

ARTICLE

# Smells like animal spirits: the sensitivity of corporate investment to sentiment

Gianni La Cava\*

e61 Institute and Macquarie University, North Ryde, NSW, Australia  
Email: [gianni.lacava@e61.in](mailto:gianni.lacava@e61.in)

## Abstract

Economists have long been interested in the effect of business sentiment on economic activity. Using text analysis, I construct a new company-level indicator of sentiment based on the net balance of positive and negative words in Australian company disclosures. Company-level investment is very sensitive to changes in this corporate sentiment indicator, even controlling for fundamentals, such as Tobin's Q, as well as controlling for measures of company-level uncertainty.

The high sensitivity of investment to sentiment could be due to several mechanisms. It could be because of animal spirits among managers or because of sentiment proxies for private information held by managers about company prospects. Overall, I find mixed evidence of the underlying causal mechanism. The effect of sentiment on investment is relatively persistent, which is consistent with managers having private information about company fundamentals. But the sensitivity of investment to sentiment is not any stronger at opaque companies in which managers are likely to be better informed than investors. Further, investment is sensitive to sentiment even when investors have an information advantage over managers by lagging the sentiment indicator by a year. Overall, the sensitivity of investment to sentiment appears to reflect both animal spirits and fundamentals.

Corporate investment has been weak since the global financial crisis (GFC) and demand-side factors, such as lower sales growth, explain more than half of this weakness. Low sentiment and heightened uncertainty weighed on investment during the GFC but have been less important factors since then.

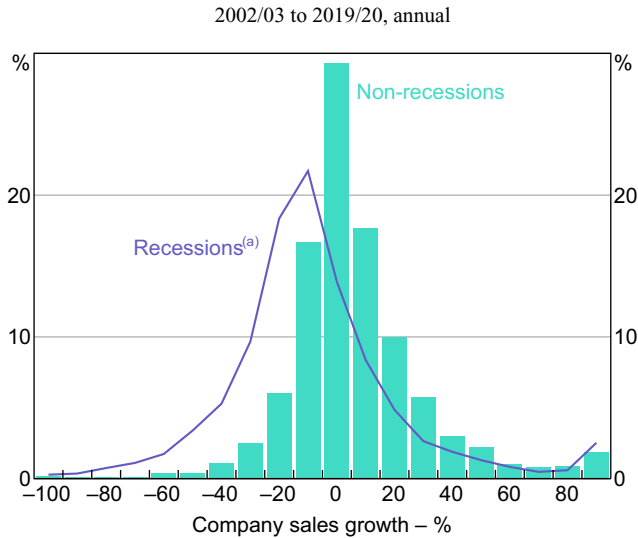
**Keywords:** Investment; sentiment; text analysis; animal spirits; business cycle

## 1. Corporate sentiment, animal spirits, and investment

Economists have long been interested in the role of sentiment in the business cycle. Since Keynes (1936) originally coined the term “animal spirits,” there have been many books written on the subject, and an extensive literature in economics, finance, and psychology has grown to study how changes in sentiment among decision-makers affect their behavior and, in turn, the overall economy.

Identifying a role for sentiment in the business cycle is challenging because it is hard to define. Economists have long recognized the importance of expectations for aggregate economic behavior, but they disagree on why expectations matter and how expectations are formed. These disagreements make it difficult to define sentiment. For example, Keynes (1936) argued that changes in expectations were not caused by rational probabilistic calculations but by animal spirits, and Pigou (1927) similarly believed that business cycles were driven by expectation errors of optimism and pessimism.<sup>1</sup> Expectations are important in modern general equilibrium models, but

\*The author wrote parts of this paper while employed by the Reserve Bank of Australia. The views expressed in this paper are those of the author and do not necessarily reflect the views of the Reserve Bank of Australia. The author is responsible for any errors.



**Figure 1.** Distribution of company-level sales growth.

Note: (a) Data are based on the three financial years of 2008/09, 2009/10, and 2019/20.

Sources: Author's calculations; Morningstar.

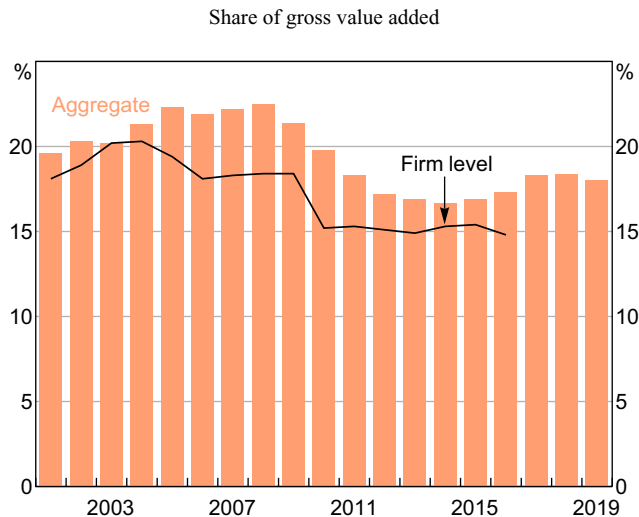
they are typically modeled according to the rational expectations hypothesis. Some rational expectation models allow for animal spirits by assuming equilibrium indeterminacy—expectation errors are a function of structural disturbances and exogenous “sunspot” variables [Benhabib and Farmer (1999)]. Similarly, in this paper, I define changes in sentiment as shifts in expectations that are exogenous to changes in economic fundamentals [Milani (2017)].

Identifying a role for sentiment is also challenging because it is not observed. Traditionally, economists have relied on surveys of consumers and businesses to measure sentiment. These surveys ask respondents about their beliefs for current and future economic conditions. But advances in machine learning and big data have allowed sentiment to be measured not just through surveys, but through alternative sources of information, such as text, audio, and visual data [Algaba et al. (2020)]. These techniques present new opportunities to measure sentiment and therefore answer long-standing questions about the role of sentiment in the business cycle.

In practice, it is also difficult to disentangle the effects of sentiment and uncertainty. If business managers have varying expectations about future growth outcomes, sentiment can be thought of as the average outcome (the first moment of the distribution) while uncertainty can be thought of as the variance of possible outcomes (the second moment).<sup>2</sup> A negative sentiment shock would cause firms to expect average growth to fall. A negative uncertainty shock would lead firms to believe that a broader range of growth outcomes is possible. For example, recessions are typically associated with both a decline in average sales growth and a higher variance (Figure 1).

Motivated by these insights, I construct a new indicator of company-level sentiment using text analysis and examine its link to the business cycle by identifying the sensitivity of company-level investment to changes in company-level sentiment. The measure of sentiment is very simple and is constructed as the net balance of positive and negative words used in the annual reports of publicly listed companies in Australia. A company that uses more positive words (or fewer negative words) in its report compared to the previous report is higher in sentiment and therefore more likely to invest, all other things being equal.

This paper aims to extend insights from text-based analysis of sentiment in behavioral finance to the domain of macroeconomics. Text analysis is relatively new in macroeconomics but is much



**Figure 2.** Non-mining business investment in Australia.

Note: The aggregate series is measured as the ratio of private business investment to total value added for non-mining industries in the national accounts, and the firm-level series is an unweighted mean of the capital spending to value-added ratio at the firm level.

Sources: ABS; Author's calculations.

more common in corporate finance [Kearney and Liu (2014)]. In standard corporate finance models, there is no role for sentiment in explaining corporate behavior. But the behavioral finance literature has consistently found that text-based measures of sentiment for investors [Zhou (2018)] and managers [Jiang et al. (2019)] have strong ability to predict equity returns. I explore whether such measures also have predictive ability for corporate investment—a key variable of interest to macroeconomists.

The focus on business investment is motivated by the observation that much of the variation in the business cycle is due to fluctuations in investment. If there is a role for sentiment in explaining economic activity, it is likely to be found in its link to business investment. The importance of business expectations in models of investment under uncertainty is well recognized [e.g. Hayashi (1982), Abel and Blanchard (1986), Chirinko (1993), Dixit and Pindyck (1994)]. But open questions remain, such as why expectations matter to investment, and whether there is a role for feelings or opinions (and hence sentiment) in influencing such decision-making. This paper explicitly examines such roles for sentiment and uncertainty.

An added motivation of this paper is to explore whether sentiment and uncertainty have some role to play in explaining the broad-based weakness in business investment observed since the global financial crisis (GFC). It is common to hear financial market participants, business managers, and the media argue that this weakness in investment is at least partly due to “a lack of confidence” or “heightened uncertainty.” The weakness in investment is apparent in both Australia and the United States. It is also apparent for both aggregate investment (in the national accounts) and for the investment of the average small business (in firm-level data) (Figure 2).<sup>3</sup> The fact that it is so prevalent points to common causes across countries and industries. Even so, there remains a long list of potential explanations for the weakness in investment [Gutiérrez and Philippon (2017)].

This paper fits into a growing literature that examines the role of both news (fundamentals) and sentiment (non-fundamentals) in driving the business cycle. This literature is divided on the role of sentiment in explaining changes in macroeconomic conditions [Nowzohour and Stracca (2020)]. There is the “fundamental” view that believes that measures of sentiment capture news

about the economy [e.g. Roberts and Simon (2001), Barsky and Sims (2012), Blanchard et al. (2013), Beaudry and Portier (2014)]. Under this view, agents receive an imperfect signal about future economic fundamentals, such as productivity, and the economy is subject to recurrent booms (if the signal is correct) and occasional busts (if the signal is false). There is also the “animal spirits” view that measures of sentiment capture non-fundamental factors [e.g. Chauvet and Guo (2003), Akerlof and Shiller (2009), Farmer (2012), Benhabib et al. (2015)]. This line of research argues that psychological waves of optimism and pessimism cause macroeconomic fluctuations, implying that expansions eventually lead to busts as fundamentals are unaffected.

This paper is also related to a vast body of empirical research that studies the effects of uncertainty on the economy [e.g. Bloom (2009)]. Most of the existing literature focuses on identifying the effect of either sentiment or uncertainty, and it is surprisingly rare to see them considered side by side. A key contribution of this paper is to develop an empirical framework in which to measure both sentiment and uncertainty on a consistent basis using text analysis. This allows me to test for differential effects of sentiment and uncertainty on investment, which may be important to understanding the drivers of the business cycle.

I motivate my empirical approach to identifying the effects of sentiment by considering a standard theoretical model of investment that is extended to allow for sentiment shocks. In this setup, corporate investment is a function of both current and expected future profits, where the relevant expectations are those of corporate managers, which can differ from market (or investor) expectations. Expected profit growth among corporate managers is based on their beliefs about fundamentals and non-fundamental “noise” or sentiment shocks.

I find strong evidence that changes in corporate sentiment are positively associated with investment. An increase in one standard deviation (SD) of the sentiment indicator is associated with the investment rate increasing from a sample mean of 10% to 16% , all other things being equal. Moreover, the relationship holds even when controlling for a broad range of proxies for corporate fundamentals, including the Tobin’s Q ratio, current and expected profitability and sales growth. This suggests that the relationship between sentiment and investment is at least partly capturing the effect of noise shocks, or animal spirits, among managers.<sup>4</sup>

The claim that the effect of sentiment on investment is due to animal spirits rests on the assumption that the sentiment indicator is a pure measure of animal spirits among company managers. But managers may know more about the company’s fundamentals than outside investors. If managers have private knowledge about the company’s prospects, the relationship between investment and sentiment may be due to fundamental factors, rather than animal spirits.

To test this, I examine whether investment is sensitive to changes in sentiment, even when investors potentially know more about the future of the company than the managers. In particular, I measure Tobin’s Q based on the share price at the end of the relevant financial year and I measure sentiment using financial reports from the prior financial year. In this case, investors should have incorporated any relevant information revealed about the company’s future prospects from the relevant corporate reports. But, even with this timing advantage, I find that investment is still more sensitive to lagged sentiment than it is to Tobin’s Q.

I also explore heterogeneity in the sensitivity of investment to sentiment across companies. If the sentiment indicator is mainly capturing private knowledge among managers, investment should be more sensitive to sentiment in companies that are more opaque to outside investors. This might include companies that are small or new or that have shares that are rarely traded. However, I find that the sentiment effect is not stronger for small, young, or rarely traded companies, which argues against the private knowledge interpretation.

To further explore the mechanism underpinning the sensitivity of investment to sentiment, I also explore the dynamics of investment in response to shocks to sentiment, uncertainty, and Tobin’s Q through a series of local projections (LP). This identification strategy assumes that sentiment will have a temporary effect on investment if it mainly reflects animal spirits, whereas it should have a more permanent effect if it reflects fundamentals [Barsky and Sims (2012)]. Here,

I find mixed evidence. A sentiment shock has a fairly persistent effect on investment, though the effect is more temporary than that of an equivalent shock to Tobin's Q. I also find that uncertainty shocks have a temporary negative effect on investment of a slightly smaller magnitude to that of a sentiment shock. Overall, I conclude that the sensitivity of investment to sentiment reflects both animal spirits and fundamentals.

The main contributions of this paper are to:

- develop new firm-level indicators of corporate sentiment and uncertainty within the same empirical framework using text analysis;
- demonstrate that firm-level investment is very sensitive to changes in sentiment, even controlling for corporate fundamentals;
- show that both corporate sentiment and uncertainty have independent roles to play in explaining business investment, suggesting that both first and second-moment shocks matter;
- show that the effect of sentiment is relatively persistent, albeit more temporary than that of a shock to Tobin's Q, which suggests that the sentiment measure is at least partly capturing animal spirits or noise shocks.

These findings are important from a policy perspective. If sentiment shocks can affect corporate behavior independently of fundamentals, this suggests that there may be a role for policy to manage business cycle fluctuations by influencing the expectations of corporate managers. So having a variety of policy communication channels that target business decision-makers could matter, including speeches, business liaison programs, and surveys dedicated to measuring the beliefs and uncertainties of respondents.

More generally, the ability of simple text-based indicators to consistently predict investment—a macro variable that is inherently difficult to forecast—is consistent with similar findings for equity returns in the corporate finance literature. Based on this, macro policymakers should consider investing more resources in machine learning techniques and extracting information from nontraditional sources of data, such as text, audio, and visual media.

## 2. The Tobin's Q model with sentiment shocks

I motivate my empirical approach to identifying the effect of sentiment on investment by outlining a simple extension to a basic Tobin's Q model. The outline closely follows the descriptions in Blundell et al. (1992) and Bond and Cummins (2001).

A representative company optimally chooses investment to maximize the present value of the stream of current and expected future profits. The firm's objective is to maximize:

$$V_t = E_t \sum_{s=0}^{\infty} \beta_{t+s} \Pi_{t+s},$$

where the expected valuation ( $V_t$ ) of the company is a function of profits in each period ( $\Pi_{t+s}$ ) and a discount factor ( $\beta_{t+s}$ ). Corporate profits are assumed to have the form:

$$\Pi_t = p_t Y(K_t, N_t) - w_t N_t - p_t^K [I_t + G(I_t, K_t)],$$

where profits in the current period equal the difference between revenue and costs. Revenue is a function of production, which in turn depends on both the capital stock ( $K_t$ ) and labor ( $N_t$ ). Costs consist of both labor and capital costs, including capital adjustment costs ( $G(I_t, K_t)$ ). The capital stock evolves according to the law of motion:

$$K_{t+s} = I_{t+s} + (1 - \delta) K_{t+s-1},$$

where the capital stock at the end of period  $t + s$  ( $K_{t+s}$ ) depends on investment during the period  $t + s$  ( $I_{t+s}$ ) as well as the capital stock outstanding from the end of the previous period  $t + s - 1$  ( $K_{t+s-1}$ ).

The firm chooses investment to maximize the company's expected valuation subject to the capital stock law of motion. The first order conditions (FOCs) for investment are:

$$\lambda_t = -\frac{\partial \Pi_t}{\partial I_t},$$

$$\lambda_t = E_t \left[ \sum_{s=0}^{\infty} \beta_{t+s} (1 - \delta)^s \left( \frac{\partial \Pi_{t+s}}{\partial K_{t+s}} \right) \right],$$

where the shadow value of an additional unit of capital is  $\lambda_t$ . Given price-taking behavior, the first of the FOCs can be written:

$$q_t - 1 = \frac{\partial G_t}{\partial I_t}.$$

Here, marginal  $q(q_t)$  is equal to the ratio of the shadow value of an additional unit of capital to its purchase cost ( $\lambda_t/p_t^K$ ). Under certain conditions (such as constant returns to scale and price taking), marginal  $q$  can be approximated by average  $q$ :

$$q_t = \frac{V_t}{p_t^K (1 - \delta) K_{t-1}}.$$

Adjustment costs are assumed to have a symmetric quadratic form:

$$G(I_t, K_t) = \frac{b}{2} \left[ \left( \frac{I_t}{K_t} \right) - c - e_t \right]^2 K_t,$$

where adjustment costs depend on the investment rate, a fixed cost component, and an idiosyncratic adjustment cost shock ( $e_t$ ). From this, the Tobin's Q model of investment can be derived:

$$\begin{aligned} \left( \frac{I_t}{K_t} \right) &= c + \frac{1}{b} \left( \frac{V_t}{p_t^K (1 - \delta) K_{t-1}} - 1 \right) + e_t \\ &= c + \frac{1}{b} (q_t - 1) + e_t. \end{aligned}$$

where the error term ( $e_t$ ) is the adjustment cost shock, observed by the firm but not by the researcher. Adjustment cost shocks are assumed to be white noise (although the key empirical results are not affected if we assume there is serial correlation in the error term).

Now assume that the company owners (or managers) can have different expectations to the market about the future value of the company. Suppose, in particular, that the company's expected valuation, which is equivalent to the valuation of the company's managers ( $V_t$ ), is equal to the valuation of investors (as measured by the stock market) ( $\Psi_t$ ) and company-specific sentiment or noise shocks ( $\mu_t$ ) that have a mean of zero and variance of  $\sigma_\mu^2$ :

$$V_t = \Psi_t + \mu_t.$$

Here, I assume that the managers of the company can observe the share price and factor this into their own valuation. The managers' valuation of the company is also affected by sentiment shocks that reflect changes in manager expectations that are exogenous to company fundamentals. (This assumes a certain timing structure of information that will be discussed in more detail later.)

Alternative explanations for a difference in the expected valuations of managers and investors are possible. For example, the managers may know more about the fundamentals of the company than shareholders, in which case there will be some fundamental component to the sentiment shocks. This would imply that the sentiment shocks are not pure noise. I test for the possibility of

private knowledge in an extension to the baseline model. Alternatively, managers and investors may have different discount factors ( $\beta_{t+s}$ ) with which they value future profits. For instance, managers may have extrapolative expectations about future investment and the weight they place on future profits differs from those of investors [Gennaioli et al. (2016)].

This assumption implies that the average  $q$  ratio can be written:

$$q_t = \frac{\Psi_t + \mu_t}{p_t^k (1 - \delta) K_{t-1}}.$$

The average  $q$  ratio is a function of the market equity value (as measured by the stock market) ( $\psi_t$ ) and sentiment shocks ( $s_t$ ):

$$q_t = \psi_t + \frac{\mu_t}{p_t^k (1 - \delta) K_{t-1}} = \psi_t + s_t.$$

The following model can therefore be estimated:

$$\left(\frac{I_t}{K_t}\right) = c + \frac{1}{b} (\psi_t - 1) + \frac{1}{b} (s_t) + e_t, \quad (1)$$

where the rate of investment is a function of a standard measure of Tobin's  $Q$  (based on equity values) and corporate sentiment shocks. Equation (1) forms the baseline model which I take to the data and test the relationship between corporate investment, sentiment and fundamentals.

### 3. Company-level information on sentiment and investment

#### 3.1. Company-level sentiment

There are two general approaches for quantifying sentiment in text—the dictionary- (or lexicon-) and the machine learning-based approaches. The dictionary-based approach relies on predefined lists of words with each word either classified as positive, negative, or neutral. The machine learning approach predicts sentiment of any given set of text after training models with a large set of text that has been assigned sentiment ratings by human readers. For example, models have been developed using social media data, such as Twitter, that provide text that is combined with user feedback to identify the sentiment of the posts. This approach is better able to capture the nuances in human language, but it is more complex and less transparent [Huang and Simon (2021)].

I follow the dictionary-based approach to construct company-level indicators of sentiment and uncertainty. The method is simple and intuitive and has been demonstrated to be sufficient to be able to predict equity returns at the company level. The sentiment indicator measures the net balance of words used in company reports that are “positive” and “negative.” When companies use more positive words and/or fewer negative words, this is an indicator that sentiment at the company has increased. The uncertainty indicator measures the share of uncertain words used (e.g. “uncertain” and “risk”).

I rely on the Loughran and McDonald (2011) (hereafter LM) dictionary of predefined positive, negative, and uncertain words that is specially designed for economics and finance. The Harvard Dictionary produces many different word lists, including positive words, negative words, and uncertain words. But nearly three-quarters of the words identified as “negative” by the Harvard Dictionary are words that are not considered negative in business terminology. For example, the words “taxes” and “debt” are not necessarily negative in the context of economics. Similarly, the word “credit” is not necessarily a positive word.

LM develop alternative word lists that better reflect tone in business terminology. For example, they identify close to 2500 negative words. Some of the most common negative words that appear in company reports include “loss,” “failure,” “default,” “termination,” and “adverse.” They then examine how such word lists are linked to company-level factors such as stock trading volume, unexpected earnings, and fraud.



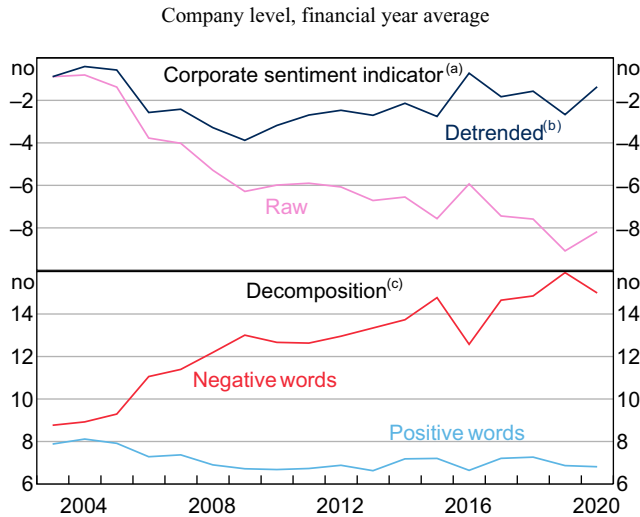
**Figure 3.** Sentiment word clouds.  
 Note: The size of each word reflects its relative frequency.  
 Sources: Author’s calculations; Connect 4.

For the sample, PDF versions of company annual reports are hand collected from the Connect 4 website and converted to text files. The LM dictionary is applied to these text files to create the sample. Common steps in the natural language processing literature are taken to clean the raw dataset before analysis: numbers, punctuation marks, white spaces, and common stop words are removed from each article. All words are then reduced to their respective “stem,” which is the part of a word that is common to all its inflections (e.g. “performs,” “performing,” and “performed” are reduced to “perform”).

The word clouds in Figure 3 indicate that the most common positive words in Australian corporate disclosures are terms such as “benefit,” “good,” and “success.” The most common negative words include terms such as “loss,” “defer,” and “impair.” These word clouds do not appear to have changed much over time, as shown by a comparison of the 2005 and 2020 clouds.

However, the word clouds mask some apparent changes in the underlying language used in corporate disclosures. For instance, the net balance of positive words shows a clear downward trend over time based on the raw (unadjusted) data (top panel of Figure 4). This is caused by companies increasingly using words with a negative connotation (bottom panel of Figure 4). This





**Figure 4.** Decomposition of corporate sentiment.  
 Notes: (a) Net balance of positive and negative words per 10,000 words. (b) Residuals from OLS regression of corporate sentiment on company dummies and a linear trend. (c) Based on unadjusted sentiment data.  
 Sources: Author’s calculations; Connect 4.

may be due to a gradual shift in corporate disclosures towards “investor-friendly” documents that are more transparent and include more discussion of risks and uncertainties to the outlook.

If the increasing propensity to use negative language is due to a shift towards more risk-based reporting, rather than growing concerns about the outlook, then this will make it more difficult to identify the true effect of corporate sentiment on investment. I adjust for the apparent trend by estimating an OLS regression of the sentiment indicator on a company fixed effect and a linear trend and take the residuals. These residual estimates are referred to as the “adjusted” corporate sentiment indicator and will be used for the remainder of the analysis in the paper. However, the key results in the paper hold even when using the unadjusted measure of sentiment.<sup>5</sup>

**3.2. Company-level investment and fundamentals**

Corporate investment is measured as the log change in the net capital stock ( $\frac{\Delta K}{K}$ ) as reported on a company’s balance sheet, which is equivalent to the net investment rate ( $\frac{I}{K} - \delta$ ):

$$\frac{\Delta K}{K} = \frac{I}{K} - \delta.$$

Here, the capital stock captures tangible assets such as property, plant, and equipment and is measured on a net basis by deducting accumulated depreciation from the gross capital stock. I choose to use the capital stock measure because it is generally more commonly reported in Australian company reports than the gross capital expenditure measure. (The key results hold though using the gross capital spending measure.)

To proxy for corporate fundamentals, I construct an estimate of Tobin’s Q using company-level information on share prices and the number of outstanding shares. Tobin’s Q is measured as:

$$Q = \frac{E + L - Inv}{A},$$

where  $Q$  is the ratio of total market value of equity ( $E$ ) plus the book value of total liabilities ( $L$ ) less inventories ( $Inv$ ) divided by the book value of total assets ( $A$ ). The total market value of equity is measured as the share price on the final day of the financial year multiplied by the number of shares outstanding at that time. This captures the value of the company at the end of the financial year.

There is extensive evidence that Tobin's  $Q$  is a poor guide to future corporate performance [e.g. Erickson and Whited (2000)]. So, in the empirical specification, I also consider a range of other firm-level indicators that could proxy for fundamentals, such as annual growth in sales (or turnover), the return on assets (measured as the ratio of earnings before interest and tax to total assets), and equity analysts' profit forecasts for the year ahead. I also explore the role of measurement error in Tobin's  $Q$  in a robustness test.

### 3.3. Publicly listed company sample

The sentiment indicator requires information on corporate disclosures, which means that the analysis is restricted to Australian publicly listed companies. The sample is an unbalanced panel of listed companies, with much of the data sourced from Morningstar. Share prices and equity analyst forecasts are sourced from Refinitiv Eikon. Before estimation, outliers are removed based on the top and bottom 1% of the distribution of each of the investment rate, the sentiment indicator, the uncertainty indicator, and the  $Q$  ratio. The estimation sample covers between 500 and 700 companies per year between 2003 and 2020.

Publicly listed companies account for about 1 in 2000 companies and are typically older and larger than the average (unlisted) company. However, it is hard to be definitive about whether this sample leads to biased estimates of the effect of sentiment on investment for the broader business population. The regression sample appears to be broadly representative of the universe of listed companies. I find that there are no statistically significant differences between firm-year observations that are in the regression sample and those that are not in the sample on most measures, including investment and sentiment. The only exception is that firms in the regression sample are a bit larger (based on the book value of assets) and have a slightly lower  $Q$  ratio than those that are not in the regression sample.

### 3.4. Information sets of company managers and investors

To empirically identify the effect of sentiment on investment, it is important to consider what is in the information sets of the managers and investors at the time of the release of the company annual reports, which are used to measure sentiment.

As an example, consider a hypothetical company that releases its annual report for the financial year 2019/20 in August 2020. This report includes balance sheet information on the book value of the capital stock at the start (1 July 2019) and end of the financial year (30 June 2020), and therefore the flow of investment during 2019/20. The managers and investors can observe the share price at any time during 2019/20.

To capture the determinants of company investment decisions, I conservatively assume the relevant measure of Tobin's  $Q$  is based on the market and book values of the capital stock at the start of the financial year (1 July 2019), as these values are observed by the managers at the time of any investment decision. I therefore restrict investor knowledge of the company, as captured in Tobin's  $Q$ , to the start of the period.

The end-of-year financial report is typically released a couple of months after the relevant financial year. This means that the language used in the report could reflect the knowledge of managers about investment-relevant events that occurred *during and even after* the reported financial year. This gives an information advantage to company managers, which may mean that the sentiment indicator is not a pure measure of animal spirits but is also capturing "insider" knowledge of

**Table 1.** Company-level statistics

Sample period: 2003 to 2020					
	Mean	Median	Standard deviation	25th percentile	75th percentile
Investment rate (%)	10.3	3.3	84.1	-20.5	31.9
Positive sentiment (per 10,000 words)	7.2	7.0	1.9	6.0	8.2
Negative sentiment (per 10,000 words)	13.3	13.2	3.5	11.1	15.4
Uncertainty (per 10,000 words)	5.7	5.7	1.9	4.5	6.9
Q ratio (times)	2.2	1.4	2.3	0.9	2.5
Return on assets (%)	-15.3	-3.7	87.7	-23.3	12.9
Sales growth (%)	10.0	7.2	110.2	-21.5	38.6

Note: Sample statistics based on estimation sample for the baseline fixed effects regression.

Sources: Author's calculations; Connect 4; Morningstar; Refinitiv Eikon.

events that are relevant to investment, but which are not observed by the market at the start of the period.

To address this, I also consider an alternative version of the model in which Tobin's Q is measured at the end of June 2020, and sentiment is measured based on the language in the 2018/19 financial report. I report on these alternative estimates in a robustness test.

### 3.5. Summary statistics

Some summary statistics are shown in Table 1. Investment is clearly skewed across the corporate population with the average company investing about 10% of its capital stock each year, while the median company invests closer to 3.3%, with a high SD. The average company also has a relatively high Q ratio, which appears to be mostly due to high valuations for mining companies during the mining boom period. This is even though the average company makes losses, as shown by the negative return on assets. The average company uses 7.2 positive words, 13.3 negative words, and 5.7 uncertain words for every 10,000 words in its annual reports.

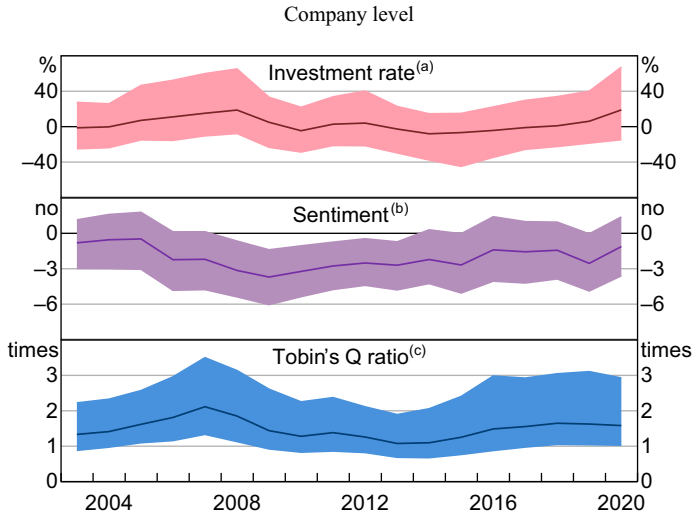
## 4. The effect of corporate sentiment shocks

### 4.1. The distribution of sentiment and investment

Before turning to the statistical analysis, it is helpful to look at the data underpinning the regression modeling. The key dependent variable is the net investment rate (or change in the net capital stock). The company-level data indicate a wide dispersion in investment outcomes across companies each year as shown by the difference between the 25th and 75th percentiles of the distribution (top panel of Figure 5). Across the company distribution, there is an apparent shift down in the rate of investment around the time of the GFC, with a recovery from around 2015.

For the corporate sentiment indicator, there is also a wide distribution of outcomes at any point in time (middle panel of Figure 5). The sentiment indicator shows a clear cyclical pattern, with sentiment declining during the GFC. There is little evidence that corporate sentiment fell during 2019/20, perhaps because the COVID-19 pandemic only affected economic activity in the last quarter of that year. The Q ratio also displays clear cyclical fluctuations (bottom panel of Figure 5).

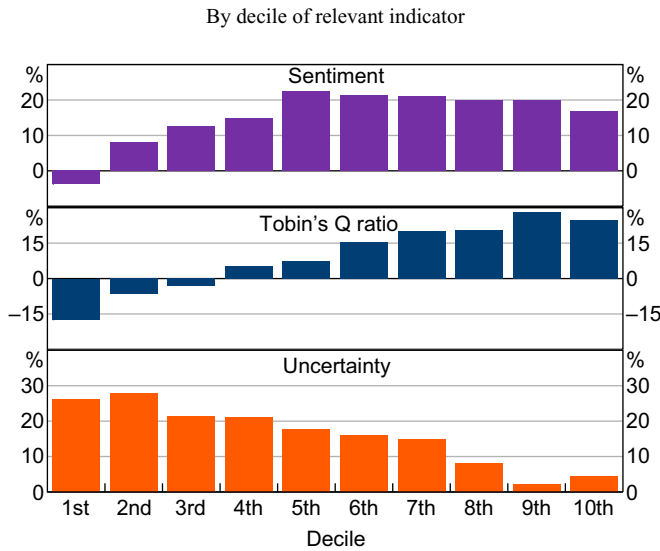
We can also look at how corporate investment is distributed across measures of sentiment, uncertainty, and fundamentals. To see this, binned scatterplots are constructed, and the average investment rate is calculated for deciles of the distribution of the corporate sentiment indicator, the Q ratio and the corporate uncertainty indicator (Figure 6). Companies that report higher levels



**Figure 5.** Distribution of corporate indicators.

Notes: Median shown by the line while the shaded area shows the 25th to 75th percentiles. (a) Measured as annual change in net capital stock. (b) Measured as the net balance of positive and negative words per 100,000 words. (c) Measured as (market value of equity plus book value of liabilities less inventories) divided by book value of assets.

Sources: Author's calculations; Connect 4; Morningstar; Refinitiv Eikon.



**Figure 6.** Corporate investment rate.

Sources: Author's calculations; Connect 4; Morningstar; Refinitiv Eikon.

of sentiment also invest more on average (top panel). Companies with particularly low sentiment levels scale back investment significantly, as shown by the bottom decile. There is a similar positive correlation in the cross-section between the corporate investment rate and the Tobin's Q ratio (middle panel). Further, there is a strong negative correlation in the cross-section between the investment rate and uncertainty (bottom panel). Taken at face value, this is consistent with investment being a function of sentiment, fundamentals, and uncertainty.

#### 4.2. The sensitivity of investment to sentiment

To explore the determinants of investment, a standard Tobin's Q model is augmented with the indicators of corporate sentiment and uncertainty:

$$\frac{\Delta K_{it}}{K_{it-1}} = \beta S_{it} + \gamma Q_{it} + \pi U_{it} + \delta \text{CONTROLS}_{it} + \theta_i + \lambda_t + \varepsilon_{it}. \quad (2)$$

The dependent variable is the change in the net capital stock  $\left(\frac{\Delta K_{it}}{K_{it-1}}\right)$  or the net investment rate, for company  $i$  in year  $t$ . The key explanatory variable is corporate sentiment ( $S_{it}$ ), measured as the number of net positive words divided by total words in each company's annual report, alongside the Tobin's Q ratio ( $Q_{it}$ ). If business investment is sensitive to sentiment, there should be a positive correlation between corporate sentiment and the rate of investment. The model also includes controls for other factors that may be associated with investment, such as profitability, growth, and size. Also considered is a regression in which firm-level uncertainty ( $U_{it}$ ) is controlled for.

To identify the causal effect of sentiment on investment, there are at least two potential identification challenges. First, the level of manager sentiment may be correlated with adjustment cost shocks that are observed by the firm. For example, a factory may have to unexpectedly shut down for a period to replace the capital. This might have an adverse effect on the sentiment of the management team. In this case, we would have a positive correlation between sentiment and the error term and the estimated coefficient on sentiment will be biased upwards:

$$\hat{\beta} = \beta + \frac{\text{cov}(S_{it}, \varepsilon_{it})}{\text{var}(S_{it})} > \beta.$$

To partly address this, I consider alternative model specifications that test the sensitivity of investment to sentiment based on prior company reports (which should contain no knowledge of any adjustment cost shock).

The OLS estimates point to a significant positive correlation between sentiment and investment (Table 2). A one SD increase in the share of net positive words (which is about 3.5 in 10,000 words) is associated with an increase in the rate of investment of about 6 percentage points (so the investment rate rises from about 10% to 16% at the sample mean).<sup>6</sup> The correlation between sentiment and investment is unaffected by either the inclusion of Tobin's Q (comparing columns 1 and 2) or the inclusion of other proxies for fundamentals, such as profits and sales growth (comparing columns 1 and 3). Moreover, the result is driven mostly by the time series (within-company) variation in sentiment and investment—companies typically invest more when they use more net positive words, all other things being equal. This is shown by the stronger effect of sentiment when company fixed effects are included (comparing columns 2 and 3).

The Q ratio is also positively associated with investment. A 1% increase in investment opportunities, as measured by Q, is associated with the rate of investment rising by 2 percentage points on average (a one SD shock is associated with the investment rate being about 5 percentage points higher, all else equal). As expected, investment is also positively correlated with other indicators of fundamentals, such as sales growth and profitability.

Furthermore, adding a measure of uncertainty to the set of control variables (column 4) we find that uncertainty is negatively associated with investment, and the effect appears to be of a similar magnitude to that of sentiment. But controlling for firm-level uncertainty has a limited effect on the sensitivity of investment to sentiment. This suggests that they both have roles to play in explaining corporate investment behavior.

**Table 2.** The effect of corporate sentiment on investment

Sample period: 2003 to 2020				
	OLS with no controls	OLS with controls	Fixed effects with controls	Fixed effects with controls and uncertainty indicator
Sentiment	0.02*** (4.05)	0.02*** (3.75)	0.03*** (5.22)	0.03*** (4.50)
Tobin's Q		0.02*** (4.98)	0.02*** (3.03)	0.02*** (3.06)
Uncertainty				-0.04** (-4.02)
Return on assets			0.11*** (4.63)	0.11*** (4.66)
Sales growth			0.16*** (8.53)	0.16*** (8.47)
Lagged sales level			0.16*** (7.84)	0.16*** (7.87)
Lagged capital stock level			-0.25*** (-13.44)	-0.25** (-13.50)
Company fixed effects	N	N	Y	Y
Year fixed effects	N	N	Y	Y
R squared	0.5%	1.6%	32.9%	33.1%
Companies	2,050	1,210	999	999
Observations	11,733	7,440	7,215	7,215

Notes: \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively, with *t*-statistics in parentheses; standard errors are two-way clustered by firm and year; coefficient estimates for constant, firm dummies, and year dummies are omitted. Investment is measured as the annual change in the net capital stock. Sentiment is measured as the net balance of positive and negative words per 100,000 words. Tobin's Q is measured as the market value of equity plus book value of liabilities less inventories divided by book value of assets. Uncertainty is measured as the number of uncertain words per 100,000 words. The return on assets is measured as the ratio of Earnings Before Interest, Tax, Depreciation, and Amortization (EBITDA) divided by the book value of assets. Sales growth is measured as the annual change in turnover. Sources: Author's calculations; Connect 4; Morningstar; Refinitiv Eikon.

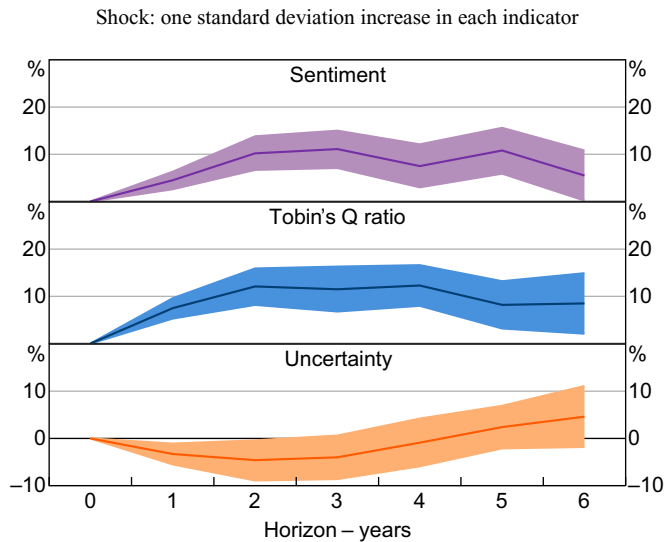
**4.3. The dynamics of corporate sentiment, uncertainty and investment**

The dynamics of investment in response to shocks to sentiment and other variables in the model may tell us more about the mechanism through which changes in sentiment are associated with changes in investment. For instance, if sentiment is a proxy for news about future company performance, then we may expect the effect of a sentiment shock on investment to be relatively persistent [Barsky and Sims (2012)]. If sentiment is instead capturing noise or animal spirits, then the effect may be expected to be temporary, or at least more temporary than a similar shock to a fundamental proxy such as Tobin's Q.

To examine the dynamics of the relationship between sentiment and investment, I estimate a series of impulse response functions using the LP method of Jordà (2005). Specifically, for each forecast horizon (*h*) I run a regression of the annual investment rate on standardized "sentiment shocks" as well as a series of lagged controls:

$$\left(\frac{I}{K}\right)_{i,t+h} - \left(\frac{I}{K}\right)_{i,t} = \alpha_{i,h} + \beta_h s_{i,t} + \gamma_h Q_{i,t} + \pi_h U_{i,t} + \mu_h CONTROLS_{i,t-1} + \varepsilon_{i,t+h}. \quad (3)$$

Here, a sentiment shock is measured by a one SD change in the sentiment indicator conditional on a set of controls that includes Tobin's Q, uncertainty, sales growth, the lagged level of the net capital stock, and the lagged level of sales. Similarly, a Q shock is measured by a one SD change in the Tobin's Q ratio conditional on sentiment and the same set of controls. Further, an uncertainty



**Figure 7.** Response of corporate investment rate to various shocks.

Notes: Shaded areas show 95% confidence interval; standard errors are two-way clustered by company and year.

Sources: Author's calculations; Connect 4; Morningstar; Refinitiv Eikon.

shock is measured by a one SD change in the uncertainty indicator conditional on sentiment, Q ratio and the controls. The sentiment, Q ratio, and uncertainty measures are standardized to z-scores by subtracting the firm-level mean and dividing by the firm-level SD.

The horizon-zero version of the LP model is almost identical to the baseline regression presented in Section 4.2 (with the full set of control variables). The only difference is that the LP include the one-year lag of each of the standardized indicators of sentiment, uncertainty, and Tobin's Q. For example, the sentiment indicator is serially correlated, so including lags is important to be able to interpret the coefficients as the response to sentiment shocks.

The impulse response of the investment rate to the sentiment shock is traced out by the estimates of the  $\beta$ s. The impulse response of the investment rate to the Q and uncertainty shocks are similarly traced out by the estimates of the  $\gamma$ s and the  $\pi$ s.

The estimated impulse response suggests that a standardized sentiment shock has a persistent positive correlation with investment, with the rate of investment being 10 percentage points higher after about three years before gradually declining (Figure 7). This would imply the average investment rate rises from 10% to 20% at the peak. The size of the investment response to a one SD Tobin's Q shock is of a similar magnitude but more persistent than a sentiment shock. The (negative) effect on investment of a standardized uncertainty shock is smaller in size to the sentiment shock and more temporary. Overall, all three shocks appear to matter to investment at the company level.

The fact that the sentiment shock has an effect that lasts beyond a couple of years suggests that the sentiment indicator is at least partly capturing news about a company's future productivity. Alternatively, it may indicate that an animal spirits shock has a self-fulfilling nature in which fundamentals adjust to the initial demand shock to render the change in sentiment rational *ex post*. Moreover, the effect of a shock to sentiment appears to be less persistent than that of a similar shock to Tobin's Q. Overall, this empirical exercise provides mixed evidence on whether the sentiment indicator is capturing news or noise.

## 5. Robustness tests and extensions

Several robustness tests and extensions are outlined below.<sup>7</sup> These tests are generally designed to inspect the mechanism(s) behind the link between sentiment and investment at the company level.

### 5.1. Why does corporate sentiment matter to investment?

#### 5.1.1. Private knowledge of company managers

I first explore whether the positive association between sentiment and investment is due to company managers being better informed than investors about the fundamentals of the company, rather than due to exogenous sentiment shocks. I refer to this as the “private information hypothesis.”

The timing of corporate disclosures may give an information advantage to managers over the market in that they know more about the fundamentals of the company when writing the financial reports. To address this, I consider an alternative version of the baseline model in which the sentiment indicator is lagged by one year and Tobin’s Q is measured based on the share price and number of outstanding shares at the end of the financial year (after the release of the financial report). So, for a hypothetical company that reports investment in 2019/20, sentiment is measured in 2018/19 and Tobin’s Q is measured at the end of June 2020. This should give the investors an information advantage over the managers because the market value of the company is measured at the end of the financial year. The results of the alternative timing structure are shown in Table 3.

Investment remains sensitive to sentiment even when investors potentially have an information advantage over the managers. In fact, the economic size and statistical significance of the sensitivity of investment to sentiment is unchanged even when sentiment is lagged by a year. This is surprising given that investors could use a similar text analysis approach to identify relevant information about company prospects based on the language used in the disclosures. The net balance of positive and negative words can be easily measured by anyone with knowledge of machine learning techniques and access to the company reports. This should mean that any information gleaned from the language in the reports is already embedded in the share price and hence captured in Tobin’s Q measured at the end of the financial year. And yet sentiment, as captured in corporate disclosures, still matters to investment.

As an alternative test of the private information hypothesis, I exploit the firm-level heterogeneity to assess whether investment is more sensitive to sentiment in companies in which managers should be expected to have a private information advantage. For instance, we should expect that the correlation between sentiment and investment is stronger at companies that are more difficult for investors to value. To test this, indicators are constructed for whether a firm is more difficult to value *ex ante* based on three metrics: (1) size, (2) age, and (3) share turnover (the total number of shares traded during the year divided by the average number of shares outstanding). Separate dummy variables ( $D_i$ ) are constructed to indicate whether the company is small (with total assets valued at less than \$10 million), young (less than four years of age), and/or low in turnover (in the bottom quartile of the stock turnover distribution). The dummy variable for hard-to-value companies is interacted with each of the indicators for sentiment, uncertainty, and Tobin’s Q in separate regressions that augment the baseline model:

$$\frac{\Delta K_{it}}{K_{it-1}} = \beta_1 S_{it} + \beta_2 S_{it} * D_i + \gamma_1 Q_{it} + \gamma_2 Q_{it} * D_i + \pi_1 U_{it} + \pi_2 U_{it} * D_i + \delta \text{CONTROLS}_{it} + \theta_i + \lambda_t + \varepsilon_{it}. \quad (4)$$

If the private information hypothesis is true, there should be a stronger positive correlation between sentiment and investment for these hard-to-value companies ( $\beta_2 > 0$ ).



**Table 3.** Testing for private knowledge of managers

Sample period: FY2003 to FY2020		
	Baseline model	Lagged sentiment and end period Tobin's Q
Sentiment	0.03** (4.50)	
Sentiment (one-year lag)		0.03*** (5.36)
Tobin's Q (start period)	0.02* (3.06)	
Tobin's Q (end period)		0.02* (2.03)
Uncertainty	-0.04** (-4.02)	-0.04*** (-3.54)
Return on assets	0.11*** (4.66)	0.14*** (4.96)
Sales growth	0.16*** (8.47)	0.13*** (6.56)
Lagged sales level	0.16*** (7.87)	0.13*** (5.78)
Lagged capital stock level	-0.25*** (-13.50)	-0.25*** (-12.13)
Company fixed effects	Y	Y
Year fixed effects	Y	Y
R squared	33.1%	33.5%
Companies	999	805
Observations	7,215	5,597

Notes: \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively, with *t*-statistics in parentheses; standard errors are two-way clustered by firm and year; coefficient estimates for constant, firm dummies, and year dummies are omitted. Investment is measured as the annual change in the net capital stock. Sentiment is measured as the net balance of positive and negative words per 100,000 words. Tobin's Q is measured as the market value of equity plus book value of liabilities less inventories divided by book value of assets. Uncertainty is measured as the number of uncertain words per 100,000 words. The return on assets is measured as the ratio of Earnings Before Interest, Tax, Depreciation, and Amortization (EBITDA) divided by the book value of assets. Sales growth is measured as the annual change in turnover.

Sources: Author's calculations; Connect 4; Morningstar; Refinitiv Eikon.

Based on these indicators, there is little evidence that the positive effect of sentiment on investment is stronger for hard-to-value companies (Table 4). The sentiment effect is slightly stronger at smaller companies, but the effect is not statistically significant. The age effects point in the opposite direction, with the sensitivity of investment to sentiment being weaker at young companies, though also not statistically significant. These tests provide limited support for the idea that the sensitivity of investment to sentiment is explained by the private knowledge of corporate managers.<sup>8</sup>

An alternative identification strategy to test whether the sensitivity of investment to sentiment is due to private knowledge is to explore the dynamics of the relationship between sentiment and company value, rather than investment. If the sentiment indicator is a proxy for managerial private knowledge about company fundamentals, then changes in sentiment should predict future company profits. I test this idea by estimating the same LP as before, but the dependent variable is changed from investment to company profits (as measured by the return on assets). I then explore how profits react to (past) changes in sentiment and Tobin's Q.

The LP estimates reveal that the return on assets increases by about 4 percentage points in the year following a one SD increase in the sentiment indicator, but the effect fades quickly (Figure 8).

**Table 4.** The heterogeneous effect of corporate sentiment on investment

Sample period: 2003 to 2020			
	Based on size	Based on age	Based on share turnover
Sentiment	0.03** (4.89)	0.03*** (4.79)	0.03*** (4.52)
Sentiment × Hard-to-value indicator	0.01 (0.54)	-0.02 (-1.57)	-0.00 (-0.48)
Tobin's Q	0.04*** (3.57)	0.02*** (2.87)	0.02*** (3.25)
Tobin's Q × Hard-to-value indicator	-0.04*** (-2.85)	0.04*** (2.22)	-0.01 (-0.57)
Uncertainty	-0.01 (-1.18)	-0.04*** (-4.26)	-0.03*** (-3.79)
Uncertainty × Hard-to-value indicator	-0.06*** (-3.45)	0.02 (0.98)	-0.01 (-0.50)
Company fixed effects	Y	Y	Y
Year fixed effects	Y	Y	Y
Time-varying controls	Y	Y	Y
R squared	34.2%	33.4%	33.2%
Companies	998	998	998
Observations	7,208	7,208	7,208

Notes: \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively, with *t*-statistics in parentheses; standard errors are two-way clustered by firm and year; coefficient estimates for the time-varying control variables (return on assets, sales growth, lagged sales and lagged capital stock), constant, firm dummies and year dummies are omitted. Investment is measured as the annual change in the net capital stock. Sentiment is measured as the net balance of positive and negative words per 100,000 words. Tobin's Q is measured as the market value of equity plus book value of liabilities less inventories divided by book value of assets. Uncertainty is measured as the number of uncertain words per 100,000 words. For the size regression, the hard-to-value indicator is a dummy variable that is equal to one if the company has total assets valued at less than \$10 million and is equal to zero otherwise. For the age regression, the hard-to-value indicator is a dummy variable that is equal to one if the company is less than four years of age and is equal to zero otherwise. For the share turnover regression, the hard-to-value indicator is a dummy variable that is equal to one if the company is in the bottom quartile of the share turnover distribution and is equal to zero otherwise.

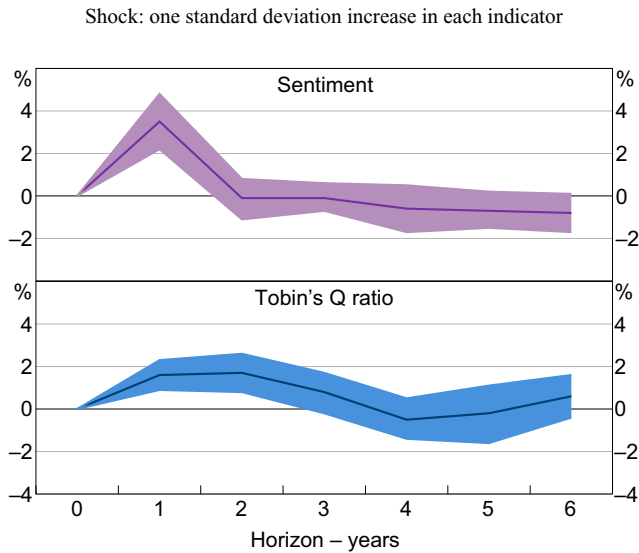
Sources: Author's calculations; Connect 4; Morningstar; Refinitiv Eikon.

The effect of a change in Tobin's Q is slightly weaker (at about 2 percentage points at the peak) but more persistent, lasting a few years. Overall, these results suggest that the sentiment indicator may provide some short-term news about the company, but given the effect is very transitory, the sensitivity of investment to sentiment does not appear to be fully explained by managers having private information about company prospects.

### 5.1.2. Positive versus negative sentiment

To further unpack the mechanism, the sentiment indicator can be decomposed into positive and negative sentiment, so that we can explore which matters more to investment. For this, the net balance measure is split into two indicators—the share of positive words ("positive sentiment") and the share of negative words ("negative sentiment") that are expressed in corporate disclosures. The model is then re-estimated using these two separate indicators simultaneously.

The results indicate that both positive and negative sentiment matter to investment, though the effect is stronger for "negativity" expressed in corporate disclosures (Table 5). This may be because negative words provide a stronger indicator of how a company is faring. Companies presumably avoid using negative words if they can, so when they do use them, it is more informative than the use of positive words. This may indicate the sensitivity of investment to sentiment is at least partly



**Figure 8.** Response of return on assets to various shocks.

Notes: Shaded areas show 95% confidence interval; standard errors are two-way clustered by company and year.

Sources: Author's calculations; Connect 4; Morningstar; Refinitiv Eikon.

due to managers having some private knowledge about the company's future (bad) prospects. However, it could also be that the text analysis is better able to capture negative language than positive language because positive language may be more nuanced. This would suggest that there is more measurement error in the positive sentiment indicator.

### 5.2. The measurement of corporate fundamentals

A key challenge to establishing a causal link between sentiment and investment is measurement error in the explanatory variables. Even if the sentiment indicator is measured perfectly, the estimated correlation between sentiment and investment will be affected by poor measurement of other explanatory variables, such as Tobin's Q. It has long been recognized that Tobin's Q can be a poor proxy for unobserved investment opportunities, and various fixes have been proposed [Erickson and Whited (2012)].<sup>9</sup>

In a bivariate regression of investment on a single explanatory variable that is measured with error, the estimated coefficient will be biased towards zero due to "attenuation bias." But, in a multivariate setting, it is more complicated and difficult to sign the effect of the bias on any one explanatory variable due to mismeasurement of other explanatory variables (Pischke 2007).

But, in some special cases, it is possible to sign the estimation bias. For instance, assume that, in the absence of error, sentiment and marginal  $q$  are positively correlated, say, because an increase in productivity increases the value of the company and makes company managers more optimistic about the future. In this case, classical error in measuring  $q$  will cause investment to be too sensitive to changes in sentiment but not sensitive enough to changes in Tobin's Q (Pischke 2007).

To identify the role of measurement error, I follow an "error-in-variables" approach and estimate the effect of sentiment on investment using the Erickson and Whited (2012) (EW) estimator. This is a minimum distance technique that relies on higher-order moments to strip out the effect of measurement error. This technique assumes that marginal  $q$  and sentiment follow non-normal distributions, which seems reasonable in practice given how skewed the observable data are.

The benchmark OLS regression estimates are shown in column 1, Table 6. The results of using the EW estimator are shown separately for the case where marginal  $q$  is assumed to be the only

**Table 5.** The effect of corporate sentiment on investment

Sample period: 2003 to 2020		
	OLS with no controls	Fixed effects with controls
Positive sentiment	-0.01* (-3.24)	0.02* (2.18)
Negative sentiment	-0.03*** (-10.89)	-0.03*** (-6.68)
Tobin's Q		0.01 (0.88)
Uncertainty		-0.03*** (-2.72)
Return on assets		0.09*** (3.26)
Sales growth		0.17*** (9.02)
Lagged sales level		0.16*** (8.34)
Lagged capital stock level		-0.26*** (-17.46)
Company fixed effects	N	Y
Year fixed effects	N	Y
R squared	1.0%	32.2%
Companies	1,964	964
Observations	11,200	6,931

Notes: \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively, with *t*-statistics in parentheses; standard errors are two-way clustered by firm and year; coefficient estimates for constant, firm dummies, and year dummies are omitted. Investment is measured as the annual change in the net capital stock. Sentiment is measured as the net balance of positive and negative words per 100,000 words. Tobin's Q is measured as the market value of equity plus book value of liabilities less inventories divided by book value of assets. Uncertainty is measured as the number of uncertain words per 100,000 words. The return on assets is measured as the ratio of Earnings Before Interest, Tax, Depreciation, and Amortization (EBITDA) divided by the book value of assets. Sales growth is measured as the annual change in turnover.

Sources: Author's calculations; Connect 4; Morningstar; Refinitiv Eikon.

variable measured with error (column 2) and where both marginal *q* and sentiment are assumed to be measured with error (column 3).

Under the assumption that Tobin's Q is the only variable that is mismeasured, the sensitivity of investment to sentiment is stronger, and the sensitivity to Tobin's Q is unchanged (comparing columns 1 and 2). Under the assumption that both Tobin's Q and sentiment are poorly measured, the sensitivity to sentiment becomes nearly ten times stronger, albeit not statistically significant (comparing columns 2 and 3). Overall, these results suggest that the effects of sentiment and Tobin's Q on investment would be even stronger in the absence of measurement error. However, these results on the impact of measurement error are sensitive to the specification of the EW estimator including the order of moments to use in estimation.

### 5.3. Explaining the post-GFC weakness in investment

Next, I quantify how much of the post-GFC weakness in investment can be explained by changes in sentiment, uncertainty, and other demand-side factors, such as profits and growth. For this

**Table 6.** Investment, sentiment, Tobin’s Q and measurement error

Sample period: 2003 to 2020			
	Baseline	Mismeasured Tobin’s Q	Mismeasured Tobin’s Q and sentiment
Sentiment	0.01*** (3.80)	0.02*** (4.40)	0.23 (1.16)
Tobin’s Q	0.02*** (4.04)	0.02 (1.09)	0.03 (1.19)
Company fixed effects	N	N	N
Year fixed effects	N	N	N
R squared	8.1%	17.3%	21.2%
Companies	999	999	999
Observations	7,215	7,215	7,215

Notes: \*, \*\*, and \*\*\* denote statistical significance at the 10, 5, and 1% levels, respectively, with *t*-statistics in parentheses; coefficient estimates for some of the control variables (return on assets, sales growth, lagged sales, and lagged capital stock) and constant are omitted. Investment is measured as the annual change in the net capital stock. Sentiment is measured as the net balance of positive and negative words per 100,000 words. Tobin’s Q is measured as the market value of equity plus book value of liabilities less inventories divided by book value of assets.

Sources: Author’s calculations; Connect4; Morningstar; Refinitiv Eikon.

empirical exercise, I consider a version of the baseline model:

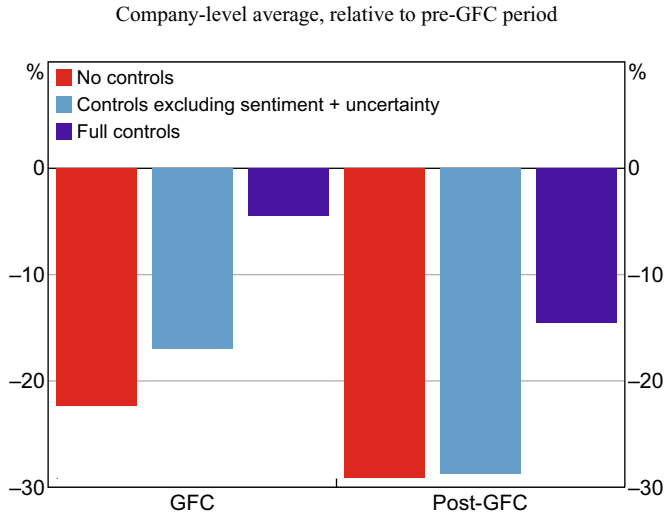
$$\frac{\Delta K_{it}}{K_{it-1}} = \beta S_{it} + \gamma Q_{it} + \pi U_{it} + \delta \text{CONTROLS}_{it} + \theta_i + \rho \text{GFC}_t + \phi \text{POST}_t + \varepsilon_{it}, \tag{5}$$

where the regression is as before, but, for simplicity, the year fixed effects have been replaced by two dummy variables—one for the GFC period ( $\text{GFC}_t$ ), which is assumed to cover the financial years from 2009 to 2010, and one for the post-GFC period ( $\text{POST}_t$ ) which is assumed to cover the financial years since 2011. The coefficient for the GFC dummy ( $\rho$ ) captures the mean difference in the rate of investment in the GFC relative to the period prior to the GFC. Similarly, the coefficient for the POST dummy ( $\phi$ ) captures the mean difference in the rate of investment in the period after the GFC relative to the period prior to the GFC.

I consider three versions of the regression. First, an unrestricted version that is estimated with all the control variables as above. Second, a partially restricted version in which investment depends on sentiment and uncertainty but none of the other variables ( $\gamma = \delta = 0$ ). Third, a fully restricted version in which there are no explanatory variables other than the company fixed effects and period dummies ( $\beta = \gamma = \pi = \delta = 0$ ).

The bars in the figure below display the coefficient estimates for the GFC ( $\rho$ ) and POST ( $\phi$ ) dummies under each of these versions of the model (Figure 9). The comparison of the unrestricted and fully restricted models indicates that the demand-side factors can explain about 80% of the decline in corporate investment during the GFC. Demand-side factors also account for more than half the decline in investment in the period since the GFC. A comparison of the unrestricted and partially restricted models shows that these measures of sentiment and uncertainty explain about a quarter of the decline in investment during the GFC, but account for very little of the post-GFC weakness.

Overall, this exercise suggests that weak demand-side factors are important for understanding the persistent weakness in corporate investment in the post-GFC period. And while low sentiment and heightened uncertainty were important contributing factors during the GFC, they have not obviously weighed on investment since that time.



**Figure 9.** Corporate investment rate.  
Sources: Author's calculations; Connect 4; Morningstar; Refinitiv Eikon.

## 6. Conclusion

In this paper, I develop new company-level indicators of corporate sentiment and uncertainty based on text analysis of corporate annual reports. I show that corporate sentiment has a statistically significant and robust positive association with company-level investment, even controlling for fundamentals and measures of uncertainty. Estimates from LP suggest that the effect of sentiment on investment is less persistent than that of a fundamentals shock, as measured by Tobin's  $Q$ , which suggests that the link between sentiment and investment is at least partly reflective of animal spirits among corporate managers. The decline in sentiment and increase in uncertainty contributed to the weakness in investment during the GFC, but other demand-side factors such as sales growth are more important in explaining the persistent weakness in corporate investment observed since then.

For policymakers, the results suggest that corporate investment is sensitive to changes in managerial sentiment so it may be worth investing more resources in behavioral macroeconomic models that allow for exogenous shocks to expectations among business decision-makers. Previous research has shown that, in such models, strict inflation targeting (as opposed to a more flexible approach based on average inflation over a longer period) can be suboptimal because it gives more scope for endogenous business cycle fluctuations that can destabilize inflation and output growth [De Grauwe (2011)].

The paper relies on a very simple text analysis approach to capture sentiment amongst companies. It may be worth exploring more sophisticated approaches that better capture the nuances of the language of economics and finance [Consoli et al. (2021)] or that capture the *emotion* as well as the *tone* of the language.

This paper focuses on the sentiment expressed in the text of corporate disclosures, which necessitates a focus on publicly listed companies, which are a very small and potentially biased sample of the business population. Therefore, there may be benefits to investing in longitudinal surveys of the broader business population which survey expectations and uncertainties about future sales, employment, and investment.

## Notes

- 1 The Macquarie Dictionary defines sentiment as "a thought influenced by or proceeding from feeling or emotion." This suggests that sentiment should be defined by the strength of feeling that agents hold in predicting future outcomes.
- 2 I assume that "sentiment" and "confidence" are the same concept, even though it may be possible to distinguish between "sentiment" as referring to beliefs about current economic conditions and "confidence" referring to beliefs about future economic conditions.
- 3 The firm-level investment data shown in Figure 2 are based on estimates for the entire population of Australian businesses and are drawn from the ABS BLADE data environment.
- 4 There is also a strong positive correlation between the firm-level sentiment indicator (aggregated to the economy-wide level) and survey-based measures of sentiment, such as the National Australia Bank business sentiment survey. This holds true even when controlling for aggregate GDP growth and large swings in economic activity during the GFC. This suggests that the sentiment indicator is capturing the beliefs of company managers, rather than other confounding factors associated with the business cycle.
- 5 Note that the net balance measure is normalized by the number of words per company report, and the trend over time in the net balance is not due to a decrease in the length of corporate disclosures (in fact, there has been an increase in average word count over time). The fact that the LM dictionary includes more negative words than positive words can explain why companies use more negative terms on average. However, the relative length of the word lists should be less of an issue for *changes over time* in sentiment, which is the main focus of the analysis in this paper.
- 6 This effect of sentiment on investment is estimated as  $\hat{\beta} \times \text{SD in sentiment} \times 100 = 0.018 \times 3.49 \times 100 = 6.3\%$ .
- 7 The key results are similar if investment is measured as the ratio of capital spending to revenue rather than the change in the net capital stock. I also find that the effect of sentiment on investment varies somewhat by industry, with the effect of sentiment being stronger in the mining sector. The effect of sentiment on investment is not any weaker or stronger during economic downturns such as the GFC and the COVID-19 pandemic.
- 8 It might be the case that firm size and age proxy for financial constraints, as well as information frictions, and that the investment behavior of such financially constrained firms may be less sensitive to sentiment shocks simply because the firms are unable to respond to such changes in expected activity. Some of the control variables will capture financial constraints, such as the return on assets and sales growth, but they are likely to be imperfect controls.
- 9 We can also gauge the importance of sentiment for investment using alternative measures of fundamentals, such as company-specific expected profits. For this exercise, the Tobin's Q measure is replaced with equity analyst forecasts for earnings in the year ahead, and the baseline regression is re-estimated. The sensitivity of investment to sentiment is unchanged, both in terms of economic magnitude and statistical significance despite the alternative expected profit indicator. These results are outlined in more detail in the working paper version [La Cava (2021)].

## References

- Abel, A. B. and O. J. Blanchard (1986) The present value of profits and cyclical movements in investment. *Econometrica* 54(2), 249–273.
- Akerlof, G. A. and R. J. Shiller (2009) *Animal Spirits: How Human Psychology Drives the Economy, and Why It Matters for Global Capitalism*. Princeton: Princeton University Press.
- Alghaba, A., D. Ardia, K. Bluteau, S. Borms and K. Boudt (2020) Econometrics meets sentiment: An overview of methodology and applications. *Journal of Economic Surveys* 34(3), 512–547.
- Barsky, R. B. and E. R. Sims (2012) Information, animal spirits, and the meaning of innovations in consumer confidence. *The American Economic Review* 102(4), 1343–1377.
- Beaudry, P. and F. Portier (2014) News-driven business cycles: Insights and challenges. *Journal of Economic Literature* 52(4), 993–1074.
- Benhabib, J. and R. E. A. Farmer (1999) Indeterminacy and sunspots in macroeconomics. In: J. B. Taylor and M. Woodford (eds.), *Handbook of Macroeconomics*, vol. 1A, Handbooks in Economics, pp. 387–448. Amsterdam: Elsevier B.V.
- Benhabib, J., P. Wang and Y. Wen (2015) Sentiments and aggregate demand fluctuations. *Econometrica* 83(2), 549–585.
- Blanchard, O. J., J.-P. L'Huillier and G. Lorenzoni (2013) News, noise, and fluctuations: An empirical exploration. *The American Economic Review* 103(7), 3045–3070.
- Bloom, N. (2009) The impact of uncertainty shocks. *Econometrica* 77(3), 623–685.
- Blundell, R., S. Bond, M. Devereux and F. Schiantarelli (1992) Investment and tobins Q: Evidence from company panel data. *Journal of Econometrics* 51(1-2), 233–257.
- Bond, S. and J. Cummins (2001) Noisy Share Prices and the Q Model of Investment, Institute for Fiscal Studies Working Paper WP01/22.
- Chauvet, M. and J. Guo (2003) Sunspots, animal spirits, and economic fluctuations. *Macroeconomic Dynamics* 7(1), 140–169.
- Chirinko, R. S. (1993) Business fixed investment spending: Modeling strategies, empirical results, and policy implications. *Journal of Economic Literature* 31(4), 1875–1911.

- Consoli, S., L. Barbaglia and S. Manzan (2021) Fine-Grained, Aspect-Based Sentiment Analysis on Economic and Financial Lexicon. Unpublished manuscript, 29 June. Available at. Available at: [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=3766194](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3766194).
- De Grauwe, P. (2011) Animal spirits and monetary policy. *Economic Theory* 47(2-3), 423–457.
- Dixit, A. K. and R. S. Pindyck (1994) *Investment under Uncertainty*. Princeton: Princeton University Press.
- Erickson, T. and T. M. Whited (2000) Measurement error and the relationship between investment and  $q$ . *Journal of Political Economy* 108(5), 1027–1057.
- Erickson, T. and T. M. Whited (2012) Treating measurement error in Tobin's  $q$ . *The Review of Financial Studies* 25(4), 1286–1329.
- Farmer, R. E. A. (2012) Confidence, crashes and animal spirits. *The Economic Journal* 122(559), 155–172.
- Gennaioli, N., Y. Ma and A. Shleifer (2016) Expectations and investment. In: M. Eichenbaum and J. A. Parker (eds.), *NBER Macroeconomics Annual 2015, vol. 30*, pp. 379–431. Chicago: University of Chicago Press.
- Gutiérrez, G. and T. Philippon (2017) Investmentless growth: An empirical investigation. *Brookings Papers on Economic Activity* Fall, 89–169.
- Hayashi, F. (1982) Tobin's marginal  $q$  and average  $q$ : A neoclassical interpretation. *Econometrica* 50(1), 213–224.
- Huang, J. and J. Simon (2021) Central Bank Communication, One Size Does Not Fit All, RBA Research Discussion Paper No 2021-05.
- Jiang, F., J. Lee, X. Martin and G. Zhou (2019) Manager sentiment and stock returns. *Journal of Financial Economics* 132(1), 126–149.
- Jordà, Ò. (2005) Estimation and inference of impulse responses by local projections. *The American Economic Review* 95(1), 161–182.
- Kearney, C. and S. Liu (2014) Textual sentiment in finance: A survey of methods and models. *International Review of Financial Analysis* 33, 171–185.
- Keynes, J. M. (1936) *The General Theory of Employment Interest and Money*. London: Macmillan and Co., Limited.
- La Cava, G. (2021) Smells like animal spirits: The effect of corporate sentiment on investment, RBA Research Discussion Paper. RDP: Reserve Bank of Australia.
- Loughran, T. and B. McDonald (2011) When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *The Journal of Finance* 66(1), 35–65.
- Milani, F. (2017) Sentiment and the U.S business cycle. *Journal of Economic Dynamics & Control* 82, 289–311.
- Nowzohour, L. and L. Stracca (2020) More than a feeling: Confidence, uncertainty and macroeconomic fluctuations. *Journal of Economic Surveys* 34(4), 691–726.
- Pigou, A. C. (1927) *Industrial Fluctuations*. London: MacMillan and Co., Limited.
- Pischke, S. (2007) Lecture notes on measurement error, lecture notes, london school of economics and political science, Department of Economics., Available at [https://econ.lse.ac.uk/staff/spischke/ec524/Merr\\_new.pdf](https://econ.lse.ac.uk/staff/spischke/ec524/Merr_new.pdf).
- Roberts, I. and J. Simon (2001) What do Sentiment Surveys Measure? RBA Research Discussion Paper No. 2001-09.
- Zhou, G. (2018) Measuring investor sentiment. *Annual Review of Financial Economics* 10(1), 239–259.