generically associated with higher awareness among investors about this firm. At the same time, dividends have been shown in the literature to increase investor attention. I therefore hypothesize that a high level of investor awareness proxied by high geographic dispersion negatively affects a firm's payout. Empirically, I find that a wider geographic dispersion of the firm predicts lower levels of dividend payouts and repurchases. Consistent with the investor awareness explanation of the proposed negative relation between firm geographic dispersion and payouts, I find that retail firms exhibit lower dividend payouts than non-retail firms. Furthermore, I show that an awareness effect is also related to the size of the potential shareholder base and geographical area of firm operations. Additional evidence suggests that the effect is attributable to smaller size firms, which are expected to profit most from an increase in investor recognition.

This paper relates to a growing number of studies which recognize the importance of a firm's geography on stock market outcomes (Hong et al., 2008; García and Norli, 2012; Bernile et al., 2015; Smajlbegovic, 2015). These studies identify states which are of economic relevance to the firm, using its 10-K filings. Although I ask a different research question, my paper is close to this research in its methodology of defining geographic firm characteristics. Secondly, a different strand of literature investigates corporate policies implications of the firm's geography. To the best of my knowledge, a single paper which employs geographic measures in the dividends context is that by John et al. (2011). However, it uses a different geographic variable, which, unlike that of my paper, is used to proxy for a severeness of firm agency problems. Researchers find that firms with headquarters located in a highly populated metropolitan statistical area exhibit lower agency costs and, therefore, pay out lower dividends. Next, my paper relates to the Google search volume literature (Da et al., 2011; Bank et al., 2011; Fink and Johann, 2014). These studies use Google search inquiries to proxy for firm-specific investor attention (general attention to a firm and demand for firm financial information) and analyze stock market effects such as turnover and volatility of stocks, abnormal returns, and market capitalization. In contrast, this study investigates real effects, specifically, the payout policy effects of investor attention.[1]

This paper contributes to existing literature by offering important new evidence that investor awareness is an important factor in firm payout policy. I rely on extensive literature suggesting investor recognition effects of dividend payouts and repurchases. I quantify this effect. I formally test whether a degree of being observable to investors relates to the location dispersion of firm operations such as stores, construction sites, plants, logistic centers, and R&D facilities. Therefore, I investigate whether a state of being more observable to investors explains relatively lower payouts in such firms. Thus, my paper relates a firm's geographic dispersion to investor awareness and firm payout policy.

Merton (1987) was the first to realize that incomplete investor information about a population of stocks is responsible for an observed portfolio under-diversification. Limited investor awareness lowers a firm's market value and increases its cost of capital. Moreover, individual investors have been shown

[1] Another study explores the relationship between demand for product information measured with Google search volume and actual monthly sales of motor vehicles and parts dealers (Choi and Varian, 2012). However, while these results can pinpoint the ability of Internet searches to predict sales reported with a time lag, they cannot suggest a causal link to a firm operating performance.

to prefer to hold stock of firms with easily recognizable products (Frieder and Subrahmanyam, 2005). Therefore, firms have incentives to expand the breadth of investor awareness.[2]

One way for an investor to become aware of a firm is by being in the geographic area of the firm.[3] There are a number of reasons to hypothesize that investor awareness of the firm increases with the firm's geographic dispersion, other things being equal. Local bias is a well-established phenomenon which describes a tendency of both institutional and retail investors to allocate their capital into stocks of well-known and geographically proximate companies (see Coval and Moskowitz (1999, 2001); Baik et al. (2010) for evidence on institutional investors' local bias; see Grinblatt and Keloharju (2002); Huberman (2001); Bodnaruk (2009); Ivkovic and Weisbenner (2005); Seasholes and Zhu (2010) for evidence on individual investors' local bias). One possible explanation for local bias is familiarity. This phenomenon is described in Huberman (2001) and Keloharju et al. (2012). Huberman (2001) documents a tendency of investors to hold stock of providers of local telephone services. Keloharju et al. (2012) investigate investment behavior of car buyers from Finland and conclude that it is a patronage behavior of investors which makes them buy stocks of firms whose products they have experienced. Evidence from the local bias and familiarity litera-

[2]Following Merton, I will use the term "investor awareness" alongside with the term "degree of investor recognition" interchangeably, as well as "better-known" or "lesser-known" firms, and "firm visibility".

[3]I do not need an assumption about the character of an investor's familiarity with the firm. Theoretically, investors may encounter the firm's branch during their daily routines, whether using services or products of the firm, being employed by the company, from local news, or by word of mouth.

ture thus suggests that geographic dispersion of the firm positively relates to potential investor awareness.

Moreover, the existing literature suggests that firms may use dividends and repurchases to increase retail investor attention to the firm. In a survey of financial executives, Brav et al. (2005) report that on a scale from -2 to +2 about 45% of respondents either agree (+1) or strongly agree (+2) that paying out dividends helps a firm attract retail investors, with the average rating being significantly different from zero. The authors also find that, according to the managers' view, the relative importance of dividends is higher for retail than it is for institutional investors. Although some respondents (one fifth) believe that repurchases also attract retail investors, on average financial executive managers are inclined to disagree with this statement. Additional evidence suggests that firms may not only have the means to attract retail investors, but also should be interested in the retail investor ownership. Brav et al. (2005) document some managers' confessions that retail investors tend to hold a firm stock longer than institutional investors if signs of troubles appear. Whereas Brav et al. (2005) offer managers' views in support of the notion that dividends are able to attract the attention of investors, Drake et al. (2012) provide a direct empirical assessment of this effect. The latter study measures abnormal Google search volume and finds that it is significantly positively associated with dividend announcements.

Combining the argument of a firm payout policy's ability to attract potential investors' attention and the above discussion of a generic investor awareness due to proximity to the firm's locations, I expect widely dispersed firms to adopt lower payout strategies. I assume that a decision on a firm's location is not driven by the firm's dividend policy. While it is very unlikely that a firm expands its geographical area for reasons related to stimulating investor recognition, it is quite probable that a firm's management considers, inter alia, the achieved level of investor recognition when setting its payout policy. This conclusion is based on the lifecycle theory of a firm, which suggests that it is usually mature firms that start paying out dividends. This suggests that a firm's decision to locate its operations precedes setting the payout policy and is independent of the latter.

In this paper I make use of firm geographic data to develop a novel way of measuring investor awareness. I do so by counting the number of state citations in the firm's 10-K filings. 10-K filings, or annual reports, contain relevant firm and market information including information on, inter alia, the location of subsidiaries, firm facilities, construction sites, production plants, and stores. Using information on economically relevant states' locations, I construct measures of investor awareness about the firm.

I conduct a number of tests to confirm that using information on a firm's geographic location is a reasonable method to proxy for investor awareness. I hypothesize that if geographic dispersion is a good proxy of awareness then it should be manifested in the Internet searches of a firm. Using Google Trends, I extract data on Google search volume of a firm name across U.S. states. Analysis of this data allows to see that firms are indeed searched for on the Internet from those states which are classified as economically relevant according to the 10-K filings. In 95% of firm-year observations, companies have a higher Google search volume from the states where they are economically present than from other states. This and other pieces of evidence suggest that key explanatory variables which I construct using geographic firm characteristics are informative about the degree of potential investors' firm awareness.

This paper's key finding is that a higher investor awareness proxied by a total number of states in the 10-K filings is associated with a lower level of firm payout, all things being equal. A growth of about three states in the firm's economic presence is associated with a 0.06 percentage point decrease in the dividend yield after controlling for the firm's market capitalization, free cash flows, investment opportunities, return on assets, option incentives, industry and year fixed effects. This result may first seem economically insignificant. However, given the mean value of the sample dividend yield of 0.9%, this result corresponds to a substantial dividend yield decrease of 7%. In a similar panel regression using repurchase yield as a dependent variable, I obtain a coefficient of -0.16 on a logarithm of one plus the total number of states, or an 8% decrease in the repurchase yield.

Next, I develop other measures of investor awareness based on the data on a firm's geographic locations. Specifically, I compute the total population in the states where firms are economically present. I also weight this measure by population wealth. I calculate the total area of states with a firm's economic presence and the measure of a firm's geographic concentration. Key results hold when implementing these geography based proxies of investor attention. In other tests I control for the dividend clientèle explanations of dividends and proximity to investors.

The remainder of the paper is organized as follows. In Section 4.2 I describe my data sampling procedure and present descriptive statistics. In Section 4.3 I provide evidence of the relationship between firm geographic characteristics and a firm payout policy. The explanation of this effect related to investor awareness of a firm, as well as robustness checks are contained in Section 4.4. Section 4.5 concludes.

4.2 Data

4.2.1 Sampling Procedure

Data for the main analysis comes from various sources. I begin with collecting firm operations data and data on control variables as described in detail in the next two sections.

First, I collect balance sheet, income statement items, payout variables, as well as some firm location information (state and county code) from Compustat North America. Secondly, I obtain data on executive compensation from the ExecuComp database. Information regarding executives' salary, bonus, or stock options only begins in 1993. So my analysis is limited to the sample with data on an annual basis that runs from 1993 to 2010. I then proceed by applying the following filters to the sample.

My sampling procedure parallels that of John et al. (2011). Specifically, I exclude firms incorporated or located outside the U.S.. To avoid confounding effects of certain regulatory environments, I exclude financial (SIC codes 6000—6999) and utility firms (SIC codes 4900—4999). Finally, I exclude firms with total asset values of less than $20 million. All variables are winsorized at the 1st and 99th percentile levels to reduce the effect of possibly spurious outliers.

Since I analyze firm payout decisions, I consider dividends, share repurchases, and total payouts as the main dependent variables. Total payouts are equal to the sum of dividends and share repurchases. For all payout variables I calculate per share measures and yields.

4.2.2 Geographic and Demographic Data

As shown in the literature, headquarters locations and, in particular, their distance to potential investors, large banks or financial centers, at least partially determine information costs (e.g. Sulaeman (2014); Malloy (2005)) and thereby affect corporate payout policy (e.g. John et al. (2011)). To account for differences in information costs due to different headquarters locations, I apply various distance measures. First, I follow an approach by Loughran and Schultz (2005) to identify centrally located firms. I use the ten largest consolidated metropolitan statistical areas (CMSAs) based on population as reported in the 2010 Census. I construct an indicator variable that is set to one if the firm's headquarters are located in one of the ten largest CMSAs based on population size, and zero otherwise.[4] According to John et al., 2011,

[4]The 10 largest CMSAs based on population are New York City, Los Angeles, Chicago, Washington-Baltimore, San Francisco, Boston, Philadelphia, Dallas, Miami, and Houston, in-

p.535, “firms located farther away from large cities with high concentration of ownership [...] pose higher monitoring costs”. Therefore, in addition to the indicator variable, I also calculate the logged distance between the firm headquarters and the closest metropolitan statistical area outside the 10 largest CMSAs. Since firms located within one of the ten largest CMSAs exhibit a distance of zero, I use the log of one plus the distance in kilometers. Also, population in the headquarters location can be responsible for the level of dividends. Becker et al. (2011) argue that firms located in counties with a high proportion of local senior investors are more likely to pay dividends. Following their definition, I calculate the proportion of individuals aged 65 or older on a state level.

By restricting firms’ locations to the headquarters, one ignores the fact that firms substantially differ in their regions of economic activity. Results previously obtained in the literature using the firm headquarters location can therefore be viewed as a part of a broader effect, which is not only related to the firm’s headquarters location but also extends to other firm locations. I therefore construct different measures of economic activity on a state level. In the spirit of García and Norli (2012), I use a 10-K based measure of economic activity. The economic relevance of a state in a given year is obtained by parsing through the company’s 10-K filing and counting the number of citations of that state. To distinguish firms that operate locally from firms that spread their economic activities over the whole U.S., I use the log of one

cluding their suburbs. In addition, I re-run all analyses based upon the 25 largest CMSAs. The other 15 cities include Atlanta, Detroit, Seattle, Minneapolis, Cleveland, Denver, Portland, Orlando, St.Louis, Pittsburg, Charlotte, Sacramento, Kansas City, Salt Lake City, and Columbus, including their suburbs. The results of these analyses (untabulated) are qualitatively similar.

plus the number of states which have at least one count in the firm's 10-K filing in a given year. I compute direct distances using latitudes and longitudes of the midpoints of each state. The coordinates are obtained from Google Maps.

Three refinements of the geographic dispersion variable are made. First, an analysis of a within-firm variation in the geographic dispersion allows us to identify cases with sudden jumps in the number of reported states with firm operations. A close-up analysis of these types of filing suggests that they mainly come from changes in reporting standards. I drop these observations from the analysis.[5] I also make a further refinement of the geographic dispersion variable. Namely, I substract one state from the total number of states mentioned in the 10-K filings in case the headquarter state differs from the state of incorporation. This adjustment of the explanatory variable is motivated by the fact that some firms are incorporated in the states due to preferable tax treatment, administrative or legal considerations. In these cases firms often act through an agent and are themselves not physically located in the state of incorporation. For this reason they are not economically

[5] I allow for both positive and negative changes in the number of state counts. This implies that firms may, for example, introduce a reporting policy of mentioning store locations or they may stop reporting store locations. The geographic dispersion variable will then be misspecified, respectively, before and after the introduction of a change in a reporting standard. Another important concern applies to sudden positive changes, because these may be due to acquisitions. Since an acquisition may trigger some other unobservable factors which affect the outcome variables, this motivates an exclusion of these cases from analysis, in addition to the aforementioned misspecification problem. Another potential misspecification problem relates to the possibility of differences in reporting standards across the firms. If these differences exist, then the geographic dispersion variable would underestimate firm geographic dispersion for firms that implement a policy of never reporting their store locations, in contrast to those firms that have the opposite policy, namely of always reporting this information. Conditional on the existence of such differences, the misspecification could introduce a bias in my estimation results. Unfortunately, I cannot identify whether and to which extent this potential misspecification problem is present in my data, and treat these cases accordingly.

present in the state in the way which motivates a usage of state counts in this study. Next, a frequency distribution of geographic dispersion is right-skewed as shown in Figure 4.2.1. To normalize the distribution, a logarithm of one plus the total number of state counts is used in the analysis.

For additional tests I compute geographic concentration, population from the states with operations, and geographical area variables. Following the literature, I define the geographic concentration measure as the sum of squared citation shares.[6] I also account for the overall population in the region of economic activity, since it positively relates to the size of the potential investor base. Since areas of the states differ in size, I account for this fact by computing the total area of the states where a firm is present. To that end, I use the state population and state area from the 2010 Census. Among the above described geography based proxies of potential investor awareness, the latter may be considered as a noisy one, because it includes barely populated or even uninhabited areas.

4.2.3 Other Firm Characteristics

Geographic measures could be correlated with a firm-specific variable that affects the level of payouts in the same direction, as I expect of the geographic dispersion (e.g. firms with more operations locations could exhibit more profitable investment opportunities and have therefore lower dividend

[6] Variations of a concentration measure have been used in the literature. Bernile et al. (2015) define a citation concentration variable as the sum of squared citation shares divided by the square of the sum of citation shares. I follow García and Norli (2012); Smajlbegovic (2015) in adapting the Hirschman-Herfindahl index to state citations.

payouts). I therefore include a set of control variables standard in the payout literature before drawing any statistical inference on the relationship between dividends and a firm's geographic dispersion. Apart from the geographic and demographic firm characteristics, I introduce in the baseline regressions, inter alia, market-to-book ratio, firm size, profitability, free cash flows, and executive stock options.

An important determinant for the choice between dividends and repurchases, as well as for the amounts disbursed to shareholders is the existence of a managerial stock option program. Managerial stock options are typically not "dividend protected". As a consequence their value is diluted when a firm pays dividends. Managers in firms with stock option plans therefore have incentives to cut on dividend payouts, and may prefer repurchases over dividends (Jolls, 1998; Kahle, 2002). To account for this, I include the number of unexecuted managerial stock options normalized by shares outstanding. CEO stock options are expected to enter dividend regressions with a negative sign (Lambert et al., 1989). Repurchases, on the contrary, have been shown to be positively affected by unexcersized executive stock options (Kahle, 2002). Existing literature suggests that dividends and repurchases can be used to disburse free cash flow and may thereby reduce agency costs. Accounting for the agency costs explanation, I also include free cash flows (Easterbrook, 1984; Jensen, 1986; Stulz, 1990).[7]

[7] In John et al. (2011) free cash flow is defined as the ratio of cash flow (operating income before depreciation, minus interest expense, minus income taxes net of the change in deferred tax and investment tax credits) to assets, times 100, if market-to-book is below one; zero otherwise. I adopt their free cash flow definition, except that I assume interest expense and income taxes net of the change in deferred tax and investment tax and investment tax credits in calculations to equal zero if these are missing. This may introduce a measurement error for the highly lev-

Moreover, managers have been shown to be primarily concerned about dividend stream stability (Lintner, 1956). Mature, profitable firms are normally more likely to sustain a steady dividend payout. I therefore include a firm's market capitalization and its return on assets (ROA) into dividend regressions and expect a positive coefficient on these variables. Growth firms exhibit significantly lower dividend yields than non-growth firms (Rozeff, 1982; Smith and Watts, 1992; Gaver and Gaver, 1993). To account for variation in dividends due to variation in investment opportunity sets, I use a market-to-book ratio.[8] Detailed definitions of control variables can be found in Appendix 4.A. Additional controls used in sensitivity tests are described in the robustness section.

4.2.4 Descriptive Statistics

Table 4.2.1 presents summary statistics for payout policy variables, geographic data, and control variables. On average firms pay an annualized dividend of 26 cents per share and exhibit an average dividend yield of 0.84%. Since not only the minimum but also the median dividend yield is zero, I

ered firms; on the benefit side I am able to retain many potential observations. Also, I set the free cash flow to missing if market-to-book is unavailable. In a different specification of free cash flow, I assume not all missing interest expense observations to equal zero, but only those for which leverage is less than the sample median leverage. Main results remain qualitatively and quantitatively similar (untabulated).

[8]The rationale behind using the market-to-book ratio is that the difference between the market and book values represents the value of the firm's investment options. However, the investment opportunity set may be misspecified when using the market-to-book ratio. Another important consideration is that dividend yields and market-to-book ratios are both defined using stock prices, which may result in spurious correlation. I follow the most recent studies on dividends in selecting my measure of investment opportunities (John et al., 2011). In order to partially account for difficulties in empirical research related to the market-to-book ratios, I also use dividends per share apart from dividend yields and dividend payout ratios in order to study payout choices.

conclude that in many cases no dividend is paid at all. To examine the use of dividends more precisely, I define a dividend payer indicator variable that equals zero if a firm never pays a dividend and one if a firm pays dividends at least once over the sample period. Of the 2,450 firms in the sample, 861 firms (or 35%) paid dividends at least at some point in the sample time period. Dividends are on average less than half of the total payouts. This is in line with the findings of Grullon and Michaely (2002), that share repurchases have gained in importance and exceeded aggregate dividend payments at least in some years since 1999. Moreover, repurchases are more volatile than dividends. This pattern is consistent with managers using share repurchase in a more flexible way than they use dividends (Jagannathan et al., 2000).

In 42% of all firm-year observations, the headquarters are located in one of the ten largest CMSAs. The average firm in the sample is located 120 kilometers from the nearest of the ten largest CMSAs. However, the median distance of five kilometers is notably smaller, indicating a right-skewed distribution. These statistics suggest that while many headquarters are located in or close to the largest cities, a substantial number of firms' headquarters are located more than 100 kilometers away. In contrast to my summary statistics, 53% of sample firms from John et al. (2011) are located in top-ten metropolitan statistical areas, based on Census 2000, with the median distance to the top-ten big city being zero kilometers. These statistics indicate that the sample firms from John et al. (2011) are located more centrally than the firms from my sample. These differences, however, may be explained with our samples composition. The Census 2000 top-ten cities include Detroit. Since then the city has gone through a major economic and demographic decline. The reduction in population explains why Detroit is no longer among the top-ten biggest cities according to the Census 2010. Instead, the Miami area, which was not previously included, has appeared on the Census 2010 list of the mostly populated areas. Moreover, the timespan covered by my sample is three years longer.

By construction, the number of distinct states cited can take a value between 1 and 50. The value of one indicates that a company operates solely in the state of incorporation.[9] A value of 50 indicates that a firm operates in all 50 states. The average firm in my sample operates in 14 states. This is a first indication that the region of economic activity is much larger than just the county or the state where the headquarters are located. The range is wide, from 1 to 50 in all years; the overall standard deviation is 10.3. These statistics suggest that sample firms substantially differ in their regions of economic activities. The cross-sectional distribution of the sum of states cited is also depicted in Figure 4.2.1.

[9]In the 10-K filings firms are obliged to name a state of incorporation and a full business address, which includes a state. The state of incorporation can deviate from the state of the headquarters location.

Table 4.2.1: Summary Statistics of the Main Variables

This table provides summary statistics of the main dependent, explanatory, and control variables. The sample includes Compustat firms with available geographic, demographic, and CEO compensation data, and excludes financial firms (SIC 6000—6999), regulated industries (SIC 4900—4999), firms with total assets below $20 million, and firms incorporated outside the USA or in the non-contiguous territories. The sample period is 1993—2010. Dividend yield is the ratio of dividends on common stock to the market value of common equity, times 100. Repurchase yield is the ratio of repurchased common stock to the market value of common equity, times 100. Total payout yield is the ratio of the sum of dividends on common stock and repurchased common stock to the market value of common equity, times 100. Dividend payout ratio is the ratio of dividends on common stock to the total payout on common equity, times 100. Dividend payer is an indicator variable equal to one if a firm pays dividends at least once over the sample period and zero if a firm never pays a dividend. Geographic dispersion is the number of states cited at least once in a firm's SEC 10-K filing. Geographic concentration is defined as the sum of squared state citation shares, where state citation share is the number of state counts in a 10-K filing divided by the total number of counts of all states in the 10-K filing (SEC 10-K filings). Central location in top 10 (25) consolidated metropolitan statistical area (CMSA) is a dummy set to one if a firm's headquarters (Compustat) are located in the top 10 (25) CMSA; zero otherwise. Distance to top 10 CMSA is the distance in kilometers or miles from the firm's headquarters location to the middle point of the closest CMSA if the firm's headquarters are located outside the top 10 CMSA; zero otherwise. Distance is the logarithm of one plus the distance in miles to the closest top-ten metropolitan area, based on the 2010 Census. Geographical area is the total area of the states which a firm mentions at least once in its 10-K filing (Census 2010). Population is the total number of the population from the states (Census 2010) for which a firm's state count is non-zero (SEC 10-K filings). Older 65 is the ratio of the population older than 65 years old to the total population from the headquarters state (Census 2000, Census 2010), times 100. Free cash flow is the ratio of cash flow (operating income before depreciation, minus interest expense (if available), minus income taxes net of the change in deferred tax and investment tax and investment tax credits (if available)) to total assets, times 100, if market-to-book is available and below one; equal to zero if market-to-book is available and higher than one; and missing if market-to-book is unavailable. Firm size is the market value of common equity, with the stock price being the average stock close price during a fiscal year. Market-to-book is the ratio of firm market value (book value of total assets, plus market value of common equity, minus book value of common equity) to total assets. ROA is the ratio of EBITDA to total assets. CEO options is the ratio of the total number of unexcercised options vested and not yet vested held by the executive at the fiscal year end to the number of shares outstanding (ExecuComp). All dependent and control variables are winsorized at the 1% and 99% percentile.

	Obs.	Mean	Median	Min	Max	Std
			Panel A. Dependent variables			
Dividend yield [%]	20,674	0.9	0	0	7.1	1.4
Repurchase yield [%]	19,209	2.1	0.2	0	23.2	4.0
Total payout yield [%]	19,173	3.1	1.6	0	26.7	4.6
Dividend / total payout [%]	14,109	42.1	29.6	0	100.0	41.7
Dividend payer	2,450	0.35	0	0	1	0.48
			Panel B. Explanatory variables			
Geographic dispersion	20,725	14.2	11.0	1.0	50.0	10.3
Geographic concentration	20,725	0.28	0.25	0.028	1	0.16
Central location (top 10)	20,725	0.42	0	0	1	0.49
Central location (top 25)	20,725	0.62	1	0	1	0.49
Distance to top 10 [km]	19,183	120.430	4.646	0	1,061.347	196.745
Distance to top 10 [miles]	19,183	74.832	2.887	0	659.490	122.252
Distance	19,183	2.28	1.36	0	6.49	2.37
Geographical area [km^2]	20,051	120,286	42,451	0	1,127,921	201,137
Population [mln]	20,944	130	116	0	308	71,1
Older 65 [%]	20,726	12.8	12.9	7.7	17.3	1.6

Table 4.2.1 continued here

			Panel C. Control variables			
Free cash flow	15,949	0.580	0.000	-2.813	13.510	2.405
Firm size	20,715	5,242.538	1,050.925	41.209	103,418.900	14,312.660
CEO options	20,715	0.029	0.022	0.000	0.130	0.025
Market-to-book	15,951	2.158	1.655	0.718	10.077	1.556
ROA	20,674	0.140	0.140	-0.257	0.428	0.103

Figure 4.2.1: Histogram of the Number of Distinct State Counts

This graph shows the frequency distribution of geographic dispersion across all firm-year observations. The sample includes Compustat firms with available geographic, demographic, and CEO compensation data, and excludes financial firms (SIC 6000—6999), regulated industries (SIC 4900—4999), firms with total assets below $20 million, and firms incorporated outside the USA or in the non-contiguous territories. The sample period is 1993—2010. Geographic dispersion equals the total number of distinct states mentioned at least once in the firms' U.S. Securities and Exchange Commission annual report (SEC 10-K filings).

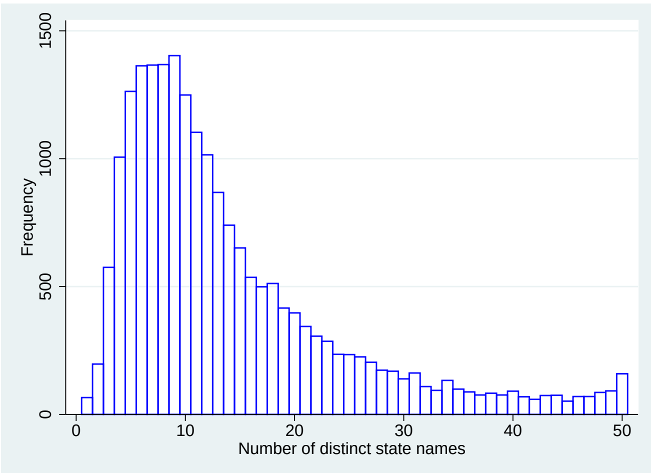

Table 4.2.2: Evolution of the Total Number of Distinct States Mentioned in the 10-K Filings

This table provides key statistics on geographic dispersion. The sample includes Compustat firms with available geographic, demographic, and CEO compensation data, and excludes financial firms (SIC 6000—6999), regulated industries (SIC 4900—4999), firms with total assets below $20 million, and firms incorporated outside the USA or in the non-contiguous territories. The sample period is 1993—2010. Geographic dispersion equals the total number of distinct states mentioned at least once in a firm's SEC 10-K filing.

Year	Obs.	Mean	Med.	Min	Max	Std.
1993	463	15.6	14	1	50	9.5
1994	751	14.4	12	1	50	9.1
1995	904	13.7	11	1	50	9.2
1996	1,258	13.3	11	1	50	9.3
1997	1,314	13.4	10.5	1	50	9.5
1998	1,318	13.5	11	1	50	9.8
1999	1,248	13.6	11	1	50	10.0
2000	1,199	13.9	11	1	50	10.2
2001	1,217	14.3	11	1	50	10.4
2002	1,230	14.4	11	1	50	10.6
2003	1,252	14.5	11	1	50	10.6
2004	1,218	14.7	11	1	50	10.8
2005	1,137	15.1	11	1	50	11.0
2006	1,211	14.7	11	1	50	10.8
2007	1,300	14.3	11	1	50	10.7
2008	1,267	14.3	11	1	50	10.7
2009	1,242	14.3	11	1	50	10.8
2010	1,196	14.5	11	1	50	11.0
Total	20,725	14.2	11	1	50	10.3

Besides cross-sectional variation, I also observe some variation over time. Table 4.2.2 shows the evolution of the number of states cited in the 10-K filings. In line with the findings of García and Norli (2012), the number of states is slightly higher in the early years, decreases until 1997 and then increases again. The high number in the early years can be explained by the fact that prior to May 1996, filing via the EDGAR system was voluntary and most likely only larger firms distributed their 10-K filings electronically.

From Table 4.3.1 I learn that the most frequently mentioned states in the 10-K filings are Delaware, California, Texas, New York, and Washington, while the least frequently mentioned are North Dakota, South Dakota, Alaska, Montana, and Wyoming.

4.3 Main Findings

I begin my analysis with univariate comparisons of different payout policies conditional on firm geographic characteristics. I identify firms as being high versus low in a particular geography attribute. Specifically, I use such geography attributes as geographic dispersion, geographic concentration, and population from states of economic presence.[10] I expect that the greater the dispersion or population, and the lower the concentration of the firm's geographical area, the greater the awareness of that firm among potential investors. Hence, these firms are less interested in paying high dividends or repurchasing stock in order to increase investor attention.

A preliminary crude test is based on a sample split by the number of states cited. As I am interested in the differences between firms that are compactly located and firms that have operations in a considerable number of states, I compare firms in the lowest decile of geographic dispersion with firms in the highest. In an unreported result, I ascertain that firms in the lowest decile pay significantly lower dividends per share and dividend yields than firms in

[10]From here on I will use the terms "geographic dispersion" or "number of states cited" interchangeably for the variable which is computed as the natural logarithm of one plus the number of states cited in the firm 10-K filing. "Highly dispersed", "widely spatially organized" are terms used to indicate firms with a high geographic dispersion variable.

Table 4.3.1: States Citation Metrics from the 10-K Filings

The sample includes Compustat firms with available geographic, demographic, and CEO compensation data, and excludes financial firms (SIC 6000—6999), regulated industries (SIC 4900—4999), firms with total assets below $20 million, and firms incorporated outside the USA or in the non-contiguous territories. The sample period is 1993—2010. For a corresponding state (column one), this table provides statistics on state counts (second column), state count shares (third column), and mean citation shares (fourth column). State count is defined as the number of 10-K filings in which a state is mentioned at least once. State count share is obtained by dividing the number of 10-K filings in which a state was mentioned at least once (second column) by the total number of 10-K filings in my sample, times 100. The fourth column shows the sample mean citation share of an individual state. State citation share is the number of state counts in the 10-K filing, divided by the total number of counts of all states in the 10-K filing.

State	State count	State count share	Mean state citation share
Alabama	5,217	22.20%	0.90%
Alaska	1,631	6.94%	0.36%
Arizona	5,854	24.91%	1.26%
Arkansas	3,761	16.01%	0.61%
California	15,906	67.69%	13.14%
Colorado	6,825	29.05%	1.55%
Connecticut	5,274	22.45%	1.38%
Delaware	18,671	79.46%	16.81%
Florida	8,977	38.20%	2.78%
Georgia	8,310	35.37%	2.50%
Hawaii	1,995	8.49%	0.22%
Idaho	2,240	9.53%	0.31%
Illinois	10,295	43.81%	3.27%
Indiana	6,236	26.54%	1.42%
Iowa	3,545	15.09%	0.67%
Kansas	5,311	22.60%	0.96%
Kentucky	4,800	20.43%	0.73%
Louisiana	5,327	22.67%	1.18%
Maine	2,108	8.97%	0.27%
Maryland	5,658	24.08%	1.08%
Massachusetts	8,579	36.51%	3.61%
Michigan	7,103	30.23%	1.88%
Minnesota	6,146	26.16%	2.26%
Mississippi	4,458	18.97%	0.77%
Missouri	5,763	24.53%	1.16%
Montana	1,908	8.12%	0.24%
Nebraska	2,705	11.51%	0.46%
Nevada	6,086	25.90%	1.43%
New Hampshire	2,380	10.13%	0.31%
New Jersey	7,904	33.64%	2.12%
New Mexico	3,187	13.56%	0.32%
New York	12,690	54.01%	7.90%
North Carolina	6,923	29.46%	1.61%
North Dakota	1,556	6.62%	0.14%
Ohio	8,479	36.09%	3.09%
Oklahoma	4,742	20.18%	0.86%
Oregon	4,427	18.84%	1.10%
Pennsylvania	9,073	38.61%	2.63%

Table 4.3.1 continued here

State	State count	State count share	Mean state citation share
Rhode Island	2,131	9.07%	0.31%
South Carolina	4,279	18.21%	0.62%
South Dakota	1,597	6.80%	0.18%
Tennessee	6,318	26.89%	1.44%
Texas	13,021	55.42%	6.51%
Utah	4,161	17.71%	0.73%
Vermont	2,330	9.92%	0.20%
Virginia	7,855	33.43%	2.13%
Washington	10,059	42.81%	2.47%
West Virginia	2,709	11.53%	0.31%
Wisconsin	5,440	23.15%	1.55%
Wyoming	2,075	8.83%	0.28%

the highest decile. The observed difference in dividends is strictly contrary to my hypothesis. However, this result is mostly driven by the fact that firms operating in several states are typically large in size and more mature. In line with the literature, these should be the firms that initiate dividend payments and exhibit higher total payouts (Gaver and Gaver, 1993; Smith and Watts, 1992). This finding does not necessarily contradict my main hypothesis, as the awareness and the size effects are not mutually exclusive. One way to disentangle the awareness and the size effects is to orthogonalize the logarithm of one plus geographic dispersion, and the logarithm of geographic concentration and population by regressing them on size measured with the logarithm of market capitalization.

The results of the sample split based on the orthogonalized variables are reported in Table 4.3.2. After eliminating the size effect, I find significantly lower payout levels of both dividends and repurchases among dispersed firms, compared to those of local firms, as shown in Panel A. Also the composition of payouts is significantly different among the two groups. Specifically, local firms distribute 30% of a total payout in the form of dividends, whereas dispersed firms distribute only 9.3% (untabulated). Total payout yield of dispersed firms is 1.57 percentage points lower than that of local firms. More dispersed firms are more likely to have headquarters in one of the largest CMSAs. This suggests that in my data firms with headquarters in the largest CMSAs exhibit lower dividend payouts, a results which is also found in John et al. (2011). As evident from column (4), the location effect amounts to almost three quarters of the dividend yield and slightly more than a half of the total payout.

In the analyses from Panels B and C in Table 4.3.2, I use other dimensions of a firm's geographic characteristics, namely, geographic concentration and population from the states with operations. Panel B from Table 4.3.2 uses a sample split by the Hirschman-Herfindahl index, adapted for state citations. Therefore, this variable should be understood as a concentration measure of firm operations, and the effect is expected to run counter to the direction predicted for geographic dispersion. An advantage of this measure of firm location is that it is continuous. Moreover, it factors in a frequency with which a certain state was mentioned in the 10-K filing. This way the measure correctly classifies a firm as local even if it mentions many states but a few more frequently than the others. In Panel C I split the sample using the size of the population from the states with operations variable.

Overall, the results in Panels B and C in Table 4.3.2, support the main inferences. In line with predictions, I find that highly concentrated firms (Panel

B) exhibit higher dividend and repurchase yields. Firms with a larger population living in the areas of their economic presence pay out lower dividend and repurchase yields (Panel C). The t-test confirms the significance of the differences in means for repurchase yields when using geographic concentration proxy of awareness (compared to the less concentrated firms, those with a high concentration spend 1.49 percentage points more on repurchases) and for dividend yields when using population (compared to firms with more populated areas, those with less populated areas exhibit dividend yields of 0.42 percentage points higher).

Table 4.3.2: Firm Geographic Dispersion and Payout: Univariate Evidence

This table provides univariate comparisons of payout policy characteristics of geographically concentrated and dispersed firms. The sample includes Compustat firms with available geographic, demographic, and CEO compensation data, and excludes financial firms (SIC 6000—6999), regulated industries (SIC 4900—4999), firms with total assets below $20 million, and firms incorporated outside the USA or in the non-contiguous territories. The sample period is 1993—2010. In order to split the sample into geographically concentrated and dispersed firms, I orthogonalize effects related to firm market capitalization and fixed effects. First, I obtain residuals from regressing the log of geographic dispersion, one minus geographic concentration, and population on the log of market capitalization, industry and year effects. Next, I split the sample using logged geographic dispersion, geographic concentration, and population (Panels A, B, and C, respectively) into groups with low and high geographic dispersion, geographic concentration, or population (columns 1 and 2, respectively), if a residual value belongs to the bottom or to the top decile of these metrics, respectively. Next, two-sample t-tests of differences in means (column 3) are performed (column 4). The null (alternative) hypothesis is that the difference of means is (is not) zero. Significance is denoted at the 1%, 5%, and 10% level with ***, **, *, respectively. Dividend yield is the ratio of dividends on common stock to the market value of common equity, times 100. Repurchase yield is the ratio of repurchased common stock to the market value of common equity, times 100. Total payout yield is the ratio of the sum of dividends on common stock and repurchased common stock to the market value of common equity, times 100. Variables are winsorized at the 1% and 99% percentile.

	Low (1)	High (2)	Δ (3)	Δ/mean(all) (4)	 (5)
Panel A. Geographic dispersion					
Dividend yield, %	1.10	0.45	-0.65	-72%	***
Repurchase yield, %	3.43	2.18	-1.25	-60%	***
Total payout yield, %	3.54	1.97	-1.57	-51%	***
Panel B. Geographic concentration					
Dividend yield, %	0.42	0.66	0.24	27%	
Repurchase yield, %	2.32	3.67	1.35	64%	***
Total payout yield, %	2.17	3.66	1.49	48%	***
Panel C. Population					
Dividend yield, %	0.81	0.39	-0.42	-47%	***
Repurchase yield, %	2.26	2.18	-0.08	-4%	
Total payout yield, %	2.20	1.94	-0.26	-8%	

The descriptive statistics above give some indication of the validity of the main hypothesis that differences in the dispersion of the region of economic activity affect corporate payout policy. Since univariate tests before orthogonalization show that other determinants could be correlated both with geographic characteristics and with payout policy, I formally test for the hypothesized relationship in a multivariate analysis. Specifically, I test if there is a negative relationship between different payout policy variables and firm geographic dispersion, controlling for a number of firm characteristics.

An important firm characteristic is size. It is very likely that the number of states cited increases with firm size. I therefore include logged market capitalization in all regressions. Apart from that, I control for free cash flows, CEO options, market-to-book, return on assets. The industry affiliation can also have an effect on both the region of economic activity and the payout policy of a firm. Special events such as the introduction of a new regulation or macroeconomic conditions may also affect the outcome variable. I therefore control for industry and year fixed effects based on the 3-digit SIC code in all regression models.

The main multivariate results are shown in Table 4.3.3. I find that after controlling for other firm characteristics, geographic coefficients are statistically significantly negative and economically relevant. A coefficient on geographic dispersion in the first model suggests that, in relation to a firm's economic presence, an increase corresponds to a 0.06 percentage points decrease in the firm dividend yield. This way the effect of geographic dispersion on dividends constitutes approximately 7% of the sample average dividend yield, and that effect on repurchases amounts to approximately 8% of the sample average repurchase yield.

In line with expectations, dividend yields increase in free cash flow, firm size, return on assets and decrease in executives' stock options and investment opportunities. Results on repurchase regressions are also generally consistent with theory. Since executive stock options set incentives for managers to pay out in the form of repurchases, the former enter repurchase regression with a positive sign as expected. Repurchases are positively related to return on assets and firm size and negatively to investment opportunities. A significantly negative coefficient on the free cash flow variable in the repurchase regressions suggests that firms, counter to their dividends policy, probably do not uniformly employ repurchases as a mechanism to mitigate agency costs. This result is consistent with the view that repurchases are used to distribute transitory components in earnings and do not serve as a credible signal of managerial commitment under these circumstances (Jagannathan et al., 2000).

The results from the main regressions from Table 4.3.3 are consistent with the conjecture that dispersed firms attract more investors than local firms due to their wide spacial dispersion, and therefore they do not depend on higher dividends to attract investors or on generating attention through higher repurchases. In the next section I present robustness checks which control for other competing explanations of dividends, and I elaborate on the investor recognition explanation of the geography effect.

Table 4.3.3: Firm Geographic Dispersion and Payout Policy

The sample includes Compustat firms with available geographic, demographic, and CEO compensation data, and excludes financial firms (SIC 6000—6999), regulated industries (SIC 4900—4999), firms with total assets below $20 million, and firms incorporated outside the USA or in the non-contiguous territories. The sample period is 1993—2010. Dividend yield is the ratio of dividends on common stock to the market value of common equity, times 100. Dividend per share is the dollar amount of dividends paid on an ordinary share. Repurchase yield is the ratio of repurchased common stock to the market value of common equity, times 100. Repurchase per share is the dollar amount paid in the repurchase of an ordinary share. Total payout yield is the ratio of the sum of dividends on common stock and repurchased common stock to the market value of common equity, times 100. Total payout per share is the dollar amount paid in dividends and/or in the repurchase of an ordinary share. Geographic dispersion here is the log of one plus a number of distinct states counts (SEC 10-K filings). Besides, regressions include standard firm-specific controls. Free cash flow is the ratio of cash flow (operating income before depreciation, minus interest expense (if available), minus income taxes net of the change in deferred tax and investment tax and investment tax credits (if available)) to total assets, times 100, if market-to-book is available and below one; equal to zero if market-to-book is available and higher than one; and missing if market-to-book is unavailable. Firm size is the market value of common equity, with the stock price being the average stock close price during a fiscal year. CEO options is the ratio of the total number of unexcercised options vested and not yet vested held by the executive at the fiscal year end to the number of shares outstanding (ExecuComp). Market-to-book is the ratio of firm market value (book value of total assets, plus market value of common equity, minus book value of common equity) to total assets. ROA is the ratio of EBITDA to total assets. All variables, excluding geographic dispersion, are winsorized at the 1% and 99% percentile. Ordinary least squares regressions of dividends are reported. Three-digit SIC industry and year dummies are included. Robust standard errors are in parentheses. Significance at 1%, 5%, and 10% is denoted with ***, **, and *, respectively.

VARIABLES	(1) Div yield	(2) DPS	(3) Rep yield	(4) RPS	(5) Total yield	(6) TPPS
Geo dispersion	-0.0611***	-0.0317***	-0.161**	-0.0105	-0.210**	-0.0522**
	(0.0214)	(0.00619)	(0.0727)	(0.0206)	(0.0817)	(0.0239)
Free cash flow	0.0301***	0.000224	0.0240	-0.00824**	0.0591***	-0.00888**
	(0.00613)	(0.00113)	(0.0197)	(0.00342)	(0.0227)	(0.00399)
Firm size	0.116***	0.0929***	0.334***	0.220***	0.400***	0.320***
	(0.00953)	(0.00309)	(0.0284)	(0.00878)	(0.0337)	(0.0103)
CEO options	-5.170***	-1.020***	17.15***	5.125***	11.18***	4.225***
	(0.434)	(0.120)	(1.914)	(0.517)	(2.169)	(0.588)
Market-to-book	-0.104***	-0.0316***	-0.495***	-0.0975***	-0.606***	-0.132***
	(0.00625)	(0.00215)	(0.0240)	(0.00786)	(0.0269)	(0.00903)
ROA	0.429***	0.143***	5.876***	2.118***	6.380***	2.310***
	(0.106)	(0.0319)	(0.424)	(0.120)	(0.495)	(0.141)
Constant	0.728***	-0.224***	-0.385	-1.234***	0.714	-1.464***
	(0.282)	(0.0502)	(0.820)	(0.247)	(0.930)	(0.261)
Observations	15,894	15,894	14,767	14,767	14,738	14,738
R-squared	0.313	0.414	0.131	0.191	0.155	0.256
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

4.4 Robustness Checks

4.4.1 Investor Awareness Explanation

To explain the geography effect shown in the previous section, I first suppose that investor awareness about the existence of the firm should be more pronounced in states that belong to a firm's region of economic activity. I test this conjecture using the search frequency in Google as an established proxy of investor awareness.

An advantage of the Google Search Volume Index (SVI) over other proxies for investor awareness is the fact that an Internet user will only actively search a firm with Google if he or she is aware of and interested in the respective firm. Da et al. (2011) and Drake et al. (2012) use ticker symbols of firm names. Instead, I follow Bank et al. (2011) and identify a firm in Google using its firm name, because it is more likely that a potential investor first becomes aware of a firm's full name rather than its abbreviation used on the stock market. As Google Trends only reports the SVI for a search item but does not allow filtering of the purpose of the search, the authors thereby try to distinguish a search demand for financial information from a search demand for other firm-specific information. However, I believe that the firm name is more appropriate for the research question in this study, since I am interested in the very fact that an investor is aware of a firm's existence. This general investor awareness is also manifested, for example, in product related searches, promotions of the firm, and its opening hours. In addition, institutional investors are likely to search for firm information using proprietary financial databases, e.g., Bloomberg, and Thomson Reuters, whereas retail investors do not usually have access to these databases, and, hence, they may be more inclined to use the Internet when searching for firm information. Hence, using Internet Google searches and firm names allows me to capture awareness about the firm among retail investors.

I download the Google SVI for each firm on a state level. GSV reflects the intensity of search queries for the time period from 2004 to 2015. In order to obtain the SVI, Google normalizes the number of firm search queries by the total number of all searches in a state to avoid potential differences in the search volume that exist due to differences in the state population. The resulting numbers are then scaled to a range of 0 (state with no search demand) to 100 (state with a high search demand).

First, I test if the Google SVI for a state increases with the relative citation frequency in the 10-K filings. Mean state citation frequency in the firm's 10-K filings is obtained as an individual state mean citation frequency over the whole time series for the firm. A firm's Google search volume indicates the intensity with which the firm was searched on the Internet from within the state. For the second test I compute tetrachoric correlations between a state citation and a firm's Google search volume binary variables. I define a firm-state citation indicator variable as equal to one if a firm cites this state at least once in one of its 10-K filings; zero otherwise. I also set a firm-state specific Google search volume indicator variable to one if the Google SVI is greater than zero; zero otherwise. In this test I exploit people's memory effect. The memory effect represents the ability of people to memorize and recall a firm even after the firm discontinues its operations in the area.[11] Construction companies provide a realistic example to illustrate this possibility. As long as a construction company is active on a construction site, it uses signage to provide outdoor advertising. Even after the construction is over and the firm leaves the site, locals may still remember the name of the company and search for information about the firm. I expect that tetrachoric correlations which allow for memory effects should be even higher than Pearson correlations.

The results from Table 4.4.1 are supportive of my expectation that with the geographic dispersion variable I am able to capture investor awareness. Table 4.4.1 (second column) shows the pairwise correlations between the Google SVI and the relative citation frequency of each state. The average correlation across all states is 22% and statistically different from zero. The tetrachoric correlations are reported in the third column of Table 4.4.1. Overall, I document an even stronger positive tetrachoric correlation between both

[11] Admittedly, some people may die or change their place of residence to a different state. As extreme case, suppose that all people who carry knowledge about the firm, which no longer operates in the state, die; hence, there should be no Internet searches of this firm from the state. Then, my Google search volume indicator variable will be biased upwards. Next, as an extreme case, suppose that all people from state A who carry knowledge of the firm leave the state for another state (B), in which the firm is not economically present. As a result, the Google search volume indicator variable will be biased upwards for state A and downwards for state B. Several observations help assure that these issues do not seriously — if at all — diminish the power of the test in the normal case, when some potential investors die or some potential investors leave for a different state. First, the average life span of a firm in my sample is 9,6 years, which is less than the length of time a person is usually active on the stock market. The latter may be estimated as the life expectancy at birth minus the age at which the average American starts investing on the stock market. The former was equal to 76.7 years in the year 2000 according to the OECD database; a conservative estimate of the latter could be 35 years old. Secondly, the percentage of movers is not economically significant. For example, according to the survey on the geographical mobility from the U.S. Census Bureau, in the period 1999—2000 only 3.1% of the total population moved to a different state. Thirdly, if people move and continue searching for a firm online from state B, these searches will be insufficiently intensive to enter the Google SVI, since the latter is being weighted by the total amount of other searches from state B.

indicator variables with an average value of 26%. Only the state of Delaware exhibits a negative correlation. At a first glance this result for Delaware may seem to be at odds with the main hypothesis but in fact the opposite is the case. 66.31% of the sample firms are incorporated in Delaware and are thereby required to cite this state in their 10-K filings. Nevertheless, this does not mean that the firms' headquarters or their production sites, sales points, or other economically relevant facilities are located in Delaware. The negative correlation confirms a conjecture that many firms are merely de jure located in Delaware and have no operations in this state. This justifies the exclusion of Delaware from the total number of states cited, in cases of a firm's citation of Delaware as a state of incorporation only and not as a state of its business address (results using this correction of the geographic dispersion variable remain qualitatively the same).

Table 4.4.1: Source of the Geography Effect: Google Search Volume and Firm Geography

The sample includes a cross-section of Compustat firms with available geographic, demographic, CEO compensation data, and Google Search Volume Index for the time period 2004—2015, and excludes financial firms (SIC 6000—6999), regulated industries (SIC 4900—4999), firms with total assets below $20 million, and firms incorporated outside the USA or in the non-contiguous territories. Simple Pearson correlation coefficients and tetrachoric correlation coefficients are shown in the second and third columns of this table, respectively. Simple Pearson correlation coefficients are computed between the mean state citation frequency in the firm's 10-K filings and the firm's Google Search Volume from this state. Mean state citation frequency in the firm's 10-K filings is obtained as the individual state mean citation frequency over the whole time series for the firm. Firm Google search volume indicates the frequency with which the firm was searched on the Internet from within the state. Tetrachoric correlation coefficients are computed between a state citation in the firm's 10-K filings (binary) and the firm's Google Search Volume from this state (binary). A state citation binary variable equals one if the state was ever mentioned in the firm 10-K filings; zero if not. A firm's Google Search Volume (binary) from the state is set to one here if the firm was ever searched in Internet from within the state; zero if not.

State	ρ_{Pears}	ρ_{tetra}
Alabama	0.24	0.29
Alaska	0.06	0.26
Arizona	0.22	0.28
Arkansas	0.14	0.24
California	0.62	0.20
Colorado	0.25	0.22
Connecticut	0.21	0.24
Delaware	0.07	-0.05
Florida	0.33	0.31
Georgia	0.33	0.30
Hawaii	0.18	0.32
Idaho	0.16	0.29
Illinois	0.35	0.28
Indiana	0.22	0.28
Iowa	0.22	0.26
Kansas	0.20	0.29
Kentucky	0.16	0.25
Louisiana	0.13	0.27
Maine	0.16	0.28
Maryland	0.25	0.23
Massachusetts	0.44	0.27
Michigan	0.28	0.30
Minnesota	0.35	0.25
Mississippi	0.13	0.21
Missouri	0.23	0.34
Montana	-0.01	0.25

Table 4.4.1 continued here

State	ρ_{Pears}	ρ_{tetra}
Nebraska	0.26	0.39
Nevada	0.21	0.27
New Hampshire	0.13	0.24
New Jersey	0.21	0.17
New Mexico	0.10	0.24
New York	0.38	0.21
North Carolina	0.23	0.27
North Dakota	0.02	0.34
Ohio	0.34	0.19
Oklahoma	0.21	0.30
Oregon	0.30	0.26
Pennsylvania	0.36	0.21
Rhode Island	0.10	0.29
South Carolina	0.19	0.33
South Dakota	0.15	0.34
Tennessee	0.23	0.31
Texas	0.44	0.17
Utah	0.18	0.27
Vermont	0.07	0.24
Virginia	0.21	0.25
Washington	0.30	0.14
West Virginia	0.16	0.30
Wisconsin	0.30	0.31
Wyoming	0.10	0.25
All states	0.22	0.26

In an additional robustness check (untabulated), I sort observations into two mutually exclusive groups and compare the number of observations in each. Specifically, for each firm-year observation I compute a search volume from states with firm operations and separately a search volume that a firm obtains from the states in which it is not economically present. Then I compare these two volumes. I find that in 1,487 (96% of cases) firm-year observations, the search volumes from states of economic presence are higher than those from the other states, and only for 67 observations does the opposite hold. Overall, results from this subsection confirm that investors living in a firm's region of economic activity are indeed more likely to be aware of the firm. Also, geographic dispersion is an appropriate proxy of investor awareness. An advantage of geographic dispersion over Google SVI as an awareness measure for my analysis is that it allows for within-firm analysis.

The above tests are designed to assess the economic validity of the 10-K based measures as a proxy of investor awareness. In the following analysis I use this evidence combined with the fact that retail firms are more visible to investors than non-retail firms, all things being equal. The former have a better reach of households, enforcing potential investors' familiarity with their products and the firm itself (e.g. Keloharju et al. (2012)). This means that more people are aware of a retail firm than of a non-retail firm, even if these two are otherwise equal, including in their geographic dispersion. My main hypothesis suggests that visibility of a firm negatively relates to its payout levels.[12] Hence, it implies that the effect of investor awareness on

[12] A high investor awareness case in the context of this paper corresponds to a high firm visibility.

dividends should be more pronounced in the retail firms subsample than in the non-retail firms subsample.

The regression results are shown in Table 4.4.2. I identify firms producing retail goods in the first two digits of the SIC code, as they identify the major industry. Firms with a 2-digit SIC code between 52 and 59 are classified as retail trade.[13] Consistent with economic intuition, the negative relation of geographic spread and dividend yield is more pronounced and highly significant (1% level) among the retail trade firms (first column) compared to non-retail firms (second column). Therefore, the more widespread firms that are also more visible to potential investors due to their end customer orientation (retail firms) exhibit a higher awareness effect on dividends, as expected under the awareness explanation of dividend payouts.

4.4.2 Robustness Check: Other Geography Based Measures of Investor Awareness

In the next set of tests I use other firm geography related measures of investor awareness: one minus geographic concentration, population from the states with operations, and geographical area. The advantage of the geographic concentration measure over that of geographic dispersion is that the former is continuous. Also, it factors in the relative economic importance of

[13] According to the SIC codes specifications, the range of SIC codes 5200—5999 belongs to the broader industry classification "Retail Trade". The other classifiable divisions include "Agriculture, Forestry and Fishing", "Mining", "Construction", "Manufacturing", "Transportation, Communications, Electric, Gas and Sanitary service" (excluded from the sample), "Wholesale Trade", "Finance, Insurance and Real Estate" (excluded from the sample), "Services", "Public Administration".

Table 4.4.2: Source of the Geography Effect: Retail/Non-Retail Split

The sample includes a cross-section of Compustat firms with available geographic, demographic, CEO compensation data, and Google Search Volume Index for the time period 2004—2015, and excludes financial firms (SIC 6000—6999), regulated industries (SIC 4900—4999), firms with total assets below $20 million, firms incorporated outside the USA or in the non-contiguous territories. Dividend yield is the ratio of dividends on common stock to the market value of common equity, times 100. Geographic dispersion here is the log of one plus a number of distinct states counts (SEC 10-K filings). Besides, regressions include standard firm-specific controls. Free cash flow is the ratio of cash flow (operating income before depreciation, minus interest expense (if available), minus income taxes net of the change in deferred tax and investment tax and investment tax credits (if available)) to total assets, times 100, if market-to-book is available and below one; equal to zero if market-to-book is available and higher than one; and missing if market-to-book is unavailable. Firm size is the market value of common equity, with the stock price being the average stock close price during a fiscal year. CEO options is the ratio of the total number of unexcercised options vested and not yet vested held by the executive at the fiscal year end to the number of shares outstanding (ExecuComp). Market-to-book is the ratio of firm market value (book value of total assets, plus market value of common equity, minus book value of common equity) to total assets. ROA is the ratio of EBITDA to total assets. All variables, excluding geographic dispersion, are winsorized at the 1% and 99% percentile. Ordinary least squares regressions of dividend yield in the sample of retail (first column) and non-retail firms (second column) are reported. Firms with SIC codes 52—59 are classified as retail; firms with SIC codes outside of this range are classified as non-retail. Three-digit SIC industry and year dummies are included. Robust standard errors are in parentheses. Significance at 1%, 5%, and 10% is denoted with ***, **, and *, respectively.

Dep. variable: Div. yield	(1) Retail	(2) Non-retail
Geo dispersion	-0.205***	-0.0425**
	(0.0402)	(0.0207)
Free cash flow	0.0304*	0.0267***
	(0.0176)	(0.00686)
Firm size	0.170***	0.149***
	(0.0237)	(0.00949)
CEO options	-2.446***	-2.388***
	(0.841)	(0.644)
Market-to-book	-0.212***	-0.0997***
	(0.0200)	(0.00722)
ROA	0.492	0.259***
	(0.314)	(0.0753)
Constant	0.416	0.292
	(0.255)	(0.209)
Observations	1,528	13,358
R-squared	0.185	0.371
Industry FE	YES	YES
Year FE	YES	YES

states proxied by the state fraction in the total number of states counts obtained from the annual reports. The *1-geographic concentration* variable is positively correlated with geographic dispersion; hence, it is also expected to obtain the positive sign in payout regressions.

As I show in the previous section, investor awareness represents a channel through which the geography of a firm affects the firm's payout level. If this line of argument is correct, dividend payouts should decrease either with the number of states in which the firm is present, or with the population living within the firm's region of economic activity, or with the area of the firm economic presence. I therefore refine the economic activity measure and sum the population of all states cited, as well as the area of the states of the firm's economic presence. Since geographic concentration, population, and cumulated areas are correlated, I include them in separate regressions.

In Table 4.4.3—Table 4.4.5 I examine the relationship between these proxies of investor attention, derived using firm geographic spread and firm payout policy. The predictive power of all three awareness measures remains in both the dividend yield and the dividend per share models (models (1)—(3) and (4)—(6) from Table 4.4.3, respectively). Results on the effect of investor awareness on repurchases are less conclusive. Only model (1) from Table 4.4.4 suggests a significant negative relationship between the *1-geographic concentration* variable and repurchase yield. Coefficients on awareness proxies from regressions (2) through (6) are not significant. These results suggest that the link between a firm's geography and its repurchases is less pronounced than that of a firm's geography and its dividends. Therefore, the achieved level of investor awareness can affect a firm's dividend payout but not the size of its repurchase programs. This evidence is in line with the marginal importance of dividends and repurchases in the ability to attract investors outlined in the motivation to this paper. Since repurchases have been shown earlier to constitute the largest fraction in the total payouts (the mean and the median values are 57.9% and 70.4%, respectively), results from the regressions of total payout yield and total payout per share should be almost the same as those of repurchases. Indeed, as evident from Table 4.4.5, only coefficients on *1-geographic concentration* in models (1) and (4) are statistically significant.

Table 4.4.3: Robustness Checks: Alternative Measures of Investor Awareness (1)

The sample includes Compustat firms with available geographic, demographic, and CEO compensation data, and excludes financial firms (SIC 6000—6999), regulated industries (SIC 4900—4999), firms with total assets below $20 million, and firms incorporated outside the USA or in the non-contiguous territories. The sample period is 1993—2010. Dividend yield is the ratio of dividends on common stock to the market value of common equity, times 100. Dividend per share is the dollar amount of dividends paid on an ordinary share. Geographic concentration is defined as the sum of squared state citation shares, where state citation share is the number of state counts in the 10-K filing divided by the total number of counts of all states in the 10-K filing (SEC 10-K filings). Population here is the logarithm of the total population in the states where a firm's geographic dispersion is non-zero (Census 2000, Census 2010). Geographical area is the total area of the states which a firm mentions at least once in its 10-K filing (Census 2010). Besides, regressions include standard firm-specific controls. Free cash flow is the ratio of cash flow (operating income before depreciation, minus interest expense (if available), minus income taxes net of the change in deferred tax and investment tax and investment tax credits (if available)) to total assets, times 100, if market-to-book is available and below one; equal to zero if market-to-book is available and higher than one; and missing if market-to-book is unavailable. Firm size is the market value of common equity, with the stock price being the average stock close price during a fiscal year. CEO options is the ratio of the total number of unexcercised options vested and not yet vested held by the executive at the fiscal year end to the number of shares outstanding (ExecuComp). Market-to-book is the ratio of firm market value (book value of total assets, plus market value of common equity, minus book value of common equity) to total assets. ROA is the ratio of EBITDA to total assets. All explained and control variables are winsorized at the 1% and 99% percentile. Ordinary least squares regressions of dividend yield ((1)—(3)) and dividend per share ((4)—(6)) are reported. Three-digit SIC industry and year dummies are included. Robust standard errors are in parentheses. Significance at 1%, 5%, and 10% is denoted with ***, **, and *, respectively.

VARIABLES	(1) Div yield	(2) Div yield	(3) Div yield	(4) DPS	(5) DPS	(6) DPS
1-Geo concentration	-0.197***			-0.0937***		
	(0.0698)			(0.0205)		
Population		-0.0664***			-0.0280***	
		(0.0189)			(0.00549)	
Geographical area			-2.35e-07***			-9.82e-08***
			(7.45e-08)			(1.99e-08)
Free cash flow	0.0300***	0.0301***	0.0321***	0.000114	0.000154	0.000725
	(0.00613)	(0.00613)	(0.00675)	(0.00113)	(0.00113)	(0.00129)
Firm size	0.112***	0.117***	0.131***	0.0908***	0.0926***	0.1000***
	(0.00922)	(0.00943)	(0.0102)	(0.00302)	(0.00306)	(0.00339)
CEO options	-5.186***	-5.150***	-5.332***	-1.027***	-1.010***	-1.072***
	(0.434)	(0.433)	(0.501)	(0.121)	(0.120)	(0.139)
Market-to-book	-0.103***	-0.104***	-0.119***	-0.0308***	-0.0312***	-0.0354***
	(0.00611)	(0.00612)	(0.00686)	(0.00214)	(0.00212)	(0.00252)
ROA	0.442***	0.417***	0.269**	0.149***	0.139***	0.103***
	(0.106)	(0.106)	(0.125)	(0.0319)	(0.0319)	(0.0382)
Constant	0.742***	1.806***	0.656*	-0.222***	0.219**	-0.394***
	(0.283)	(0.437)	(0.387)	(0.0503)	(0.109)	(0.0526)
Observations	15,894	15,894	12,748	15,894	15,894	12,748
R-squared	0.313	0.314	0.333	0.413	0.414	0.440
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Table 4.4.4: Robustness Checks: Alternative Measures of Investor Awareness (2)

This table provides summary statistics of the main dependent, explanatory, and control variables. The sample includes Compustat firms with available geographic, demographic, and CEO compensation data, and excludes financial firms (SIC 6000—6999), regulated industries (SIC 4900—4999), firms with total assets below $20 million, and firms incorporated outside the USA or in the non-contiguous territories. The sample period is 1993—2010. Repurchase yield is the ratio of repurchased common stock to the market value of common equity, times 100. Repurchase per share is the dollar amount paid in the repurchase of an ordinary share. Geographic concentration is defined as the sum of squared state citation shares, where state citation share is the number of state counts in the 10-K filing divided by the total number of counts of all states in the 10-K filing (SEC 10-K filings). Population here is the logarithm of the total population in the states where a firm's geographic dispersion is non-zero (Census 2000, Census 2010). Geographical area is the total area of the states which a firm mentions at least once in its 10-K filing (Census 2010). Besides, regressions include standard firm-specific controls. Free cash flow is the ratio of cash flow (operating income before depreciation, minus interest expense (if available), minus income taxes net of the change in deferred tax and investment tax and investment tax credits (if available)) to total assets, times 100, if market-to-book is available and below one; equal to zero if market-to-book is available and higher than one; and missing if market-to-book is unavailable. Firm size is the market value of common equity, with the stock price being the average stock close price during a fiscal year. CEO options is the ratio of the total number of unexcercised options vested and not yet vested held by the executive at the fiscal year end to the number of shares outstanding (ExecuComp). Market-to-book is the ratio of firm market value (book value of total assets, plus market value of common equity, minus book value of common equity) to total assets. ROA is the ratio of EBITDA to total assets. All explained and control variables are winsorized at the 1% and 99% percentile. Ordinary least squares regressions of repurchase yield ((1)—(3)) and repurchase per share ((4)—(6)) are reported. Three-digit SIC industry and year dummies are included. Robust standard errors are in parentheses. Significance at 1%, 5%, and 10% is denoted with ***, **, and *, respectively.

VARIABLES	(1) Rep yield	(2) Rep yield	(3) Rep yield	(4) RPS	(5) RPS	(6) RPS
1-Geo concentration	-0.723***			-0.0280		
	(0.239)			(0.0659)		
Population		-0.0384			0.0148	
		(0.0625)			(0.0175)	
Geographical area			4.09e-07			7.69e-08
			(2.96e-07)			(8.64e-08)
Free cash flow	0.0240	0.0227	0.00992	-0.00829**	-0.00848**	-0.00897**
	(0.0197)	(0.0197)	(0.0215)	(0.00342)	(0.00342)	(0.00390)
Firm size	0.328***	0.319***	0.279***	0.220***	0.217***	0.209***
	(0.0273)	(0.0280)	(0.0307)	(0.00852)	(0.00872)	(0.00952)
CEO options	17.11***	17.20***	17.20***	5.124***	5.126***	5.256***
	(1.915)	(1.917)	(2.231)	(0.518)	(0.518)	(0.604)
Market-to-book	-0.495***	-0.485***	-0.474***	-0.0972***	-0.0956***	-0.0904***
	(0.0236)	(0.0237)	(0.0279)	(0.00779)	(0.00781)	(0.00922)
ROA	5.908***	5.895***	6.003***	2.120***	2.125***	2.178***
	(0.425)	(0.425)	(0.500)	(0.119)	(0.120)	(0.140)
Constant	-0.212	-0.0113	0.0603	-1.236***	-1.522***	-0.973***
	(0.827)	(1.419)	(1.166)	(0.251)	(0.409)	(0.344)
Observations	14,767	14,767	11,919	14,767	14,767	11,919
R-squared	0.131	0.130	0.141	0.191	0.191	0.211
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Table 4.4.5: Robustness Checks: Alternative Measures of Investor Awareness (3)

The sample includes Compustat firms with available geographic, demographic, and CEO compensation data, and excludes financial firms (SIC 6000—6999), regulated industries (SIC 4900—4999), firms with total assets below $20 million, and firms incorporated outside the USA or in the non-contiguous territories. The sample period is 1993—2010. Total payout yield is the ratio of the sum of dividends on common stock and repurchased common stock to the market value of common equity, times 100. Geographic concentration is defined as the sum of squared state citation shares, where state citation share is the number of state counts in the 10-K filing divided by the total number of counts of all states in the 10-K filing (SEC 10-K filings). Population here is the logarithm of the total population in the states where a firm's geographic dispersion is non-zero (Census 2000, Census 2010). Geographical area is the total area of the states which a firm mentions at least once in its 10-K filing (Census 2010). Besides, regressions include standard firm-specific controls. Free cash flow is the ratio of cash flow (operating income before depreciation, minus interest expense (if available), minus income taxes net of the change in deferred tax and investment tax and investment tax credits (if available)) to total assets, times 100, if market-to-book is available and below one; equal to zero if market-to-book is available and higher than one; and missing if market-to-book is unavailable. Firm size is the market value of common equity, with the stock price being the average stock close price during a fiscal year. CEO options is the ratio of the total number of unexcercised options vested and not yet vested held by the executive at the fiscal year end to the number of shares outstanding (ExecuComp). Market-to-book is the ratio of firm market value (book value of total assets, plus market value of common equity, minus book value of common equity) to total assets. ROA is the ratio of EBITDA to total assets. All explained and control variables are winsorized at the 1% and 99% percentile. Ordinary least squares regressions of total payout yield are reported. Three-digit SIC industry and year dummies are included. Robust standard errors are in parentheses. Significance at 1%, 5%, and 10% is denoted with ***, **, and *, respectively.

VARIABLES	(1) Total yield	(2) Total yield	(3) Total yield	(4) TPPS	(5) TPPS	(6) TPPS
1-Geo concentration	-0.884***			-0.180**		
	(0.263)			(0.0782)		
Population		-0.0763			-0.0210	
		(0.0695)			(0.0206)	
Geographical area			5.19e-08			-5.20e-08
			(3.27e-07)			(9.70e-08)
Free cash flow	0.0590***	0.0577**	0.0485*	-0.00899**	-0.00923**	-0.00923**
	(0.0227)	(0.0227)	(0.0248)	(0.00398)	(0.00398)	(0.00451)
Firm size	0.392***	0.384***	0.366***	0.317***	0.316***	0.314***
	(0.0326)	(0.0335)	(0.0367)	(0.00991)	(0.0102)	(0.0110)
CEO options	11.13***	11.24***	11.03***	4.218***	4.242***	4.454***
	(2.170)	(2.171)	(2.516)	(0.590)	(0.589)	(0.685)
Market-to-book	-0.605***	-0.595***	-0.602***	-0.131***	-0.130***	-0.131***
	(0.0265)	(0.0265)	(0.0307)	(0.00895)	(0.00895)	(0.0104)
ROA	6.420***	6.394***	6.420***	2.320***	2.313***	2.361***
	(0.496)	(0.495)	(0.587)	(0.141)	(0.141)	(0.164)
Constant	0.900	1.675	1.035	-1.445***	-1.190***	-1.403***
	(0.934)	(1.579)	(1.266)	(0.265)	(0.459)	(0.352)
Observations	14,738	14,738	11,899	14,738	14,738	11,899
R-squared	0.156	0.155	0.165	0.256	0.256	0.282
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

4.4.3 Robustness Check: Geography Measures of Agency Costs

A prominent explanation of dividends includes that of free cash flows. According to the free cash flow hypothesis, dividends constitute a pre-commitment mechanism for managers to mitigate possible agency problems (Jensen, 1986). John et al. (2011) use geography-based measures to proxy for severeness of such agency problems. Unlike the approach in this study, their research design is based on using firms' headquarters locations. Firms with headquarters in the densely populated areas are believed to have lower agency costs and are expected to pay out lower dividends. At the same time, these firms may exhibit a higher investor awareness. Therefore, it proves important to disentangle the effects of the headquarters location and the region of economic activity on dividend payouts.

I construct a top ten indicator variable from John et al. (2011), which is set to one if the firm's headquarters are located in one of the ten largest (based on population size) CMSAs and zero otherwise. As the indicator variable would treat firms closely located to one of the ten largest CMSAs the same way as it would remotely located firms, I also use the logarithm of one plus the distance between the firm's headquarters and the closest top ten CMSA.[14] The effect of the headquarters location might be stronger if firms suffer from higher agency costs of free cash flows. I test this conjecture by including the interaction of my distance measure with free cash flows.

[14]More precisely, I use a middle point of the closest CMSA.

The results of the benchmark models are reported in Table 4.4.6. In line with the results of John et al. (2011), I find that firms located in one of the ten largest CMSAs pay a significantly lower dividend (first column). I also find a positive, although not statistically significant, relation when I use the logarithm of the distance to the headquarters instead of the indicator variable (second column). In line with expectations, free cash flows are positively associated with dividend yield; however, the combined effect with distance to the top 10 is significantly negative (third column). I use these benchmark models and additionally include my main explanatory variable, geographic dispersion (columns four to six). I find that the effect of the firm's operations locations is robust to an inclusion of the headquarters variables. Coefficients on geographic dispersion

Table 4.4.6: Robustness Checks: Geography Measures of Agency Costs

The sample includes Compustat firms with available geographic, demographic, and CEO compensation data, and excludes financial firms (SIC 6000—6999), regulated industries (SIC 4900—4999), firms with total assets below $20 million, and firms incorporated outside the USA or in the non-contiguous territories. The sample period is 1993—2010. Dividend yield is the ratio of dividends on common stock to the market value of common equity, times 100. Central location in top 10 (25) consolidated metropolitan statistical area (CMSA) is a dummy set to one if a firm's headquarters (Compustat) are located in the top 10 (25) CMSA; zero otherwise. Distance to top 10 CMSA is the distance in kilometers from the firm's headquarters location to the middle point of the closest CMSA if the firm's headquarters are located outside the top 10 CMSA; zero otherwise. Geographic dispersion here is the log of one plus the number of distinct states counts (SEC 10-K filings). Besides, regressions include standard firm-specific controls. Free cash flow is the ratio of cash flow (operating income before depreciation, minus interest expense (if available), minus income taxes net of the change in deferred tax and investment tax and investment tax credits (if available)) to total assets, times 100, if market-to-book is available and below one; equal to zero if market-to-book is available and higher than one; and missing if market-to-book is unavailable. Firm size is the market value of common equity, with the stock price being the average stock close price during a fiscal year. CEO options is the ratio of the total number of unexcercised options vested and not yet vested held by the executive at the fiscal year end to the number of shares outstanding (ExecuComp). Market-to-book is the ratio of firm market value (book value of total assets, plus market value of common equity, minus book value of common equity) to total assets. ROA is the ratio of EBITDA to total assets. All variables, excluding geographic dispersion, are winsorized at the 1% and 99% percentile. Ordinary least squares regressions of dividend yield are reported. Three-digit SIC industry and year dummies are included. Robust standard errors are in parentheses. Significance at 1%, 5%, and 10% is denoted with ***, **, and *, respectively.

VARIABLES	(1) Div yield	(2) Div yield	(3) Div yield	(4) Div yield	(5) Div yield	(6) Div yield
Central location	-0.107***			-0.111***		
	(0.0209)			(0.0209)		
Distance to top 10		0.00487	0.00534		0.00453	0.00499
		(0.00387)	(0.00382)		(0.00387)	(0.00382)
Free cash flow*			-0.00127**			-0.00125**
Distance to top 10			(0.000637)			(0.000636)
Geo dispersion				-0.0662***	-0.0625***	-0.0623***
				(0.0214)	(0.0220)	(0.0219)
Free cash flow	0.0296***	0.0314***	0.0353***	0.0302***	0.0320***	0.0359***
	(0.00613)	(0.00632)	(0.00698)	(0.00614)	(0.00632)	(0.00698)
Firm size	0.111***	0.0914***	0.0917***	0.120***	0.0991***	0.0994***
	(0.00906)	(0.00952)	(0.00952)	(0.00954)	(0.00998)	(0.00999)
CEO options	-5.028***	-5.052***	-5.063***	-5.039***	-5.068***	-5.079***
	(0.432)	(0.436)	(0.436)	(0.433)	(0.437)	(0.437)
Market-to-book	-0.101***	-0.0904***	-0.0903***	-0.106***	-0.0952***	-0.0951***
	(0.00599)	(0.00608)	(0.00609)	(0.00627)	(0.00640)	(0.00640)
ROA	0.403***	0.496***	0.511***	0.389***	0.485***	0.500***
	(0.106)	(0.108)	(0.109)	(0.106)	(0.108)	(0.108)
Constant	0.614**	0.835**	0.835**	0.744***	0.956**	0.956**
	(0.280)	(0.383)	(0.385)	(0.283)	(0.386)	(0.387)
Observations	15,894	14,803	14,803	15,894	14,803	14,803
R-squared	0.314	0.314	0.315	0.315	0.315	0.315
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

are all strongly significantly negative and economically sensible. In contrast to the mixed results for the headquarters location, the remaining controls are all significant (at the 1% level) with the expected signs.

4.4.4 Robustness Check: Other Control Variables

It may be the case that local firms are located in economically depressed rural areas which exhibit a higher proportion of elderly population due to urbanization and rural migration. These firms were shown to cater to the needs of the retired investors and pay out dividends, since their investor clientèle is dependent on the dividend income (Becker et al., 2011). To avoid a potential problem of spurious correlations between investor awareness and dividend payouts, I control for the dividend clientèle explanation. Moreover, the higher the percentage of retired investors in the region of a firm's economic presence, the higher the chances that they represent a group of a firm potential investors. Furthermore, not only size, but also the characteristics of a firm's potential investor base may influence its payout policy. Therefore, it proves necessary to control for the dividend demand in the sense of Becker et al. (2011) in my dividend regressions. In the first model from Table 4.4.7, I include the proportion of the population aged over 65 years living in the state where the firm is headquartered as a dummy variable set to one if the proportion is higher than the sample median proportion; and zero otherwise.[15] The geographic dispersion variable is highly significant in

[15]To be consistent with Becker et al. (2011), I use U.S. Census Bureau 2000 data on the headquarter state population for the years before 2000 and Census 2010 data for subsequent years.

terms of standard confidence levels after controlling for dividend demand from the elderly population. The elderly population enters the regression with a significantly positive coefficient, which confirms the dividend clientèle explanation of dividends.

Next, I examine cross-sectional differences in the awareness effect on dividends. Specifically, I explore whether the effect of awareness on dividend payouts is different among lesser-known and better-known firms. I expect that smaller firms should profit from an increase in the state economic presence more than firms that are already large and enjoy a relatively high investor recognition than that of smaller firms. Hence, smaller firms should exhibit higher magnitudes of the awareness effect compared to bigger firms. To sort observations into size quintiles, I use logged market capitalization. Next, I construct Size 1, Size 2, Size 3, Size 4, and Size 5 dummy variables equal to one if an observation logged market capitalization is in the first, second, third, fourth, or fifth quintile of the sample logged market capitalization, respectively; and zero otherwise. Coefficients on the interaction terms of a firm's size quintile dummy and a firm's geographic dispersion should provide evidence on the magnitude of the awareness effect across different firm size groups. Results from Table 4.4.7 show that coefficients on the interaction terms monotonically decrease with the firm's size. Since interaction terms with the first two size quintiles are significant, I conclude that the awareness effect is evident among the smaller firms.

In the next set of tests I exploit the fact that the awareness effect on dividend payouts should primarily be driven by potential and not current investors.

As motivated in the introduction, firms pay out dividends in order to attract investors who are not yet aware of the firm; that is, to attract potential investors. In the subsequent regression specifications I interact geographic dispersion with a firm's current shareholder structure and not that of potential investors, since the latter is not directly observable. Specifically, I introduce a free float variable which is computed as the percentage of total shares in issue available to retail investors. This variable is not an accurate measure of retail investor ownership, but can be viewed as an upper bound for the latter. Taking into account the limitation of the proxy for retail shareholder base, this analysis serves as a soft test of the awareness effect on dividends. I expect that the current retail ownership structure proxied by free float should neither economically significantly amplify nor weaken the awareness effect.

Evidence from both the dividend yield and the dividends per share models (model (3) and model (4) from Table 4.4.7, respectively) is compliant with my expectation. As follows from Table 4.4.7, geographic dispersion remains highly statistically significant in both dividend yields and per share model specifications after controlling for free float. Free float does not explain the whole cross-section of dividend yields. The interaction term is statistically significantly positive in the dividend yield model (model (3)). Therefore, the combined effect of awareness and free float on dividend yield is

Table 4.4.7: Robustness Checks: Other Control Variables

The sample includes Compustat firms with available geographic, demographic, and CEO compensation data, and excludes financial firms (SIC 6000—6999), regulated industries (SIC 4900—4999), firms with total assets below $20 million, and firms incorporated outside the USA or in the non-contiguous territories. The sample period is 1993—2010. Dividend yield is the ratio of dividends on common stock to the market value of common equity, times 100. Dividend per share is the dollar amount of dividends paid on an ordinary share. Geographic dispersion here is the log of one plus a number of distinct states counts (SEC 10-K filings). Older 65 is a dummy variable equal to one if the proportion of the population aged no younger than 65 years old in the total headquarter state population is higher than the sample median fraction; and equal zero otherwise (Census 2000, Census 2010). I sort observations into size quintiles based on logged market capitalization. Next, I construct Size 1, Size 2, Size 3, Size 4, and Size 5 dummy variables. Size 1, Size 2, Size 3, Size 4, and Size 5 are equal to one if logged market capitalization is in the first, second, third, fourth, or fifth quintile, respectively; and zero otherwise. The fifth quintile is excluded from regressions to avoid multicollinearity. Free float is obtained as the percentage of total shares in issue available to ordinary investors (Datastream). Besides, regressions include standard firm-specific controls. Free cash flow is the ratio of cash flow (operating income before depreciation, minus interest expense (if available), minus income taxes net of the change in deferred tax and investment tax and investment tax credits (if available)) to total assets, times 100, if market-to-book is available and below one; equal to zero if market-to-book is available and higher than one; and missing if market-to-book is unavailable. Firm size is the market value of common equity, with the stock price being the average stock close price during a fiscal year. CEO options is the ratio of the total number of unexcercised options vested and not yet vested held by the executive at the fiscal year end to the number of shares outstanding (ExecuComp). Market-to-book is the ratio of firm market value (book value of total assets, plus market value of common equity, minus book value of common equity) to total assets. ROA is the ratio of EBITDA to total assets. All variables, excluding geographic dispersion and older 65, are winsorized at the 1% and 99% percentile. Ordinary least squares regressions of dividend yield ((1)—(3)) and dividend per share ((4)) are reported. Three-digit SIC industry and year dummies are included. Robust standard errors are in parentheses. Significance at 1%, 5%, and 10% is denoted with ***, **, and *, respectively.

VARIABLES	(1) Div yield	(2) DPS	(3) Div yield	(4) DPS	(5) Div yield	(6) DPS
Geo dispersion*Size 1			-0.0991*	-0.111***		
			(0.0581)	(0.0170)		
Geo dispersion*Size 2			-0.0984*	-0.112***		
			(0.0530)	(0.0171)		
Geo dispersion*Size 3			-0.0705	-0.0904***		
			(0.0508)	(0.0174)		
Geo dispersion*Size 4			-0.0104	-0.0605***		
			(0.0474)	(0.0170)		
Geo dispersion	-0.0631***	-0.0323***	-0.000753	0.0453***	-0.304***	-0.0683***
	(0.0214)	(0.00619)	(0.0399)	(0.0155)	(0.0603)	(0.0192)
Older 65	0.0146**	0.00438**				
	(0.00627)	(0.00174)				
Size 1			0.572***	0.422***		
			(0.169)	(0.0541)		
Size 2			0.387***	0.330***		
			(0.149)	(0.0506)		
Size 3			0.204	0.222***		
			(0.141)	(0.0491)		
Size 4			-0.0654	0.0943**		
			(0.132)	(0.0476)		
Geo dispersion*Free float					0.00231***	0.000243
					(0.000826)	(0.000266)
Free float					-0.00322	0.000755
					(0.00223)	(0.000719)
Observations	15,894	15,894	15,894	15,894	9,122	9,122
R-squared	0.314	0.414	0.318	0.428	0.323	0.431
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

weaker than that of awareness alone — albeit very modestly. Also, regression results explaining dividends per share are not indicative of a significant effect of current retail shareholder base on the awareness effect (model (4)). Further, the interaction term is non-significant in all other payout specifications, including repurchase yield and repurchase per share, total yield, and total payout per share (not tabulated). Combined, these pieces of evidence suggest that the mechanism of attracting retail investors with payouts becomes less relevant or even irrelevant for firms with an already high fraction of current retail investors in their shareholder base.

4.5 Conclusion

The aim of this paper was to explore whether the well-documented firm-benefiting value effects of high investor awareness carry over to a firm's payout policy. Specifically, I ask whether a high firm geographic spread, which is generically associated with a high investor awareness, is responsible for a management decision to pay out less than local but otherwise similar firms.

I document that geographically widespread firms, on average, pay lower dividends and repurchases, an empirical fact that also holds for firms within a high population density and in large geographical areas. The geography-related difference in dividends amounts to approximately 70% of an average sample dividend yield (or 7% after accounting for other determinants of dividends).

I find that the effect of geographic spread is robust to controlling for other geography-related explanations of dividends from the literature. In particular, I check for the dividend clientèle effect, using the firm's headquarters locations. I also control for the central location of a firm in the presence of high free cash flows to account for the severity of agency problems.

In addition, I propose investor awareness to be a channel of the geography effect. I identify an overlap between states in which a firm maintains an economical presence and states from which a firm was searched for on the Internet. Retail firms, which are highly visible to potential investors, exhibit a stronger awareness effect than non-retail firms. I also find that this affect of investor awareness on dividends is contingent on a firm's size: it is most pronounced among the firms in the lowest size quintiles, which are expected to profit more from an increase in investor recognition.

The results of this study have implications for payout policies of joint stock companies. The evidence presented here highlights the importance of general investor awareness about the firm on setting a payout policy. This paper empirically confirms that investor awareness increases with the firm's geographic spread, making it less critical to pay out to investors in order to attract their attention. This paper sheds light on the importance of generic firm characteristics, such as geographic locations on investor awareness. Further work could investigate whether more easily adjustable and dynamically changing factors of investor awareness such as, for instance, marketing expenses affect a firm payout policy.

4.A Data Appendix to Chapter 4

Variable	**Definition and source**
	Panel A. Firm geography and 10-K based measures
Geographic dispersion	In Table 4.2.1 and Figure 4.2.1, the variable is defined as the number of distinct states cited at least once in the firm's annual financial statement; in all other tables as the logarithm of one plus the number of states cited at least once in the 10-K of a firm. Source: U.S. Securities and Exchange Commission (SEC) 10-K filings
Geographic concentration	The sum of squared state citation shares. Source: SEC 10-K filings
State citation share	The number of state counts in the 10-K filing, divided by the total number of counts of all states in the 10-K filing. Source: SEC 10-K filings
State count share	The number of 10-K filings in which a state was mentioned at least once, divided by the total number of 10-K filings in my sample. Source: SEC 10-K filings
Population	In Table 4.2.1, the variable is defined as the total population in states which a firm mentions at least once in its SEC 10-K filing. In all other tables the variable is logged. Source: Census 2010
Geographical area	The total area of the states which a firm mentions at least once in its 10-K filing. Source: Census 2010
Older 65	The proportion of the population older than 65 years old in the total population of the headquarter state, times 100. Source: Census 2000, Census 2010
Google search volume (GSV)	The search volume of the firm in the state, scaled to a range of 0 to 100 over the period from 2004 till present. Source: Google Trends
	Panel B. Payout variables
Dividend yield	Dividends paid on common stock divided by the market value of common equity, times 100. Source: Compustat
Repurchase yield	The value of repurchased common and preferred stock, minus redemption value of preferred stock (if reported), divided by the market value of common equity, times 100. Source: Compustat
Total payout yield	Dividends paid on common stock, plus repurchase of common stock, divided by the market value of common equity, times 100. Source: Compustat
Dividend per share	Dividends paid on common stock, divided by the number of shares outstanding, in USD. Source: Compustat
Repurchase per share, USD	Repurchases of common stock, divided by the number of shares outstanding, in USD. Source: Compustat
Total payout per share, USD	Dividends paid on common stock, plus repurchase of common stock, divided by the number of shares outstanding, in USD. Source: Compustat
Dividends/payout	Dividends paid on common stock, divided by the total payout on common stock, times 100. Source: Compustat
Dividend payer	The indicator variable equals one if a firm pays dividends at least once over the sample period and zero if a firm never pays a dividend. Source: Compustat

Section 4.A continued here	
	Panel C. Control variables
Central location in top 10 CMSA	The indicator variable is set to one if a firm's headquarters (Compustat) are located in the top-ten cumulative metropolitan statistical area (CMSA) (Census 2000); zero otherwise. Source: Compustat, Census 2000
Distance to top 10 CMSA	The distance in kilometers from the firm's headquarters location (Compustat) to the middle point of the closest CMSA (Census 2000) if a firm's headquarters are located outside the top-ten CMSA; zero otherwise. Source: Compustat, Census 2000, Google Maps, own computations
Distance	The logarithm of one plus the distance in miles to the closest top-ten CMSA (Census 2010). Source: Compustat, Census 2010, Google Maps, own computations
Free cash flow	The ratio of operating income before depreciation, minus interest expense, minus income taxes net of the change in deferred tax and investment tax and investment tax credits to total assets. Source: Compustat
Firm size	Market capitalization, the number of common shares outstanding, times the stock close price during a fiscal year. Source: Compustat
CEO options	The ratio of the total number of unexcercised options vested and not yet vested held by the executive at the fiscal year end to the number of shares outstanding. Source: Compustat ExecuComp
Market-to-book	The ratio of the sum of total assets and the sum of all issue-level market values, minus common shareholders' interest in a company in the event of liquidation of company assets, to total assets. Source: Compustat
ROA	The ratio of earnings before interest, taxes, depreciation, and amortization to the total assets. Source: Compustat
Free float	The percentage of total shares in issue available to ordinary investors. Source: Datastream

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