Three Essays on Behavioral Aspects in Accounting and Economics

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1 Introduction

The core of this thesis is based on three essays. While the individual parts can be read independently, all three essays are connected by taking on a behavioral view on accounting and economics. Defined loosely, behavioral research draws on insights from cognitive psychology and attempts to narrow the gap between human behavior and behavior in economic models (Kahneman 2003). It goes back at least to Simon (1957), who coins the term of bounded rationality to describe behavior that deviates from perfect rationality. DellaVigna and Pollet (2009) organize behavioral research around the following three building blocks. The first block deals with nonstandard preferences, suggesting that individuals (i) make decisions that are time-inconsistent, (ii) evaluate gains and losses relative to reference points, (iii) or care about the welfare of others. The second block draws on psychological evidence indicating that belief formation deviates from perfect rationality in that it can be affected by cognitive biases (nonstandard beliefs). And, third, given preferences and beliefs, research on nonstandard decision making shows that individuals use simple heuristics to solve complex problems or are able to process only part of the available information due to constraints such as limited attention.

The first two essays of this thesis contribute to the field of nonstandard beliefs. More specifically, the second chapter allows managerial behavior to deviate from perfect rationality, examining the influence of managerial overconfidence on cost behavior. Chapter three draws on the concept of investor sentiment and is concerned with real consequences that arise from less than perfectly rational investor behavior. The fourth chapter is related to the field of nonstandard decision making. Turning to consumer behavior, it applies the concept of limited attention to the field of behavioral energy economics, examining which factors drive consumers' attention devoted to fuel-efficient technologies. In the following, I

provide some background information on each chapter and present key results.

In recent years, much work has been devoted to understanding the consequences arising from managerial overconfidence.[1] Research in accounting associates two biases with overconfidence (Libby and Rennekamp 2012; Hribar and Yang 2013). The first bias is referred to as miscalibration in the psychology literature (Fischhoff, Slovic, and Lichtenstein 1977; Moore 1977; Oskamp 1965). Miscalibration describes the tendency to overestimate the precision of the own knowledge (Hirshleifer 2001; Odean 1998), which is modeled as underestimation of variance in the behavioral finance literature (Baker and Wurgler 2011). The second bias associated with overconfidence is referred to as dispositional optimism in the psychology literature (Scheier and Carver 1985; Taylor and Brown 1988; Weinstein 1980). Dispositional optimism, a stable character trait, describes the tendency to hold generalized favorable expectations about future events. In the behavioral accounting and finance literature, dispositional optimism is defined as overestimation of the mean of uncertain outcomes (Baker and Wurgler 2011).

While research in psychology documents that overconfidence is widespread and affects a variety of decisions, two questions arise. First, why do individuals not learn from past mistakes and, hence, overcome biases? Sharot, Korn, and Dolan (2011) document an asymmetry in belief updating. More specifically, they show that individuals learn more strongly from pleasant or confirming information than from unpleasant information that conflicts with or challenges prior beliefs. Hence, Sharot et al. (2011) provide evidence for what can be described as selective updating. In addition, Johnson and Fowler (2011) make an evolutionary argument explaining why individuals may be overconfident. Johnson and Fowler (2011) model a situation in which two contestants compete about a valuable resource, assuming that both contestants have imperfect information about each other's capabilities.

[1] See, for example, Ahmed and Duellman (2013), Hilary and Hsu (2011), Hirshleifer, Low, and Teoh (2012), Libby and Rennekamp (2012), Malmendier and Tate (2005, 2008), or Schrand and Zechman (2012).

Their evidence suggests that overconfidence may prevail in many environments because overconfident individuals will be more likely to claim resources than their rational (or underconfident) counterparts who will back off more frequently. As long as the resource at stake exceeds the cost of competing for it, overconfidence may be evolutionary stable, contrary to intuition that natural selection works against individuals with biased beliefs.

Second, does the evidence on overconfidence from psychological studies extend to corporate executives? Goel and Thakor (2008) address this question, arguing that it is more likely that an overconfident than a non-overconfident manager gets appointed as CEO. Goel and Thakor (2008) argue that promotion depends on past performance, which, in turn, depends on the amount of risk taken by managers. Underestimation of risk induces overconfident managers to choose riskier projects than non-overconfident managers, thereby increasing the variance of their performance. Hence, there is reason to believe that overconfident managers will be over-represented in the high-performance group from which board of directors eventually choose a CEO. In addition, Malmendier and Tate (2005) argue that factors that predict overconfidence are particularly likely to be present in the context of executive decision making, e.g., abstract reference points, illusion of control, and commitment (also see Camerer and Malmendier 2007). Survey evidence confirms the arguments made in these studies. Ben-David, Graham, and Harvey (2012) conduct a survey with top financial executives, documenting both dispositional optimism and miscalibration. Similarly, the evidence in Graham, Harvey, and Puri (2013) shows that executives are more optimistic than the lay population. Finally, Libby and Rennekamp (2012, p. 200) conduct interviews with experienced managers who "strongly agree that managers are, in general, overconfident".

The second chapter of this thesis, which is based on a study with Clara Xiaoling Chen and

Julia Nasev[2], questions if managerial overconfidence affects cost behavior. In an influential study, Anderson, Banker, and Janakiraman (2003) document that costs are sticky. That is, variable costs decline less following a decline in activity than they increase following an increase in activity of equal magnitude. The concept of cost stickiness highlights the role of managerial discretion in the process of resource adjustment, which contrasts with traditional cost models, assuming that variable costs mechanically respond to changes in activity (Anderson et al. 2003).

Building on the psychology literature and its application in behavioral accounting and finance, we expect a positive association between managerial overconfidence and cost stickiness. Prior literature documents that overconfident managers overestimate future demand (Malmendier, Tate, and Yan 2011), and that demand expectations are key to the concept of cost stickiness (Banker et al. 2014). We, therefore, expect that overconfident managers assess reductions in demand as less permanent than their non-overconfident counterparts. If overconfident managers expect demand to restore in the next period, they should be more likely to keep unutilized resources following a decline in demand, which should increase cost stickiness. We further predict that cost stickiness driven by managerial overconfidence should be less efficient than cost stickiness driven by economic reasons. If this is the case, we expect cost stickiness driven by managerial overconfidence to negatively affect future firm performance compared to cost stickiness that is not driven by overconfidence.

To test our first prediction, we use a sample of 20,615 firm-years from the intersection of ExecuComp, CRSP, and Compustat over the period 1992-2011. Consistent with our expectation, we find that cost stickiness increases with managerial overconfidence. More specifically, our results show that overconfident CEOs are more likely to keep excess

[2] Chen, Gores and Nasev, 2013, Managerial Overconfidence and Cost Stickiness, Working Paper.

resources than non-overconfident CEOs when sales decrease but overconfident CEOs do not build up excess resources when sales increase. The test of our second prediction is based on the fundamental analysis literature (Abarbanell and Bushee 1997; Anderson et al. 2007; Lev and Thiagarajan 1993). Confirming our expectation, we find evidence indicating that cost behavior driven by managerial overconfidence is suboptimal. Collectively, the results of our analyses show that managerial overconfidence affects cost behavior.

The third chapter of this thesis, based on a study with Carsten Homburg and Julia Nasev[3], builds on the concept of investor sentiment. It grounds on three assumptions. The first assumption differentiates between two types of investors: Rational arbitrageurs and irrational or noise traders subject to sentiment. Baker and Wurgler (2007, p.127) define investor sentiment as "a belief about future cash flows and investment risks that is not justified by the facts at hand". This definition builds on prior literature offering plenty of examples concerning investor behavior that is difficult to reconcile with perfect rationality. Shiller (1984), for instance, argues that stock prices are affected by social movements. Black (1986) uses the term noise traders to describe trading that is based on noise as opposed to news. Other studies document that overconfidence (Barber and Odean 2001), conservatism and representativeness (Barberis, Shleifer, and Vishny 1998), or sensation-seeking (Grinblatt and Keloharju 2009) affect trading or stock prices.[4]

The second assumption is concerned with the limits of arbitrage. For one, arbitrage may be limited due to implementation costs or short sale constraints (Miller 1977). To the extent that it is not possible to find perfect substitutes, arbitrage additionally requires bearing of fundamental risk (Barberis and Thaler 2003). Most importantly, however, a combination of noise trader risk and agency problems may limit the effectiveness of arbitrage (De Long et al. 1990; Shleifer and Vishny 1997). Noise trader risk can limit arbitrage because arbitrageurs

[3] Gores, Homburg, and Nasev, 2015, The Impact of Investor Sentiment on Operating Expenditure – a Catering Perspective, Working Paper.
[4] See Barberis and Thaler (2003) or Hirshleifer (2001) for surveys of the literature.

are exposed to unpredictable fluctuations in noise traders' future opinions (De Long et al. 1990). If an arbitrageur, for example, shorts a stock that is overpriced he has to bear the risk that – in the short term – noise traders get even more bullish and push the price even further away from its intrinsic value (De Long et al. 1990). This implies that arbitrageurs have to be able and willing to bear potentially steep short-term losses. This insight is important because arbitrageurs likely do not invest their own money but that of their capital lenders (Shleifer and Vishny 1997). In absent of perfect information, it is reasonable to assume that capital lenders will try to infer the ability or skill of their investors based on the returns they generate (Barberis and Thaler 2003). Recognizing that bad performance may motivate capital lenders to withdraw their funds, arbitrageurs may decide to not bet against mispricing given that arbitrage can deteriorate short-term performance. Hence, a separation of "brains and resources" may limit the effectiveness of arbitrage (Shleifer and Vishny 1997, p.36).

Finally, noise traders' misperceptions have to be systematic. Kumar and Lee (2006) provide empirical support for this assumption. Using a large-scale data set of retail investor transactions, they show that retail trading is systematically correlated. Moreover, Kumar and Lee (2006) find that these trades more strongly affect those stocks that are more likely to be held by retail investors. Hence, there is evidence supporting the assumption that retail investors trade in concert.

These assumptions imply that noise traders can affect asset prices. Several studies support this prediction. Baker and Wurgler (2006, 2007), for example, document that stocks that are more likely to be held by noise traders realize lower returns than stocks that are less likely to be held by noise traders following periods of high sentiment. Other studies reach similar conclusions (Brown and Cliff 2005; Lemmon and Portniaguina 2006).

Building on this evidence, chapter three is concerned with real implications of investor sentiment. The so-called catering theory explains how noise trading can affect corporate

policies. In essence, the theory predicts that managers can boost the current stock price if they adjust their corporate policies to the misperceptions of noise traders (Baker and Wurgler 2011; Stein 1996).[5] In this study, we examine the association between investor sentiment and operating expenditure. We expect there are two opposing channels linking investor sentiment and operating expenditure. First, prior literature argues that noise traders have optimistically biased expectations about future cash flows in periods of high sentiment (Baker and Wurgler 2006, 2007; Stein 1996). Such overestimation of investment opportunities may create pressure on managers' investment behavior. Given that operating expenditure such as research and development (Eberhart, Maxwell, and Siddique 2004; Lev and Sougiannis 1996; Sougiannis 1994), advertising (Chan, Lakonishok, and Sougiannis 2001; Hirschey and Weygandt 1985; Madden, Fehle, and Fournier 2006), and selling, general and administrative (SG&A) resources (Anderson et al. 2007; Banker, Huang, and Natarajan 2011; Tronconi and Marzetti 2011) has long-term value-relevance, we argue that managers will cater to investors' optimistic investment expectations by overspending on operating expenditure in periods of high relative to periods of average sentiment.

Second, prior literature documents that investors' have inflated earnings expectations in periods of high sentiment (Hribar and McInnis 2012; Mian and Sankaraguruswamy 2012; Seybert and Yang 2012). Literature on real earnings management shows that operating expenditures, such as research and development (R&D) expenses, are easy targets that can be manipulated to meet earnings expectations (Baber, Fairfield, and Haggard 1991; Burgstahler and Dichev 1997; Roychowdhury 2006). Hence, managers may alternatively reduce spending on operating expenditure to meet earnings targets. We, therefore, argue that managers face a trade-off between catering to noise traders' investment and earnings expectations. While we expect to observe a positive association for firms that do not face earnings targets, we argue

[5] The theory implicitly assumes that managers are able to recognize investor sentiment. Hribar and Quinn (2013) provide support for this assumption, documenting that managers' trades are negatively associated with investor sentiment.

the association between operating expenditure and investor sentiment should be less pronounced or may even turn negative for those firms that have incentives to meet earnings.

Empirically, we find support for our predictions. Our results suggests that managers increase spending on R&D expenditure, advertisement and SG&A resources as means of catering to noise traders' misperceptions. Results from further analyses indicate that (i) catering per SG&A resources increases as the value-relevance of these resources increases, (ii) catering is more pronounced for those firms that are more strongly affected by investor sentiment, and (iii) catering increases as managers' horizons decrease. Finally, our results suggest that managers refrain from overspending on operating expenditure when facing earnings targets, indicating a trade-off between catering to noise traders' investment and earnings expectations. Taken together, our results show that investor sentiment affects spending on operating expenditure.

The fourth chapter, joint work with Stefan Thoenes[6], builds on the capacity model of attention following Kahneman (1973). This chapter takes on a behavioral view on energy economics, attempting to contribute to our understanding of when and why consumers invest in fuel-efficient technologies such as hybrid vehicles. Answering this question is important because increasing the fuel-efficiency of vehicles is considered as a promising way to reduce greenhouse gas emissions (Enkvist, Nauclér, and Rosander 2007). While fuel-efficient technologies have higher initial purchasing prices, the advanced technology results in lower energy consumption and, therefore, lower fuel costs over the lifetime of the investment. Hence, just like any other investment, the profitability of fuel-efficient technologies should be evaluated by computing net present values of future cash flows, which – in this case – depend on future gasoline prices or fuel costs. Allcott (2011), however, presents survey evidence indicating that about 40% of US consumers do not think about fuel costs at all when

[6] Thoenes and Gores, 2012, Attention, Media and Fuel Efficiency, Working Paper.

purchasing a vehicle. Similarly, Turrentine and Kurani (2007) document that consumers are not able to thoroughly assess fuel costs when purchasing automobiles. Given these results, it becomes an important question to understand how consumers make their purchase decisions.

The fourth chapter of this thesis relies on the concept of limited attention to analyze consumers' decision-making. The capacity model of attention following Kahneman (1973) views attention as a resource that is necessary to process information. It further assumes that the supply of attention is limited, suggesting that attention is a scarce resource that has to be allocated among alternative or competing activities. The concept of limited attention, hence, implies that individuals are limited in their ability of processing information. In this regard, the model differs from neo-classical economics which implicitly assumes that individuals are able to process all information (DellaVigna and Pollet 2009). The framework further suggests that individuals are more likely to process salient information that grabs their attention. Barber and Odean (2008), for example, show that individual investors are net buyers of stocks that are excessively covered in the news or stock that experience large one day returns. Similarly, Yuan (2011) shows that attention-grabbing events, such as record levels of the Dow Jones index or prominent media coverage, i.e., front page articles about the stock market, affect trading behavior of individual investors.

We expect two channels to alter the attention that consumers devote to hybrid vehicles. First, we expect that changes in gasoline prices affect consumers' attention because changes in gasoline prices determine the profitability of investments in fuel-efficient technologies. In this regard, we additionally focus on new or all time record prices. Tversky and Kahneman (1991) suggest that gains and losses are evaluated relative to reference points. We assume that consumers regard prior record prices as reference points. Price increases that exceed existing reference points may be perceived as losses, resulting in a stronger reaction because of loss aversion. Second, we expect that media coverage on topics related to hybrid vehicles

and gasoline costs affects consumers' attention, assuming that media has the potential to influence which topics are perceived as important McCombs and Shaw (1972).

To test our prediction, we construct a weekly panel data set for 19 metropolitan areas in the United States. For each metro area, we obtain Google search queries related to hybrid vehicles as our measure of consumer attention. We further collect data on local newspaper coverage related to hybrid vehicles for each metro area. Empirically, we relate consumer attention to local newspaper coverage, gasoline prices, record prices and national television and national newspaper reports. Consistent with our expectation, we find that changes in gasoline prices, unprecedented record prices, and local newspaper coverage affect the attention that consumers devote to hybrid vehicles.

Our results, thus, document the presence of limited attention in the context of long-lived consumer goods. We thereby extend prior literature, which has primarily focused on consequences arising from limited attention, by documenting which factors likely influence attention. Our results, therefore, should be of interest for policy makers interested in increasing the adoption of fuel-efficient technologies in that we show when consumers are likely to pay attention to the topic of fuel efficiency.

2 Managerial Overconfidence and Cost Stickiness

2.1 Introduction

A growing accounting and finance literature examines the impact of specific managerial characteristics, such as ability, reputation, integrity, and overconfidence, on managerial decisions and firm outcomes (Ahmed and Duellman 2013; Cianci and Kaplan 2010; Das 1986; Demerjian et al. 2013; Libby and Rennekamp 2012; Schrand and Zechman 2012). In particular, research in finance has examined the effect of managerial overconfidence on capital expenditures (Malmendier and Tate 2005), merger and acquisitions (Malmendier and Tate 2008), and financing decisions (Malmendier et al. 2011). However, we know very little about how managerial characteristics in general and managerial overconfidence in particular affect managers' cost management decisions. It is important to examine the effect of overconfidence on managers' cost decisions because even though merger and acquisitions and capital expenditures examined in prior finance literature are major decisions made by management, they are relatively rare. In contrast, cost decisions are made more frequently by managers and have important impact on firm performance.

Our study takes the first step toward understanding the impact of managerial characteristics on cost management decisions. Understanding cost behavior is one of the central issues in management accounting because it is important for several stakeholders. It is important for managers and board of directors who monitor managers' cost decisions. Effective cost management can be key in building and sustaining a firm's competitive advantage such as cost leadership (Porter 1985). In addition, cost management matters for investors and analysts because it signals operational efficiency and thus provides key inputs to earnings predictions and firm valuation (Anderson et al. 2007; Lev and Thiagarajan 1993).

We examine the following two related research questions: (1) How does managerial overconfidence influence cost stickiness? (2) How does cost stickiness driven by managerial

overconfidence influence subsequent firm performance?

Anderson et al. (2003) provide robust and economically significant evidence of "cost stickiness". Costs are "sticky" if they decrease less following a decrease in activity than they increase following an increase in activity of equal magnitude. In contrast to traditional cost models, which assume that variable costs mechanically follow activity changes, this asymmetric cost behavior suggests an important role for managerial discretion in the resource adjustment process (Anderson et al. 2003). Focusing on cost stickiness enables us to examine managers' cost decisions in sales decreasing periods relative to the sales increasing periods. Cost control in sales decreasing periods could be a particular challenge for overconfident CEOs, which we will discuss below.

Drawing on the psychology and finance literatures on overconfidence, we expect managerial overconfidence to increase the degree of cost stickiness. This is because overconfident managers are likely to overestimate expected future demand (Malmendier et al. 2011) and positive future demand expectations are an important driver of cost stickiness (Banker et al. 2014). Specifically, we expect overconfident managers to assess demand reductions as less permanent than non-overconfident managers. If this is the case, overconfident managers will be more likely to keep unutilized resources when sales decline, resulting in greater cost stickiness. Since overconfidence is a behavioral bias, cost stickiness driven by overconfidence should be less efficient than cost stickiness driven by legitimate economic reasons. Therefore, our second hypothesis predicts that cost stickiness driven by overconfidence will be associated with lower future performance than cost stickiness not driven by overconfidence.

Our main measure of overconfidence is based on CEOs' option exercising behavior (e.g., Malmendier and Tate 2005; Malmendier et al. 2011; Campbell et al. 2011; Ahmed and Duellman 2013; Hirshleifer et al. 2012). Following this literature, we consider CEOs as

overconfident who persistently fail to exercise options that are deep in-the-money. We measure cost stickiness using the dummy interaction specification suggested by Anderson et al. (2003) and control for economic and agency factors that have been documented to influence the degree of cost stickiness (Anderson et al. 2003; Chen, Lu, and Sougiannis 2012; Dierynck, Landsman, and Renders 2012; Kama and Weiss 2013).

We test our first hypothesis using a sample of 20,615 firm-years from the intersection of ExecuComp, CRSP, and Compustat over the period 1992-2011. Consistent with our prediction, we find a positive association between CEO overconfidence and cost stickiness. Our results show that overconfident CEOs keep more costs than non-overconfident CEOs when sales decline but do not differ in their cost behavior when sales increase. To assess the sensitivity of our results, we conduct a large number of robustness tests including different cost categories, alternative option- and investment-based measures of CEO overconfidence and alternative control variables. We additionally demonstrate that our finding reflects the effect of an innate personality trait rather than optimistic demand expectations conditioned by external cues such as past sales trends (Banker et al. 2014).

To test our second hypothesis, we draw on the fundamental analysis literature (Abarbanell and Bushee 1997; Anderson et al. 2007; Lev and Thiagarajan 1993). Our prior results show that cost stickiness due to overconfidence is driven primarily by differences in cost behavior when sales decrease. If overconfident CEOs indeed erroneously overestimate future demand and, therefore, keep more costs than non-overconfident CEOs when sales decline, the cost behavior of overconfident CEOs should have a negative impact on future earnings compared to the cost behavior of non-overconfident CEOs when sales decline. Our empirical analysis supports this conjecture. This finding is robust to alternative measures of performance and alternative measures of overconfidence.

Our study makes two primary contributions to the accounting literature. First, we

contribute to a growing accounting literature that examines how specific managerial characteristics affect managerial decisions (Ahmed and Duellman 2013; Cianci and Kaplan 2010; Das 1986; Demerjian et al. 2013; Schrand and Zechman 2012; Seiler and Bartlett 1982). Our study is one of the first empirical studies on the relation between managers' personality traits and their cost management decisions. In so doing, our paper also extends the accounting literature on overconfidence. Prior studies have documented that overconfidence increases the likelihood of accounting fraud (Schrand and Zechman 2012), the likelihood of issuing management forecasts, the optimism in these forecasts (Hilary and Hsu 2011; Hribar and Yang 2013; Libby and Rennekamp 2012) and accounting conservatism (Ahmed and Duellman 2013). Our study documents the impact of overconfidence on cost decisions and cost behavior.

Second, we extend the cost stickiness literature by providing a behavioral explanation for cost stickiness. This behavioral explanation differs fundamentally from the economic explanations suggested in prior studies (e.g., Anderson et al. 2003; Balakrishnan and Gruca 2008; Banker et al. 2014). While economic explanations assume unbiased managerial expectations, overconfidence reflects a persistent managerial characteristic that indicates a positive bias in CEOs' expectations. Our explanation also differs from agency-based explanations documented in prior literature. While CEOs motivated by agency considerations keep or cut excess resources for opportunistic reasons, e.g., to build empires (Chen et al. 2012) or to manage earnings (Dierynck et al. 2012; Kama and Weiss 2013), overconfident CEOs keep excess resources because they believe they act in the best interest of shareholders. By focusing on a manager-level factor, our results provide strong support for the role of managerial discretion in cost management.

Our study complements a recent study by Banker et al. (2014), which finds that prior sales changes affect managers' demand expectations for future sales, which, in turn, influence

cost stickiness. Banker et al. (2014) consider the results consistent with either managers' rational statistical inferences or a behavioral bias to extrapolate past trends, or both. In this study, we identify a specific behavioral bias, overconfidence, and show its effect on cost stickiness. Our study differs from prior studies because measures of optimism used in prior cost stickiness literature such as past sales trends and GDP growth capture managers' beliefs that are conditioned by external cues. Extrapolation of sales trends, for example, implies that managers overreact to recent news (Barberis et al. 1998; De Bondt 1993). Our study, in contrast, identifies aspects of optimism that are driven by innate personality traits of the manager and thus are not conditioned by external cues. We show that our overconfidence measure is incrementally informative about managers' cost decisions even after controlling for the other optimism proxies such as past sales trends used in prior literature.

Our study has important practical implications. Our finding that overconfidence affects cost management has important implications for corporate governance and labor market practices. In particular, unlike cost decisions driven by agency problems or other incentive-related issues, cost decisions driven by managerial overconfidence cannot be addressed with incentive contract design because overconfident CEOs believe they are maximizing firm value. More promising ways to mitigate overconfidence-driven cost decisions include questioning and challenging the expectations of overconfident CEOs. These endeavors need not be limited to the board of directors. Sophisticated market participants and the media can use the option-based overconfidence classification to identify overconfident CEOs and question the CEOs' expectations about future sales and associated cost decisions. Our findings also have implications for labor market practices. When cost management is particularly important for an organization, the organization needs to be cautious in hiring an overconfident CEO.

The remainder of the paper is organized as follows. We review the literature on

overconfidence and develop the hypotheses in section 2. In section 3, we discuss the sample selection, measures, and research design. Section 4 presents the results and section 5 concludes.

2.2 Hypothesis Development

A large body of research in psychology shows that individuals tend to be overconfident (Alicke 1985; Svenson 1981; Scheier and Carver 1985; Weinstein 1980; Fischhoff et al. 1977). Building on the psychology literature, research in corporate finance examines the effect of overconfidence at the executive-level on corporate policies such as capital expenditures (Malmendier and Tate 2005), merger and acquisitions (Malmendier and Tate 2008), dividends (Cordeiro 2009), financing decisions (Malmendier et al. 2011), and innovation (Hirshleifer et al. 2012). However, little is known about how overconfidence affects managers' cost management decisions. Although merger and acquisitions and investment examined in prior studies are major decisions made by managers, they are relatively rare. By contrast, costs decisions are made more frequently by managers and have important impact on firm performance.

We examine the effect of managerial overconfidence on a well-documented cost behavior: Cost stickiness. Cost stickiness, i.e., costs fall less when sales decline than they rise when sales increase, arises from asymmetric adjustment costs for sales increasing vs. decreasing periods (Anderson et al. 2003). Following an increase in demand, managers ramp up resources in so far as to accommodate additional sales (Anderson et al. 2003). Adjustment costs are relatively low when demand increases. However, when demand decreases, firms must incur greater adjustment costs to dispose of unutilized resources and to replace those resources later if demand is restored. Such adjustment costs include both tangible and intangible costs. The former comprises costs such as severance pay upon dismissal of employees or search and training costs upon hiring of new employees. The latter comprises

costs such as reduction in employee morale and productivity due to dismissals and layoffs. Therefore, when demand decreases, managers have to weigh the expected costs of keeping excess resources during periods of low demand against the anticipated adjustment costs of first reducing and then having to ramp up resources when demand rebounds in the future (Anderson et al. 2003). The expected adjustment costs critically hinge on future demand expectations (Banker et al. 2014). In particular, if managers have positive demand expectations, they may keep excess resources in sales decreasing periods to avoid the costs of adding resources when sales rebound in the future.

We expect managerial overconfidence to increase the degree of cost stickiness. More specifically, we expect overconfidence to affect managers' future demand expectations and, as a consequence, drive up the asymmetry in adjustment costs for increasing vs. decreasing sales, resulting in greater cost stickiness. The main behavioral bias associated with overconfidence that we rely on is referred to as dispositional optimism in the psychology literature (Scheier and Carver 1985; Weinstein 1980; Taylor and Brown 1988).[7] In the behavioral accounting and finance literature, dispositional optimism is frequently defined as the overestimation of the mean of uncertain outcomes (Hribar and Yang 2013; Baker and Wurgler 2011). Malmendier et al. (2011), for example, argue that overconfident CEOs overestimate their firms' future cash flows.[8] In our setting, dispositional optimism (overestimating the mean) implies that overconfident managers will overestimate expected future sales.

We next discuss in more detail how overconfidence-induced overestimation of future

[7] For example, Scheier and Carver (1985, p. 219) define optimism as individuals' expectations "that good rather than bad things will happen to them.". According to Weinstein (1980, p. 806) people are unrealistically optimistic if they "expect others to be victims of misfortune, not themselves" implying "not merely a hopeful outlook on life, but an error in judgment". When the overestimation is relative to others it is referred to as the better-than-average effect (Larwood and Whittaker 1977; Svenson 1981; Alicke 1985; Alicke et al. 1995; Camerer and Lovallo 1999).

[8] Additionally, Larwood and Whittaker (1977) provide experimental evidence that overconfident managers tend to overestimate the sales growth of their firms.

demand affects cost stickiness. When current sales decline, overconfident CEOs are expected to assess a demand reduction as less permanent than non-overconfident CEOs. If overconfident CEOs expect demand to restore sufficiently fast, they should be more likely to keep excess resources, resulting in greater cost stickiness.

When current sales increase, there are two possible scenarios. In the first scenario, the assumption is that expanding resources cannot be accomplished just in time to accommodate sales increases, so managers will build up excess resources in the current period when sales increase to prepare for accommodating expected future demand increases. Because overconfident managers overestimate expected future sales, they may also build up more excess resources required in future periods when current sales increase. For firms with overconfident managers, this would result in greater cost increases when sales increase, magnifying cost stickiness. In this scenario, overconfident mangers will differ from non-overconfident managers in their cost management practices both when sales increase and when sales decrease, resulting in more pronounced cost stickiness.

In the second, a more likely scenario suggested by prior literature (Anderson et al. 2003), expanding resources can be done just in time to accommodate demand increases. Thus, both overconfident and non-overconfident CEOs are expected to expand resources to the extent necessary to accommodate increased demand in the current period. Overconfident managers are likely to ramp up resources when necessary in future periods when demand further increases rather than start building up excess capacity in the current period. In this scenario, overconfident managers will not differ from non-overconfident managers in their cost management practices when sales increase and the effect of managerial overconfidence on cost stickiness will be driven primarily by differences in cost behavior when sales decrease. Which scenario dominates remains an empirical question. However, regardless of which scenario is assumed for cost behavior under increasing demand, we expect an overall positive

association between managerial overconfidence and cost stickiness. We expect this positive association to be magnified under the first scenario. Thus, we posit the following hypothesis:

HYPOTHESIS 1: Managerial overconfidence is positively associated with cost stickiness.

As overconfidence implies a misassessment of future demand, cost decisions based on such inaccurate estimates should be suboptimal. Specifically, cost stickiness leads to a smaller cost adjustment when activity level declines, and hence, results in idle capacity costs and lower cost savings for a firm (see also Weiss 2010). Other things being equal, idle capacity costs and lower cost savings, in turn, should lead to lower future firm performance. Thus, we predict that suboptimal cost decisions driven by managerial overconfidence will be negatively associated with future firm performance.

HYPOTHESIS 2: Cost stickiness driven by overconfidence is negatively associated with future firm performance.

2.3 Research Design

2.3.1 Sample Selection

Our sample is based on the intersection of ExecuComp, Compustat, and CRSP over the period 1992-2011. First, we merge ExecuComp with Compustat to construct the overconfidence and agency variables. Second, we use the merged CRSP and Compustat database by WRDS and follow the sample selection procedure in Anderson et al. (2003) to construct the cost stickiness and economic variables. We drop (1) financial firms and utilities (sic codes 6000 to 6999 and 4900 to 4999), (2) firm-years with negative sales or negative SG&A costs, and (3) observations for which SG&A costs are larger than sales. Finally, we merge the ExecuComp-Compustat sample with the CRSP-Compustat sample. We winsorize the top and bottom 1% of all continuous variables. The final sample comprises 20,615 firm-years.

2.3.2 Overconfidence

2.3.2.1 Overconfidence Measurement

In our main analyses, we measure overconfidence based on the option-exercising behavior of CEOs following the approach suggested by Malmendier and Tate (2005). Option-based measures exploit the fact that CEOs are overexposed to their own firms' idiosyncratic risk (Malmendier and Tate 2005). CEOs are typically compensated with large amounts of stocks and options of their own firms. To align the CEOs' interests with those of the shareholders, they can neither trade nor hedge their options. In addition, the CEOs' human capital is invested in their firms. Negative firm performance, thus, affects both the CEOs' direct holdings and the CEOs' labor market opportunities. Several studies on executive compensation and stock option design, therefore, argue that risk-averse and under-diversified CEOs have incentives to exercise options that are deep in-the-money in order to reduce their exposure to their firms' idiosyncratic risk (Hall and Murphy 2000, 2002; Huddart 1994; Lambert, Larcker, and Verrecchia 1991; Meulbroek 2001). Malmendier et al. (2011) argue that overconfident CEOs overestimate their firms' future cash flows and, as a consequence, delay the exercise of in-the-money options to benefit from the expected increase in firm performance. Not exercising deep in-the-money options, thus, should indicate CEOs' overly optimistic outlook concerning their own firms, reflecting the overestimation of mean future cash flows. In our setting, the overestimation of future cash flows (or demand) should affect cost decisions and lead to more pronounced cost stickiness.

We follow Malmendier and Tate (2005) and Hirshleifer et al. (2012) and define a CEO as overconfident if the average intrinsic value of his options exceeds 67% of the average exercise price ($Overconf_{i,t}$). The classification starts with the first time an option has been

held too long.[9] Since Malmendier and Tate (2005) use proprietary data, we follow Hirshleifer et al. (2012) and determine option moneyness as follows (also see Campbell et al. 2011). First, we compute the average realizable value per option by dividing the total realizable value of all unexercised but exercisable options by the number of exercisable options held by the CEO (ExecuComp mnemonics OPT_UNEX_EXER_EST_VAL and OPT_UNEX_ EXER_NUM, respectively). We then compute the strike price as the fiscal year end stock price (PRCCF) minus the average realizable value per option. We obtain average option moneyness by dividing the fiscal year end stock price by the estimated strike price minus one. Note that the analysis includes only options that are exercisable to ensure that CEOs choose to hold rather than exercise their options.[10]

Malmendier and Tate (2005) provide an in-depth discussion of potential alternative explanations related to the overconfidence measure. Because Malmendier and Tate (2005) are able to rule out alternative explanations, their measure of overconfidence is widely used in studies that analyze consequences of overconfidence. Recent studies that either directly follow or use measures that are similar in concept to Malmendier and Tate (2005) include Ahmed and Duellman (2013), Campbell et al. (2011), Hirshleifer et al. (2012) and Malmendier et al. (2011).

Here, we refer to Malmendier and Tate (2005) and discuss inside information as an example for one potential alternative explanation. The concern is that instead of overconfidence early option exercising may reflect positive inside information. First, positive inside information and overconfidence differ in persistence. While overconfidence represents a persistent character trait, private information is transitory by nature. It is very unlikely that the same CEO holds favorable inside information in multiple years of his tenure. An

[9] Malmendier and Tate (2005) justify the benchmark of 67% in two ways. First, they use the theoretical model by Hall and Murphy (2002) to derive the benchmark. Second, they vary the threshold between 50% and 150% and show that the results remain qualitatively similar.

[10] We split-adjust the fiscal year end stock price (PRCCF) and the number of options held by the CEO (OPT_UNEX_ EXER_NUM) by dividing and multiplying with the split adjustment factor (AJEX), respectively.

explanation based on inside information, therefore, predicts that CEOs hold options when they have favorable and exercise options when they have unfavorable inside information. Malmendier and Tate (2005), in contrast, document that CEOs either persistently exercise options late or persistently exercise options early. This phenomenon is inconsistent with the transitory nature of inside information. Instead, this phenomenon is more consistent with an explanation based on overconfidence in that the non-exercise of deep in-the-money options reflects CEOs' overly optimistic outlook concerning their own firms.

The second main difference between inside information and overconfidence is performance. An explanation based on private information implies that CEOs fail to exercise their options because they have positive inside information, which should result in abnormal returns. However, Malmendier and Tate (2005) document that CEOs who fail to exercise their options do not earn abnormal returns. In fact, Malmendier and Tate (2005) show that, on average, CEOs would have been better off if they had exercised their deep in-the-money options and invested in a broad index.

Collectively, Malmendier and Tate (2005) present strong evidence against the conjecture that their measurement of overconfidence reflects inside information. Despite this compelling evidence, to further separate overconfidence from inside information, we control for future stock returns when testing our first hypothesis. Finally, in the robustness section, we also present and discuss various alternative measures of overconfidence including additional option-based and investment-based measures.

2.3.3 Cost Stickiness Measurement

We use the dummy interaction specification suggested by Anderson et al. (2003) to measure cost stickiness.

$$\Delta \ln \text{Cost}_{i,t} = \beta_0 + \beta_1 \cdot \Delta \ln \text{Sales}_{i,t} + \beta_2 \cdot \Delta \ln \text{Sales}_{i,t} \cdot \text{DecrDum}_{i,t} + \varepsilon_{i,t} \quad (2.1)$$

where i is a firm index and t a time index. The coefficient β_1 measures the percentage

increase in costs with a 1% increase in sales. Since the value of DecrDum is one when sales decrease, the sum of ($\beta_1 + \beta_2$) measures the percentage decrease in costs if sales decrease by 1%. A positive and significant coefficient β_1 and a significantly negative coefficient β_2 would be consistent with cost stickiness, indicating a smaller cost reaction when sales decrease than when sales increase (Anderson et al. 2003).

2.3.4 Model Specification

To estimate the effect of overconfidence on cost stickiness, we expand equation (2.1) by including the overconfidence measure ($Overconf_{i,t}$). We control for economic and agency control variables known to affect cost stickiness following Anderson et al. (2003) and Chen et al. (2012). In addition, we check the sensitivity of our results regarding earnings targets controls following Dierynck et al. (2012) and Kama and Weiss (2013) in the robustness section. We estimate the following regression model:

$$\begin{aligned}\Delta \ln Cost_{i,t} = &\left(\alpha_1 \cdot Overconf_{i,t} + \sum_{c=2}^{7} \alpha_c \cdot Controls_{i,t} + \alpha_8 + \alpha_{IndFE} + \alpha_{YearFE}\right) \cdot \Delta \ln Sales_{i,t} \cdot DecrDum_{i,t} \\ &+ \left(\beta_1 \cdot Overconf_{i,t} + \sum_{c=2}^{7} \beta_c \cdot Controls_{i,t} + \beta_8 + \beta_{IndFE} + \beta_{YearFE}\right) \cdot \Delta \ln Sales_{i,t} \\ &+ \left(\gamma_1 \cdot Overconf_{i,t} + \sum_{c=2}^{7} \gamma_c \cdot Controls_{i,t} + \gamma_8 + \gamma_{IndFE} + \gamma_{YearFE}\right) \cdot DecrDum_{i,t} \\ &+ \left(\delta_1 \cdot Overconf_{i,t} + \sum_{c=2}^{7} \delta_c \cdot Controls_{i,t} + \delta_8 + \delta_{IndFE} + \delta_{YearFE}\right) + \varepsilon_{i,t}\end{aligned} \quad (2.2)$$

i is a firm index and t a time index. $\Delta lnCost_{it} = ln(Cost_{it}/Cost_{it-1})$ is the log change in operating costs which comprise expenditure on manufacturing goods, marketing, distribution, and service related expenses. This approach follows prior cost stickiness studies including Balakrishnan and Gruca (2008), Banker, Byzalov, and Chen (2013) and Kama and Weiss (2013). Operating costs are defined as sales less operating income after depreciation [Compustat mnemonic SALE minus OIADP]. $\Delta lnSales_{it} = ln(Sales_{it}/Sales_{it-1})$ is the log change in sales [Compustat mnemonic SALE], and DecrDum is one if sales in t are lower than sales in t-1 and zero otherwise.

We expect the coefficient on $\Delta lnSales_{i,t} \cdot DecrDum_{i,t} \cdot Overconf_{i,t}$, α_1, to be negative, which

would indicate greater cost stickiness for firms with overconfident CEOs. We report three specifications based on equation (2.2). In the first specification, we add overconfidence to the baseline cost stickiness model in Anderson et al. (2003). In the second specification, we add economic and agency control variables following Anderson et al. (2003) and Chen et al. (2012). In the third specification, we additionally include year- and industry-fixed effects. Year-fixed effects control for potentially unobserved factors that change over time but affect all firms in a similar way such as macroeconomic changes that we do not capture with the economic control variables. Industry-fixed effects control for potentially unobserved industry specific factors that are constant over time. Specifically, industry-fixed effects help rule out the alternative explanation that overconfident CEOs are overrepresented in industries with greater cost stickiness. In this specification, industry fixed-effects are based on Fama-French 12 industry dummy variables. We use the third specification as our main specification (equation (2.2), model (3) in Table 2.3). All standard errors are clustered at the firm level allowing for heteroskedasticity and arbitrary within-firm correlation (Petersen 2009).

In addition to year- and industry-fixed effects, we follow prior literature and include two sets of control variables: Economic and agency variables. We control for four economic factors that may affect the asymmetry in cost behavior. First, we control for employee and asset intensity. As proxies for adjustment costs, both are expected to result in more pronounced cost stickiness (Anderson et al. 2003). Employee intensity (EmplInt) is the natural logarithm of the number of employees divided by sales [Compustat mnemonics EMP and SALE], and asset intensity (AssetInt) is defined as the natural logarithm of total assets divided by sales [Compustat mnemonics AT and SALE]. Second, we follow Anderson et al. (2003) and control for successive sales decreases, expecting that managers will regard decreases in demand as more persistent if demand declines in two consecutive years. The dummy variable SD equals one if sales are lower in year t-1 than in year t-2, otherwise the

variable is set to zero. Finally, we follow Chen et al. (2012) and control for stock performance (StockPerf), which is the natural logarithm of one plus the annual raw stock return measured at the beginning of the fiscal year. If higher stock performance reflects a more efficient cost control, it should have a negative effect on cost stickiness. If, however, higher stock performance signals positive expectations of future performance, it may have a positive effect on cost stickiness because managers may want to keep excess resources in anticipation of higher future capacity utilization. This control variable is also important to rule out the possibility that delayed option exercise reflects positive future performance expectations instead of overconfidence.

Following Chen et al. (2012), we control for two agency factors. First, we control for free cash flow (FCF), which is calculated as cash flow from operating activities [Compustat mnemonic OANCF] less common and preferred dividends [Compustat mnemonics DVC and DVP] divided by total assets [Compustat mnemonic AT]. High levels of FCF allow managers to overinvest when demand increases and to postpone cost cuts when demand decreases. Hence, higher levels of FCF should increase cost stickiness (Chen et al. 2012). Second, we control for CEO fixed pay because prior studies suggest that executive compensation affects empire building incentives (Kanniainen 2000). We measure fixed pay (FixedPay) as the sum of salary and bonus which we divide by total compensation. The latter comprises salary, bonus, value of restricted stocks and options, and all other annual payouts (Chen et al. 2012).

2.4 Results

2.4.1 Descriptive Statistics

Table 2.1 provides descriptive statistics. The sample comprises 20,615 observations for the period between 1992-2011. The mean (median) annual percentage changes in operating

costs is about 8.9% (7.9%).[11]

Table 2.1

Descriptive Statistics

	Mean	Median	Std Dev
Cost Stickiness			
ΔlnOpCosts	0.089	0.079	0.19
ΔlnSales	0.088	0.08	0.202
Economic Variables			
EmplInt	1.463	1.508	0.804
AssetInt	-0.006	-0.027	0.584
SD	0.244	0	0.429
StockPerf	0.059	0.085	0.464
Agency Variables			
FCF	0.094	0.09	0.078
FixedPay	0.444	0.386	0.281
Overconfidence Measure			
Overconf	0.575	1	0.494

The sample comprises 20,615 firm-years between 1992-2011. All variables are defined in Table 2.7.

The mean sales change of 8.8% is slightly larger than the median sales change of 8%. Regarding the economic variables, the average firm has 6.1 (median = 4.5) employees per million dollars of sales and $1.2 million assets (median = $0.97) per million dollars of sales.[12] The median firm does not experience sales decreases in period t-1 (mean = 0.24) and the average raw stock return equals 0.06 (median = 0.09). Turning to the agency controls, the average ratio of free cash flow to total assets is about 9% (median = 0.09), and salary and bonus correspond to about 44% of total CEO compensation (median = 39%). In 58% of all firm-years CEOs meet the definition of our main measure of overconfidence, Overconf, based on Hirshleifer et al. (2012), which is comparable to data reported in their study. Table

[11] Strictly speaking, the percentage change in a variable X_t equals $X_t / X_{t-1} - 1$. Log differences, $\ln(X_t / X_{t-1}) = \ln(X_t) - \ln(X_{t-1}) = \Delta \ln(X_t)$, however, provide almost exact approximations if the percentage changes are of small magnitude.

[12] In the regression analyses we use log values of both ratios. The log values are reported in Table 2.1. Since interpreting the logs is uninformative, we describe the non-log values here.

2.2 presents Pearson correlation coefficients indicating that correlations among the independent variables are of small magnitude.

Table 2.2

Correlations

	V1	V2	V3	V4	V5	V6	V7
V1:ΔlnSales							
V2: EmplInt	**-0.048**						
V3: AssetInt	0.002	**-0.119**					
V4: SD	**-0.180**	-0.006	**0.064**				
V5: StockPerf	**0.387**	**-0.032**	**-0.033**	**-0.168**			
V6: FCF	**0.145**	**-0.034**	**-0.072**	**-0.157**	**0.136**		
V7: FixedPay	**-0.016**	**0.173**	**-0.162**	**0.014**	**-0.033**	**-0.071**	
V8: Overconf	**0.170**	**-0.025**	**0.025**	**-0.142**	**0.159**	**0.161**	**-0.068**

This table displays Pearson correlation coefficients. Bold parameters are significant at the 5% level or below. All variables are defined in Table 2.7.

2.4.2 Test of H1

We start by replicating Anderson et al. (2003) (eq. (2.1)) and in untabulated results find similar magnitude of cost stickiness (β_2=-0.25, t=-13.72 in our sample compared with β_2=-0.19, t=-26.14 in the Anderson et al. 2003 sample).

Table 2.3 contains the results of our test of Hypothesis 1. H1 predicts a positive association between managerial overconfidence and cost stickiness, so we expect a negative coefficient on $\Delta lnSales_{i,t} \cdot DecrDum_{i,t} \cdot Overconf_{i,t}$. The specification without controls in model (1), provides initial support for our hypothesis. The coefficient of interest, α_1, is negative and statistically significant at the 1% level (α_1=-0.116, t=-4.52), indicating that the degree of cost stickiness increases with overconfidence. The coefficient of interest declines slightly in magnitude and remains statistically significant at the 1% level after we include economic and agency controls (model (2) of Table 2.3) and year- and industry-fixed effects (model (3) of Table 2.3). Collectively, these results provide strong support for H1, indicating a positive

association between managerial overconfidence and cost stickiness.

The difference in cost stickiness between overconfident and non-overconfident CEOs can arise from differences in cost behavior when sales decrease, when sales increase, or both. We find that cost stickiness due to overconfidence is driven to a greater extent by the differences in cost behavior when sales decrease than by the differences in cost behavior when sales increase. More specifically, when sales decrease by 1%, operating costs decrease by 0.076%[13] less for overconfident CEOs in our main specification (model (3)). When sales increase by 1%, operating costs increase by 0.002% more for overconfident CEOs but the coefficient is not statistically significant at conventional levels. These findings suggest that overconfident CEOs keep more excess resources when sales decrease but it is less clear whether they build up more excess resources when sales increase. Our findings are consistent with the assumption made in prior literature (e.g., Anderson et al. 2003) that managers expand resources to the extent necessary to meet additional demand when sales increase. It is when demand decreases that managers' expectation about future demand plays a more significant role and the trade-off between the expected costs of carrying unutilized or excess resources and the expected adjustment costs becomes more critical.

In the following, we discuss the effects of the interacted control variables ($\Delta lnSales_{i,t} \cdot DecrDum_{i,t} \cdot Control_{i,t}$) for model (3) of Table 2.3. Both proxies for adjustment costs – employee and asset intensity – have the expected coefficient and the effect of asset intensity is statistically significant at the 10% level. The successive decrease variable has the expected effect and is statistically significant at the 1% level. Stock performance is not statistically significant. FCF and fixed pay should control for agency incentives. While fixed pay is insignificant, FCF reduces stickiness of operating costs, contrary to expectations.

[13] $\alpha_1 + \beta_1 = -0.078+0.002 = -0.076$ (t-value: -3.33).

Table 2.3

The Effect of Managerial Overconfidence on Cost Stickiness

	(1) Main Variables		(2) + Economic and Agency Controls		(3) + Year- and Industry Fixed Effects	
Main Variables						
ΔlnSales*DecrDum*Overconf	-0.116***	(-4.52)	-0.088***	(-3.64)	-0.078***	(-3.14)
ΔlnSales*Overconf	0.002	(0.19)	0.004	(0.37)	0.002	(0.13)
ΔlnSales*DecrDum	-0.058***	(-3.70)	-0.112***	(-3.67)	-0.046	(-0.36)
ΔlnSales	0.905***	(78.10)	0.949***	(52.33)	0.970***	(24.35)
DecrDum*Overconf	0	(0.11)	0.001	(0.14)	0.001	(0.20)
Overconf	0.002	(1.36)	0.001	(0.86)	0.002	(1.02)
DecrDum	0.003	(1.18)	0.013**	(2.30)	0.016	(1.41)
Economic Controls						
ΔlnSales*DecrDum*EmplInt			-0.018	(-1.33)	-0.018	(-1.39)
ΔlnSales*DecrDum*AssetInt			-0.065***	(-2.89)	-0.042*	(-1.88)
ΔlnSales*DecrDum*SD			0.194***	(7.19)	0.133***	(4.58)
ΔlnSales*DecrDum*StockPerf			0.031	(1.28)	0.018	(0.63)
ΔlnSales*EmplInt			0.033***	(4.85)	0.017**	(2.52)
ΔlnSales*AssetInt			-0.058***	(-5.24)	-0.052***	(-4.18)
ΔlnSales*SD			-0.153***	(-8.38)	-0.108***	(-5.76)
ΔlnSales*StockPerf			-0.001	(-0.11)	0.004	(0.30)
DecrDum*EmplInt			0.005*	(1.80)	0.001	(0.57)
DecrDum*AssetInt			0.010**	(2.35)	0.010**	(2.37)
DecrDum*SD			-0.018***	(-4.89)	-0.015***	(-3.78)
DecrDum*StockPerf			0.011**	(2.55)	0.009*	(1.81)
EmplInt			-0.003**	(-2.24)	-0.001	(-0.70)
AssetInt			0.004**	(2.12)	0.005**	(2.49)
SD			-0.007***	(-3.22)	-0.007***	(-3.15)
StockPerf			0	(0.16)	0	(0.15)
Agency Controls						
ΔlnSales*DecrDum*FCF			0.675***	(4.84)	0.565***	(4.08)
ΔlnSales*DecrDum*FixedPay			0.074*	(1.83)	0.052	(1.35)
ΔlnSales*FCF			-0.414***	(-5.15)	-0.368***	(-4.84)
ΔlnSales*FixedPay			-0.032*	(-1.80)	-0.030*	(-1.72)
DecrDum*FCF			-0.067**	(-2.00)	-0.064*	(-1.94)
DecrDum*FixedPay			0.008	(1.29)	0.001	(0.18)
FCF			-0.027	(-1.64)	-0.026	(-1.64)
FixedPay			-0.001	(-0.44)	-0.001	(-0.16)
Constant	0.003**	(2.25)	0.012***	(4.10)	0.007	(1.39)
Year-Fixed Effects	No		No		Yes	
FF 12 Ind.-Fixed Effects	No		No		Yes	
N	20615		20615		20615	
R2adj	0.8444		0.859		0.8643	

The dependent variable is log change in operating costs. All variables are defined in Table 2.7. Standard errors are clustered at the firm level. T-statistics are in parentheses. *,**,*** represent significance at the 10%, 5% and 1% level.

2.4.3 Addressing Alternative Explanations for H1

In this section, we address potential alternative explanations. We first demonstrate that the association between overconfidence and cost behavior we document in our study is distinct from the association between overconfidence and investment documented in prior literature. We then show that our results are driven by an innate personality trait, managerial overconfidence, rather than by optimistic expectations of future demand conditioned by past sales trends (Banker et al. 2014) by controlling for prior sales changes and still documenting an incremental effect of our overconfidence measure on cost stickiness. Finally, we alleviate self-selection concerns by additionally controlling for time-constant unobserved factors and time-varying factors that may be associated with selection mechanisms.

2.4.3.1 Cost Behavior vs. Investment

Since Malmendier and Tate (2005) show that overconfident CEOs exhibit heightened investment-cash flow sensitivity, one may argue that firms with overconfident CEOs who initiate new investment projects will mechanically exhibit more pronounced cost stickiness. To document that overconfidence has an independent effect on cost behavior beyond its effect on investment, we additionally control for investment. Following Malmendier and Tate (2005), we define investment as capital expenditure (Compustat mnemonic CAPX) normalized with beginning of year capital (PPENT). We then replicate our main analysis controlling for (i) investment in period t, (ii) investment in both period t and t-1, and (iii) investment in period t, t-1 and t+1.

Table 2.4

Estimating the Effect of Managerial Overconfidence on Cost Stickiness Controlling for Investment

	(1) Current Investment		(2) + Past Investment		(3) + Future Investment	
Main Variables						
ΔlnSales*DecrDum*Overconf	-0.078***	(-3.02)	-0.080***	(-3.12)	-0.078***	(-3.03)
ΔlnSales*Overconf	-0.01	(-0.63)	-0.007	(-0.46)	-0.009	(-0.56)
ΔlnSales*DecrDum	0.044	(0.35)	0.052	(0.42)	0.025	(0.20)
ΔlnSales	0.943***	(23.54)	0.924***	(24.26)	0.939***	(23.65)
DecrDum*Overconf	-0.002	(-0.54)	-0.002	(-0.53)	-0.002	(-0.53)
Overconf	0.001	(0.61)	0.001	(0.41)	0.001	(0.49)
DecrDum	0.012	(0.95)	0.009	(0.68)	0.009	(0.72)
Investment Controls						
ΔlnSales*DecrDum*CurrentInv	-0.197	(-1.47)	-0.203	(-1.54)	-0.205	(-1.56)
ΔlnSales*DecrDum*PastInv			0.434	(1.14)	0.437	(1.13)
ΔlnSales*DecrDum*FutureInv					-0.011	(-0.03)
ΔlnSales*CurrentInv	-0.017	(-0.82)	-0.01	(-0.48)	-0.009	(-0.44)
ΔlnSales*PastInv			0.028	(0.15)	-0.003	(-0.02)
ΔlnSales*FutureInv					-0.403*	(-1.67)
DecrDum*CurrentInv	0.025*	(1.76)	0.026*	(1.81)	0.026*	(1.81)
DecrDum*PastInv			0.026	(0.32)	0.014	(0.18)
DecrDum*FutureInv					-0.078	(-0.88)
CurrentInv	0.046***	(8.58)	0.045***	(8.47)	0.045***	(8.47)
PastInv			0.285***	(6.60)	0.288***	(6.79)
FutureInv					-0.052	(-1.10)
Economic Controls	Yes		Yes		Yes	
Agency Controls	Yes		Yes		Yes	
Year-Fixed Effects	Yes		Yes		Yes	
FF 12 Ind.-Fixed Effects	Yes		Yes		Yes	
N	19905		19905		19905	
R2adj	0.8499		0.8514		0.8518	

The dependent variable is the log change in operating costs. Investment is defined as capital expenditure (Compustat mnemonic CAPX) normalized with beginning of year capital (PPENT). All variables are defined in Table 2.7. Standard errors are clustered at the firm level. T-statistics are in parentheses. *,**,*** represent significance at the 10%, 5% and 1% level.

The results are shown in Table 2.4. In model (1) to (3) of Table 2.4, we include the additional investment control variables. In all analyses, we find that the associations between overconfidence and cost stickiness remain unchanged. More specifically, holding constant current investment, the coefficient of interest remains statistically significant (α_1-0.078, t=-3.02), as shown in model (1) of Table 2.4. Further, after we additionally control for past or past and future investment, the coefficient of interest remains statistically significant (α_1-0.08,

t=-3.12 and α_1-0.078, t=-3.03, respectively), as shown in model (2) and (3). Taken together, these results suggest that the association between overconfidence and cost behavior is distinct from the association between overconfidence and investment. Thus, the results we document in our study cannot be explained by the link between overconfidence and overinvestment documented by Malmendier and Tate (2005).

2.4.3.2 Controlling for Prior Sales Changes

In this section, we check the sensitivity of our results to using an alternative cost stickiness model. The analysis builds on the framework of Banker et al. (2014) (hereafter "BBCM") who refine the model of Anderson et al. (2003). In particular, BBCM highlight the role of managers' demand expectations.[14] BBCM use prior sales changes as a proxy for managers' expectations of future demand, relying on two arguments to justify this choice. First, since sales changes are positively correlated, sales increases in prior periods point to a greater likelihood of further sales increases in future periods, thereby increasing managers' expectations about future sales. Second, since behavioral studies suggest that managers are likely to extrapolate past trends, BBCM argue that managers will anticipate further increases in sales and, hence, will be more optimistic about future demand following a prior sales increase.

After a prior period's sales increase, BBCM predict cost stickiness. If prior sales increased, managers are more optimistic about future sales and more willing to retain unutilized resources should current sales decline. Conversely, should current sales continue to increase, BBCM expect managers to ramp up resources proportionally to meet the additional demand. Thus, the cost reaction following two consecutive sales increases should be of larger extent than the cost reaction following an increase in the prior but a decrease in the current period,

[14] BBCM also extend the cost stickiness model in Anderson et al. (2003) by allowing for anti-stickiness, i.e., costs decrease more when sales decrease compared to the extent they increase when sales increase. Since we do not make predictions regarding the anti-stickiness case, we do not discuss it here.

consistent with cost stickiness.

To distinguish the overconfidence explanation of cost stickiness from BBCM's explanation, we first replicate their specification, which conditions the Anderson et al. (2003) cost stickiness model on prior periods' sales changes as a proxy for managers' demand expectations (see Model (A) on p.16 in Banker et al. 2014):

$$\begin{aligned}\Delta \ln Cost_{i,t} = \beta_0 + IncrDum_{i,t-1} \cdot \left(\beta_1 \cdot \Delta \ln Sales_{i,t} + \beta_2 \cdot DecrDum_{i,t} \cdot \Delta \ln Sales_{i,t}\right) \\ + DecrDum_{i,t-1} \cdot \left(\beta_3 \cdot \Delta \ln Sales_{i,t} + \beta_4 \cdot DecrDum_{i,t} \cdot \Delta \ln Sales_{i,t}\right) + \varepsilon_{i,t}\end{aligned} \tag{2.3}$$

where $\Delta lnCost_{it}$ and $\Delta lnSales_{it}$ are defined as in section 3.3. The dummy variable $IncrDum_{i,t-1}$ equals one for a sales increase in period t-1. Similarly, $DecrDum_{i,t}$ and $DecrDum_{i,t-1}$ are dummy variables that equal one for sales declines in period t and t-1, respectively. A negative coefficient on β_2 would be consistent with cost stickiness in the BBCM framework. In untabulated results, we find that if sales increase 1% in both the prior and the current period, operating costs increase by 0.936% (β_1 = 0.936, t=169.64). If sales increase in the prior but decline 1% in the current period, operating costs are reduced by 0.724% (0.936%-0.212%) (β_2 = -0.212, t=-14.4). This result is consistent with the cost stickiness prediction by BBCM.

To estimate the impact of overconfidence on cost stickiness beyond the BBCM effect, we include interactions with our proxy for managerial overconfidence (Overconf) as follows:[15]

[15] The control variables comprise the economic and agency variables that we use in the previous sections.

Table 2.5

Estimating the Effect of Managerial Overconfidence on Cost Stickiness Conditional on Prior Sales Changes (BBCM Framework)

	(1)
BBCM	
$IncrDum_{i,t-1} \cdot \Delta lnSales_{i,t}$	0.975***
	(32.74)
$IncrDum_{i,t-1} \cdot DecrDum_{i,t} \cdot \Delta lnSales_{i,t}$	-0.291
	(-1.44)
$DecrDum_{i,t-1} \cdot \Delta lnSales_{i,t}$	0.794***
	(10.33)
$DecrDum_{i,t-1} \cdot DecrDum_{i,t} \cdot \Delta lnSales_{i,t}$	0.259**
	(2.27)
Interaction with Overconfidence	
$IncrDum_{i,t-1} \cdot \Delta lnSales_{i,t}$	0.011
	(1.41)
$IncrDum_{i,t-1} \cdot DecrDum_{i,t} \cdot \Delta lnSales_{i,t}$	-0.085***
	(-3.36)
$DecrDum_{i,t-1} \cdot \Delta lnSales_{i,t}$	0.008
	(0.32)
$DecrDum_{i,t-1} \cdot DecrDum_{i,t} \cdot \Delta lnSales_{i,t}$	-0.119***
	(-4.04)
Constant	0.006***
	(8.21)
Economic Controls	Yes
Agency Controls	Yes
Year-Fixed Effects	Yes
FF 12 Ind.-Fixed Effects	Yes
N	20615
R2adj	0.8641

The dependent variable is the log change in operating costs. All variables are defined in Table 2.7. Standard errors are clustered at the firm level. T-statistics are in parentheses. *,**,*** represent significance at the 10%, 5% and 1% level.

$$
\begin{aligned}
\Delta \ln Cost_{i,t} = {} & \beta_0 + IncrDum_{i,t-1} \cdot \left(\beta_1 \cdot \Delta \ln Sales_{i,t} + \beta_2 \cdot DecrDum_{i,t} \cdot \Delta \ln Sales_{i,t} \right. \\
& + \beta_3 \cdot \Delta \ln Sales_{i,t} \cdot Overconf_{i,t} + \beta_4 \cdot DecrDum_{i,t} \cdot \Delta \ln Sales_{i,t} \cdot Overconf_{i,t} \\
& + \beta_{Control} \cdot \Delta \ln Sales_{i,t} \cdot Controls_{i,t} + \beta_{Control} \cdot DecrDum_{i,t} \cdot \Delta \ln Sales_{i,t} \cdot Controls_{i,t} \\
& + \beta_{Industry} \cdot \Delta \ln Sales_{i,t} + \beta_{Industry} \cdot DecrDum_{i,t} \cdot \Delta \ln Sales_{i,t} \\
& \left. + \beta_{Year} \cdot \Delta \ln Sales_{i,t} + \beta_{Year} \cdot DecrDum_{i,t} \cdot \Delta \ln Sales_{i,t} \right) \\
& + DecrDum_{i,t-1} \cdot \left(\beta_5 \cdot \Delta \ln Sales_{i,t} + \beta_6 \cdot DecrDum_{i,t} \cdot \Delta \ln Sales_{i,t} \right. \\
& + \beta_7 \cdot \Delta \ln Sales_{i,t} \cdot Overconf_{i,t} + \beta_8 \cdot DecrDum_{i,t} \cdot \Delta \ln Sales_{i,t} \cdot Overconf_{i,t} \\
& + \beta_{Control} \cdot \Delta \ln Sales_{i,t} \cdot Controls_{i,t} + \beta_{Control} \cdot DecrDum_{i,t} \cdot \Delta \ln Sales_{i,t} \cdot Controls_{i,t} \\
& + \beta_{Industry} \cdot \Delta \ln Sales_{i,t} + \beta_{Industry} \cdot DecrDum_{i,t} \cdot \Delta \ln Sales_{i,t} \\
& \left. + \beta_{Year} \cdot \Delta \ln Sales_{i,t} + \beta_{Year} \cdot DecrDum_{i,t} \cdot \Delta \ln Sales_{i,t} \right) + \varepsilon_{i,t}
\end{aligned}
\tag{2.4}
$$

We predict that cost stickiness will increase in the degree of overconfidence after controlling for management demand expectations reflected in prior sales. Thus, we expect β_4 to take on a negative sign. Consistent with our prediction, results in Table 2.5 show that β_4 is significantly negative (β_4 = -0.085, t= -3.36). This result suggests that overconfidence has an impact on cost stickiness above and beyond managerial demand expectations reflected in prior sales changes.

2.4.3.3 Addressing Self-Selection

In this section we address the possibility that the positive association between managerial overconfidence and cost stickiness could be affected by self-selection. If overconfident CEOs are more likely to self-select into or be hired by firms with certain characteristics, and firms with these characteristics have greater cost stickiness, then our result might be driven by self-selection.

To the extent that self-selection is driven by characteristics that are constant across industries, we control for these factors with industry-fixed effects. Model (3) of Table 2.3 reports results using Fama-French 12 industry dummies and in the robustness section we discuss results using two-digit SIC code industry dummies. In both specifications, we document a significantly positive association between managerial overconfidence and cost

stickiness.[16]

While the previous tests control for potentially omitted variables that are constant at the industry-level, we next control for time-varying factors that may be associated with selection mechanisms. If overconfident CEOs are associated with growth firms and if growth firms exhibit more pronounced cost stickiness, then growth potential may be an omitted variable. We therefore rerun our analyses by controlling for two proxies of growth potential. We first control for Tobin's Q since high values of Q indicate future growth potential (Tobin 1969).[17] Alternatively, we control for demand volatility, assuming that higher demand volatility characterizes growth firms (Banker et al. 2011).[18] Untabulated results suggest that our results are robust to controlling for both proxies of growth (α_1=-0.08, t=-2.89 and α_1=-0.076, t=-3.11, respectively).

Finally, we follow Hirshleifer et al. (2012) and estimate our main specification on a restricted sample that focuses on firm-years that are supposed to be less strongly affected by self-selection. The test builds on the idea that overconfidence is a persistent character trait that remains stable over time. In contrast, firm characteristics that may induce self-selection, such as growth opportunities, vary over time as the firm environment changes. To the extent that there is self-selection, potential matching effects will be most severe in the first years of each CEO's tenure. Hirshleifer et al. (2012), therefore, suggest excluding the first years of each CEO's tenure as these years are most likely to reflect self-selection. The remaining sample should be less affected by self-selection. We rerun our main specification excluding the first two, three and four years of each CEO's tenure. In all specification, we obtain results that are comparable with our main analysis (α_1=-0.072, t=-2.44, α_1=-0.074, t=-2.02 and

[16] The tables of all further sensitivity checks are available on request.
[17] We define Tobin's Q as the market value of equity (Compustat mnemonic CSHO·PRCCF) plus total assets (AT) minus book value of equity (CEQ + TXDB), divided by total assets (Chen, Chen, and Wei 2011).
[18] We define demand volatility as the "standard deviation of sales revenue over the five years prior to the event year divided by the mean of sales revenue over the five years prior to the event year" (Banker et al. 2011, p. 801).

α_1=-0.09, t=-1.98 respectively), further mitigating self-selection concerns.

Collectively, the evidence presented in this section suggests that our main result is not driven by sticky firms selecting overconfident CEOs or overconfident CEOs selecting to work for cost sticky firms.

2.4.4 Robustness Checks for H1

To assess the robustness of the association between managerial overconfidence and cost stickiness, we conduct the following sensitivity analyses: we (1) examine alternative cost categories, (2) employ alternative overconfidence measures, (3) control for earnings targets following the recent studies of Dierynck et al. (2012) and Kama and Weiss (2013), (4) address the criticism of Anderson and Lanen (2009) by following their treatment of influential observations and of Balakrishnan, Labro, and Soderstrom (2014) by estimating a linear instead of the logarithmic specification, (5) use alternative agency controls, (6) check the robustness to an alternative industry classification, and (7) control for future stock returns. The tables of all robustness results are available upon request. Below we briefly describe the findings.

First, we test other cost categories. We alternatively examine (i) selling, general, and administrative costs (Compustat mnemonic XSGA), (ii), cost of good sold (COGS), (iii) total cost (SALE - IB) and (iv) employment (EMP). In all analyses, we find qualitatively similar results (α_1=-0.082, t=-2.15, α_1=-0.113, t=-3.35, α_1=-0.096, t=-2.52, and , α_1=-0.101, t=-2.36[19], respectively).

Second, we re-estimate equation (2.2) using additional option- and investment-based overconfidence measures. All overconfidence measures are defined in Table 2.7. Regarding the option-based measures, we use the option exercising measure following Malmendier et al. (2011) and Campbell et al. (2011). The measure of Malmendier et al. (2011) requires CEOs

[19] We do not control for employee intensity when analyzing employment stickiness.

to twice hold options that are more than 67% in-the-money to be classified as overconfident. The option exercising measure following Campbell et al. (2011) requires CEOs to twice hold options that are more than 100% in-the-money. In addition, the measure allows for reclassifications upon early option exercise. In both analyses, we find qualitatively similar results (α_1=-0.076, t=-2.95 and α_1=-0.094, t=-3.35, respectively). Concerning the investment-based measures, we use the capital expenditure measure following Ahmed and Duellman (2013) and the investment measure following Campbell et al. (2011). While the investment measure following Ahmed and Duellman (2013) is not statistically significant (α_1=-0.031, t=-1.04), we find similar results using the investment-based overconfidence measure following Campbell et al. (2011) (α_1=-0.121, t=-2.95).

Third, we augment our main model (equation (2.2)) and additionally control for the influence of earnings targets and managerial incentives on cost stickiness following the recent studies of Dierynck et al. (2012) and Kama and Weiss (2013). Our conclusion remains unchanged after controlling for small positive earnings (α_1=-0.078, t=-3.15) or small increases in earnings (α_1=-0.082, t=-3.31) as defined in Kama and Weiss (2013, p. 211).

Fourth, we address the criticism of Anderson and Lanen (2009) and follow their suggestion to exclude observations when costs and sales move in opposite directions. Additionally, we follow the approach suggested in Balakrishnan et al. (2014) and estimate a linear model instead of the logarithmic specification (we divide both the change in costs and sales by lagged sales) and obtain comparable results (α_1=-0.07, t=-3.40 and α_1=-0.074, t=-2.88, respectively).[20]

Fifth, to control for agency factors and variables correlated with stock options influencing cost stickiness, we follow Chen et al. (2012) and include free cash flow and fixed pay as controls in our main regression model. We alternatively use the following controls instead of

[20] We refer to Banker and Byzalov (2013) for an in-depth discussion of both concerns.

fixed pay: (1) Following Malmendier and Tate (2005) we use stock ownership and vested options, (2) following Ahmed and Duellman (2013) we use stock ownership, and (3) following Schrand and Zechman (2012), we control for salary, bonus, option grants and total holdings (unexercised options and shares owned). All variables are defined in Table 2.7. Using all three specifications, we obtain similar results (α_1=-0.078, t=-3.27, α_1=-0.081, t=-3.21, and α_1=-0.074, t=-2.73).

Sixth, we also find qualitatively similar results if we construct industry dummies based on the two-digit SIC codes following Hirshleifer et al. (2012) instead of Fama-French 12 industries (α_1=-0.074, t=-2.84). Finally, our conclusion remains unchanged if we control for future stock returns (α_1=-0.082, t=-3.20).

2.4.5 Test of H2

So far, we provide strong evidence for a positive association between managerial overconfidence and cost stickiness. Our second hypothesis predicts that cost stickiness driven by managerial overconfidence should be negatively associated with future firm performance compared to cost stickiness not driven by managerial overconfidence.

To test our H2, we proceed as follows. Our prior results show that overconfident CEOs exhibit more pronounced cost stickiness than non-overconfident CEOs. More specifically, our results show that cost stickiness due to overconfidence is driven to a greater extent by differences in cost behavior when sales decrease than by differences in cost behavior when sales increase. If overconfident CEOs indeed erroneously overestimate future demand and, therefore, keep more costs than non-overconfident CEOs when sales decline, the cost behavior of overconfident CEOs when sales decline should have a negative impact on future earnings compared to the cost behavior of non-overconfident CEOs when sales decline.

Empirically, we use the following specification. We first define a dummy variable that is one if a CEO is overconfident and sales decline ($OC\_Dec_{i,t}$). To ensure that we compare

overconfident and non-overconfident CEOs when sales decline, we need to define two additional variables. The variable $OC\_Inc_{i,t}$ is one if a CEO is overconfident and sales increase. The variable $NonOC\_Inc_{i,t}$ is one if a CEO is non-overconfident and sales increase.[21] The overconfidence classification is based on our overconfidence dummy, $Overconf_{i,t}$. The resulting regression model is given in equation (2.5). We expect $\beta_1 < 0$.

$$CEPS1_{i,t+1} = \beta_0 + \beta_1 \cdot OC\_Dec_{i,t} + \beta_2 \cdot OC\_Inc_{i,t} + \beta_3 \cdot NonOC\_Inc_{i,t} + \sum_{c=4}^{18} \beta_c \cdot Controls + \varepsilon_{i,t} \quad (2.5)$$

The regression model specification builds on the fundamental analysis literature (Abarbanell and Bushee 1997; Anderson et al. 2007; Lev and Thiagarajan 1993). The dependent variable, $CEPS1_{i,t+1}$, is earnings per share (Compustat mnemonic EPSPX) in t+1 less earnings per share in t and this difference is deflated by the lagged stock price (PRCCF) in t-1.[22] The economic control variables are defined in Table 2.7 and serve as proxies for other fundamental signals following Abarbanell and Bushee (1997) and Anderson et al. (2007).[23] In addition, we include agency controls following Malmendier and Tate (2005).

The results of estimating equation (2.5) are shown in Table 2.6. Consistent with our hypothesis, the coefficient on $OC\_Dec_{i,t}$ is negative and statistically significant at the 1% level (β_1 = -0.014, t-value =-3.13). This finding is consistent with our second hypothesis, indicating that cost stickiness driven by overconfidence has significantly negative consequences for future firm performance.

[21] There are two drawbacks associated with the firm-specific cost stickiness measure of Weiss (2010). First, the measure requires firms to have both declining and increasing sales in the last four quarters. Second, the measure requires sales and costs to change in the same direction. Both requirements lead to substantial data loss and selection bias, effectively precluding the use of the measure in our setting (Banker and Byzalov 2013).
[22] To account for stock splits, we divide both EPSPX and PRCCF with the split adjustment factor (AJEX).
[23] See Lev and Thiagarajan (1993) for a detailed discussion of the fundamental signals. About 35% of all observations of the fundamental signal effective tax rate (ETR) are missing. We replace missing values of ETR with zero and define a dummy variable that is one whenever ETR is missing.

Table 2.6

Future Earnings, Cost Stickiness and Managerial Overconfidence

OC_Dec	-0.014***	(-3.13)
OC_Inc	-0.047***	(-12.53)
NonOC_Inc	-0.047***	(-11.15)
CEPS	-0.100***	(-5.74)
INV	-0.264***	(-5.98)
AR	0.072**	(2.02)
CAPEX	-0.141**	(-2.03)
GM	0.025	(0.68)
ETR	-0.287***	(-6.06)
ETR_Missing	-0.003*	(-1.78)
EQ	0.008***	(5.25)
AQ	0.001	(0.74)
LF	0	(0.00)
LEV	0.003	(1.25)
SGROWTH	0.013***	(3.06)
SGA-RATIO	-0.039	(-0.86)
ShrOwn	0	(0.01)
VestedOptions	-0.005	(-0.63)
Constant	0.046***	(12.43)
N	17947	
R2adj	0.0522	

The dependent variable is earnings per share in t+1 less earnings per share in t and this difference is deflated by the lagged stock price in t-1. All variables are defined in Table 2.7. Standard errors are clustered at the firm level. T-statistics are in parentheses. *,**,*** represent significance at the 10%, 5% and 1% level.

To assess the robustness of the association between cost stickiness driven by managerial overconfidence and future firm performance, we conduct the following robustness checks.

As a first robustness check, we re-estimate equation (2.5) using the alternative overconfidence measures defined in the previous section. Using the option-based measures following Malmendier et al. (2011) and Campbell et al. (2011), we find qualitatively similar results (β_1=-0.014, t-value=-3.06 and β_1=-0.014, t-value=-3.00, respectively). While the investment-based overconfidence measure following Campbell et al. (2011) is not statistically significant at conventional levels (β_1=-0.008, t-value=-1.27), we find

qualitatively similar results using the investment-based overconfidence measure following Ahmed and Duellman (2013) (β_1=-0.03, t-value=-6.53).

As a second robustness check, we re-estimate equation (2.5) using alternative performance measures. If we alternatively define the dependent variable as change in net income, scaled by lagged assets, or as change in income before extraordinary items, scaled by lagged assets, we find qualitatively similar results (β_1=-0.005, t-value=-1.91 and β_1=-0.005, t-value=-1.90, respectively). Third, we obtain qualitatively similar results after controlling for industry- and year-fixed effects (β_1 =-0.017, t-value=-3.74). Fourth, our results are similar if we alternatively drop missing values of the fundamental signal effective tax rate instead of setting them to zero (β_1 =-0.014, t-value=-2.35). Finally, our conclusion remains unchanged if we – in addition to our variables of interest – allow our set of control variables to vary with decreasing and increasing sales (β_1 =-0.016, t-value=-3.49).

Overall, the above results provide strong evidence in support of H2, indicating that cost stickiness driven by overconfidence has significantly negative consequences for future firm performance.

Table 2.7

Variable Definitions

Cost stickiness variables		
$\Delta lnCost_{i,t}$	$ln(Cost_{i,t}/Cost_{i,t-1})$	We use five different cost categories: (1) operating costs are defined as sales less operating income after depreciation [SALE minus OIADP]; (2) SG&A costs are based on Compustat mnemonic XSGA; (3) cost of good sold are based on Compustat mnemonic COGS (4) total costs equal sales less income before extraordinary items [SALE minus IB] and (5) employment is based on Compustat mnemonic EMP
$\Delta lnSales_{i,t}$	$ln(SALE_{i,t}/SALE_{i,t-1})$	SALE = Sales
$DecrDum_{i,t}$	1 if $SALE_{i,t}<SALE_{i,t-1}$, 0 otherwise	
$EmplInt_{i,t}$	$ln((1000 \cdot EMP_{i,t}/SALE_{i,t}))$	EMP = Employees
$AssetInt_{i,t}$	$ln(AT_{i,t}/SALE_{i,t})$	AT = Assets total
$SD_{i,t}$	1 if $SALE_{i,t-1}<SALE_{i,t-2}$, 0 otherwise	
$StockPerf_{i,t-1}$	ln(1+ annual raw stock return in t-1)	RETX = Raw stock return
$FCF_{i,t}$	$[OANCF_{i,t}-(DVC_{i,t}+DVP_{i,t})]/AT_{i,t}$	OANCF = Cash flow from operating activities; DVC = Common dividends; DVP = Preferred dividends
$FixedPay_{i,t}$	$[SALARY_{i,t}+BONUS_{i,t})]/TDC1_{i,t}$	TDC1 = Total Compensation (Salary + Bonus + Other Annual + Restricted Stock Grants + LTI)
The BBCM framework		
$IncrDum_{i,t-1}$	1 if $SALE_{i,t-1}>SALE_{i,t-2}$, 0 otherwise	
$DecrDum_{i,t-1}$	1 if $SALE_{i,t-1}<SALE_{i,t-2}$, 0 otherwise	
Overconfidence measures		
$Overconf_{i,t}$; Option exercising measure following Hirshleifer et al. (2012, p.1463)	If a CEO once fails to exercise options that are more than 67% in-the-money, this variable is set to one for this and the following years. The variable is zero otherwise (Hirshleifer et al. 2012).	
Option exercising measure following Malmendier et al. (2011)	If a CEO fails to exercise options that are more than 67% in-the-money in two years of his tenure, this variable is set to one. The classification starts with the first time an option has been held too long and remains unchanged for the entire tenure. The variable equals zero otherwise (Malmendier et al. 2011).	
Option exercising	Campbell et al. (2011) define a semi-permanent measure of overconfidence. If a CEO fails	

measure following Campbell et al. (2011, p. 699)	to exercise options that are more than 100% in-the-money in two years of his tenure, this variable is set to one (from the first time on forward). This measure allows for reclassifications. If the CEO exercises options that are less than 30% in-the-money and if he does not hold any other exercisable options that are more than 30% in-the-money in two years of his tenure, the variable is reset to zero again (Campbell et al. 2011).	
Investment-based measure following Campbell et al. (2011, p. 702)	We first build the investment rate as capital expenditures (Compustat item: CAPX) divided by beginning of year property, plant, and equipment (Compustat item: PPENT). This variable is industry adjusted by subtracting the annual 3-digit industry median. The investment-based measure equals one if the firm is in the top quintile of all firms sorted on industry-adjusted investment rates for two consecutive years, starting with the first of the two years. The classification remains unchanged unless the firm is in the bottom quintile of all firms sorted on industry-adjusted investment rates for two consecutive years in which case the variable is reset to zero again (Campbell et al. 2011).	
Investment-based measure following Ahmed and Duellman (2013, p. 8)	The variable equals one if capital expenditures divided by prior year's total assets exceed the Fama-French 12 industry median of that year, otherwise zero (Ahmed and Duellman 2013).	

Alternative agency variables

$ShrOwn_{i,t}$ = Stock $Ownership_{i,t}$	$SHROWN\_EXCL\_OPTS_{i,t} \cdot 10^3 / CSHO_{i,t} \cdot 10^6$	SHROWN_EXCL_OPTS = shares owned, options excluded; CSHO = common shares outstanding
Vested $Options_{i,t}$	$(OPT\_UNEX\_EXER\_NUM_{i,t} \cdot 10^3 / CSHO_{i,t} \cdot 10^6) \cdot 10$	OPT_UNEX_EXER_NUM = unexercised exercisable options
$LnSalary_{i,t}$	$\ln(SALARY_{i,t}+0.01)$	
$LnBonus_{i,t}$	$\ln(BONUS_{i,t}+0.01)$	
$LnOption_{i,t}$	Before 2006:[24] $\ln(OPTION\_AWARDS\_BLK\_VALUE_{i,t} +0.01)$ Since 2006: $\ln(OPTION\_AWARDS\_FV_{i,t}+0.01)$	OPTION_AWARDS_BLK_VALUE = aggregate value of options granted using Compustat Black-Scholes methodology; OPTION_AWARDS_FV = grant date fair value of options granted
$LnHoldings_{i,t}$	$\ln((OPT\_UNEX\_EXER\_EST\_VAL_{i,t} + OPT\_UNEX\_UNEXER\_EST\_VAL_{i,t}) + (SHROWN\_EXCL\_OPTS_{i,t} \cdot PRCCF_{i,t}))$	OPT_UNEX_EXER_EST_VAL = estimated value of in-the-money unexercised exercisable options; OPT_UNEX_UNEXER_EST_VAL = estimated value of in-the-money unexercised unexercisable options; SHROWN_EXCL_OPTS = shares owned - options excluded; PRCCF = price close - annual – fiscal

[24] Note that due to changes in equity compensation reporting (FAS 123R) we use the ExecuComp item OPTION_AWARDS_BLK_VALUE before 2006 and the ExecuComp item OPTION_AWARDS_FV as of 2006 to determine the Black Scholes value of option grants awarded.

Future earnings, cost stickiness and overconfidence

$CEPS1_{i,t+1}$	$(EPSPX_{i,t+1} - EPSPX_{i,t})/ PRCCF_{i,t-1}$	EPSPX (=Earnings Per Share (Basic) - Excluding Extraordinary Items). In robustness checks, we replace EPSPX with NI (net income) and IB (income before extraordinary items), which we scale with lagged total assets (AT) instead of PRCCF.
$CEPS_{i,t}$	$(EPSPX_{i,t} - EPSPX_{i,t-1})/PRCCF_{i,t-1}$	
$OC\_Dec_{i,t}$	$OC\_Dec_{i,t} = \begin{cases} 1 \text{ if } Overconf_{i,t} = 1 \,\&\, DecrDum_{i,t} = 1 \\ 0 \text{ else} \end{cases}$	
$OC\_Inc_{i,t}$	$OC\_Inc_{i,t} = \begin{cases} 1 \text{ if } Overconf_{i,t} = 1 \,\&\, DecrDum_{i,t} = 0 \\ 0 \text{ else} \end{cases}$	
$NonOC\_Inc_{i,t}$	$NonOC\_Inc_{i,t} = \begin{cases} 1 \text{ if } Overconf_{i,t} = 0 \,\&\, DecrDum_{i,t} = 0 \\ 0 \text{ else} \end{cases}$	
$INV_{i,t}$	$INVT_{i,t}/SALE_{i,t} - INVT_{i,t-1}/SALE_{i,t-1}$	INVT = Inventories Total
$AR_{i,t}$	$RECT_{i,t}/SALE_{i,t} - RECT_{i,t-1}/SALE_{i,t-1}$	RECT = Receivables - Total
$CAPEX_{i,t}$	$\frac{CAPXV_{i,t}}{Ind(CAPXV_{i,t})} - \frac{CAPXV_{i,t-1}}{Ind(CAPXV_{i,t-1})}$	CAPXV = Capital Expenditures. Industry capital expenditures are calculated by aggregating firm figures for all firms with the same two-digit SIC code each year (Abarbanell and Bushee 1997).
$GM_{i,t}$	$\frac{SALE_{i,t-1} - COGS_{i,t-1}}{SALE_{i,t-1}} - \frac{SALE_{i,t} - COGS_{i,t}}{SALE_{i,t}}$	COGS = Cost of Goods Sold
$ETR_{i,t}$	$\left[\left(\frac{1}{3}\sum_{\tau=1}^{3} TaxRate_{i,t-\tau}\right) - TaxRate_{i,t}\right] \cdot CEPS_{i,t}$, where $TaxRate_{i,t} = \frac{TXT_{i,t}}{PI_{i,t} + AM_{i,t}}$	TXT = Income Taxes, Total; PI = Pretax Income; DP = Depreciation and Amortization. Missing values are set to zero.
$ETR\_Missing_{i,t}$	$ETR\_Missing_{i,t} = \begin{cases} 1 \text{ if ETR is missing} \\ 0 \text{ else} \end{cases}$	
$EQ_{i,t}$	0 for LIFO, 1 for FIFO or other	INVVAL = Inventory Valuation Method
$AQ_{i,t}$	0 for unqualified, 1 for qualified or other	AUOP = Auditor Opinion
$LF_{i,t}$	$\left(\frac{SALE_{i,t-1}}{EMP_{i,t-1}} - \frac{SALE_{i,t}}{EMP_{i,t}}\right) \Big/ \frac{SALE_{i,t}}{EMP_{i,t}}$	EMP = Employees
$LEV_{i,t}$	$DLTT_{i,t}/CEQ_{i,t} - DLTT_{i,t-1}/CEQ_{i,t-1}$	DLTT = Long-Term Debt, CEQ = Common Equity,
$SGROWTH_{i,t}$	$SALE_{i,t}/SALE_{i,t-1} - SALE_{i,t-1}/SALE_{i,t-2}$	
$SGA\text{-}RATIO_{i,t}$	$XSGA_{i,t}/SALE_{i,t} - XSGA_{i,t-1}/SALE_{i,t-1}$	

2.5 Conclusion

In this study, we examine the association between a managerial characteristic, overconfidence, and cost stickiness. We find strong support for our prediction of a positive association between managerial overconfidence and cost stickiness. Our results are robust to many sensitivity checks, including alternative measures of overconfidence, different cost categories and controlling for managers' rational expectations of future demand. We also find that the effect of managerial overconfidence on cost stickiness is primarily driven by the differences in cost behavior when sales decline.

Furthermore, we predict and find that cost stickiness driven by managerial overconfidence is negatively associated with future firm performance compared to cost stickiness not driven by managerial overconfidence. The results are similar for alternative performance measures and alternative overconfidence proxies. Overall, the results of this analysis provide support for our argument that overconfident CEOs erroneously overestimate future demand, and hence, make suboptimal cost adjustment decisions.

Our study extends a growing accounting literature on the effect of personality traits and other managerial characteristics on managerial decisions by providing one of the first empirical evidence on the relation between a managerial characteristic and cost management decisions. Our results also contribute to the debate on the role of managerial overconfidence in managerial decision-making. Prior studies have documented some of the potential benefits and costs of managerial overconfidence. For example, Malmendier and Tate (2008) document that overconfident CEOs conduct value-destroying mergers, while Hirshleifer et al. (2012) find that overconfident CEOs are better innovators. Our study contributes to this discussion by presenting evidence of the influence of managerial overconfidence on cost behavior and the resulting consequences.

In addition, our study contributes to the cost stickiness literature by documenting a managerial characteristic as a determinant of cost stickiness. In doing so, we provide strong

and direct support for the role of managerial discretion in cost management. More generally, our study represents a first step towards understanding the impact of managerial characteristics on cost decisions and cost behavior.

Our findings that overconfidence affects cost management and potentially reduces future firm performance have important practical implications.

First, our study has practical implications for the design of corporate governance mechanisms. When cost stickiness is driven by legitimate economic reasons (e.g. rational expectations about future demand, capacity utilization, or adjustment costs), boards of directors should not intervene in managers' cost decisions. When cost stickiness is driven by agency explanations (e.g. empire building incentives), strengthening corporate governance would help deter overspending on the part of the managers. In contrast to these two types of cost stickiness, what we document in our study is a type of cost stickiness that is driven for well-intentioned (but misguided) reasons due to a behavioral bias. Under these circumstances, modifying the incentive system design would not help mitigate overconfidence-driven cost mismanagement. We suggest that a more effective way is to mitigate managers' upward bias in expectations. For example, boards of directors can take measures to challenge the expectation assumptions of overconfident CEOs and enhance overconfident CEOs' awareness of their own potential behavioral biases.

Second, to the extent that sophisticated market participants and the media can use the option-based overconfidence classification to identify overconfident CEOs, market participants can also mitigate the potential negative impact of managerial overconfidence by challenging overconfident CEOs' expectations about future sales and associated cost decisions.

Third, our findings also have implications for labor market practices. When cost management is particularly important for an organization, the organization needs to be

especially cautious in hiring an overconfident CEO.

Finally, our results that cost stickiness driven by managerial overconfidence has negative impact on future firm performance also generate new insights for financial accounting research. Managers' cost decisions influence cost behavior, which affects earnings behavior and ultimately impacts firm valuations. For example, the results of our study have implications for earnings properties, earnings prediction models, and analyst forecasts.

3 The Impact of Investor Sentiment on Operating Expenditure – a Catering Perspective

3.1 Introduction

This study belongs to a stream of literature that intends to increase our understanding of how investor sentiment can affect corporate policies. The concept of investor sentiment relaxes the assumption of perfect rationality, differentiating between two types of investors: Rational arbitrageurs and irrational (or noise) traders (Baker and Wurgler 2006, 2007). The so-called catering theory states that the existence of noise traders allows managers to boost the short-term stock price by adjusting their corporate policies to noise traders' misperceptions (Stein 1996; Baker and Wurgler 2011). Drawing on this theory, prior literature documents that investor sentiment affects a variety of corporate decisions, including decisions on corporate name changes, corporate disclosure, or dividends.[25] Most closely related to our study is the finding that catering affects decisions on long-term investment projects (Polk and Sapienza 2009). So far, there is, however, no evidence on how investor sentiment affects short-term or operating expenditure. While the catering theory predicts an unambiguously positive association between capital expenditure and investor sentiment, we argue that there are two opposing channels linking investor sentiment and operating expenditure.

First, prior literature suggests that noise traders have optimistically biased cash flow expectations in periods of high sentiment (Baker and Wurgler 2006, 2007; Stein 1996). If noise traders overestimate investment opportunities, managers may feel pressure to alter their investment behavior. There is ample evidence documenting the long-term value-creating potential for research and development (R&D) expenditure (Eberhart et al. 2004; Lev and Sougiannis 1996; Sougiannis 1994), advertising expenses (Chan et al. 2001; Hirschey and

[25] See Cooper, Dimitrov, and Rau (2001); Cooper et al. (2005); Bergman and Roychowdhury (2008); Brown et al. (2012); Baker and Wurgler (2004); Li and Lie (2006).

Weygandt 1985; Madden et al. 2006), and selling, general and administrative (SG&A) resources (Anderson et al. 2007; Banker et al. 2011; Tronconi and Marzetti 2011). To the extent that managers cater to investors' optimistic investment expectations, we, therefore, expect to observe a positive association between investor sentiment and operating expenditure.

Second, there is evidence indicating that investors have overly optimistic earnings expectations in periods of high sentiment (Hribar and McInnis 2012; Mian and Sankaraguruswamy 2012; Seybert and Yang 2012; Walther and Willis 2013). Exacerbated earnings expectations may induce managers to reduce spending on operating expenditure because reducing operating expenditure allows to boost current-period income (Baber et al. 1991; Burgstahler and Dichev 1997; Roychowdhury 2006). Managers will be less likely to consider current-period income effects when making decisions on capital expenditure, given that capital expenditure is depreciated over multiple periods and, hence, has little effect on current earnings (Baber et al. 1991; Dechow and Sloan 1991). In our setting, we, therefore, argue that mangers face a trade-off between catering to investors' cash flow and catering to investors' earnings expectations. In absence of incentives to meet earnings, we expect to observe a positive association between investor sentiment and operating expenditure. For firms that face earnings targets, we, however, argue the expected positive association should be significantly less pronounced or may even turn negative.

In the empirical analysis, we measure investor sentiment using the annual sentiment index proposed by Baker and Wurgler (2006). They extract the common component underlying several sentiment measures that have been used in prior literature on investor sentiment. The index measures investor sentiment at the aggregate market level and is widely used by subsequent studies (e.g., Brown et al. 2012; Hribar and McInnis 2012; McLean and Zhao 2014; Mian and Sankaraguruswamy 2012).

To test the catering hypothesis, we regress changes in operating expenditure on changes in sentiment controlling for both firm- and macro-level determinants of operating expenditure. Our sample is based on the intersection of Compustat, CRSP and data on GDP, comprising 105,885 observations from 1972 till 2010. Consistent with the catering theory, we find a positive association between investor sentiment and operating expenditure. More specifically, we find that managers increase spending on R&D expenditure, advertisement and various components of SG&A costs in response to high sentiment. We also document that catering extends to employment decisions in that managers hire more aggressively in periods of high relative to periods of average sentiment.

In further analyses, we find results that are consistent with cross-sectional predictions of the catering theory. First, our results indicate that managers tend to increase spending on SG&A resources if these resources have high future value creating potential. Second, we find catering tendencies to increase as managers' horizons decrease, and, third, our results indicate that catering is more pronounced for those firms that are more strongly affected by investor sentiment.

Finally, our results suggest that the association between investor sentiment and SG&A costs, R&D expenditure and employment is significantly less pronounced if firms face incentives to avoid losses. These results support our second hypothesis indicating that managers are less likely to increase spending on operating expenditure when facing earnings targets.

We make two contributions to prior literature. We first contribute to prior literature that examines real effects of investor sentiment. Existing studies show that investor sentiment affects management earnings forecasts (Bergman and Roychowdhury 2008), pro-forma earnings disclosure (Brown et al. 2012), or accrual-based earnings management (Simpson 2013; Ali and Gurun 2009). More closely related to our study are the findings that managers

cater to investors' misperceptions by changing their dividend policy (Baker and Wurgler 2004; Li and Lie 2006) and by overspending on capital expenditure (Polk and Sapienza 2009). We contribute to this literature by documenting that catering extends to decisions on research and development expenditure, advertisement and selling, general and administrative costs. Since caterers act in the interest of short-term shareholders only, our study has monitoring implications for board of directors. This is particularly relevant since SG&A costs, for example, make up about one third of total assets.[26]

In a related vein, our finding that managers cater to investors' misperceptions by hiring more aggressively complements the findings in McLean and Zhao (2014). They likewise build on the model of Stein (1996) but test the equity instead of the catering channel, which suggests that investor sentiment can influence corporate policies because it reduces the cost of external finance (Baker and Wurgler 2011; Stein 1996). Hence, while McLean and Zhao (2014) show that investor sentiment affects employment decisions through the equity channel, we show how investor sentiment affects employment decisions through the catering channel.[27]

Second, this study contributes to our understanding of how managerial discretion affects cost behavior. In an influential study, Anderson et al. (2003) document that many cost changes arise as a result of deliberate managerial decisions, which contrasts with the traditional model of fixed and variable costs postulating that cost behavior is mechanically related to changes in activity. Building on this finding, Chen et al. (2012) show that empire building incentives affect cost behavior in that empire builders refrain from reducing costs when sales fall. Banker et al. (2011) show that equity incentives induce managers to increase spending on SG&A resources when these resources create high future value. We contribute

[26] In our sample, the average ratio of SG&A to total assets is about 34%. This number is comparable to other studies. Banker et al. (2011), for example, document an average ratio of SG&A to total assets of 31%.

[27] To control for the equity channel, we follow Polk and Sapienza (2009) and include equity issuance as a control variable in all our analyses.

to this literature by documenting that catering incentives induce managers to increase spending on various components of operating expenditure as means of addressing investment expectations in periods of high sentiment.

In addition, our study contributes to prior literature examining how incentives to meet earnings targets affect managers' cost decisions. Dierynck et al. (2012) and Kama and Weiss (2013) document that earnings targets affect managers' cost decisions in that managers are less likely to keep costs when sales decline upon facing earnings targets. Prior literature on real earnings management further shows that managers cut costs in order to avoid reporting losses, to meet last year's earnings or analysts' expectations (Baber et al. 1991; Burgstahler and Dichev 1997; Graham, Harvey, and Rajgopal 2005; Roychowdhury 2006). We contribute to this literature by documenting that incentives to meet earnings targets reduce managers catering incentives, thereby providing support for the role of managerial discretion in the process of resource adjustment.

The remainder of the paper is organized as follows: In section 2, we discuss our hypothesis development. In section 3, we present our research design. We present our results in section 4. Section 5 concludes.

3.2 Hypothesis Development and Related Literature

3.2.1 Investor Sentiment

This section provides background on the concept of investor sentiment, discusses the underlying assumptions, and provides additional information on the catering theory.

The concept of investor sentiment grounds on four assumptions (Baker and Wurgler 2011). The first assumption allows investor behavior to deviate from perfect rationality. The behavioral accounting and finance literature, thus, differentiates between two types of investors: Rational arbitrageurs and irrational or noise traders (Baker and Wurgler 2007). Irrationality can stem from a variety of sources. Early explanations include Shiller (1984)

who argues that social movements affect asset prices, or Black (1986) who argues that irrational investors trade on noise rather than news. The theoretical model of Daniel, Hirshleifer, and Subrahmanyam (1998) allows investors to be overconfident about the accuracy of their private information signals and to further exhibit biased self-attribution which implies that investors attribute favorable outcomes to their own decisions and unfavorable outcomes to bad luck (also see Barber and Odean 2001). In Barberis et al. (1998), investor behavior is characterized by both representativeness and conservatism. Grinblatt and Keloharju (2009) analyze the association between trading activity and sensation seeking. Hong and Stein (1999), in contrast, focus less on particular cognitive biases but more on the interplay between two types of boundedly rational investors, news-watchers and momentum traders, who are not able to process the entire amount of publicly available information. Baker and Wurgler (2007, 129) try to combine the various facets of noise trading by defining investor sentiment as "a belief about future cash flows and investment risks that is not justified by the facts at hand".

In order for noise traders to persist, arbitrage has to be limited. The second assumption thus deals with arbitrage constraints. Miller (1977), for example, argues that short-sale constraints can move prices away from fundamental value (also see Berkman et al. 2009). In De Long et al. (1990), the unpredictability of noise traders' future opinions creates a risk that dampens the willingness of rational arbitrageurs, who have short horizons and are risk-averse, to bet against them. Shleifer and Vishny (1997) highlight the role of agency problems and information asymmetries between professional investors, the arbitrage force in financial markets, and their capital lenders that may limit the effectiveness of arbitrage.

Third, the biases of investors have to be systematic, otherwise they would cancel out. In this regard, Kumar and Lee (2006) provide large scale empirical evidence documenting that retail investor trading is correlated across individuals and across groups of stocks. These

effects are more pronounced for stocks that are more costly to arbitrage and have higher individual investor concentration. Collectively, the evidence of Kumar and Lee (2006) suggests that retail investors trade in concert.

Combining these three assumptions, noise traders can affect stock prices. Baker and Wurgler (2006, 2007) document that periods of high sentiment result in overvaluation and subsequently are followed by low stock returns as prices revert to their intrinsic value. Lemmon and Portniaguina (2006) and Brown and Cliff (2005) obtain similar results.

The fourth assumption characterizes the behavior of managers. Whereas investors' earnings expectations are upwardly biased in periods of high sentiment (Hribar and McInnis 2012; Seybert and Yang 2012; Stein 1996), managers are assumed to both form rational expectations and be able to perceive variations in sentiment (Hribar and Quinn 2013). Given the existence of investor sentiment, Baker and Wurgler (2011) argue that managers balance two conflicting goals. The first goal consists in maximizing fundamental value. The second goal consists in maximizing the current stock price. While both goals are the same in a rational world, maximizing the short-term stock price turns into a distinct objective once investor behavior is allowed to differ from perfect rationality.

The catering theory implies that managers who are interested in maximizing the short-term stock price have to adjust their corporate polices to the sentiment-driven demands of investors by "packaging the firm and its securities in a way that maximizes appeal to investors" (Baker and Wurgler 2011, 13). If investors, for example, overvalue the prospects of a firm's assets, managers can, in fact, boost the short-term stock price by investing more aggressively in these assets (Stein 1996). This may, e.g., imply that managers should be willing to invest in negative NPV projects as long as noise traders perceive these projects as profitable (Baker and Wurgler 2011; Polk and Sapienza 2009; Stein 1996). More generally, catering refers to corporate policies that intend to exploit or encourage stock market

mispricing in order to increase the short-term stock price (Baker and Wurgler 2011). This tendency should be more pronounced as managers' horizons shorten (Baker and Wurgler 2011). Notably, even managers with long horizons will not completely ignore sentiment but potentially cater to investors' short-term demands, too. Since managers with long horizons act in the interest of long-term shareholders, they may decide to exploit the current mispricing by, for example, issuing overvalued or repurchasing undervalued shares (see for example Baker and Wurgler 2000; Graham and Campbell 2001).

In addition to distorting asset prices, there, hence, are real consequences of investor sentiment. Prior literature has shown that the presence of noise traders affects corporate decisions such as investment (Gilchrist, Himmelberg, and Huberman 2005; Polk and Sapienza 2009), equity issuance (Baker and Wurgler 2002), initiating dividends (Baker and Wurgler 2004; Li and Lie 2006), earnings management (Simpson 2013; Ali and Gurun 2009) or disclosure (Hribar and McInnis 2012; Seybert and Yang 2012).

3.2.2 Investor Sentiment and Operating Expenditure

To link operating expenditure and investor sentiment we build on the catering theory. Essentially, the theory states that managers can boost the short-term stock price by adjusting their corporate policies to noise traders' misperceptions (Stein 1996; Baker and Wurgler 2011). Drawing on the catering theory, we expect that there are two opposing channels linking investor sentiment and operating expenditure. First, several studies suggest that investors have optimistically biased cash flow expectations in periods of high sentiment (Baker and Wurgler 2006, 2007; Stein 1996). We argue that increasing operating expenditure is one way of catering to investors' overly optimistic investment expectations. This view builds on prior literature documenting that operating expenditure has long-term value-creating potential. With regard to research and development expenditure, Sougiannis (1994) documents that R&D expenditure has a positive effect on operating income that persists up to

seven years. Lev and Sougiannis (1996) find that R&D capital is associated with abnormal subsequent stock returns. Similarly, Eberhart et al. (2004) document that R&D increases result in both long-term abnormal stock returns and long-term abnormal operating performance. Further, several studies show that the value creation of advertising expenditure is not limited to the period in which the expenses are incurred. Hirschey and Weygandt (1985) show that advertising has a positive effect on the market value of the firm, persisting between one and five years. In addition, Chan et al. (2001) and Madden et al. (2006) document that advertising-intensive firms earn abnormal returns.

Also, there is evidence from recent research on fundamental analysis (Anderson et al. 2007; Baumgarten, Bonenkamp, and Homburg 2010), executive compensation (Banker et al. 2011) and organization capital (Lev and Radhakrishnan 2005; De and Dutta 2007; Tronconi and Marzetti 2011) documenting that selling, general and administrative (SG&A) resources have a positive impact on future firm performance. While Lev and Thiagarajan (1993) find a negative association between future stock returns and SG&A costs, Abarbanell and Bushee (1997) fail to find an association between future earnings and SG&A. In contrast, Anderson et al. (2007) and Baumgarten et al. (2010) document that increases in SG&A are positively associated with future earnings in revenue-declining periods and if these increases can be seen as intentional by the management, respectively. Further, providing evidence from research on executive compensation, Banker et al. (2011) document that managers increase spending on SG&A expenditure upon receiving equity incentives when SG&A resources create high future value. More generally, Matejka (2011) regards the key contribution of Banker et al. (2011) in documenting the long-term value creating potential of SG&A resources.

The literature on organization capital provides additional evidence on the value relevance of SG&A cost. Building on Lev and Radhakrishnan (2005), several studies advocate the use

of SG&A expenditure as a measure of organization capital given that SG&A comprises expenditure on employee training, brand enhancement, information technology, human resource development or customer relationship management (Eisfeldt and Papanikolaou 2013; Eisfeldt and Papanikolaou 2014). Further, Lev and Radhakrishnan (2005) document that organization capital has a positive impact on firm performance. Measuring organization capital by capitalizing SG&A expenditure, Tronconi and Marzetti (2011) and Eisfeldt and Papanikolaou (2013) obtain similar results (also see De and Dutta 2007).

Collectively, there is ample evidence indicating that various components of operating expenditure create long-term value. Hence, to the extent that managers cater to investors' optimistic investment expectations, we expect to observe a positive association between operating expenditure and investor sentiment.

H1: Managers cater to investors' sentiment driven demands by overspending on operating expenditure in periods of high relative to periods of average sentiment.

The second channel draws on prior literature documenting that investors have upwardly biased earnings expectations in periods of high sentiment (Hribar and McInnis 2012; Mian and Sankaraguruswamy 2012; Seybert and Yang 2012; Walther and Willis 2013). Facing exaggerated earnings expectations, managers may alternative decide to reduce rather than increase spending on operating expenditure. This view builds on prior literature that examines managers' responses to earnings targets. There are several studies documenting that managers reduce spending on, e.g., R&D if these expenditures hamper reporting positive or increasing income in the current period, Baber et al. (1991) is one example. Similarly, Roychowdhury (2006) finds evidence indicting that managers reduce R&D and SG&A expenditure to avoid reporting losses or to meet analysts' forecasts. Further, Gunny (2010) finds reductions in spending on R&D and SG&A for firms that just meet zero or last year' earnings. Graham et al. (2005) extend the findings of these archival studies by providing

survey evidence. Most of the CFOs they interview state that companies should or would take actions such as postponing or reducing R&D to meet earnings targets.

We argue the insights of these studies should be particularly relevant in periods of high sentiment since several studies document that investors' earnings expectations are upwardly biased when there is high sentiment. For example, Hribar and McInnis (2012) show that analysts' earnings forecasts are optimistically biased in periods of high sentiment (also see Walther and Willis 2013). Since analysts can clearly be seen as sophisticated investors, this finding should likely extend to nonprofessional investors. Focusing on management earnings forecasts, Seybert and Yang (2012) likewise show that investors have overly optimistic earnings expectations in periods of high sentiment (also see Mian and Sankaraguruswamy 2012; Skinner and Sloan 2002).

Building on this literature, we assume that the cost of, for example, reporting losses increases as investors' earnings expectations increase. Given that operating expenditure is completely charged and expensed against the earnings of the period in which it is incurred (Banker et al. 2011), we argue that managers will be less likely to cater by overspending on operating expenditure if it increases the risk of falling short of investors' earnings expectations. In sum, we expect that firms that have incentives to meet earnings targets cater less than firms that do not have incentives to meet earnings targets in periods of high sentiment. Depending on the distance to the earnings targets, there are two possible scenarios. First, if it suffices to cater less to reach investors' earnings expectations, the association between investor sentiment and operating expenditure should be of smaller magnitude in the presence of earnings targets. If, however, reaching investors' inflated earnings expectations requires cutting of operating expenditure, the association between investor sentiment and operating expenditure may even turn negative conditional on earnings targets.

H2: Managers are less likely to cater by overspending on operating expenditure in periods of high relative to periods of average sentiment if catering entails a risk of missing earnings targets.

3.3 Research Design

3.3.1 Sample Selection

Our sample is based on the intersection of CRSP/Compustat, GDP and investor sentiment data. From CRSP/Compustat we drop (1) financial firms and utilities (sic codes 6000 to 6999 and 4900 to 4999), (2) firm-years with negative sales or negative selling, general and administrative (SG&A) costs, and (3) require the currency to be USD. We obtain both data on real GDP and the GDP deflator from the Federal Reserve Bank of St. Louis and adjust all monetary variables for inflation by dividing with the GDP deflator.[28] The investor sentiment data is available on Jeffrey Wurgler's homepage.[29] The final sample comprises 105,885 firm-years from 1972 to 2010. We winsorize the top and bottom 1% of all continuous variables.

3.3.2 Investor Sentiment Measurement

In the empirical analysis, we use the annual sentiment index by Baker and Wurgler (2006). The index is an attempt to capture the common sentiment component of several sentiment proxies that have been identified and used in prior literature: The closed-end fund discount, trading volume (NYSE share turnover), the number and average first-day returns on initial public offerings (IPOs), the dividend premium and the equity share in new issues. The index is defined as the first principal component of these variables and captures sentiment at the aggregate market level.

Since Baker and Wurgler (2006, 2007) discuss the choice of the individual proxies in great detail, we only provide brief motivation for two variables. With regard to the closed-end fund (CEF) discount, for example, Lee, Shleifer, and Thaler (1991) argue that changes in the

[28] http://www.research.stlouisfed.org/
[29] http://people.stern.nyu.edu/jwurgler/

discounts on closed-end funds result from variation in investor sentiment. A CEF is an investment company that issues a fixed number of shares that then trade at secondary markets (Anderson, Born, and Schnusenberg 2010). Closed-end funds usually trade at a discount which corresponds to the difference between the funds' net asset value and its market value. Prior literature has offered a number of explanations for why there are discounts on closed-end funds, including agency costs (e.g., excessive management fees), illiquidity of assets (suggesting that CEFs' net asset values are overstated) and tax liabilities (Lee et al. 1991). However, none of the prior approaches has been able to provide a thorough explanation.

Lee et al. (1991) argue that investor sentiment drives the discount on closed-end funds. They build on the work of De Long et al. (1990) who theoretically model how noise traders can affect stock prices. Essentially, De Long et al. (1990) argue that the existence of noise traders creates an additional source of risk on assets' resale prices. Key to the model is the assumption that changes in noise traders' sentiment are stochastic and unpredictable. Further, De Long et al. (1990) assume that rational investors have short horizons, i.e., they are interested in the interim resale price of their assets. Since rational investors cannot know whether noise traders are bullish or bearish when they intend to sell their assets, rational investors will not be willing to hold assets that are affected by noise traders' sentiment unless they are compensated for bearing the risk that arises from the unpredictability of future sentiment. De Long et al. (1990), hence, argue that unpredictable fluctuations in noise traders' future opinions create a further source of risk for the stocks they trade.

Lee et al. (1991) provide evidence that noise traders rather invest in closed-end funds than their underlying assets. Holding closed-end funds, therefore, is riskier than holding the underlying portfolio. Hence, closed-end funds have to yield, on average, higher required rates of return than their underlying portfolios. This implies that, on average, closed-end funds must sell at a discount to their net asset value due to the unpredictability of changes in noise

traders' sentiment. Taken together, the evidence in Lee et al. (1991) suggests that variation in discounts on closed-end funds proxies for changes in investor sentiment. Hence, Baker and Wurgler (2006, 2007) use the (value-weighted) average discount on closed-end funds as one proxy for investor sentiment.

As an alternative proxy for investor sentiment, Baker and Wurgler (2006, 2007) focus on the market for IPOs. Derrien (2005), for example, argues that investor optimism contributes to the often tremendous initial returns on initial public offerings (IPO). Similarly, Ritter (1991) argues the underperformance of IPOs over longer horizons is indicative of market timing in that firms go public when investors are overly optimistic. The sentiment-index, therefore, reflects both the number and the average first-day returns of IPOs.[30]

While the choice of the individual sentiment proxies is guided by prior literature, which identifies the proxies as measures of investor sentiment, a natural question is whether the index may, nonetheless, reflect economic fundamentals. The main findings of Baker and Wurgler (2006, 2007), however, help to rule out the conjecture that the sentiment index simply reflects economic fundamentals and, hence, captures systematic risk.

Baker and Wurgler (2006, 2007) analyze the association between future stock returns and investor sentiment, arguing that the effect of investor sentiment on firms' stock prices varies cross-sectionally. Compared to bond-like firms that have long earnings histories, pay dividends and have tangible assets, investor sentiment should have a stronger effect on the stock prices of firms that are relatively young, currently unprofitable, have opaque assets but at the same time exhibit high growth potential since valuations of these firms are both subjective and difficult to arbitrage. In periods of high sentiment, investor optimism, hence, should push stock prices of these difficult-to-arbitrage firms to a larger extent than those of bond-like firms. This, however, implies that difficult-to-arbitrage firms should realize lower

[30] See Baker and Wurgler (2006, 2007) for an in-depth motivation of the remaining sentiment proxies.

future stock returns than bond-like firms as fundamentals revert and the mispricing gets corrected. Baker and Wurgler (2006, 2007) confirm this conjecture empirically. While one may clearly argue that young firms that are unprofitable and have opaque assets are more risky than bond-like firms, risk-based asset pricing models, such as the capital-asset pricing model, predict them to earn higher expected returns. This prediction, however, contrasts with the findings in Baker and Wurgler (2006, 2007) who, in fact, document the opposite. Their finding that firms, which are more risky realize lower expected returns than firms that are less risky following periods of high sentiment helps to alleviate concerns that the index is contaminated by economic fundamentals. Despite this compelling evidence, we test the sensitivity of our results to using an alternative index of investor sentiment that has been orthogonalized to a set of macroeconomic variables in the robustness section.

3.3.3 Research Design of H1

To test H1, we relate changes in operating expenditure to changes in investor sentiment controlling for both firm and macro level determinants of operating expenditure. We estimate the following regression model:

$$\begin{aligned}\Delta OpEx_{i,t} = {} & \beta_o + \beta_1 \cdot \Delta Sent_t + \beta_2 \cdot \Delta Sale_{i,t} + \beta_3 \cdot \Delta CashFlow_{i,t} + \beta_4 \cdot \Delta Leverage_{i,t} \\ & + \beta_5 \cdot \Delta EqIss_{i,t} + \beta_6 \cdot \Delta \ln GDP_t + \beta_7 \cdot \Delta \ln GDP_{t-1} + \varepsilon_{i,t}\end{aligned} \tag{3.1}$$

i is a firm index, t is a time index, Δ is the difference operator and ln is the natural logarithm. Depending on the specification, $\Delta OpEx_{i,t}$ is the change in selling, general and administrative costs (Compustat mnemonic XSGA), scaled by lagged total assets (AT), or the log change in employment (EMP). In further analyses, we split SG&A costs in research and development expenses (XRD), advertisement expenditures (XAD) and other SG&A (XSGA-XRD-XAD). We likewise scale the change in these variables with lagged total assets.

$Sent_t$ is the annual sentiment index by Baker and Wurgler (2006). In our regressions, we use the first difference of the index, which we standardize to have a mean of zero and a

standard deviation of one.

When using panel data, there are two approaches to control for unobserved heterogeneity: First differences (FD) and firm-fixed effects (FE). Both alternatives enable to control for all variables that are time-constant at the firm level and potentially correlate with both investor sentiment and operating expenditure. FE is appropriate if the variable of interest has an impact on the long-term level of the dependent variable. FD, in contrast, is appropriate if the variable of interest has an impact on the change of the dependent variable between two adjacent periods (Andreß, Golsch, and Schmidt 2013). Given that investors' misperceptions eventually revert (Baker and Wurgler 2006, 2007; Brown and Cliff 2005; Lemmon and Portniaguina 2006), the catering theory implies that investor sentiment has a short-term, as opposed to long-term, impact on corporate policies (Baker and Wurgler 2011). Hence, we favor FD over FE in our setting and estimate equation (3.1) using first differences.

To differentiate between investor sentiment and managers' demand expectations, we include two sets of control variables. To control for firm-specific factors that affect managers' demand expectations, we control for changes in sales since sales drive many of the components of operating expenditure. The change in sales also controls for growth options. We expect changes in sales to be positively associated with changes in operating expenditure. To control for the macroeconomic environment that may likewise affect managers' demand expectations and, hence, spending on operating expenditure, we control for both current and lagged growth in real GDP (Anderson et al. 2003). These controls are further important to rule out the alternative explanation that our variable of interest may reflect macroeconomic conditions rather than investor sentiment. Note that Baker and Wurgler (2006) document that the index does not reflect economic fundamentals, see section 3.2.

We further control for changes in cash flow because increasing cash flow may induce managers to overspend regardless of changes in investor sentiment and, hence, catering

incentives (Chen et al. 2012). Since our dependent variable is expenditure on SG&A, we use pre SG&A cash flow (Banker et al. 2011), which equals earnings before extraordinary items plus SG&A expenditure minus total accruals. We expect this variable to take on a positive coefficient. We control for change in leverage since firms may be less likely to cater to investors' misperceptions if catering increases the risk of violating debt covenants (Duke and Hunt 1990). We expect a negative association between leverage and operating expenditure. Finally, we follow Polk and Sapienza (2009) and control for change in equity issuance because prior research shows that equity financing influences how investor sentiment affects corporate policies (Baker, Stein, and Wurgler 2003; McLean and Zhao 2014). A positive coefficient on equity issuance is expected.

We cluster standard errors at the firm level allowing for heteroskedasticity and arbitrary within-firm correlation (Petersen 2009).

If managers cater to investors' misperceptions through operating expenditure, we expect $\beta_1>0$.

3.3.4 Research Design of H2

To test our second hypothesis, we estimate eq. (3.2):

$$\begin{aligned}\Delta OpEx_{i,t} = {} & \beta_o + \beta_1 \cdot \Delta Sent_t + \beta_2 \cdot EarningsTarget_{i,t} + \beta_3 \cdot \Delta Sent_t \cdot EarningsTarget_{i,t} \\ & + \beta_4 \cdot \Delta Sale_{i,t} + \beta_5 \cdot \Delta CashFlow_{i,t} + \beta_6 \cdot \Delta Leverage_{i,t} + \beta_7 \cdot \Delta EqIss_{i,t} \\ & + \beta_8 \cdot \Delta \ln GDP_t + \beta_9 \cdot \Delta \ln GDP_{t-1} + \varepsilon_{i,t}\end{aligned} \tag{3.2}$$

i is a firm index, t is a time index, Δ is the difference operator and ln denotes the natural logarithm. $\Delta OpEx_{i,t}$ is defined as in section 3.3.[31] We use the same set of controls as in equation (3.1) and cluster standard errors by firm.

The variable of interest is the interaction between our sentiment measure $\Delta Sent_t$ and the

[31] Depending on the specification, $\Delta OpEx_{i,t}$ is the change in selling, general and administrative costs (Compustat mnemonic XSGA), scaled by lagged total assets (AT), or the log change in employment (EMP). In further analyses, we split SG&A costs in research and development expenses (XRD), advertisement expenditures (XAD) and other SG&A (XSGA-XRD-XAD). We likewise scale the change in these variables with lagged total assets.

dummy variable $EarningsTarget_{i,t}$, which is one if net income (Compustat mnemonic NI) divided by lagged total assets (AT) is in the interval between 0 and 0.01. The focus on small positive earnings as a measure of incentives to reach earnings targets follows prior literature on managerial myopia and real earnings management (Baber et al. 1991; Burgstahler and Dichev 1997; Roychowdhury 2006). Our second hypothesis predicts that catering tendencies should be attenuated if managers face earnings targets: $\beta_3<0$.

Table 3.1

Variable Definitions

Dependent Variables	
$SG\&A_{i,t}$	is the change in selling, general and administrative (SG&A) costs, scaled by lagged total assets. $(XSGA_{i,t} - XSGA_{i,t-1})/AT_{i,t-1}$
$R\&D_{i,t}$	is the change in research and development expenditure, scaled by lagged total assets. $(XRD_{i,t} - XRD_{i,t-1})/AT_{i,t-1}$
$Adv_{i,t}$	is the change in advertisement, scaled by lagged total assets. $(XAD_{i,t}-XAD_{i,t-1})/AT_{i,t-1}$
$OtherSG\&A_{i,t}$	is the change in other SG&A costs, scaled by lagged total assets. $(OtherSGA_{i,t} - OtherSGA_{i,t-1})/AT_{i,t-1}$ $OtherSGA_{i,t} = XSGA_{i,t} - XRD_{i,t} - XAD_{i,t}$
$Empl_{i,t}$	is the logarithm of the change in employment. $\ln(EMP_{i,t}/EMP_{i,t-1})$
Independent Variables	
$\Delta Sent_t$	$Sent_t$ is the investor sentiment index following Baker and Wurgler (2006). $\Delta Sent_t$ is standardized to have a mean of zero and a standard deviation of one.
$\Delta Sales_{i,t}$	is the change in sales, scaled by lagged total assets: $(SALE_{i,t}-SALE_{i,t-1})/ AT_{i,t-1}$
$\Delta CashFlow_{i,t}$	is the change in income before extraordinary items plus SG&A costs minus total accruals, scaled by lagged total assets. Total accruals are defined as in Dechow, Sloan, and Sweeney (1995). $(CF_{i,t} - CF_{i,t-1})/AT_{i,t-1}$, $CF_{i,t} = IB_{i,t} + XSGA_{i,t} - TotalAccruals_{i,t}$ $TotalAccruals_{i,t} = \Delta ACT_{i,t} - \Delta LCT_{i,t} - \Delta CHE_{i,t} + \Delta DLC_{i,t} - DP_{i,t}$
$\Delta Leverage_{i,t}$	is the change in long-term debt plus debt in current liabilities over assets. $(Lev_{i,t} - Lev_{i,t-1})$, $Lev_{i,t} = (DLTT_{i,t} + DLC_{i,t})/AT_{i,t}$
$\Delta EqIss_{i,t}$	is the change in equity issuance, defined as the sale of common and preferred stock minus the purchase of common and prefereed stock, scaled by lagged total assets. $(EQ_{i,t} - EQ_{i,t-1})/AT_{i,t-1}$ $EQ_{i,t} = SSTK_{i,t} - PRSTKC_{i,t}$
$\Delta \ln GDP_t$	is the logarithm of the change in real GDP. $\ln(GDP_t)/\ln(GDP_{t-1})$

Additional Variables, Cross-Sectional Analyses

$HighValueRelevance_j$	For each two digit SIC industry, Banker et al. (2011) regress return on assets on both current and lagged SG&A expenditure to obtain an industry-specific measure of the value relevance of SG&A resources. Based on these results, we first obtain the median value of the value relevance of SG&A resources across all industries. We then set the dummy variable $HighValueRelevance_j$ to one for those industries that exceed the median value.
$HighTradingVol_{i,t}$	The dummy variable $HighTradingVol_{i,t}$ is one if the share turnover of a given firm, $TradingVol_{i,t-1}$, exceeds the median share turnover of all firms in a year.
$TradingVol_{i,t-1}$	Trading volume is the annual average of the ratio of monthly trading volume to monthly shares outstanding (CRSP mnemonic VOL and SHROUT, respectively).
$HighVolatility_{i,t}$	The dummy variable $HighVolatility_{i,t}$ is one if the stock return volatility of a given firm, $Volatility_{i,t-1}$, exceeds the median stock return volatility of all firms in a year.
$Volatility_{i,t-1}$	Stock return volatility is the annual standard deviation of a firm's monthly stock returns (CRSP mnemonic RET).

Additional Variables, H2

$EarningsTarget_{i,t}$	1 if net income divided by lagged total assets is larger than 0 and smaller than 0.01: 1 if $0 <= NI_{i,t}/AT_{i,t-1} <= 0.01$, 0 else

Additional Variables, Alternative Explanation

$\Delta Inv_{i,t}$	Is the change in capital expenditure, scaled by beginning-of-year net property, plant, and equipment. $(CAPX_{i,t} - CAPX_{i,t-1})/PPENT_{i,t-1}$
$SuccessiveIncrease_{i,t}$	1 if $(SALE_{i,t-2} < SALE_{i,t-1}) \,\&\, (SALE_{i,t-1} < SALE_{i,t})$, 0 else

Additional Variables, Robustness

$\Delta Sent_t^{\perp}$	$\Delta Sent_t^{\perp}$ is the investor sentiment index following Baker and Wurgler (2006) that has been orthogonalized to a set of macroeconomic variables: (i) the industrial production index, (ii) growth in consumer durables, nondurables, and services, (iii) and a dummy variable indicating NBER recessions. $\Delta Sent_t^{\perp}$ is standardized to have a mean of zero and a standard deviation of one.

i is a firm index, j is an industry index, t is a time index, Δ is the difference operator and ln denotes the natural logarithm.

Table 3.2

Descriptive Statistics

	Mean	Median	Std Dev	Observations
$SG\&A_{i,t}$	0.0179	0.0094	0.0884	105885
$R\&D_{i,t}$	0.0026	0	0.0299	62144
$Adv_{i,t}$	0.0019	0.0004	0.0174	39822
$OtherSG\&A_{i,t}$	0.0153	0.0079	0.077	105885
$Empl_{i,t}$	0.027	0.02	0.2513	105885
$\Delta Sent_{t}$	0	0.0285	1	105885
$\Delta Sales_{i,t}$	0.0845	0.0529	0.3351	105885
$\Delta CashFlow_{i,t}$	0.0242	0.0192	0.1756	105885
$\Delta Leverage_{i,t}$	0.0046	0	0.0941	105885
$\Delta EqIss_{i,t}$	0.0073	0	0.1369	105885
$\Delta lnGDP_{t}$	0.0286	0.034	0.0206	105885
$HighValueRelevance_{j}$	0.4975	0	0.5	83865
$TradingVol_{i,t-1}$	0.0947	0.0524	0.1154	95129
$Volatility_{i,t-1}$	0.1447	0.1243	0.0831	104274
$EarningsTarget_{i,t}$	0.0417	0	0.1999	105885

All variables are defined in Table 3.1.

Table 3.3

Correlations

	v1	v2	v3	v4	v5	v6	v7	v8	v9	v10	v11	v12	v13	v14
v1: $SG\&A_{i,t}$														
v2: $R\&D_{i,t}$	**0.538**													
v3: $Adv_{i,t}$	**0.533**	**0.173**												
v4: $OtherSG\&A_{i,t}$	**0.916**	**0.208**	**0.343**											
v5: $Empl_{i,t}$	**0.463**	**0.293**	**0.266**	**0.43**										
v6: $\Delta Sent_{t}$	**0.054**	**0.057**	**0.048**	**0.044**	**0.06**									
v7: $\Delta Sales_{i,t}$	**0.598**	**0.208**	**0.386**	**0.593**	**0.524**	**0.042**								
v8: $\Delta CashFlow_{i,t}$	**0.341**	**0.085**	**0.206**	**0.351**	**0.144**	-0.002	**0.327**							
v9: $\Delta Leverage_{i,t}$	**0.067**	**0.029**	**0.03**	**0.065**	**0.063**	**-0.039**	**0.012**	**-0.203**						
v10: $\Delta EqIss_{i,t}$	**0.125**	**0.072**	**0.046**	**0.112**	**0.113**	**0.04**	**0.092**	**-0.011**	**-0.19**					
v11: $\Delta lnGDP_{t}$	**0.102**	**0.049**	**0.08**	**0.095**	**0.104**	**0.28**	**0.149**	**0.009**	**0.029**	**-0.011**				
v12: $HighValueRelevance_{j}$	**0.038**	-0.004	**0.029**	**0.039**	**0.022**	**-0.015**	**0.045**	**0.024**	0.006	0.001	**-0.013**			
v13: $TradingVol_{i,t-1}$	**0.089**	**0.077**	**0.041**	**0.073**	**0.072**	**-0.022**	**0.049**	**0.059**	**0.016**	**-0.033**	**-0.149**	**0.114**		
v14: $Volatility_{i,t-1}$	**-0.017**	**-0.034**	**-0.024**	**-0.013**	**-0.031**	**-0.016**	-0.003	**0.011**	-0.003	**0.049**	**-0.025**	**0.103**	**0.225**	
v15: $EarningsTarget_{i,t}$	**-0.042**	**-0.016**	**-0.021**	**-0.041**	**-0.027**	**-0.014**	**-0.055**	**-0.023**	-0.006	**-0.011**	**-0.014**	-0.003	**-0.018**	0

This table displays Pearson correlation coefficients. Bold parameters are significant at the 5% level or below. All variables are defined in Table 3.1.

3.4 Results

3.4.1 Test of H1

Table 3.4 presents estimation results of equation (3.1) testing the impact of investor sentiment on operating expenditure. When the dependent variable is based on SG&A costs (model (1)), the coefficient on $\Delta Sent_t$ is positive (β_1=0.0033) and significant at the 1% level (t=12.93). In terms of economic magnitude, the change in SG&A as a percentage of total assets increases by an additional 0.33% in response to a one standard deviation increase of investor sentiment. Compared to the annual sample mean of the change in SG&A as a percentage of total assets (1.79%, see Table 3.2), this effect is economically large, corresponding to approximately 18% of the sample mean.[32] When decomposing SG&A into R&D expenses, advertisement and other SG&A costs, we find qualitatively similar results, as shown in models (2) to (4) of Table 3.4.

When the dependent variable in equation (3.1) is the log change in employment, the coefficient on our measure of investor sentiment is positive (β_1=0.0072) and significant at the 1% level (t=9.88). If sentiment increases by one standard deviation, employment increases by an additional 0.72%, which corresponds to approximately 27% of the sample mean of the log change in employment (which equals 2.7%, see Table 3.2). Collectively, the results in Table 3.4 provide support for the hypothesis that managers increase spending on operating expenditure in response to rising sentiment.

Turning to the control variables, we find that managers increase spending on operating expenditure in response to increasing sales, as shown by the positive and significant coefficient on $\Delta Sales_{i,t}$. Further, we find that spending on operating expenditure is significantly positively associated with cash flow and leverage. In addition, managers invest part of funds raised per equity issuance in SG&A resources or employment. Finally, we find

[32] 0.0033/0.0179 = 0.184 ≈ 18%.

a positive association between operating expenditure and economic conditions, as measured by growth in GDP.

Table 3.4

The Association between Operating Expenditure and Investor Sentiment

	(1) $SG\&A_{i,t}$	(2) $R\&D_{i,t}$	(3) $Adv_{i,t}$	(4) $OtherSG\&A_{i,t}$	(5) $Empl_{i,t}$
$\Delta Sent_t$	**0.0033*** **	**0.0015*** **	**0.0006*** **	**0.0022*** **	**0.0072*** **
	(12.93)	**(11.20)**	**(6.09)**	**(10.14)**	**(9.88)**
$\Delta Sales_{i,t}$	0.1369***	0.0178***	0.0194***	0.1177***	0.3870***
	(76.33)	(24.51)	(32.23)	(76.19)	(89.45)
$\Delta CashFlow_{i,t}$	0.0987***	0.0047***	0.0087***	0.0909***	-0.0135**
	(33.17)	(3.37)	(9.24)	(35.28)	(-2.05)
$\Delta Leverage_{i,t}$	0.1121***	0.0154***	0.0091***	0.0961***	0.1906***
	(27.98)	(7.59)	(6.77)	(27.67)	(16.54)
$\Delta EqIss_{i,t}$	0.0652***	0.0123***	0.0030***	0.0500***	0.1419***
	(18.39)	(6.98)	(2.67)	(17.20)	(19.05)
$\Delta lnGDP_t$	0.0137	-0.0007	0.0135***	0.0003	0.2770***
	(1.22)	(-0.13)	(3.45)	(0.03)	(8.09)
$\Delta lnGDP_{t-1}$	0.0986***	0.0285***	-0.0037	0.0770***	-0.1941***
	(8.77)	(4.96)	(-0.94)	(8.18)	(-5.90)
Constant	-0.0002	0	-0.0003*	0.0001	-0.0097***
	(-0.55)	(0.06)	(-1.83)	(0.43)	(-7.92)
N	105885	62144	39822	105885	105885
R2	0.4014	0.051	0.1574	0.3967	0.2861

In model (1), the dependent variable is the change in SG&A costs, scaled by lagged total assets. In model (2), (3) and (4), the dependent variable is the change in R&D expenditure, advertisement and other SG&A, respectively, scaled by lagged total assets. In model (5), the dependent variable is the log change in employment. All variables are defined in Table 3.1. Standard errors are clustered at the firm level. T-statistics are in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent level.

3.4.2 Cross-Sectional Analyses

To further probe hypothesis one, we test cross-sectional predictions of the catering theory. In all of the analyses, we modify equation (3.1) and estimate a variation of the following regression model:

$$\begin{aligned}\Delta OpEx_{i,t} = {} & \beta_o + \beta_1 \cdot \Delta Sent_t + \beta_2 \cdot Z + \beta_3 \cdot \Delta Sent_t \cdot Z \\ & + \beta_4 \cdot \Delta Sale_{i,t} + \beta_5 \cdot \Delta CashFlow_{i,t} + \beta_6 \cdot \Delta Leverage_{i,t} + \beta_7 \cdot \Delta EqIss_{i,t} \\ & + \beta_8 \cdot \Delta \ln GDP_t + \beta_9 \cdot \Delta \ln GDP_{t-1} + \varepsilon_{i,t}\end{aligned} \quad (3.3)$$

i is a firm index, t is a time index, Δ is the difference operator and ln denotes the natural logarithm. The dependent variables are defined as in the section 3.3.[33] We use the same set of controls as in equation (3.1) and cluster standard errors by firm. Depending on the specification, the dummy variable Z is either a firm or industry characteristic that moderates the association between operating expenditure and investor sentiment. In all analyses, we expect $\beta_3>0$.

3.4.2.1 The Association between Operating Expenditure and Investor Sentiment Differentiating between High and Low SG&A Future Value Creation

The concept of investor sentiment implies that managers cater to investors' short-term demand by investing in those assets that noise traders are optimistic about (Stein 1996; Baker and Wurgler 2011). We, therefore, analyze whether catering through SG&A resources increases as the value relevance of SG&A resources increases, assuming that investors are more likely to be optimistic about the prospects of SG&A resources, the greater the future value potential of these resources for a given firm. To test this prediction, we allow the effect of sentiment to differ with respect to the future value relevance of SG&A expenditures following Banker et al. (2011).

For each two digit SIC industry, Banker et al. (2011) regress return on assets on both current and lagged SG&A expenditure to obtain an industry-specific measure of the value relevance of SG&A resources (see Table 2 of Banker et al. 2011). Based on these results, we first obtain the median value of the value relevance of SG&A resources across all industries. When estimating equation (3.3), we set the dummy variable Z to one for those industries that

[33] As before, $\Delta OpEx_{i,t}$ is the change in selling, general and administrative costs (Compustat mnemonic XSGA), scaled by lagged total assets (AT), or the log change in employment (EMP). In further analyses, we split SG&A costs in research and development expenses (XRD), advertisement expenditures (XAD) and other SG&A (XSGA-XRD-XAD) and we scale the change in these variables with lagged total assets.

exceed the median value. We expect the coefficient on the interaction between $\Delta Sent_t$ and Z to be positive: $\beta_3 > 0$.

The results are shown in Table 3.5. We find that catering via SG&A resources is more pronounced for firms that operate in industries for which SG&A costs exhibit high compared to low value relevance (β_3=0.0034, t=6.47). This result provides support for our prediction, indicating that managers are more likely to cater to investors' misperceptions by increasing SG&A resources as the value-relevance of these resources increases. Decomposing SG&A costs, we obtain qualitatively similar results for R&D expenditure (β_3=0.0006, t=2.36) and other SG&A (β_3=0.003, t=6.71) but not for advertisement. Compared to the data that is available on SG&A, we, however, note that the sample size is reduced by about 40% for advertisement. Since cross-sectional analyses require further partitioning of the sample, loss of statistical power may be one potential explanation for this result.

3.4.2.2 The Association between Operating Expenditure and Investor Sentiment Differentiating between High and Low Investor Trading Volume

The catering theory predicts that managers are more likely to follow investors' misperceptions as managers' horizon decrease, as more emphasis is put on the short-term stock price (Stein 1996; Baker and Wurgler 2011). Following Polk and Sapienza (2009), we use share turnover to proxy for the relative amount of trading activities by short-term investors, assuming that investor short-termism results in managerial short-termism (Bushee 1998; Shleifer and Vishny 1990; Stein 1988). We define share turnover as the annual average of the ratio of monthly trading volume to monthly shares outstanding (CRSP mnemonic VOL and SHROUT, respectively). In equation (3.3), we set Z to one if the share turnover of a given firm is above the median share turnover of the year, assuming that the high trading volume group comprises managers who act more myopically. We expect β_3>0.

The results are shown in Table 3.6. Consistent with our expectation, we find that catering

via SG&A resources increases as managers' horizon decrease. Our results show that managers who likely have shorter horizons cater by an additional 0.22% in response to a one standard deviation increase in sentiment compared to managers who likely have longer horizons (β_3=0.0022, t=4.81). When analyzing components of SG&A costs, we find qualitatively similar results for R&D expenditure and other SG&A, while the association between advertisement and investors sentiment does not differ with horizon, as shown in model (2) to (4) of Table 3.6. Turning to employment, our results suggest that catering via employment increases as managers' horizon decrease (β_3=0.0062, t=4.48). Taken together, the analysis provides support for our prediction.

3.4.2.3 The Association between Operating Expenditure and Investor Sentiment Differentiating between High and Low Stock Return Volatility

Baker and Wurgler (2007) argue that investor sentiment should more strongly affect those firms that have higher stock return volatility. On the one hand, Baker and Wurgler (2007) argue that a firm's speculative appeal increases as the firm's stock return volatility increases. To the extent that investor sentiment reflects the propensity to speculate by noise traders, sentiment should have a stronger effect on those firms that exhibit higher stock return volatility. Alternatively, since the risk of arbitrage increases with stock return volatility, sentiment should reduce the willingness of arbitrageurs to bet against high-volatility stocks. Both channels suggest that investor sentiment more strongly affects those firms that exhibit higher stock return volatility. We, therefore, expect catering to be more pronounced for those firms that are more strongly affected by investor sentiment.

When estimating equation (3.3), we set Z to one if the stock return volatility of a given firm exceeds the median stock return volatility of all firms in a year. We define stock return volatility as the standard deviation of a firm's monthly stock returns (CRSP mnemonic RET) following Baker and Wurgler (2007). A positive β_3 would be consistent with our prediction.

Table 3.7 contains the results. When the dependent variable is the change in SG&A cost scaled by total assets, we find results that are consistent with our expectation, as shown by the significantly positive coefficient on the interaction between our measure of investor sentiment and the dummy variable indicating high stock return volatility (β_3=0.0045, t=10.26). We obtain similar results when analyzing R&D and advertisement expenditure as well as other SG&A. The last column of Table 3.7 shows that catering via employment increases as stock return volatility increases (β_3=0.0081, t=6.09). Collectively, our results provide support for our prediction, suggesting that catering is more pronounced for those firms that are more strongly affected by investor sentiment.

Table 3.5

The Association between Operating Expenditure and Investor Sentiment Differentiating between High and Low SG&A Future Value Creation

	(1) $SG\&A_{i,t}$	(2) $R\&D_{i,t}$	(3) $Adv_{i,t}$	(4) $OtherSG\&A_{i,t}$
$\Delta Sent_t$	0.0024***	0.0015***	0.0005***	0.0012***
	(6.99)	(8.31)	(4.25)	(4.10)
$HighValueRelevance_{j,t}$	0.0016***	-0.0007***	0.0006***	0.0015***
	(2.92)	(-2.60)	(3.27)	(3.35)
$\Delta Sent_t \cdot$ $HighValueRelevance_j$	**0.0034*** (6.47)**	**0.0006** (2.36)**	**0.0001 (0.37)**	**0.0030*** (6.71)**
$\Delta Sales_{i,t}$	0.1480***	0.0199***	0.0197***	0.1268***
	(76.63)	(24.04)	(30.44)	(75.24)
$\Delta CashFlow_{i,t}$	0.0945***	0.0048***	0.0058***	0.0883***
	(29.59)	(3.25)	(6.48)	(31.47)
$\Delta Leverage_{i,t}$	0.1139***	0.0151***	0.0078***	0.0988***
	(25.86)	(6.98)	(5.73)	(25.36)
$\Delta EqIss_{i,t}$	0.0611***	0.0102***	0.0028**	0.0476***
	(15.56)	(5.51)	(2.52)	(14.45)
$\Delta lnGDP_t$	-0.008	-0.0086	0.0085**	-0.0116
	(-0.64)	(-1.36)	(2.06)	(-1.07)
$\Delta lnGDP_{t-1}$	0.1088***	0.0266***	-0.0028	0.0840***
	(8.49)	(4.25)	(-0.68)	(7.76)
Constant	-0.0010*	0.0005*	-0.0005***	-0.0006
	(-1.89)	(1.87)	(-3.11)	(-1.49)
N	83865	49690	32690	83865
R2	0.4235	0.0627	0.1659	0.4152

In model (1), the dependent variable is the change in SG&A costs, scaled by lagged total assets. In model (2), (3) and (4), the dependent variable is the change in R&D expenditure, advertisement and other SG&A, respectively, scaled by lagged total assets. All variables are defined in Table 3.1. Standard errors are clustered at the firm level. T-statistics are in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent level.

Table 3.6

The Association between Operating Expenditure and Investor Sentiment

Differentiating between High and Low Investor Trading Volume

	(1) $SG\&A_{i,t}$	(2) $R\&D_{i,t}$	(3) $Adv_{i,t}$	(4) $OtherSG\&A_{i,t}$	(5) $Empl_{i,t}$
$\Delta Sent_t$	0.0023***	0.0010***	0.0005***	0.0016***	0.0045***
	(7.34)	(6.61)	(4.09)	(6.11)	(4.64)
$HighTradingVol_{i,t}$	0.0084***	0.0031***	0.0008***	0.0056***	0.0170***
	(17.67)	(12.29)	(4.75)	(13.73)	(12.14)
$\Delta Sent_t \cdot HighTradingVol_{i,t}$	**0.0022*** (4.81)**	**0.0010*** (4.12)**	**0.0002 (1.00)**	**0.0013*** (3.30)**	**0.0062*** (4.48)**
$\Delta Sales_{i,t}$	0.1390***	0.0188***	0.0202***	0.1193***	0.3943***
	(72.58)	(23.68)	(30.06)	(72.07)	(84.26)
$\Delta CashFlow_{i,t}$	0.0974***	0.0038**	0.0087***	0.0905***	-0.0125*
	(31.52)	(2.49)	(8.86)	(33.37)	(-1.79)
$\Delta Leverage_{i,t}$	0.1105***	0.0157***	0.0083***	0.0951***	0.2014***
	(26.85)	(7.05)	(5.78)	(26.68)	(16.53)
$\Delta EqIss_{i,t}$	0.0617***	0.0118***	0.0026**	0.0477***	0.1414***
	(16.84)	(6.21)	(2.13)	(15.71)	(17.98)
$\Delta lnGDP_t$	0.0323***	0.0077	0.0209***	0.0104	0.2481***
	(2.75)	(1.27)	(4.82)	(1.04)	(6.73)
$\Delta lnGDP_{t-1}$	0.1131***	0.0248***	-0.0042	0.0932***	-0.2008***
	(9.37)	(4.01)	(-0.96)	(9.18)	(-5.62)
Constant	-0.0059***	-0.0020***	-0.0010***	-0.0038***	-0.0178***
	(-11.78)	(-7.23)	(-5.83)	(-9.21)	(-12.12)
N	95129	56210	34840	95129	95129
R2	0.4038	0.055	0.1609	0.3972	0.2872

In model (1), the dependent variable is the change in SG&A costs, scaled by lagged total assets. In model (2), (3) and (4), the dependent variable is the change in R&D expenditure, advertisement and other SG&A, respectively, scaled by lagged total assets. In model (5), the dependent variable is the log change in employment. All variables are defined in Table 3.1. Standard errors are clustered at the firm level. T-statistics are in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent level.

Table 3.7

The Association between Operating Expenditure and Investor Sentiment Differentiating between High and Low Stock Return Volatility

	(1) $SG\&A_{i,t}$	(2) $R\&D_{i,t}$	(3) $Adv_{i,t}$	(4) $OtherSG\&A_{i,t}$	(5) $Empl_{i,t}$
$\Delta Sent_t$	0.0011***	0.0005***	0.0004***	0.0007***	0.0033***
	(4.99)	(4.43)	(4.13)	(3.61)	(4.20)
$HighVolatility_{i,t}$	-0.0006	-0.0002	-0.0008***	-0.0006*	-0.0104***
	(-1.48)	(-0.94)	(-5.40)	(-1.73)	(-7.90)
$\Delta Sent_t \cdot HighVolatility_{i,t}$	**0.0045*** (10.26)**	**0.0021*** (8.98)**	**0.0003* (1.89)**	**0.0031*** (8.28)**	**0.0081*** (6.09)**
$\Delta Sales_{i,t}$	0.1362***	0.0181***	0.0194***	0.1172***	0.3891***
	(76.34)	(24.55)	(32.06)	(75.74)	(88.60)
$\Delta CashFlow_{i,t}$	0.1005***	0.0051***	0.0088***	0.0926***	-0.0096
	(34.55)	(3.61)	(9.54)	(36.39)	(-1.45)
$\Delta Leverage_{i,t}$	0.1147***	0.0157***	0.0094***	0.0989***	0.1952***
	(28.97)	(7.55)	(6.98)	(28.78)	(16.77)
$\Delta EqIss_{i,t}$	0.0622***	0.0113***	0.0030***	0.0484***	0.1415***
	(17.78)	(6.26)	(2.65)	(16.67)	(18.62)
$\Delta lnGDP_t$	0.0151	-0.0014	0.0140***	0.0016	0.2700***
	(1.38)	(-0.24)	(3.57)	(0.17)	(7.88)
$\Delta lnGDP_{t-1}$	0.0984***	0.0260***	-0.0045	0.0791***	-0.1926***
	(8.87)	(4.57)	(-1.15)	(8.45)	(-5.81)
Constant	0	0.0002	0.0002	0.0003	-0.0046***
	(0.08)	(0.70)	(1.00)	(1.00)	(-3.49)
N	104274	61250	39244	104274	104274
R2	0.4043	0.0531	0.1587	0.3986	0.2863

In model (1), the dependent variable is the change in SG&A costs, scaled by lagged total assets. In model (2), (3) and (4), the dependent variable is the change in R&D expenditure, advertisement and other SG&A, respectively, scaled by lagged total assets. In model (5), the dependent variable is the log change in employment. All variables are defined in Table 3.1. Standard errors are clustered at the firm level. T-statistics are in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent level.

3.4.3 Test of H2

Results from estimating equation (3.2), testing H2, are shown in Table 3.8. Focusing on SG&A costs first, consistent with our previous results, we find a significantly positive association between SG&A costs and investor sentiment for those firms that do not face earnings targets (β_1=0.0035, t=13.25). Next, turning to firms that have incentives to meet earnings targets, while we do find a negative association between SG&A costs and investor sentiment, the coefficient is not statistically significant at conventional levels ($\beta_1+\beta_3$=0.0035-0.0042=-0.0007, t=-0.99). This shows that investor sentiment does not induce managers to cut costs conditional on earnings targets. What our results, however, do suggest is that managers who face earnings targets increase SG&A costs by less than managers who do not face earnings targets, as shown by the significantly negative coefficient on the interaction between our measure of investor sentiment and earnings targets (β_3=-0.0042, t=-5.26), indicating that earnings targets moderate catering through SG&A costs. This difference is economically large. The change in SG&A costs as a percentage of total assets is 0.42% less pronounced for firms that face earnings targets compared to firms that do not face earnings targets, which corresponds to about 23% of the sample mean.

Decomposing SG&A costs, we find similar results for research and development expenditure and other SG&A but not for advertisement (β_3=-0.0014, t=-3.24, β_3=-0.0033, t=-4.64, and β_3=-0.0004, t=-1.27, respectively). Further, our results suggest that earnings targets moderate catering via employment (β_3=-0.0061, t=-1.94, respectively). While we report these results for completeness, we note that studies on real earnings management focus on R&D or SG&A rather than employment and advertisement expenses (e.g., Baber et al. 1991; Bushee 1998; Dechow, Kothari, and Watts 1998). Taken together, we argue the results provide support for H2, indicating that managers are less likely to overspend on operating expenditure as means of addressing investors' misperceptions when facing earnings targets.

Table 3.8

The Moderating Impact of Earnings Targets

on the Association between Operating Expenditure and Investor Sentiment

	(1) $SG\&A_{i,t}$	(2) $R\&D_{i,t}$	(3) $Adv_{i,t}$	(4) $OtherSG\&A_{i,t}$	(5) $Empl_{i,t}$
$\Delta Sent_t$	0.0035***	0.0016***	0.0006***	0.0023***	0.0074***
	(13.25)	(11.32)	(6.14)	(10.49)	(10.01)
$EarningsTarget_{i,t}$	-0.0030***	-0.0007	0	-0.0024***	0.0032
	(-3.63)	(-1.50)	(-0.13)	(-3.30)	(1.06)
$\Delta Sent_t \cdot$ $EarningsTarget_{i,t}$	**-0.0042*** (-5.26)**	**-0.0014*** (-3.24)**	**-0.0004 (-1.27)**	**-0.0033*** (-4.64)**	**-0.0061* (-1.94)**
$\Delta Sales_{i,t}$	0.1368***	0.0178***	0.0194***	0.1176***	0.3871***
	(76.21)	(24.45)	(32.16)	(76.08)	(89.35)
$\Delta CashFlow_{i,t}$	0.0986***	0.0047***	0.0087***	0.0909***	-0.0135**
	(33.16)	(3.36)	(9.24)	(35.28)	(-2.05)
$\Delta Leverage_{i,t}$	0.1121***	0.0154***	0.0091***	0.0961***	0.1908***
	(27.98)	(7.59)	(6.78)	(27.67)	(16.55)
$\Delta EqIss_{i,t}$	0.0652***	0.0123***	0.0030***	0.0500***	0.1419***
	(18.38)	(6.97)	(2.67)	(17.19)	(19.06)
$\Delta lnGDP_t$	0.0141	-0.0006	0.0135***	0.0006	0.2778***
	(1.26)	(-0.11)	(3.46)	(0.06)	(8.12)
$\Delta lnGDP_{t-1}$	0.0982***	0.0284***	-0.0037	0.0768***	-0.1945***
	(8.74)	(4.93)	(-0.95)	(8.15)	(-5.91)
Constant	-0.0001	0	-0.0003*	0.0002	-0.0099***
	(-0.26)	(0.18)	(-1.79)	(0.71)	(-7.98)
N	105885	62144	39822	105885	105885
R2	0.4015	0.0511	0.1574	0.3968	0.2861

In model (1), the dependent variable is the change in SG&A costs, scaled by lagged total assets. In model (2), (3) and (4), the dependent variable is the change in R&D expenditure, advertisement and other SG&A, respectively, scaled by lagged total assets. In model (5), the dependent variable is the log change in employment. All variables are defined in Table 3.1. Standard errors are clustered at the firm level. T-statistics are in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent level.

3.4.4 Alternative Explanations

In this section, we address two potential alternative explanations. We document that the association between operating expenditure and investor sentiment is robust to controlling for investment, and we document that our conclusions remains unchanged when controlling for managerial optimism.

3.4.4.1 Controlling for Investment

Since Polk and Sapienza (2009) show that managers cater by increasing capital expenditure, we re-estimate equation (3.1) and additionally control for changes in both current and past capital expenditure to rule out that catering based on operating expenditure is mechanically driven by catering based on capital expenditure. If the association between operating expenditure and investor sentiment is driven by changes in capital expenditure only, the effect of sentiment on costs should disappear once we control for capital expenditure. Conversely, if the association between operating expenditure and investor sentiment remains unchanged, this would provide support for an independent catering effect via operating expenditure.

The results are shown in Table 3.9. Consistent with our previous results, we find a positive association between SG&A costs and investor sentiment (β_1=0.0027, t=11.28) as well as employment and investor sentiment (β_1=0.0053, t=7.61). Further, decomposing SG&A, the association between research and development expenditure and investor sentiment remains positive and statistically significant at the 1% level (β_1=0.0012, t=9.57). Likewise, the association between advertisement (β_1=0.0005, t=5.23) and other SG&A (β_1=0.0018, t=8.78) and investor sentiment remains statistically significant at conventional levels. Taken together, we argue the results indicate that catering via operating expenditure is not mechanically driven by catering via capital expenditure, suggesting an independent operating expenditure effect.

Table 3.9

The Association between Operating Expenditure and Investor Sentiment Controlling for Investment

	(1) $SG\&A_{i,t}$	(2) $R\&D_{i,t}$	(3) $Adv_{i,t}$	(4) $OtherSG\&A_{i,t}$	(5) $Empl_{i,t}$
$\Delta Sent_t$	**0.0027*** **	**0.0012*** **	**0.0005*** **	**0.0018*** **	**0.0053*** **
	(11.28)	**(9.57)**	**(5.23)**	**(8.78)**	**(7.61)**
$\Delta Sales_{i,t}$	0.1226***	0.0116***	0.0178***	0.1079***	0.3477***
	(69.81)	(16.53)	(29.01)	(70.49)	(81.39)
$\Delta CashFlow_{i,t}$	0.0899***	0.0016	0.0083***	0.0848***	-0.0321***
	(31.02)	(1.19)	(8.78)	(33.51)	(-5.03)
$\Delta Leverage_{i,t}$	0.0833***	0.0048**	0.0066***	0.0761***	0.1154***
	(21.15)	(2.34)	(4.88)	(22.32)	(10.17)
$\Delta EqIss_{i,t}$	0.0533***	0.0087***	0.0019*	0.0422***	0.1042***
	(15.66)	(4.96)	(1.71)	(15.11)	(14.51)
$\Delta lnGDP_t$	0.0221**	0.0026	0.0136***	0.0063	0.2658***
	(2.03)	(0.47)	(3.50)	(0.67)	(7.90)
$\Delta lnGDP_{t-1}$	0.0677***	0.0161***	-0.0056	0.0554***	-0.2542***
	(6.26)	(2.88)	(-1.43)	(6.05)	(-7.91)
$\Delta Inv_{i,t}$	0.0496***	0.0201***	0.0057***	0.0337***	0.1636***
	(33.74)	(25.37)	(11.34)	(26.58)	(43.16)
$\Delta Inv_{i,t-1}$	0.0268***	0.0098***	0.0013***	0.0190***	0.0412***
	(29.76)	(20.30)	(3.90)	(24.86)	(16.20)
Constant	-0.0089***	-0.0033***	-0.0007***	-0.0061***	-0.0236***
	(-18.60)	(-12.77)	(-4.11)	(-15.03)	(-17.25)
N	104668	61401	39460	104668	104668
R2	0.4323	0.0912	0.1641	0.4167	0.3176

In model (1), the dependent variable is the change in SG&A costs, scaled by lagged total assets. In model (2), (3) and (4), the dependent variable is the change in R&D expenditure, advertisement and other SG&A, respectively, scaled by lagged total assets. In model (5), the dependent variable is the log change in employment. All variables are defined in Table 3.1. Standard errors are clustered at the firm level. T-statistics are in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent level.

3.4.4.2 Controlling for Managerial Optimism

In this section, we intend to differentiate our explanation from an explanation based on managerial optimism. Prior literature documents variation in managerial optimism (Graham et al. 2013). Optimistic managers have been shown to overestimate future demand (Malmendier et al. 2011). Overly optimistic demand expectations may induce managers to overspend on operating expenditure. Hence, while an explanation based on the catering theory predicts that rational managers perceive changes in investor sentiment and adjust their corporate policies accordingly, an explanation based on managerial optimism predicts that overly optimistic demand expectations induce managers to overspend on operating expenditure, regardless of catering incentives.

To differentiate between managerial optimism and investor sentiment, we proceed as follows. In a recent study, Banker et al. (2014) document that managerial optimism affects cost behavior. Empirically, Banker et al. (2014) argue that successive sales changes affect managers demand expectations, reflecting rational statistical inference and behavioral biases. First, since sales changes are positively correlated, sales increases in consecutive periods point to a greater likelihood of sales increases in future periods, thereby increasing managers' expectations about future demand. Second, Banker et al. (2014) argue that managers are likely to extrapolate sales trends, which likewise suggests that managers will be more likely to expect future sales increases following successive sales increases. Hence, to differentiate between managerial optimism and investor sentiment, we augment equation (3.1) with a dummy variable indicating successive sales increases and replicate our prior analysis.

The results are shown in Table 3.10. Consistent with our prior results, we find a positive association between operating expenditure and investor sentiment. When the dependent variable is based on SG&A costs, the coefficient on $\Delta Sent_t$ is positive and statistically significant at the 1% level (β_1=0.0031, t=12.34). We obtain similar results for R&D, advertisement and other SG&A, as shown in model (2) to (4) of Table 3.10. Finally, the last

column of Table 3.10 shows that the association between employment and investor sentiment remains unchanged (β_1=0.0067, t=9.19). Collectively, the results document that the association between operating expenditure and investor sentiment is robust to controlling for managerial optimism.

Table 3.10

The Association between Operating Expenditure and Investor Sentiment Controlling for Managerial Optimism

	(1) $SG\&A_{i,t}$	(2) $R\&D_{i,t}$	(3) $Adv_{i,t}$	(4) $OtherSG\&A_{i,t}$	(5) $Empl_{i,t}$
$\Delta Sent_t$	**0.0031*** **	**0.0015*** **	**0.0005*** **	**0.0021*** **	**0.0067*** **
	(12.34)	**(10.87)**	**(5.89)**	**(9.68)**	**(9.19)**
$\Delta Sales_{i,t}$	0.1288***	0.0148***	0.0182***	0.1122***	0.3539***
	(66.86)	(19.04)	(27.25)	(67.07)	(77.14)
$\Delta CashFlow_{i,t}$	0.0956***	0.0037***	0.0083***	0.0888***	-0.0242***
	(32.26)	(2.64)	(8.81)	(34.56)	(-3.70)
$\Delta Leverage_{i,t}$	0.1120***	0.0156***	0.0091***	0.0960***	0.1913***
	(28.02)	(7.68)	(6.75)	(27.65)	(16.66)
$\Delta EqIss_{i,t}$	0.0667***	0.0129***	0.0032***	0.0511***	0.1480***
	(18.83)	(7.29)	(2.92)	(17.55)	(19.91)
$\Delta lnGDP_t$	0.0207*	0.0018	0.0141***	0.0051	0.3001***
	(1.86)	(0.32)	(3.62)	(0.53)	(8.77)
$\Delta lnGDP_{t-1}$	0.0608***	0.0144**	-0.0088**	0.0519***	-0.3513***
	(5.36)	(2.47)	(-2.18)	(5.44)	(-10.52)
$SuccessiveIncrease_{i,t}$	0.0119***	0.0043***	0.0016***	0.0080***	0.0494***
	(20.14)	(14.40)	(7.53)	(16.04)	(31.02)
Constant	-0.0041***	-0.0014***	-0.0008***	-0.0025***	-0.0256***
	(-8.98)	(-5.84)	(-5.37)	(-6.61)	(-19.57)
N	105738	62081	39783	105738	105738
R2	0.4047	0.0548	0.1588	0.3985	0.2935

In model (1), the dependent variable is the change in SG&A costs, scaled by lagged total assets. In model (2), (3) and (4), the dependent variable is the change in R&D expenditure, advertisement and other SG&A, respectively, scaled by lagged total assets. In model (5), the dependent variable is the log change in employment. All variables are defined in Table 3.1. Standard errors are clustered at the firm level. T-statistics are in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent level.

3.4.5 Robustness

In this section, we test the sensitivity of our results to using an alternative measure of

investor sentiment and to clustering standard errors at the firm- and year level. The tables of all further robustness checks are available on request. We, here, briefly discuss the findings.

As a first robustness check, we test the sensitivity of our results to using an alternative sentiment index. In constructing the sentiment index that we have used so far, Baker and Wurgler (2006) combine six proxies for investor sentiment via principal component analysis. Even though the choice of the underlying variables follows prior literature on investor sentiment (see section 3.2 for motivation), one may criticize this procedure arguing that the index reflects a common business cycle rather than a common investor sentiment component. To address this concern, Baker and Wurgler (2006) regress each of the six sentiment measures on a set of macroeconomic variables comprising (1) growth in the industrial production, (2) growth in consumer durables, nondurables, and services, (3) and a dummy variable indicating NBER recessions. Baker and Wurgler (2006) combine the residuals from these regressions via principal component analysis and form an index that has been orthogonalized to macroeconomic conditions. The data on this alternative index is available on Jeffrey Wurgler's homepage.[34]

Consistent with our previous results, we find a positive association between expenditure on SG&A and investor sentiment (β_1=0.0025, t=10.54) when re-estimating equation (3.1) using the alternative investor sentiment index. Likewise, the association between research and development expenditure (β_1=0.0011, t=9.07), advertisement (β_1=0.0004, t=5.2), and other SG&A (β_1=0.0015, t=7.64) remains positive. Further, we find a positive association between employment and investor sentiment (β_1=0.0069, t=10.03). Collectively, our conclusion remains unchanged with the alternative measure of investor sentiment.

Finally, we re-estimate equation (3.1) when clustering standard errors at the firm and year level. When clustering standard errors at the firm and year level, we continue to find a

[34] http://people.stern.nyu.edu/jwurgler/

positive association between investor sentiment and SG&A costs (β_1=0.0033, t=3.04), R&D (β_1=0.0015, t=4.14) and advertisement expenditure (β_1=0.0006, t=3.18), other SG&A (β_1=0.0022, t=2.38) and employment (β_1=0.0072, t=2.98).

3.5 Conclusion

This paper intends to increase our understanding of real consequences that arise from investor sentiment. Building on the catering theory (Baker and Wurgler 2011; Stein 1996), our results suggests that mangers overspend on research and development expenditure, advertisement, selling, general and administrative costs and employment in order to cater to investors' misperceptions in periods of high relative to periods of average sentiment. In further analyses, we find results that are consistent with cross-sectional predictions of the catering theory: (1) Managers are more likely to overspend on SG&A costs when these resources have high value creating potential, (2) managers with short-horizons, and (3) managers' of firms that are particularly affected by investor sentiment are more likely to cater by overspending on operating expenditure. However, our results indicate that managers refrain from overspending through operating expenditure when facing earnings targets, which suggests a trade-off between catering to investors' real and financial expectations.

4 Attention, Media and Fuel Efficiency

4.1 Introduction

The emissions of motor vehicles are one of the major sources of greenhouse gas emissions leading to climate change. For example, in the United States, the transportation sector accounts for 34% of the carbon dioxide emissions.[35] These emissions could be decreased with improved technologies that offer a better fuel efficiency.[36] For this reason, it is crucial to understand which factors are relevant for the diffusion of fuel-efficient technologies.

We argue that the consumer purchasing decision process and the question when consumers are willing to invest in fuel efficiency play an important role in this context. As Allcott (2011) indicates, 40% of US consumers do not consider a vehicle's gasoline consumption when purchasing a car. Therefore, the amount of attention devoted to energy efficient vehicles and fuel costs should be a major determinant for the diffusion of new technologies. Following this rationale, we attempt to capture the dynamics of the consumers' attention to hybrid electric vehicles.[37] However, attention is not directly observable and thus, finding an adequate measure for attention is challenging. We make use of Google's search query data as a direct and observable proxy for the revealed attention. By analyzing online search behavior, we effectively examine the consumers' process of gathering information about the topic to which they pay attention. Data on aggregate regional online search behavior is obtained from the service "Google Insights for Search", enabling us to track the development of the search volume of a specific query.

It is expected that there are two main channels that alter the attention devoted to

[35] Source: United States Department of Energy, "Emissions of Greenhouse Gases in the United States 2009", DOE/EIA-0573(2009), Figure 4.3, U.S. energy-related carbon dioxide emissions by sector, 2009.

[36] The fuel economy of a vehicle is defined as the output (miles) per input (gallons of gasoline). In contrast, fuel efficiency, as a form of thermal efficiency, is the ratio of energy used for propulsion compared to the total amount of energy consumed. Thus, a small vehicle with a high fuel economy could still be less fuel-efficient than a larger vehicle with a lower fuel economy, e.g. because a vehicle with a heavier weight also requires more physical work to drive the same distance.

[37] We focus on hybrid electric vehicles as they are considered to be a promising technology for increasing fuel efficiency. Furthermore, Enkvist et al. (2007) indicate that increasing the fuel efficiency of vehicles is one of the least costly ways to reduce the overall global greenhouse gas emissions.

environmentally friendly vehicles. First, as the reduced gasoline consumption is the main advantage of energy efficient vehicles, the gasoline price should be an important determinant of the consumers' attention devoted to hybrid vehicles. Tversky and Kahneman (1991) indicate that consumers also evaluate prices based on reference points. If the gasoline price is higher than such a reference point, consumers would consider a price increase as a loss and may show a stronger reaction due to loss aversion. Thus, unprecedented record gasoline prices could have an additional effect on the consumers' attention if the highest previous gasoline price is such a reference point. Second, consumers may react to media coverage of topics such as hybrid vehicles and gasoline costs.[38] We draw upon the agenda-setting theory by McCombs and Shaw (1972), arguing that mass media influences the public agenda by determining which topics are seen as important.

However, the causality of whether media covers topics of general interest or whether media determines the general interest is not always clear. For our case, it is difficult to identify the causal influence of media because the consumers' attention and media coverage are both directly affected by gasoline prices and other possibly unobserved factors. Similar to Engelberg and Parsons (2011), we circumvent this problem by observing the behavior of different geographical groups. These groups react to the same underlying event, but are exposed to different information sources, i.e. their local newspaper. Our analysis is based on a novel weekly panel dataset consisting of 19 metropolitan areas in the United States covering the years 2004 to 2011. We control for local gasoline prices, national television reports and national newspaper coverage. In order to estimate the causal effect of local newspaper coverage on our attention measure, we allow each local newspaper to have an

[38] This hypothesis is supported by several studies indicating that economic actions are affected by media coverage. For example, Eisensee and Strömberg (2007) analyze the impact of mass media coverage on the US relief for natural disasters. To identify the effect of media coverage, they use an instrument variable, which measures the availability of other newsworthy events that crowd out media coverage of marginally newsworthy natural disasters. Tetlock (2007) analyzes the relationship between the content of newspaper articles and stock market outcomes. He shows that the sentiment of media has a distinct impact on stock prices.

effect on all other metropolitan areas. Thus, we estimate the supplemental effect that a newspaper has in its own region compared to the effect on all other regions. This identification strategy allows us to disentangle the underlying event and the causal media effect.

Our results indicate that the consumers' attention devoted to hybrid vehicles is affected by both channels. We find that local media coverage causally affects the consumers' attention and that consumers react to both gasoline price changes and unprecedented levels of the gasoline price. Building on these findings, we validate that our proxy for the attention to hybrid vehicles is relevant to the purchasing behavior. We use a panel dataset of monthly state-level hybrid vehicle registrations and market shares for the period covering the years 2006 to 2011 to show that our attention measure is robustly related to actual consumer purchasing decisions. Overall, our findings suggest that attention effects have a distinct impact on the market for hybrid vehicles.

This is the first study to analyze the determinants of the consumers' attention to a long-lived consumer good. Until now, most studies in the area focus on showing how attention effects influence economic decision making, but do not systematically analyze the determinants of the attention. The most advanced analysis of the impact of attention effects on economic choices is primarily in the finance literature. Barber and Odean (2008) show that the stock purchasing decision of individual investors is influenced by the attention to a certain choice. Given the scarcity of the resource attention and the large set of possible investments, attention-based decision making implies that investors are more likely to buy investments that grab their attention. Da, Engelberg, and Gao (2011) indicate that Google search queries are a valid direct measure of retail investor attention, which is found to affect

the retail investors' behavior in financial markets.[39] In the context of consumer behavior, Chetty, Looney, and Kroft (2009) show that the consumers' reaction to taxation depends on the salience of the tax. Masatlioglu, Nakajima, and Ozbay (2012) provide a theoretical framework for limited attention effects. Their model describes a decision process under the constraint of a limited consideration set and examines the implications for revealed preferences and revealed attention.

Our study also extends the literature on the consumer search behavior in reaction to gasoline price changes. There is a range of literature (see for example Chandra and Tappata 2011) that focuses on the relationship between the consumer search behavior and the price dispersion between different gas stations, or more broadly the competition in gasoline markets. In contrast to these studies, we do not focus on the search behavior related to the gasoline purchasing decision, but rather on the long-term reaction, i.e. the search behavior accompanying the vehicle purchase. Lewis and Marvel (2011) find that the consumers' reaction to price changes is not symmetric. Consumers increase their search effort when faced with rising gasoline prices, but do not react strongly to falling prices. Our findings are similar regarding the asymmetric consumer search behavior. Additionally, we identify a distinguished attention effect for record gasoline prices. This evidence is consistent with the results in the finance literature. For example, Yuan (2011) measures the impact of attention-grabbing events like record levels of the Dow Jones index and front page articles about the stock market. It is shown that attention influences trading behavior of individual investors. Similarly, Li and Yu (2012) show that psychological reference points of past record levels can also have an impact on aggregate stock market outcomes.

The remainder of the article is organized as follows: Section 2 describes the market for

[39] There are several other studies about attention effects in financial markets. For example, DellaVigna and Pollet (2009) indicate the existence of weekday effects due to investors' limited attention. Gilbert et al. (2012) argue that inattention leads to a temporary market reaction to stale information. Engelberg, Sasseville, and Williams (2012) examine the market impact of television stock recommendations, which are interpreted as shocks to the retail investors' attention.

hybrid vehicles and discusses the consumers' purchasing motives. Section 3 gives detailed information about the construction of our unique dataset. In section 4, we analyze how media coverage and gasoline prices affect the attention devoted to hybrid vehicles. In section 5, we show that online search queries are a relevant measure and have a robust correlation with actual sales volumes. Finally, we give a short conclusion of our findings in section 6.

4.2 Hybrid Vehicle Market and Consumer Attitudes

Hybrid electric vehicles have both an internal combustion engine and an electric motor. This combination allows improved fuel efficiency compared to similar non-hybrid vehicles because the combustion engine is mostly used to support the electric motor. The battery of the electric motor is recharged while driving with gasoline and also while recovering the braking energy. Thus, as for most fuel-efficient technologies, hybrid electric vehicles have a higher purchasing price due to the increased complexity of including advanced technological parts such as an electric motor, a lithium-ion battery and a braking energy recovery system. The upfront investment expenses result in lower gasoline consumption and lower costs during the lifetime of the vehicle. Therefore, the profitability of the investment in fuel efficiency depends on future gasoline prices.

In 1999, the Honda Insight was the first hybrid vehicle to be introduced in the United States. The Toyota Prius, still the best selling hybrid vehicle in the US, was introduced in 2000. However, in the first six years, only a total of 197,483 hybrid vehicles were sold. In the following two years, during 2005 and 2006, there were 462,347 hybrid vehicles sold in the US.[40] Even at the start of our sample period in December 2006, the market share of all hybrid vehicles was still at a rather low level of 1.65%. Thus, the hybrid car market can be considered a new market, which means that the initial awareness related to this market is relatively low.

[40] Source: US Department of Energy, http://www.afdc.energy.gov/afdc/data/vehicles.html

Several studies show that the hybrid vehicle market is mainly driven by three factors: Gasoline prices, government subsidies and non-monetary factors like symbolic values or environmental concern. There are a range of studies focusing on the impact and effectiveness of government programs that foster the sales of hybrid vehicles. For example, Beresteanu and Li (2011) find that both high gasoline prices and tax incentives have a significantly positive effect on hybrid sales. Gallagher and Muehlegger (2011) present similar results and show that sales tax waivers have a much higher impact than income tax waivers, which are less salient and transparent. Chandra, Gulati, and Kandlikar (2010) find that government incentives have a positive effect on hybrid sales but are not very cost effective. Diamond (2009) indicates that gasoline prices may have a higher impact than government incentives.

The literature also identifies several distinct, non-monetary factors that influence the hybrid vehicle market. Kahn (2007) shows that environmental concern is one aspect that influences purchase decisions, as green party voters are more likely to buy hybrid vehicles. Heffner, Kurani, and Turrentine (2007) argue that in addition to economic factors, hybrid car owners incorporate different symbolic values in their decision. These range from obvious stereotypes, like overall environmental concern, to other factors such as wanting to be seen as a moral and intelligent person, opposing war, opposing oil producers or possessing the latest technology. In this context, Griskevicius, Tybur, and Van Den Bergh (2010) find that social motives and concern for status are important factors for purchasing decisions in general. From a psychological perspective, seemingly altruistic behavior, like publicly demonstrating ownership of green products, can be seen as a costly signal to improve social status. Following this rationale, Sexton and Sexton (2011) show that the Toyota Prius benefits from its distinct recognizability as a hybrid car, which makes the Prius more attractive for status-concerned car buyers.

However, these non-monetary factors are subject to changes in the public agenda. Thus,

the hybrid vehicle market should be affected by agenda-setting, in terms of media coverage increasing the general public awareness about the existence and the environmental benefits of hybrid cars.

Several considerations about the hybrid car market can also be extended to the more general topic of fuel efficiency. Despite the fact that the gasoline price is found to have an impact on consumer decisions, there is evidence that consumers are not able to fully assess the value of fuel efficiency. For example, Turrentine and Kurani (2007) use a survey approach to show that many consumers are not able to calculate the lifetime cost of their vehicle or to make informed decisions about the fuel efficiency of a car they would like to purchase. The authors point out that drivers know the price paid at the gas station a few weeks ago, but do not use a decision-making process that is consistent with economic assumptions and theories. Furthermore, consumers also assign a symbolic value to fuel efficiency. The consumers' decision process described by Turrentine and Kurani (2007) suggests that the attention devoted to the gasoline price and fuel efficiency should have an even stronger effect than the gasoline price itself. If vehicle buyers cannot assess the present value of the investment, non-monetary effects will have a stronger impact.[41]

The question of how consumers value fuel efficiency is a topic of ongoing discussion and research. Greene (2010) reviews 28 econometric studies from the years 1995 to 2010, which do not draw a conclusive picture whether consumers undervalue or overvalue fuel efficiency. The attention and media effects found in the present article are factors that need to be considered in such studies.

4.3 Data

In this study, two unique panel datasets for the United States are considered. Our empirical

[41] This view is also supported by Baker and Wurgler (2007), who show that investor sentiment has a stronger effect on stocks that are more speculative and difficult to arbitrage or value. This argument also holds for our setting, as vehicles are relatively illiquid assets and consumers have difficulties assessing the life-time fuel costs.

setup focuses on four types of data: Attention measures, media coverage, gasoline prices and vehicle registrations. In the main analysis, we use local news coverage and weekly online searches in 19 metropolitan areas in the US. The dataset is an unbalanced panel from January 4th, 2004 to October 23rd, 2011 and is used to determine the causal impact of local media coverage on attention. Additionally, we test whether there is a robust relationship between our measure of attention and actual sales volumes. For this purpose, we use monthly US state-level car registration data, which was kindly provided by R. L. Polk & Co. The panel for vehicle registration data ranges from December 2006 to February 2011. We analyze the number of hybrid vehicle registrations and the hybrid technology's market share.

As a proxy for attention, we use Google search query data as a direct measure of the public interest. Time series of regional search trends are available at "Google Insights for Search" and range back to January 2004.[42] We collect weekly search trends for the terms "hybrid" and "mileage" in the category "Autos and Vehicles".[43] These queries represent the interest in the technology of hybrid vehicles and in fuel economy in general. We obtain weekly search trends for the 19 metropolitan areas and additionally aggregate weekly state-level search trends in order to derive a monthly search measure for the analysis in section 5. Google constructs the trend index by calculating the amount of search queries that are associated with the term of interest. That number is then divided by the total number of search queries within this period and region, which yields a time series of the relative interest for the search term. The final index scales this time series to have a maximum value of 100. Table 4.1 shows that search terms related to automotive fuel efficiency and hybrid vehicles have several million search queries per month.

[42] Available at http://www.google.com/insights/search.

[43] Google Insights for Search does not report a search index if the amount of searches is below a certain threshold. This happens frequently during the earlier years and for smaller states or metropolitan areas. Thus, we focus on the search trends for the terms "hybrid" and "mileage" as they represent the highest search volumes for each topic. Search volumes for other relevant terms are presented in Table 4.1.

Table 4.1

Average Monthly US Google Search Volume for Fuel Efficiency Related Terms

Keyword	Monthly search volume
mileage	3,350,000
hybrid	2,740,000
mpg	2,740,000
prius	1,000,000
fuel economy	450,000
fuel efficiency	246,000

Notes: Average monthly search volume according to Google Keyword Tool, which is available at http://adwords.google.com/select/KeywordToolExternal. The figures are for the category "Vehicles", English language, for the US only and were obtained on January 31, 2012. The reported volume is an estimate of the average monthly search volume during the last 12 months and is calculated by Google.

One benefit of this dataset is that the Google search query data reflects real search behavior and does not suffer from biases that may be introduced by survey methodology. Self-reporting about subjective questions, such as the current level of attention devoted to hybrid vehicles, can lead to substantial biases and inconsistencies. Bertrand and Mullainathan (2001) point out that subjective data should not be used as a dependent variable because the inherent measurement errors usually correlate with other relevant characteristics.

For the local news coverage, we construct a daily measure of the number of articles in large local newspapers. We focus on the newspapers in the 19 metropolitan areas listed in Table 4.2 and additionally use USA Today and The New York Times as a proxy for national newspaper coverage. The newspaper articles are obtained from the LexisNexis database. Our measure of the amount of news coverage is derived by summing the number of relevant articles for each newspaper and time period. We also distinguish between articles regarding the topics of "gasoline prices" and those of "efficient vehicle technologies". The detailed search queries for both topics are described in Table A.1 in the Appendix and are structured

to be a reasonable compromise between relevancy and completeness. We generate the newspaper coverage variable by counting the number of relevant articles for each newspaper and time period (i.e. weekly or monthly). Therefore, the purpose is not to analyze the content but rather to focus on the mere presence of media coverage. The methodology has the drawback that the sentiment of media coverage may be positive or negative, which may influence both the attention and sales impact. Regarding this point, Berger, Sorensen, and Rasmussen (2010) show that new and less-known products benefit from both positive and negative publicity. Thus, we assume that all media coverage can be treated equally in our setup because hybrid vehicles are still a relatively new and less-known product.

Additionally, we use data on television news coverage from the Vanderbilt Television News Archive. The Vanderbilt database provides access to the evening news of the four major US national broadcast networks: ABC, CBS, NBC, and CNN. We construct two daily time series of television news coverage, one for the topic of "gasoline prices and fuel economy" and one for "hybrid vehicles and efficiency technologies". For the first topic, we use the following keywords: Gasoline, gas price, mileage, gallon and mpg. For the second topic, we use the keywords: Hybrid and fuel efficiency. Then, we eliminate all duplicates within each topic and hand-check for the relevancy of each news segment. We generate our variables by counting the total number of news segments across all networks for each topic and for a given time period (i.e. weekly or monthly).

Two different datasets of gasoline prices are obtained from the US Energy Information Administration (EIA). In section 4, for the analysis of the determinants of consumers' attention, we use weekly retail gasoline prices for all grades and formulations. Depending on data availability, we match our 19 metropolitan areas with gasoline prices on a regional or state level. For the analysis of the actual purchasing behavior in section 5, we use the monthly state-level retail price of motor gasoline.

Table 4.2

List of Newspapers Used in the Analysis

Metropolitan Area	State	Newspaper
Atlanta	Georgia	The Atlanta Journal Constitution
Austin	Texas	The Austin American Statesman
Boston	Massachusetts	Telegram Gazette
Chicago	Illinois	The Chicago Sun-Times
Denver	Colorado	The Denver Post
Detroit	Michigan	The Detroit News
Houston	Texas	The Houston Chronicle
Las Vegas	Nevada	Las Vegas Revue Journal
Los Angeles	California	The Orange County Register; The Daily News of Los Angeles
Madison	Wisconsin	Wisconsin State Journal
Minneapolis-Saint Paul	Minnesota	Star Tribune
New York	New York	The New York Post
Norfolk-Portsmouth	Virginia	The Virginian Pilot
Philadelphia	Pennsylvania	The Philadelphia Inquirer; Philadelphia Daily News
Salt Lake City	Utah	The Salt Lake Tribune
San Francisco	California	The San Francisco Chronicle
St. Louis	Missouri	St. Louis Post-Dispatch
Tampa	Florida	St. Petersburg Times; The Tampa Tribune
Washington	District of Columbia	The Washington Times
National	National	New York Times
National	National	USA Today

Notes: The choice of included newspapers depends on the availability of data in LexisNexis and the relevancy of each newspaper within a certain metropolitan area. Additionally, only metropolitan areas with sufficient available data from Google are considered. Given these binding restrictions, 19 metropolitan areas and their major newspapers are used in the analysis.

The time structure of the weekly gasoline prices and Google searches is as follows: The EIA measures the gasoline price on Mondays, for which reason the provided weekly data only reflects the gasoline price on this particular day. In contrast, the data provided by Google Insights for Search reflects the search behavior of the entire week (Sunday to Saturday). As the search behavior is supposed to follow the gasoline price development, the weekly queries are matched with the gasoline price of the following Monday. The gasoline

price changes from the current week are reflected in the subsequent – and not the contemporaneous – gasoline price. All media variables are built from daily data and match the time structure of the Google searches. Table A.2 in the Appendix reports summary statistics for both panel datasets used for the analyses presented in sections 4 and 5.

4.4 What Drives the Attention Devoted to Hybrid Vehicles?

In this section, we investigate which factors influence the attention devoted to hybrid vehicles. As outlined in the introduction, we focus on two main channels: The observable gasoline price and the media coverage concerning hybrid vehicles. The causal influence of both unprecedented record gasoline prices and local media coverage is of particular interest. However, one issue related to this analysis is that the effect of media is expected to be limited if consumers are well informed. As a robustness test, this hypothesis is tested in a supplementary analysis using the local newspaper coverage concerning gasoline prices and the online search queries for "mileage" as a proxy for the attention to fuel economy.

We begin with the analysis of the determinants of the consumer's attention devoted to hybrid vehicles. Before proceeding with the regression analysis, the relationship between the relevant variables is discussed. Figure 4.1 shows the weekly US gasoline price in US Dollars per gallon, the number of television news segments covering hybrid vehicles, the sum of newspaper articles about hybrid vehicles or fuel efficiency in all sample newspapers and the search trend for "hybrid" for the time period from January 2004 to September 2011. The shaded areas indicate weeks with a high relative interest in hybrid vehicles.

Graphical inspection suggests that the variation of searches is closely connected to the gasoline price and news coverage. Figure 4.1 also shows that in 2005 and 2008, there were new record price levels that lead to the highest interest during the sample period. The actual search behavior far exceeds the amount of searches that can be explained as a proportional reaction to the gasoline price increase only. When the price drops after a period of very high

prices, there is a strong sign of relief, which is mirrored by a plunge in consumers' interest in hybrid vehicles. The graphical analysis also suggests that consumers and media react to price increases rather than to high price levels. Once the gasoline price stops rising, but remains at a high level, both consumers and media quickly lose their interest.

The periods of high attention levels always coincide with periods having steep gasoline price increases, record gasoline prices or a high media coverage on hybrid vehicles. However, there is one peak of news coverage in the first week of December 2008, which is not reflected in the Google searches. This peak of news coverage is due to the US Big Three car manufacturers' bailout discussion and their CEOs using hybrid vehicles for the journey to the Senate hearing. Another event leading to increased news coverage on hybrid vehicles is the North American International Auto Show in Detroit, which takes place every year in January.

In the following part, we examine the impact of local media coverage and record gasoline prices on the attention devoted to hybrid vehicles. We thereby proceed in three steps. First, we describe the variables used in our setup, second we discuss our regression model specifications and third we present the results from estimating our regression models.

For our identification strategy, we rely on local newspaper coverage. Despite the omnipresence of the internet, local newspapers are usually read only within one city and its surroundings. Compared to media coverage on a national level, focusing on local media therefore allows to have varying media exposure for the same event and to subsequently observe the reactions of metropolitan areas which have been exposed to a different degree of media coverage. Thus, all regression models are estimated using panel data for 19 US metropolitan areas, which enables us to examine more precisely whether local newspaper coverage affects the attention to hybrid vehicles when controlling for other news coverage or

time-fixed effects.[44] We make use of several control variables for national media coverage. For the specifications without time-fixed effects, we use national television news coverage on gasoline prices and on hybrid vehicles as controls. Additionally, we include the news coverage in two national newspapers, USA Today and The New York Times.

Gasoline price changes are expected to have a major influence on the attention devoted to hybrid vehicles. We include asymmetric specifications of gasoline price changes as rising and falling prices may have a different influence on attention.[45] There are three different time frames included: The change (i.e. log difference) during the current week, the short-term price movement (week t-2 to t-6) and the mid-term perspective (week t-7 to t-18). The results of Yuan (2011) indicate that record gasoline prices may have a distinct effect on attention. Thus, we include the variable "Record Price Length" to count the consecutive number of weeks with an unprecedented price level during a price surge.[46] The variable reflects the fact that the attention rises directly with the duration of an intense price increase.

Government incentives such as tax credits are not taken into account explicitly. However, our fixed effects specification controls for all state-specific incentives that do not vary over time. Furthermore, the time-fixed effects account for all federal incentives. As the hybrid vehicle market matures, government incentives become less substantial compared to the early phase before our sample period. Marketing expenditures could be another source of an omitted variable bias that may influence both the attention and the purchasing decision modeled in section 5. There is no data available on regional marketing focusing on hybrid vehicles or fuel efficiency; however it is likely that large and influential marketing campaigns

[44] Note that our setup directly controls for the possibility that a local newspaper is also read by non-local readers and vice versa. A higher share of non-local readers makes it less likely to find a causal effect of local media coverage.
[45] This specification is consistent with the findings of Lewis and Marvel (2011).
[46] For instance, if there are five record prices in a row then the variable equals 5 in the last week. In order to account for minor gaps within such periods, the variable stagnates in case of a single week without an unprecedented price level if another record price follows afterwards. If – in our example – there has been a break in the fourth week, the variable would twice indicate that three weeks of record prices occurred and would end with a count of 4 in the last week.

are targeted at a national audience and are thus captured by our time-fixed effects.

We estimate our regression models using five different specifications. In the first specification, we control for the gasoline price, national television coverage, national newspaper coverage, year-fixed effects and time-invariant characteristics of metropolitan areas by fixed effects. However, we do not control for spillover effects of local news coverage in other metropolitan areas. Therefore, we estimate the average effect of local newspaper coverage, which can be interpreted as the correlation between newspaper coverage and online searches.

The second specification additionally includes all local newspapers as control variables. Thus, each local newspaper is also allowed to have an effect on the non-local metropolitan areas. Following Engelberg and Parsons (2011), the impact of local newspapers is now identified by the difference in the reaction between a newspaper's local and non-local readership. If there is a significant positive marginal effect of the local newspaper coverage, it can be concluded that local newspaper treatment has a causal effect on the readers' attention. For example, a newspaper may feature an article about the benefits of hybrid vehicle technology. The article could have an influence on the readership by increasing the awareness about hybrid vehicles and by encouraging the readership to search for more information online. In this case, there is an increased search volume in the metropolitan area with the newspaper coverage of the hybrid vehicle technology, whereas the metropolitan areas without a local news treatment do not exhibit an increased level of attention.

For robustness reasons, we also employ alternative estimation techniques and setups. The third specification includes time-fixed effects, for which reason only variables with local variation will be included. The fourth and fifth specification explicitly account for the underlying panel data structure, which is characterized by many time periods and relatively few units of observation (large T and small N). Using a panel consisting of regional groups,

such as metropolitan areas, makes it important to control for cross-sectional correlation, as it is very unlikely that the patterns in different geographical areas are mutually independent. Besides accounting for this kind of spatial correlation, it is also necessary to adequately model the serial correlation of the error term as the number of time periods increases. The fourth specification therefore estimates the same model as the second specification, but uses a Prais-Winsten type feasible GLS panel estimator with a panel-specific AR(1) structure and panel-corrected standard errors. Alternatively, the fifth specification uses robust Driscoll-Kraay standard errors, which account for general forms of cross-sectional correlations, autocorrelation and heteroskedasticity.

Table 4.3 shows the panel regression results for our model with Google searches for "hybrid" as the dependent variable. The dependent variable measures the search volume in each of the 19 metropolitan areas. Our results show that local newspaper coverage of topics related to hybrid vehicles ("Local Newspaper Hybrid") has a significant impact on the consumers' attention, regardless of the specification. For specifications (2) - (5), the local newspaper variable measures the supplemental effect that each local newspaper has in its own region, which we interpret as a causal effect following Engelberg and Parsons (2011). Our results suggest that local newspapers influence the local attention devoted to hybrid vehicles, despite other information sources available. Television news coverage about gasoline prices has a significant correlation with the search volumes for hybrid. This finding is intuitive as the gasoline price affects the profitability of an investment in a hybrid vehicle. The effect of television news coverage regarding hybrid vehicles has a positive, but not conclusive, effect on the searches for hybrid.

The impact of record gasoline prices is significant in most specifications. This finding supports the hypothesis that consumers react to reference points. Following Tversky and Kahneman (1991), consumers perceive a price increase as a loss if it is above the reference

point of the most recent record price. In this case, loss aversion leads to a stronger reaction in the amount of search volumes reflecting a higher level of attention.

An alternative explanation for the record price effect could be that the consumers' expectations of future gasoline prices are not consistent with the random walk hypothesis.[47] The profitability of an investment in automotive fuel efficiency depends on future gasoline prices. If consumers expect that trends of rising gasoline prices will continue in the future, the consumers' attention would rise disproportionately during periods of extended price increases. However, Anderson et al. (2011) show that it is generally a reasonable approach to assume a no-change forecast for consumers' fuel price expectations, which is consistent with the random walk hypothesis. Nevertheless, our alternative explanation cannot be ruled out completely because Anderson et al. (2011) still observe a large dispersion of individual forecasts during periods of extreme price fluctuations as seen in the year 2008.

In conclusion, the regression models indicate that consumers react to movements of the gasoline price by adjusting their search intensity. Additionally, unprecedented record gasoline prices and local media coverage raise the attention devoted to hybrid vehicles in a causal relationship.

We proceed with the supplementary analysis and examine whether local media coverage regarding gasoline prices likewise affects the attention devoted to fuel economy. As the gasoline price is directly observable, media coverage is expected to have a less distinct effect. The gasoline price is the most obvious factor that influences the attention devoted to fuel economy. When gasoline prices rise, consumers are likely to be forced to change their general consumption behavior. For example, Gicheva, Hastings, and Villas-Boas (2010) and Ma et al. (2011) show that increases in gasoline prices lead to changes in the grocery purchasing behavior due to changes in residual disposable income. The pressure to change

[47] The random walk hypothesis assumes that the current price is the best estimate for future prices regardless of the price history.

general consumption patterns could also lead to an increased interest in fuel economy.

The variables for the supplementary analysis are displayed in Figure 4.2, which shows the weekly US gasoline price, the number of television news segments covering the gasoline price or fuel economy, the sum of newspaper articles about gasoline prices in all sample newspapers and the search trend for "mileage" for the time period from January 2004 to September 2011. The shaded areas indicate weeks with a high relative interest in fuel economy.

Similar to the setup for hybrid vehicles, the variation of searches for fuel economy is closely connected to the gasoline price and media coverage. Comparing Figures 4.1 and 4.2, the newspaper coverage of "hybrid vehicles and fuel efficiency" is noisier than the coverage of "gasoline prices". However, the topic of efficient technologies has a more general character and is not as closely tied to the gasoline price movement. Furthermore, the search trends for "mileage" and "hybrid" are very similar. This finding indicates that the increased fuel efficiency of hybrid vehicles is indeed perceived as the major advantage of hybrid vehicles.

In April 2006, there was a peak of television coverage on gasoline prices, with up to 35 relevant news segments in one week. During this time, several economic and political events occurred that constituted the increased television reporting. First, there was a strong increase of gasoline prices from \$2.41 on March 13th to \$2.96 on April 24th. Second, on April 25th, George W. Bush held a speech on energy policy, which was widely covered by the media. Lastly, discussions about oil companies' high profits and a windfall profit tax gained increased media attention.

Table 4.4 presents the results of regressing Google searches for "mileage" on media coverage, record gasoline prices and gasoline price changes. The basic setup of the regression model is the same as for the results shown in Table 4.3. However, all newspaper variables are

now constructed to reflect the news coverage on gasoline prices.[48]

The results shown in Table 4.4 indicate that the relationship between the local news coverage concerning gasoline prices and the attention to fuel economy is as expected. Only in the first specification, there is a significant relationship between the two variables. As in Table 4.3, the first specification estimates the average effect of local newspaper coverage without controlling for other local news coverage in the remaining metropolitan areas or for time-fixed effects. Thus, we find a strong positive correlation between newspaper coverage and searches. However, when estimating effects with a causal interpretation (i.e. the supplemental regional effect of local newspaper coverage on the attention devoted to mileage), the results indicate that the interest in searching for mileage is unaffected by media coverage. Therefore, it can be concluded that the treatment of local newspaper coverage in regards to gasoline prices has no causal influence on the attention devoted to fuel economy. However, the length of unprecedented gasoline prices has a positive impact on the attention level. This finding indicates that gasoline expenditures become a "top of mind" topic when the prices reach new all-time highs.

Overall, the aim of the main analysis is to examine which factors influence the attention devoted to hybrid vehicles. We demonstrate that both local media coverage and unprecedented record gasoline prices significantly increase the attention devoted to hybrid vehicles. The supplementary analysis examines whether local media coverage concerning gasoline prices similarly affects the attention devoted to fuel economy. We observe a strong correlation, but we do not find a causal effect. An intuitive explanation for this finding is that consumers can be assumed to be rather well informed about the current gasoline price, which can be easily observed at gas stations. Therefore, the media coverage concerning gasoline prices does not provide much additional information and has consequently no causal effect on

[48] See Table A.1 for a precise definition of the relevant search terms.

attention. In contrast, hybrid vehicles are a relatively new fuel-efficient technology and consumers may not be fully aware of the existence and benefits of hybrid vehicles. Thus, media coverage has the ability to increase the amount of attention devoted hybrid vehicles.

The finding that media coverage alters the consumers' attention to hybrid vehicles is of interest in two regards. First, this result indicates that consumers would most likely invest more in new, efficient technologies if they had a deeper knowledge of the topic. This insight may be of importance to both policymakers and car manufacturers dealing with the distribution of environmentally friendly vehicles. Second, and more generally, our finding is interesting concerning the role of the media as a part of an individual's decision-making process. Our results seem to reject the hypothesis that the media merely replicates publically available information and does not influence the consumers' considerations. However, the impact of media coverage depends on the specific topic considered and cannot be generalized for all circumstances.

Table 4.3

Hybrid Vehicle Technology and Attention

	Dependent Variable: Google Search Queries for Hybrid				
	(1)	(2)	(3)	(4)	(5)
Local Newspaper Hybrid	0.361 ***	0.203 **	0.216 **	0.085 ***	0.203 ***
	(0.037)	(0.09)	(0.092)	(0.031)	(0.042)
TV Gasoline	1.042 ***	0.908 ***		0.675 ***	0.908 ***
	(0.053)	(0.051)		(0.096)	(0.154)
TV Hybrid	0.681 ***	0.444 ***		0.188	0.444
	(0.113)	(0.115)		(0.32)	(0.48)
Record Price Length	0.796 ***	0.733 ***	0.145 *	0.722 ***	0.733 ***
	(0.077)	(0.074)	(0.083)	(0.107)	(0.243)
$\Delta \text{Gas Price}^{Pos}_{t,t-1}$	63.553 ***	61.742 ***	19.985 *	49.764 ***	61.742 *
	(8.439)	(7.993)	(9.611)	(12.936)	(33.328)
$\Delta \text{Gas Price}^{Neg}_{t,t-1}$	40.059 ***	44.1 ***	33.838 **	31.994 *	44.1
	(7.458)	(7.572)	(14.748)	(18.482)	(30.217)
$\Delta \text{Gas Price}^{Pos}_{t-2,t-6}$	55.285 ***	52.868 ***	23.278 **	43.906 ***	52.868 ***
	(4.17)	(4.02)	(8.226)	(7.984)	(11.935)
$\Delta \text{Gas Price}^{Neg}_{t-2,t-6}$	42.344 ***	39.086 ***	11.185 **	37.996 ***	39.086 ***
	(2.258)	(2.233)	(4.288)	(7.507)	(8.701)
$\Delta \text{Gas Price}^{Pos}_{t-7,t-18}$	24.284 ***	19.691 ***	13.518 ***	17.983 ***	19.691 ***
	(2.016)	(2.229)	(4.619)	(5.458)	(6.76)
$\Delta \text{Gas Price}^{Neg}_{t-7,t-18}$	11.096 ***	12.245 ***	10.359 ***	14.038 ***	12.245 ***
	(0.683)	(0.696)	(3.559)	(4.029)	(2.724)
Newspaper USA Today	-0.112 *	-0.191 ***		0.029	-0.191
	(0.057)	(0.057)		(0.128)	(0.161)
Newspaper NYT	0.29 ***	0.194 ***		0.006	0.194 *
	(0.024)	(0.024)		(0.064)	(0.096)
Intercept	25.173 ***	22.56 ***	30.225 ***	25.638 ***	22.56 ***
	(1.109)	(1.081)	(1.405)	(1.48)	(1.524)
R^2	0.63	0.649	0.812	0.471	0.649
N	7208	7208	7227	7208	7208
Newspaper Spillover Controls	NO	YES	NO	YES	YES
Metro-Fixed Effects	YES	YES	YES	NO	YES
Time-Fixed Effects	NO	NO	YES	NO	NO
Year-Fixed Effects	YES	YES	NO	YES	YES

Standard errors are clustered by metropolitan area in models (1), (2) and (3). Model (4) is estimated using a Prais-Winsten regression with a panel-specific AR(1) structure and panel-corrected standard errors. Driscoll-Kraay standard errors are used in model (5).
*, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

Table 4.4

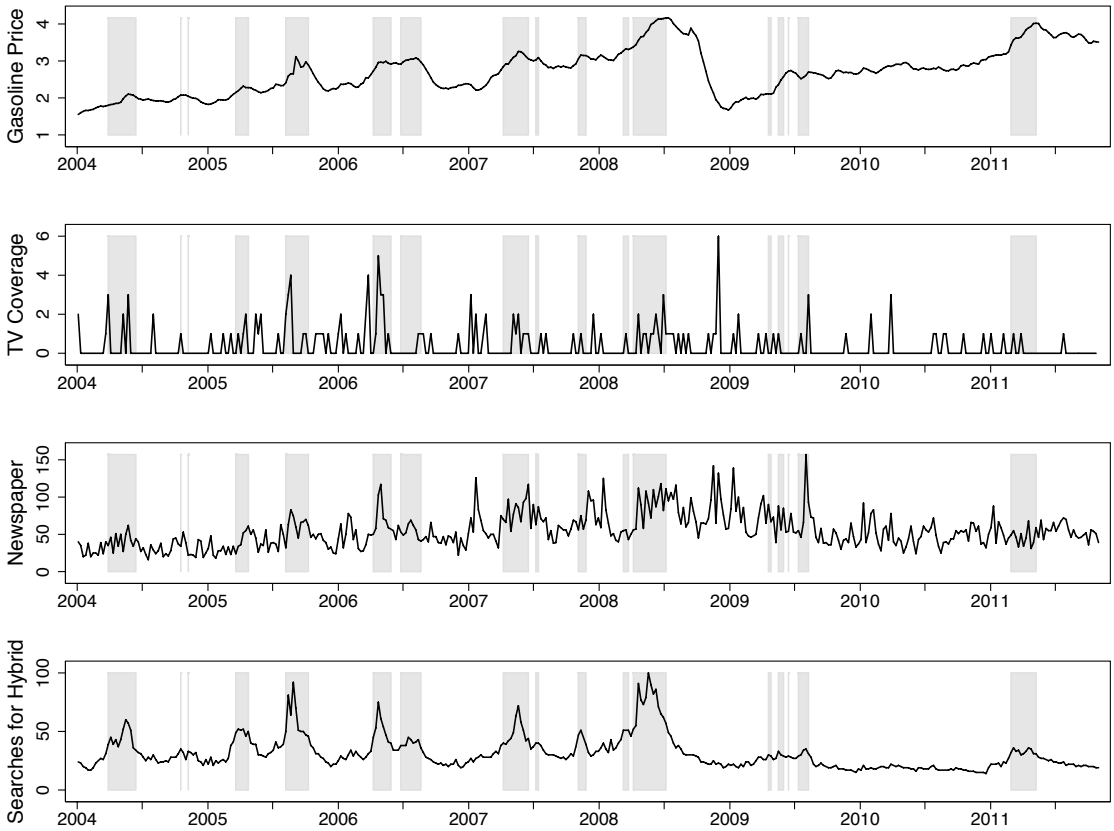
Fuel Economy Technology and Attention

	Dependent Variable: Google Search Queries for Mileage				
	(1)	(2)	(3)	(4)	(5)
Local Newspaper Gasoline	0.424 ***	-0.013	-0.006	-0.046	-0.013
	(0.095)	(0.081)	(0.08)	(0.029)	(0.039)
TV Gasoline	0.539 ***	0.252 ***		0.222 ***	0.252 **
	(0.051)	(0.058)		(0.076)	(0.103)
TV Hybrid	-0.094	-0.026		-0.059	-0.026
	(0.099)	(0.106)		(0.227)	(0.371)
Record Price Length	0.503 ***	0.378 ***	0.105	0.448 ***	0.378 *
	(0.092)	(0.081)	(0.14)	(0.086)	(0.207)
$\Delta \text{Gas Price}^{Pos}_{t,t-1}$	34.572 ***	9.961	10.317	9.272	9.961
	(8.322)	(7.788)	(9.551)	(9.906)	(19.059)
$\Delta \text{Gas Price}^{Neg}_{t,t-1}$	45.488 ***	75.996 ***	12.522	32.673 **	75.996 ***
	(8.451)	(10.276)	(12.849)	(14.571)	(23.765)
$\Delta \text{Gas Price}^{Pos}_{t-2,t-6}$	28.923 ***	18.629 ***	28.173 ***	19 ***	18.629 **
	(3.082)	(3.082)	(7.293)	(6.397)	(7.559)
$\Delta \text{Gas Price}^{Neg}_{t-2,t-6}$	40.106 ***	37.693 ***	22.808 ***	33.064 ***	37.693 ***
	(2.441)	(2.263)	(5.735)	(6.064)	(6.759)
$\Delta \text{Gas Price}^{Pos}_{t-7,t-18}$	17.215 ***	7.103 ***	13.207 ***	6.443	7.103
	(1.655)	(1.449)	(3.136)	(4.517)	(8.246)
$\Delta \text{Gas Price}^{Neg}_{t-7,t-18}$	12.765 ***	13.248 ***	16.82 **	14.137 ***	13.248 ***
	(0.703)	(0.696)	(7.679)	(3.261)	(1.931)
Newspaper USA Today	0.489 ***	0.259 ***		0.211 ***	0.259 *
	(0.033)	(0.031)		(0.08)	(0.14)
Newspaper NYT	0.387 ***	-0.169 ***		-0.036	-0.169
	(0.04)	(0.033)		(0.056)	(0.109)
Intercept	17.479 ***	17.636 ***	22.218 ***	18.709 ***	17.636 ***
	(1.063)	(1.034)	(2.104)	(1.21)	(1.259)
R^2	0.613	0.673	0.823	0.52	0.673
N	6956	6870	6973	6870	6870
Newspaper Spillover Controls	NO	YES	NO	YES	YES
Metro-Fixed Effects	YES	YES	YES	NO	YES
Time-Fixed Effects	NO	NO	YES	NO	NO
Year-Fixed Effects	YES	YES	NO	YES	YES

Standard errors are clustered by metropolitan area in models (1), (2) and (3). Model (4) is estimated using a Prais-Winsten regression with a panel-specific AR(1) structure and panel-corrected standard errors. Driscoll-Kraay standard errors are used in model (5).
*, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

Figure 4.1:

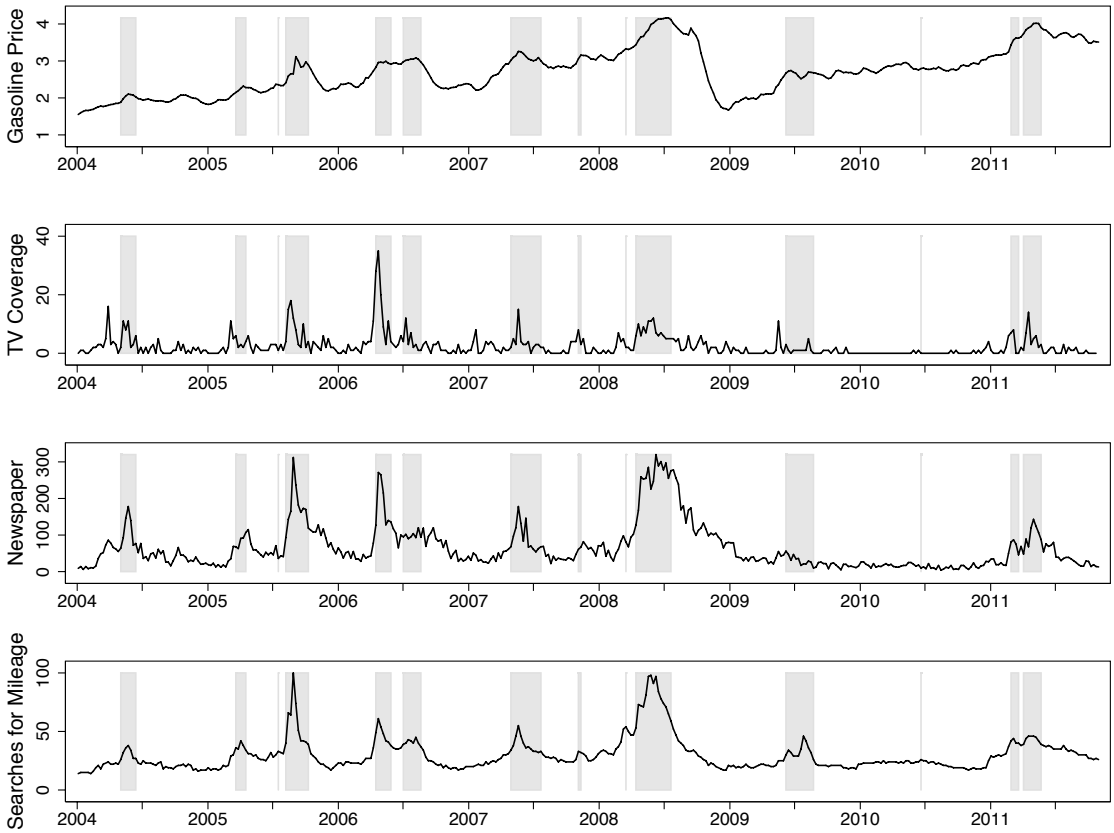
Gasoline Price, Media Coverage and Attention Devoted to Hybrid Vehicles



Notes: The first panel shows the weekly US retail gasoline price for all grades and formulations in US Dollars per gallon, the second panel shows the weekly sum of TV evening news segments about hybrid vehicles, the third panel shows the sum of newspaper articles about hybrid vehicles or fuel efficiency in all sample newspapers and the fourth panel shows the Google online search queries for "hybrid". The shaded area indicates weeks with a high attention to hybrid vehicles, which is defined as a Google search index that is above the overall median and in the highest tertile per year.

Figure 4.2:

Gasoline Price, Media Coverage and Attention Devoted to Fuel Economy



Notes: The first panel shows the weekly US retail gasoline price for all grades and formulations in US Dollars per gallon, the second panel shows the weekly sum of TV evening news segments about gasoline prices or fuel economy, the third panel shows the sum of newspaper articles about gasoline prices in all sample newspapers and the fourth panel shows the Google online search queries for "mileage". The shaded area indicates weeks with a high attention to fuel economy, which is defined as a Google search index that is above the overall median and in the highest tertile per year.

4.5 Attention and Hybrid Vehicle Purchases

In this section, we examine the validity of our attention measure by analyzing the relationship between monthly state-level hybrid vehicle registrations and online search queries. First, the relation between our key variables is graphically illustrated. Figure 4.3 shows the monthly US retail gasoline price for all grades and formulations (in US Dollars per gallon), the Google online search queries for "hybrid" as a measure of attention, the monthly number of hybrid vehicle registrations in the US (in thousands per month) and the market share of hybrid vehicles (in %). The shaded area indicates months with a high attention.

The graphical analysis shows that the changes in the gasoline price and the search volume are closely related to both the total number and the market share of hybrid vehicle registrations. Figure 4.3 also reveals the effect of one-time events that have a major influence on the hybrid vehicle market. For instance, the impact of the Cash Allowance Rebate System (C.A.R.S.), commonly known as "Cash for Clunkers", can be seen in the increase of sales and hybrid vehicle market shares during July and August 2009. The drop in sales after March 2011 is partially due to supply chain problems resulting from the disastrous earthquake and tsunami in Japan.[49]

In the next step, we use monthly state-level registration data to examine the actual hybrid vehicle purchasing behavior. Table 4.5 shows the results of the regression analysis for the hybrid vehicle registrations as the dependent variable. Similarly, the results in Table 4.6 represent the same model specifications, but use the market share of hybrid vehicles as the dependent variable. The Google variable measures the monthly state-level search queries for "hybrid" and is supposed to mirror the consumers' attention related to hybrid vehicles. As both the dependent variables and the Google variables are transformed into logarithms, the regression parameters can be interpreted as elasticities. The variable "Record Price" is built as a dummy indicating months with an unprecedented high gasoline price.

[49] These one-time events do not affect our analysis as the time-fixed effects account for such occurrences.

In specification (1), we use state-fixed effects, year-fixed effects and control for national media coverage, gasoline price movements and record price levels. Specifications (4) and (5) include the same variables, but are estimated with a Prais-Winsten type panel estimator and Driscoll-Kraay standard errors, respectively. Specifications (2) and (3) include state- and time-fixed effects, and Specification (3) uses an alternative gasoline price variable, i.e. the logarithm of the gasoline price instead of price changes.

Focusing first on Table 4.5, we show that Google searches for "hybrid" have a significantly positive effect on hybrid vehicle registrations for all specifications. Our estimates indicate that an increase of the search volume by 1% is associated with an increase of hybrid vehicle purchases in the range between 0.12% and 0.22%. Thus, it can be concluded that our attention measure is valid and robustly related to sales volumes.

The results of the regressions with the market share of hybrid vehicles as the dependent variable are shown in Table 4.6. The evidence for the relationship to our attention measure is positive, but not as strong as for the number of registrations. Given the definition of our Google variable, which reflects the number of search queries related to a topic, a less distinct relationship between searches and market shares is plausible. If the search queries for hybrid vehicles were expressed as a share of all search queries in the automotive category, we would expect a more distinct relationship with market shares rather than sales volumes.

The television news coverage on gasoline prices and fuel economy has a significantly positive effect on the number of hybrid vehicle registrations. However, the television news coverage on hybrid vehicles is not significant, which may be caused by the fact that the overall amount of news coverage is very low. In the regression with the market share of hybrid vehicles as the dependent variable, the results for television coverage are similar.

The results for the gasoline price variables are in line with economic intuition. Since the profitability of hybrid cars depends on the gasoline price, a positive association between

these two variables is assumed. We find that rising gasoline prices have a positive impact on hybrid registrations and market shares. In model (3), which includes the logarithm of the gasoline price as well as state- and time-fixed effects, the record price variable has a significant coefficient while the logarithm of the gasoline price is insignificant.

Overall, the most credible specifications for both dependent variables indicate a positive relationship between our attention measure and hybrid vehicle registrations. Our results show that the variables used in the main part of our study, section 4, are relevant for the hybrid vehicle market and thus valid proxies for the empirical analysis pursued.

Table 4.5

Hybrid Vehicle Registrations and Attention

	Dependent Variable: Log of # of Hybrid Registrations				
	(1)	(2)	(3)	(4)	(5)
ln(Google Hybrid)	0.222 ***	0.123 ***	0.121 ***	0.199 ***	0.222 ***
	(0.033)	(0.036)	(0.038)	(0.06)	(0.054)
TV Gasoline	0.008 ***			0.008 **	0.008 **
	(0.001)			(0.003)	(0.004)
TV Hybrid	0.005			0.01	0.005
	(0.004)			(0.011)	(0.015)
Record Price	0.001	0.027	0.036 **	0.056 *	0.001
	(0.017)	(0.017)	(0.018)	(0.029)	(0.031)
$\Delta \text{Gas Price}^{Pos}_{t,t-1}$	0.907 ***	0.663 ***		0.637 **	0.907 ***
	(0.141)	(0.195)		(0.309)	(0.309)
$\Delta \text{Gas Price}^{Neg}_{t,t-1}$	0.397 ***	-0.211		0.392	0.397
	(0.09)	(0.329)		(0.263)	(0.257)
$\Delta \text{Gas Price}^{Pos}_{t-2,t-3}$	1.67 ***	0.415 *		1.259 ***	1.67 ***
	(0.112)	(0.224)		(0.299)	(0.401)
$\Delta \text{Gas Price}^{Neg}_{t-2,t-3}$	0.699 ***	-0.228		0.366	0.699 ***
	(0.069)	(0.204)		(0.259)	(0.204)
$\Delta \text{Gas Price}^{Pos}_{t-4,t-6}$	0.334 ***	-0.075		0.301	0.334
	(0.067)	(0.157)		(0.233)	(0.252)
$\Delta \text{Gas Price}^{Neg}_{t-4,t-6}$	0.183 ***	0.211 *		-0.065	0.183
	(0.034)	(0.104)		(0.158)	(0.137)
USA Today Hybrid	-0.001			-0.004	-0.001
	(0.001)			(0.003)	(0.003)
NYT Hybrid	-0.002 ***			0	-0.002
	(0.000)			(0.002)	(0.002)
USA Today Gas	0.004 **			-0.001	0.004
	(0.002)			(0.004)	(0.005)
NYT Gas	-0.006 ***			-0.003 *	-0.006 **
	(0.001)			(0.002)	(0.002)
ln(Gas Price)			0.061		
			(0.172)		
Intercept	5.215 ***	4.585 ***	4.612 ***	5.478 ***	5.215 ***
	(0.111)	(0.099)	(0.119)	(0.232)	(0.167)
R^2	0.502	0.967	0.967	0.965	0.502
N	2117	2117	2117	2117	2117
State-Fixed Effects	YES	YES	YES	NO	YES
Time-Fixed Effects	NO	YES	YES	NO	NO
Year-Fixed Effects	YES	NO	NO	YES	YES

Standard errors are clustered by state in models (1), (2) and (3). Model (4) is estimated using a Prais-Winsten regression with a panel-specific AR(1) structure and panel-corrected standard errors. Driscoll-Kraay standard errors are used in model (5).
*, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

Table 4.6

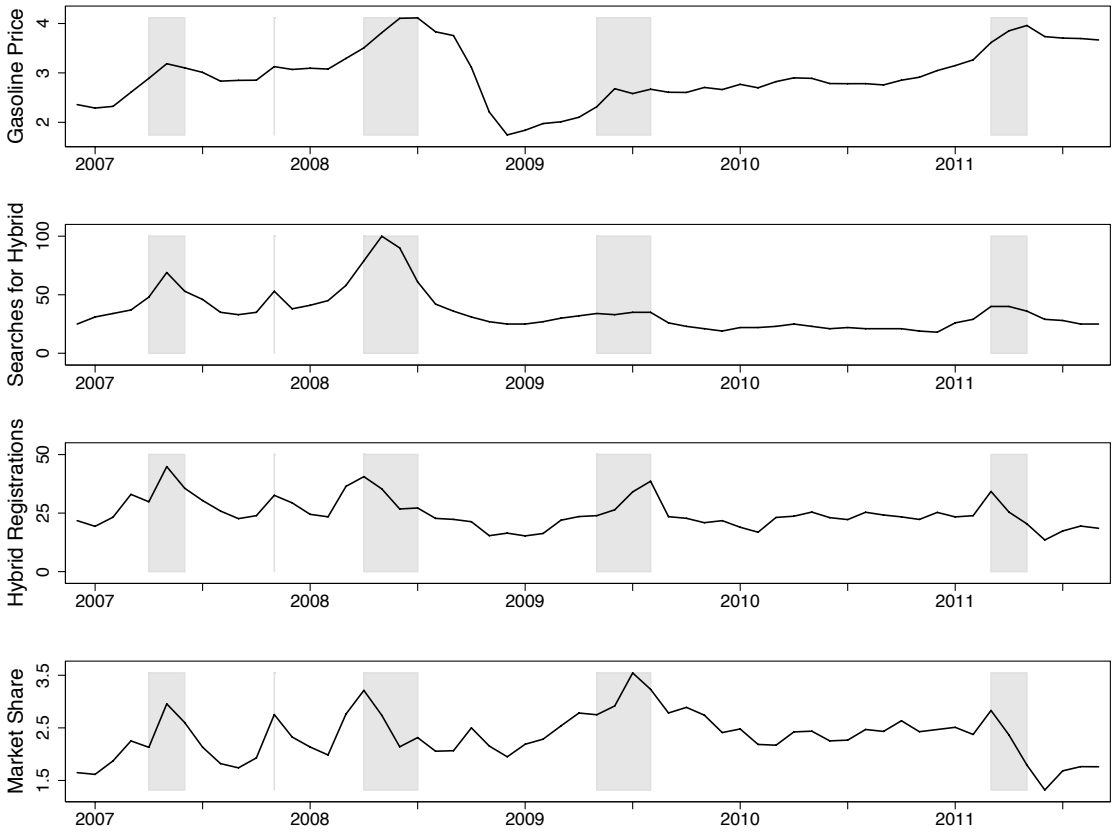
Hybrid Technology's Market Share and Attention

	Dependent Variable: Log of Hybrid Technology's Market Share				
	(1)	(2)	(3)	(4)	(5)
ln(Google Hybrid)	0.094 ***	0.076 *	0.069 *	0.216 ***	0.094 *
	(0.028)	(0.039)	(0.038)	(0.057)	(0.052)
TV Gasoline	0.007 ***			0.005 *	0.007 *
	(0.001)			(0.003)	(0.004)
TV Hybrid	-0.004			0.006	-0.004
	(0.004)			(0.011)	(0.013)
Record Price	0.025 *	0.029 **	0.039 ***	0.019	0.025
	(0.014)	(0.012)	(0.012)	(0.028)	(0.025)
$\Delta \text{Gas Price}^{Pos}_{t,t-1}$	0.735 ***	0.962 ***		0.582 *	0.735 ***
	(0.121)	(0.175)		(0.297)	(0.248)
$\Delta \text{Gas Price}^{Neg}_{t,t-1}$	-0.391 ***	-0.349		-0.413 *	-0.391 *
	(0.09)	(0.373)		(0.236)	(0.224)
$\Delta \text{Gas Price}^{Pos}_{t-2,t-3}$	0.743 ***	0.358 *		0.537 *	0.743 **
	(0.123)	(0.205)		(0.289)	(0.356)
$\Delta \text{Gas Price}^{Neg}_{t-2,t-3}$	0.414 ***	-0.286		0.073	0.414 **
	(0.08)	(0.285)		(0.23)	(0.186)
$\Delta \text{Gas Price}^{Pos}_{t-4,t-6}$	0.226 ***	0.05		0.331	0.226
	(0.062)	(0.146)		(0.216)	(0.292)
$\Delta \text{Gas Price}^{Neg}_{t-4,t-6}$	0.021	-0.112		-0.172	0.021
	(0.034)	(0.136)		(0.139)	(0.096)
USA Today Hybrid	0.000			-0.001	0.000
	(0.001)			(0.003)	(0.003)
NYT Hybrid	-0.000			-0.001	-0.000
	(0.000)			(0.002)	(0.001)
USA Today Gas	0.007 ***			0.004	0.007 *
	(0.001)			(0.004)	(0.004)
NYT Gas	-0.006 ***			-0.004 **	-0.006 ***
	(0.000)			(0.002)	(0.002)
ln(Gas Price)			0.18		
			(0.168)		
Intercept	0.186 *	-0.46 ***	-0.466 ***	-0.061	0.186
	(0.098)	(0.118)	(0.12)	(0.217)	(0.15)
R^2	0.372	0.882	0.88	0.509	0.372
N	2117	2117	2117	2117	2117
State-Fixed Effects	YES	YES	YES	NO	YES
Time-Fixed Effects	NO	YES	YES	NO	NO
Year-Fixed Effects	YES	NO	NO	YES	YES

Standard errors are clustered by state in models (1), (2) and (3). Model (4) is estimated using a Prais-Winsten regression with a panel-specific AR(1) structure and panel-corrected standard errors. Driscoll-Kraay standard errors are used in model (5).
*, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

Figure 4.3:

Gasoline Price, Attention and Registrations of Hybrid Vehicles



Notes: The first panel shows the monthly US retail gasoline price for all grades and formulations in US Dollars per gallon, the second panel shows the Google online search queries for "hybrid", the third panel shows the monthly number of hybrid vehicle registrations in the US (in thousands per month) and the fourth panel shows the market share of hybrid vehicles (in %). The shaded area indicates months with a high attention, which is defined as a Google search index that is above the overall median and in the highest tertile per year.

4.6 Conclusion

The study extends the research on consumer attention effects to the area of energy efficiency. Specifically, the analysis indicates which factors alter the consumers' attention devoted to fuel-efficient technologies like hybrid vehicles. We use a novel panel dataset to show that the revealed consumer attention to hybrid vehicles depends on the gasoline price, unprecedented record gasoline price levels and media coverage. In our empirical setup, attention is measured by Google online search behavior. As search queries reflect real-life actions of millions of United States citizens, this data most importantly does not suffer from possible survey biases. The accuracy of our attention measure is validated by the robust relationship to the actual purchasing behavior. Given that we analyze a market for high-cost durable goods, a setting in which consumers should exhibit a high effort in decision making, the empirical findings from this study are also of relevance to economic decisions in other markets.

The finding that attention effects influence the diffusion of innovative and energy efficient technologies leads to important policy implications. In order to limit greenhouse gas emissions and to reduce the dependency on oil imports, fuel-efficient technologies must become a "top of mind" topic in any vehicle purchasing decision. Initiatives aiming at increasing awareness and education about such technologies may be an important tool to foster the adoption of hybrid vehicles. A more general finding is that periods of rising gasoline prices are more effective at drawing temporary attention to fuel efficiency than periods of steadily high gasoline prices. In fact, volatile gasoline prices provoke strong reactions of both the media and consumers. Therefore, it can be inferred that volatile gasoline prices, as they occurred in the years 2005 to 2008, have a positive impact on the diffusion of green technologies.

Given that consumers' attention levels have a fluctuating nature, car manufacturers should consider the current level of the attention devoted to efficient vehicles when planning their

marketing effort and campaign contents. During periods of steep gasoline price increases or record gasoline prices, consumers have a much higher interest and are more receptive to information about fuel-efficient technologies.

Despite the fact that our study focuses on one specific market, the results have wide implications. We argue that firms should generally be aware of how and why their customers' attention fluctuates. Future research could highlight the interaction of marketing and attention as it is defined in our framework. Interesting questions include how marketing efforts are able to influence attention or how the efficiency of marketing campaigns depends on the current attention level.

5 Conclusion

This thesis makes several contributions to prior literature. The second chapter contributes to the recently developing accounting literature which examines how managerial characteristics affect corporate policies. Prior studies in behavioral accounting show that managerial overconfidence affects management forecasts (Hilary and Hsu 2011; Hribar and Yang 2013; Libby and Rennekamp 2012), accounting conservatism (Ahmed and Duellman 2013), and financial misreporting (Schrand and Zechman 2012). We contribute to this literature by documenting how managerial overconfidence affects cost behavior. Prior literature in behavioral finance shows that managerial overconfidence affects capital expenditures (Malmendier and Tate 2005) or merger and acquisitions (Malmendier and Tate 2008). Given that mergers and acquisitions, for example, are relatively rare events, we argue that it is important to examine the association between managerial overconfidence and cost behavior because cost decisions are made more frequently and are key to firm profitability (Porter 1985).

In addition, this study further contributes to the cost stickiness literature. While prior studies have examined how economic considerations and agency problems affect cost stickiness, we document the influence of managerial overconfidence on cost stickiness. Our explanation differs from both existing views on cost stickiness. The economic view implies that managers' demand expectations are unbiased (Anderson et al. 2003; Balakrishnan and Gruca 2008; Balakrishnan, Petersen, and Soderstrom 2004), whereas we allow overconfidence to affect demand expectations. In addition, we differ from prior studies examining the role of agency conflicts on cost stickiness. In contrast to the agency view, which implies that cost stickiness results from empire building (Chen et al. 2012) or earnings management incentives (Dierynck et al. 2012; Kama and Weiss 2013) of self-interested managers, we argue that overconfident managers intend to maximize firm value but are

affected by behavioral biases. Collectively, our study provides strong support for the role of managerial discretion in resource adjustment.

This study further entails practical implications. Our finding that managerial overconfidence affects cost behavior should be of interest for board of directors. While it is well known that agency costs, such as empire building, can be addressed per incentive pay (Murphy 1999), behavioral costs, such as managerial overconfidence (Shefrin 2001), cannot be addressed with incentive pay because overconfident CEOs believe they are maximizing firm value. This insight should be especially of importance if cost behavior lies at the heart of a firm's competitive advantage.

The third chapter of this thesis contributes to our understanding of real consequences arising from investor sentiment. Prior literature shows that investor sentiment affects earnings forecasts (Bergman and Roychowdhury 2008), earnings management (Ali and Gurun 2009; Simpson 2013), pro-forma earnings disclosure (Brown et al. 2012), dividend policies (Baker and Wurgler 2004; Li and Lie 2006) and decisions on capital expenditure (Polk and Sapienza 2009). We extend the findings in these studies by documenting that catering extends to decisions on research and development expenditure, advertisement and selling, general and administrative costs. Further, we complement the findings in McLean and Zhao (2014) who show that investor sentiment affects employment decisions. While McLean and Zhao (2014) argue that investor sentiment affects corporate policies because it lowers the cost of external finance, we show that catering incentives affect employment decisions.

This essay further contributes to prior literature examining how managerial discretion affects cost behavior. Chen et al. (2012) show that empire-building incentives motivate managers to refrain from cutting costs when sales decline. Banker et al. (2011) document that managers increase spending on SG&A resources upon receiving equity incentives. We contribute to this literature by documenting that catering incentives induce managers to

increase spending on various components of operating expenditure.

Finally, our results contribute to prior literature examining how incentives to meet earnings targets affect cost behavior. Prior literature shows that managers cut discretionary expenditure in order to meet last year's earnings, to avoid reporting losses, or to meet analysts' earnings forecasts (Baber et al. 1991; Burgstahler and Dichev 1997; Roychowdhury 2006). Other studies show that managers keep less costs when sales decline upon facing earnings targets (Dierynck et al. 2012; Kama and Weiss 2013). We contribute to this literature by documenting that managers refrain from overspending on operating expenditure when it conflicts with meeting investors' earnings expectations in periods of high relative to periods of average sentiment. Our findings, thus, confirm the notion that managerial discretion affects cost behavior from a behavioral setting.

Our results should be of interest for board of directors because managers who address noise traders' misperceptions act in the interest of short-term shareholders only. The fact that SG&A costs make up about one third of total assets reinforces this argument.[50]

The fourth chapter of this thesis contributes to our understanding of limited attention. While prior literature in behavioral accounting and finance recognizes the importance of limited attention, there is only scarce evidence in the field of behavioral energy economics. More specifically, prior accounting research suggests that limited attention may be one reason explaining why investors primarily fixate on earnings and do not consider separately the components of earnings – cash flows and accruals (Hirshleifer and Teoh 2003; Ali and Gurun 2009). Similarly, research in finance documents the influence of limited attention on individual investors' trading behavior (Barber and Odean 2008; Da et al. 2011). Turning to consumer behavior, Chetty et al. (2009) show that the salience of taxes affects consumer' attention and, hence, their reaction to taxation. We contribute to this literature by examining

[50] In Banker et al. (2011), the average ratio of SG&A costs to total assets is about 31%, suggesting that data used in our sample is comparable to that used in other studies.

factors that are able to alter consumers' attention devoted to a long-lived consumer good. These findings should be of interest for policy makers. Our results suggest that informational campaigns may be one method to inform consumers about fuel-efficient technologies such as hybrid vehicles. Similarly, our results should be of interest for car manufactures. Examining when and why consumers' attention fluctuates may allow improving efficiency of marketing campaigns.

6 Appendix

Table A.1

LexisNexis Database Search Queries for all Newspapers

Panel A. LexisNexis search command related to hybrid vehicles and fuel efficiency
fuel efficiency
OR (fuel W/2 standard)
OR (efficient W/10 mileage)
OR (ALLCAPS (CAFE) W/10 (standard OR fuel OR efficient OR regulation))
OR (gas W/2 guzzler)
OR (electric W/2 (car OR vehicle))
OR ((plug W/2 in) W/2 (car OR vehicle))
OR (hybrid W/2 (car OR vehicle))
OR toyota prius
OR ((toyota OR Honda OR Hyundai Or Lexus OR Ford) W/2 Hybrid)

Notes: The search query should take into account both the completeness and the relevancy of the found articles. It reflects news coverage concerning fuel efficiency, electric vehicle technology, hybrid vehicles and related regulation standards. The command W/2 indicates that two words are in the text within 2 words distance. The command ALLCAPS requires a word to be written in capital letters.

Panel B. LexisNexis search command related to gasoline prices
(gas! OR pump)
W/4 (cost OR price)
W/6 (record OR high OR soar! OR ris! OR surg!
OR climb! OR jump! OR spik! OR peak OR expensive
OR sink! OR low! OR drop! OR plung! OR down! OR fall!
OR fell OR declin! OR cheap! OR tumbl! OR crash!)
NOT W/seg (jet OR airline OR kerosine OR kerosene OR shale OR natural)

Notes: The search query should take into account both the completeness and the relevancy of the found articles. It reflects news coverage concerning gasoline price movements and levels without focusing on either rising or sinking prices. The syntax as follows: ! is used as a wild card, e.g. surg! includes surging. The command W/4 indicates that two words are in the text within 4 words distance. NOTW/seg does not allow the following word to be in the same segment within one article.

Table A.2

Summary Statistics

Panel Dataset for Section 4					
	Mean	Std. Dev.	Min.	Max.	N
Google Hybrid	30.404	14.922	7	100	7227
Google Mileage	28.747	13.701	8	100	6984
Local Newspaper Hybrid	2.294	2.872	0	56	7771
Local Newspaper Gasoline	2.908	3.846	0	37	7760
TV Hybrid	0.373	0.797	0	6	7752
TV Gasoline	2.387	3.717	0	35	7752
Newspaper USA Today Hybrid	2.824	1.963	0	9	7771
Newspaper NYT Hybrid	8.335	4.755	0	27	7771
Newspaper USA Today Gasoline	3.308	3.468	0	20	7771
Newspaper NYT Gasoline	6.672	6.386	0	40	7771
Record Price Length	0.998	3.007	0	25	7771
$\Delta \text{Gas Price}^{\text{Pos}}_{\text{t,t-1}}$	0.01	0.017	0	0.228	7771
$\Delta \text{Gas Price}^{\text{Neg}}_{\text{t,t-1}}$	-0.009	0.016	-0.134	0	7771
$\Delta \text{Gas Price}^{\text{Pos}}_{\text{t-2,t-6}}$	0.033	0.043	0	0.315	7771
$\Delta \text{Gas Price}^{\text{Neg}}_{\text{t-2,t-6}}$	-0.025	0.055	-0.438	0	7771
$\Delta \text{Gas Price}^{\text{Pos}}_{\text{t-7,t-18}}$	0.068	0.08	0	0.403	7771
$\Delta \text{Gas Price}^{\text{Neg}}_{\text{t-7,t-18}}$	-0.046	0.116	-0.841	0	7771

Notes: The dataset consists of weekly observations for the 19 metropolitan areas listed in Table 4.2 and ranges from January 4th, 2004 to October 23rd, 2011.

Table A.2 – *continued*

Panel Dataset for Section 5					
	Mean	Std. Dev.	Min.	Max.	N
ln(Market Share Hybrid Registrations)	0.726	0.492	-1.565	2.249	2117
ln(Hybrid Registrations)	5.825	0.995	3.401	9.218	2117
ln(Google Hybrid)	3.227	0.416	2.015	4.508	2117
TV Hybrid	1.529	1.636	0	7	2117
TV Gasoline	7.787	8.98	0	38	2117
USA Today Hybrid	13.92	5.093	5	31	2117
NYT Hybrid	37.041	10.112	19	66	2117
USA Today Gasoline	12.846	13.228	1	56	2117
NYT Gasoline	26.372	27.068	1	112	2117
Record Price	0.258	0.438	0	1	2117
$\Delta \text{Gas Price}^{\text{Pos}}_{t,t-1}$	0.039	0.048	0	0.253	2117
$\Delta \text{Gas Price}^{\text{Neg}}_{t,t-1}$	-0.03	0.079	-0.539	0	2117
$\Delta \text{Gas Price}^{\text{Pos}}_{t-2,t-3}$	0.038	0.049	0	0.253	2117
$\Delta \text{Gas Price}^{\text{Neg}}_{t-2,t-3}$	-0.033	0.081	-0.539	0	2117
$\Delta \text{Gas Price}^{\text{Pos}}_{t-4,t-6}$	0.06	0.081	0	0.382	2117
$\Delta \text{Gas Price}^{\text{Neg}}_{t-4,t-6}$	-0.063	0.151	-0.975	0	2117
ln(Gas Price)	0.829	0.23	0.036	1.375	2117

Notes: The dataset consists of monthly state-level observations from February 2011.

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