Sentiment Contagion Across Firms*

Torsten Jochem
University of Amsterdam

Florian S. Peters
University of Amsterdam

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Keywords: Managerial optimism; Managerial sentiment; Contagion; Propagation

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*Torsten Jochem: University of Amsterdam. Email: t.jochem@uva.nl. Florian Peters: University of Amsterdam. Email: f.s.peters@uva.nl.

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Abstract

We provide evidence that management sentiment spreads across firms via customer-supplier networks. We use management earnings forecasts to measure time-varying optimistic beliefs, and – separating correlation of rational expectations from correlation of biases – document a robust and economically large propagation of sentiment from customers to suppliers. The effect is stronger when customer forecasts are more salient, i.e. for more recent customer forecasts and for more important customers. In addition, we find evidence for real effects: leverage, inventories and investment increase, while cash holdings decrease with propagated sentiment. Our results showing contagion and real effects of sentiment suggest the possibility of sentiment-driven business cycles.

I. Introduction

The question of how sentiment originates and spreads across individuals, investors, and firms, has long been of interest to academics, practitioners, and policymakers. For instance, in his book *Irrational Exuberance*, Shiller (2000) argues that stock market bubbles are often fueled by excessively optimistic beliefs that are disseminated and amplified through social interaction.

However, there is little microeconomic evidence of how exactly sentiment propagates among economic agents. This is likely due to the fact that there is limited data available on individuals' beliefs, and, maybe more importantly, that the various channels of propagation are difficult to identify. In general, sentiment spreads through social interaction within peer groups. But peer groups are often hard to identify empirically. In this paper, we investigate one specific channel through which the beliefs of corporate managers spread across firms: customer-supplier networks. Customer firms are natural peers and focal points for supplier firms in the context of belief formation about future earnings. Management teams of economically linked firms communicate regularly to exchange information on various aspects of their business relationship. It is thus plausible that beliefs about future earnings – both rational and irrational ones – propagate through this channel.

Our analysis focuses on the *time-varying* component of optimism among managers which, in line with DeLong, Shleifer, Summers, and Waldmann (1990), we refer to as sentiment. We estimate sentiment contagion by regressing suppliers' earnings forecasts on those of their customers, while controlling for the earnings realizations of both firms.

Using forecasts and controlling for realizations is similar in spirit to using forecast errors as a measure of optimism (see, e.g., Landier and Thesmar (2009), Ben-David, Graham, and Harvey (2013), and Hribar and Yang (2013)).[1] One concern with our analysis could be that the correlation of forecasts is driven by the correlation of rational expectations about firms' fundamentals rather than the correlation of biases. The identification problem arises from the fact that a managerial bias is not directly observable, and the observable quantity – the management forecast – is the sum of the bias and the rational expectation. However, because earnings realizations are the sum of the rational expectation and a random earnings shock, controlling for customers' and suppliers' earnings realizations removes the correlation of rational expectations from the forecast correlation, thereby isolating the correlation of biases. Our setting is a special case of a measurement error problem where a nuisance term (the rational expectation) is unobservable and could confound our correlation of interest, but observing a noisy measure of it (the realization) and controlling for it allows us to remove its confounding effects. We show this formally and discuss it in detail in section II.

We construct a matched customer-supplier sample to investigate how sentiment propagates through customer-supplier networks. As our main result we document a strong positive relationship between customer and supplier sentiment. The economic magnitude of this effect is large: a one percent increase in the forecast optimism of a customer representing 100% of supplier sales leads to a 0.40 to 0.60 percent increase in supplier optimism. Given the magnitude of this "sentiment pass-through rate" and the fact that

[1] The advantage of using forecasts instead of forecast errors is that forecasts do not contain unexpected earnings shocks. Therefore, the forecast correlation is not affected by the correlation (or propagation) of real shocks.

customers often have many suppliers – both proximate ones as well as more distant ones in the supply chain – an initial sentiment shock to a large firm may generate significant aggregate effects.

We address causality concerns in several ways. First, we find that sentiment contagion only occurs for customer forecasts that are issued *before* supplier forecasts, not (shortly) after. This is consistent with sentiment contagion, because the propagation of beliefs from customer to supplier can only occur after the customer's beliefs come to be known. Further, it is inconsistent with a correlation of rational expectations because rational expectations of customers and suppliers should be correlated irrespective of the sequence and exact timing of forecasts.

Second, we find that belief propagation is more pronounced when suppliers are less confident about their future earnings, that is, when they issue a forecast range instead of a point estimate and, conditional on issuing a range, when the forecast range is wider. This also points to bias propagation, since less confident suppliers should be more eager to incorporate outside signals into their own forecasts.

Third, our results indicate that contagion is stronger for more salient customer forecasts. We construct different measures of forecast salience. First, we determine how recently the customer forecast was issued relative to the supplier's forecast issuance date, and find stronger (weaker) contagion effects for more recent (distant) customer forecasts. Second, we define two measures of the economic importance of a customer to its supplier: the percentage of the supplier's total sales going to that customer and the correlation of the supplier's stock price with that of its customer. We find that contagion is increasing in both measures of customer importance. This further supports our hypothesis, because more salient customer forecasts should be more likely to influence suppliers' beliefs.

Fourth, our results hold with a broad set of fixed effects, including supplier fixed effects or customer-supplier-pair fixed effects. These fixed effects isolate the time-varying component of optimism. Thus, our results are not driven by a tendency of optimistic managers to form business links with firms of similarly optimistic managers. Our results also hold when we further add quarter or quarter-customer industry fixed effects. This ensures that our results are not due to market-wide or industry-wide waves of sentiment.

Fifth, we run falsification tests in which we randomly draw same-industry pseudo-customers, and use the pseudo-customer's forecast instead of the actual customer's forecast. We find that the estimated spillover effect using actual customers lies in the top 0.1% of the empirical distribution of pseudo-customer coefficients. This suggests that our results are indeed due to the specific customer-supplier relationship, and are not driven by industry unobservables.

Finally, we investigate the real effects of sentiment. Existing literature documents that *permanent*, person-specific managerial attitudes affect firm policies (see, e.g., Malmendier and Tate (2005); Malmendier, Tate, and Yan (2011); Ben-David, Graham, and Harvey (2013); Graham, Harvey, and Puri (2013)). In contrast, we investigate whether *time-varying* optimism affects corporate policies. Relating sentiment of a firm's management to *its own* corporate policies, we find that leverage, inventories and investment increase, while cash holdings decrease. This complements earlier findings of the effects of permanent, person-specific attitudes on firm policies. Importantly, we find similar results when we investigate the effects of *propagated* sentiment on a firm's corporate policies where we estimate propagated sentiment as the component of a supplier's sentiment that is predicted by its customers' sentiment. Again, as discussed in section II, these results are not driven by the propagation of rational expectations, but instead isolate the effect of management biases.

Taken together, our findings show that sentiment spreads along supply chains, and that these changes in beliefs prompt changes in corporate policies of connected firms. An initial shock to the beliefs of the managers of large corporations could thus have significant aggregate effects on the amount and structure of investment and financing in the economy. First, because an initial sentiment shock to a large firm spreads across many firms – to all proximate suppliers as well as to the suppliers of suppliers along the entire value chain. And second, because those beliefs could affect corporate decisions in all of these firms. This mechanism could potentially induce sentiment-driven business cycles and could be regarded as the corporate analogue to the sentiment-driven stock market bubbles described by Shiller (2000, Ch. 8).

This paper is related to three sets of literatures. First, it relates to a large literature on peer effects in financial decisions. For instance, Hong, Kubik, and Stein (2004) find that households which interact more with their neighbors are more likely to invest in the stock market. Similarly, Brown, Ivkovic, Smith, and Weisbenner (2008) show that an individual's stock market participation is positively affected by the average stock market participation in the individual's community. Hong, Kubik, and Stein (2005) document that fund managers located in the same city make correlated buying decisions even for non-local stocks. Kaustia and Knüpfer (2012) show that portfolio returns experienced by households influence stock market participation of other households located in geographic proximity. Finally, Simon and Heimer (2012) find that traders with good short-term performance are more likely to initiate communications with other traders, who subsequently increase their trading activity. In all of these cases, individuals appear to be influenced in their financial decisions by their peers. Our paper is related to these studies because customers can be thought of as natural peers for suppliers, and hence may influence their suppliers' views about future earnings. Our analysis however differs from the above papers by studying peer effects in *beliefs* rather than *decisions*.

A second strand of literature relates managerial attitudes to corporate policies. Malmendier and Tate (2005, 2008) and Malmendier, Tate, and Yan (2011) link CEO overconfidence to corporate investment, acquisitions, and financing decisions. They measure overconfidence as the CEO's failure to exercise in-the-money stock options which a rational CEO should have exercised in order to diversify his or her exposure to firm risk. Ben-David, Graham, and Harvey (2013) find that firms whose CFOs underestimate risk, tend to invest more and use more leverage. Finally, Graham, Harvey, and Puri (2013) find that optimistic CEOs use more short-term debt and engage in more mergers. The latter two papers measure optimism based on survey questions that elicit the managers' views about future outcomes. We also assess the effect of managerial attitudes on corporate policies, but our analysis differs from the above-mentioned studies in that we focus on time-varying optimistic beliefs, and, in particular, on how their propagation affects real policies.

Finally, our paper contributes to the broader literature on sentiment (Baker and Wurgler, 2007; Baker, Wurgler, and Yuan, 2012; Soo, 2013; Stambaugh, Yu, and Yuan, 2012). These studies are mostly concerned with the effect of investor sentiment on asset prices and use aggregate, market-wide sentiment indicators. In contrast, our analysis focuses on beliefs of management teams of individual firms, and how the propagation of those beliefs may affect corporate actions.

II. Identifying Sentiment Propagation

In this section we formally show how we empirically identify sentiment propagation in customer-supplier networks using management forecasts. Our goal is to estimate the following equation:

$$b_{it}^{S} = \alpha + \beta b_{it}^{C} + u_{it}, \tag{1}$$

where b_{it} is the bias in management's expectation about future earnings and u_{it} is a mean-zero error term which is uncorrelated with the regressor. If b_{it} is positive (negative), the forecast is "optimistic" ("pessimistic"). In this equation, subscript i references a customer-supplier pair, t indexes the fiscal period, and the superscript indicates the customer (superscript "C") or supplier firm (superscript "S"). Importantly, data on the supplier's bias is measured shortly *after* that of the customer's so that belief propagation from customer to supplier can occur. Note also that we explicitly allow the bias b_{it} to vary over time. In line with DeLong, Shleifer, Summers, and Waldmann (1990), we refer to this time-varying component of the bias as sentiment.

The problem with the above regression is that biases are not directly observable. However, we can observe management earnings forecasts which are the sum of the rational expectation of earnings, μ, and the bias, b,[2]

$$\hat{e}_{it}^{S} = \mu_{it}^{S} + b_{it}^{S}, \tag{2a}$$

$$\hat{e}_{it}^{C} = \mu_{it}^{C} + b_{it}^{C}. \tag{2b}$$

Relating forecasts of suppliers to those of their customers hence creates the challenge of separating the propagation of biases from the propagation of rational expectations that is due to the business link between the two firms. Therefore, simply replacing the biases in equation (1) with the terms in equations (2) and rearranging,

$$\hat{e}_{it}^{S} - \mu_{it}^{S} = \alpha + \beta(\hat{e}_{it}^{C} - \mu_{it}^{C}) + u_{it} \tag{3}$$

$$\hat{e}_{it}^{S} = \alpha + \beta \underbrace{\hat{e}_{it}^{C}}_{\mu_{it}^{C}+b_{it}^{C}} + \underbrace{\mu_{it}^{S} - \beta\mu_{it}^{C} + u_{it}}_{\nu_{it}}, \tag{4}$$

leads to a biased coefficient β. This occurs, because the error term, ν_{it}, is correlated with the regressor through two channels. First, because both the regressor and the error term contain μ_{it}^{C}. And second, because the error term also contains μ_{it}^{S}, which, due to the real channel, is likely correlated with μ_{it}^{C}. In other words, a positive coefficient β could be caused by a correlation of the biases – due to the belief contagion we are interested in – or by a correlation of the rationally expected earnings – due to the real business link between the firms.

Removing this bias requires controlling for the rational expectations of earnings, μ_{it}^{S}

[2]Consistent with the literature on heuristics and biases, any error in expectation formation is attributed to the bias, see Kahneman and Tversky (1982). Therefore biases could be due to obviously irrational expectations which cannot be justified by the facts at hand, or due to incomplete or wrong explicit or mental forecasting models.

and μ_{it}^C. While we again cannot separately observe those quantities, we observe a noisy measure thereof, the realized earnings:

$$e_{it}^S = \mu_{it}^S + \varepsilon_{it}^S, \tag{5a}$$

$$e_{it}^C = \mu_{it}^C + \varepsilon_{it}^C, \tag{5b}$$

where ε_{it} is an unexpected mean-zero earnings shock which is uncorrelated with the rational expectations and biases of suppliers and customers. Adding both the supplier's and customer's realized earnings to equation (4) then provides us with an unbiased estimate of β:

$$\hat{e}_{it}^S = \alpha + \beta \underbrace{\hat{e}_{it}^C}_{\mu_{it}^C + b_{it}^C} + \gamma \underbrace{e_{it}^C}_{\mu_{it}^C + \varepsilon_{it}^C} + \delta \underbrace{e_{it}^S}_{\mu_{it}^S + \varepsilon_{it}^S} + \underbrace{\mu_{it}^S - \beta \mu_{it}^C + u_{it}}_{\nu_{it}} \tag{6}$$

$$= \alpha + \beta \underbrace{\hat{e}_{it}^C}_{\mu_{it}^C + b_{it}^C} + (\gamma - \beta)\mu_{it}^C + (1 + \delta)\mu_{it}^S + \underbrace{\gamma \varepsilon_{it}^C + \delta \varepsilon_{it}^S + u_{it}}_{\eta_{it}}. \tag{7}$$

In this regression η_{it} is the new effective error term, containing the customer's and supplier's real shocks to earnings, ε_{it}^C and ε_{it}^S, as well as the original regression error term, u_{it}. From this, one can see that the new error term is no longer correlated with any of the regressors since μ_{it}^C, μ_{it}^S and b_{it}^C are uncorrelated with the unexpected earnings shocks, ε_{it}^C and ε_{it}^S as well as u_{it}. Moreover, the propagation of real shocks from customer to supplier – that is, a correlation between ε_{it}^C and ε_{it}^S – does not confound the coefficient of interest. Hence, while we regress customer on supplier forecasts, the coefficient of the customer forecast needs to be interpreted as the correlation of customer and supplier biases.

Our approach of regressing supplier on customer forecasts and controlling for realized customer and supplier earnings is similar to regressing customer on supplier *forecast errors* and controlling for realized customer and supplier earnings. Intuitively, the latter approach also requires controlling for the realized earnings, because the forecast error is the difference between the expectation bias and the real shock: $\hat{e}_{it} - e_{it} = b_{it} - \varepsilon_{it}$. That is, the forecast error is also a noisy measure of the expectation bias. Here, the univariate correlation between forecast errors of customers and suppliers could be driven by the correlation of biases or by the correlation, or propagation, of real shocks. This alternative approach, however, needs the somewhat stronger assumption that μ_{it} is uncorrelated with b_{it} (instead of ε_{it} being uncorrelated with μ_{it} and b_{it}) in order for β to be unbiased. We therefore prefer regressions using customer and supplier forecasts instead of forecast errors.

From the above framework it is apparent why even rational suppliers may copy an optimistic bias b_{it} from their customers. As suppliers can only observe the customer forecast $\hat{e}^C_{it}$, they cannot easily disentangle the customer's rational expectation μ^C_{it} from the bias b^C_{it}. In addition, since the bias is time-varying, learning about the customer's bias is difficult. This is unlike permanent, trait-based optimism which can be filtered out by observing forecasts repeatedly over time.

III. Data

A. Sample Construction

The core of our dataset consists of management forecasts – also called management guidance – of both quarterly and annual earnings per share. Since the implementation of Regulation Fair Disclosure (Reg FD) in 2000, issuing management guidance has become the norm for public corporations.[3] We use management forecasts from Thomson Reuters' IBES guidance database for the period 2001 to 2013.

From the guidance database we extract the point estimate of the management forecast, the lower and upper bounds of the forecast range, a variable indicating whether the forecast relates to quarterly or annual earnings, the fiscal period end date to which the forecast pertains, the date at which the forecast was published, and the IBES company identifier (IBES ticker). Most companies (85% of our sample) provide a forecast range instead of a single point estimate of earnings. In these cases, we define the point estimate as the midpoint between the upper and lower bound of the range. We add to this the reported realized EPS for the respective fiscal period from the IBES actuals database along with the announcement date of the actual.

We then link each IBES ticker with its respective CRSP PERMNO using the CRSP-IBES linking algorithm provided by WRDS. From the CRSP daily stock file, we obtain the closing share price from five trading days prior to the announcement of the earnings forecast. Historical IBES guidance and actuals data are continuously split-adjusted to reflect earnings per share on the basis of the most current number of shares outstanding. Since we scale all guidance and actuals numbers by the stock price, we split-adjust historical stock prices using CRSP's historical split adjustment factor.

We then supplement our dataset with accounting data from the CRSP/COMPUSTAT Merged Database (CCM). From annual CCM data, we construct several firm-level control variables. We measure firm size as the logarithm of total assets. We compute Tobin's Q as the ratio of market value of assets to book value of assets. We measure asset tangibility as

[3]The 2015 National Investor Relations Institute Report states that 86% of publicly listed firms issue EPS guidance.

property, plant and equipment scaled by total assets. We also report two other measures of firm size, total sales and market value, as well as profitability and book leverage.[4]

Finally, for every IBES company with non-missing guidance data, we identify all officially disclosed customer firms using COMPUSTAT's customer segment files. Regulation SFAS No. 131 requires firms to report the identity of all customers representing more than 10% of total sales in interim financial reports issued to shareholders. From the customer segment file we extract both the identity of the customers as well as the dollar value of sales accounted for by that customer. COMPUSTAT segment files contain the customer name as reported by the company only. We thus use a string matching algorithm to identify the CRSP PERMNO of customer firms, if available. Because of the 10% reporting threshold and since we require customer firms to have a valid CRSP PERMNO, we do not use all customers of a given firm in our analysis. For each supplier forecast, we then merge in the *most recently issued* customer forecast for the same fiscal periodicity (i.e. we use the customer's most recent quarterly (annual) EPS forecast if the supplier forecast is for quarterly (annual) results) and for the closest fiscal period end. We keep only those supplier forecasts for which there is at least one customer with a matched forecast.

Our final dataset contains 9,797 supplier-forecast observations and 9,653 customer-supplier-forecast combinations originating from 1,921 unique suppliers and 570 unique customers.

[Insert Table I here]

[4] For details on the variable definitions, see table IX.

Table I shows descriptive statistics of customers and suppliers. Panel A contains basic statistics on sample size and customer-supplier relationships. The average number of unique suppliers in our sample is 163 per year but varies across years from 56 to 245. There are, on average, 73 customers per year, varying from a minimum of 24 to a maximum of 104 per year. The average number of customers per supplier in our sample is 1.57. This is due to the fact that we do not identify all customers of a given firm, but only those which are disclosed and recorded in CRSP. In the last two rows of Panel A, we report two measures of the economic importance of a given customer to the supplier. The first measure is the share of total sales of the supplier pertaining to that customer. The second measure is the correlation between the excess stock returns of the customer and the supplier, a stock market-based measure of the importance of a customer.

Panel B reports statistics for a range of firm characteristics, separately for suppliers and customers. The first three rows show that the average (median) customer is more than ten (twenty) times larger than the average (median) supplier. On most other dimensions (market-to-book, PP&E, profitability, capex), customers and suppliers are similar.

B. Measuring Optimism

We use management earnings forecasts in combination with the respective realized earnings to measure and analyze management optimism. As detailed in Section II, our regressions use both the forecasted and the realized earnings per share as independent variables. We scale these variables by the stock price from five trading days prior to the announcement of the forecast, so that the variables can be interpreted as forecasted or realized earnings yields.

Using forecasted and realized values of uncertain quantities to gauge the optimism of individuals has precedents in the literature. For instance, Ben-David, Graham, and Harvey (2013) use the forecast error of Chief Financial Officers about the S&P500 index return to document that, on average, corporate managers are too optimistic. Landier and Thesmar (2009) use entrepreneurs' forecast errors about their own firm's employment and sales growth as a measure of optimism to show that optimistic entrepreneurs tend to use short-term, rather than long-term debt.

Forecasts are more direct measures of beliefs than proxies derived from managerial option exercise or stock trading decisions such as those proposed by Malmendier and Tate (2005, 2008). This is because management forecasts directly reflect beliefs while observed choices only reflect revealed beliefs which are a possible but not a necessary consequence of underlying beliefs. Using a direct measure of optimistic beliefs also avoids another limitation of choice-based measures of managerial attitudes, namely that it is often difficult to disentangle whether the respective financial decisions are driven by optimism (an upwards biased expectation), overconfidence (an underestimation of risk) or risk tolerance.

[Insert Table II here]

Table II reports some basic forecast statistics. We split these statistics by suppliers and customers as well as by whether the forecast is for quarterly or yearly earnings. We report both the management forecast, and the realized earnings. All quantities are expressed in percent of the stock price. The average (median) annual earnings forecast is 6.46 (6.16) percent for suppliers. At 6.16 (6.10) percent, the average realized earnings are slightly lower, resulting in a small positive forecast error on average. Quarterly forecasts are slightly lower than actuals, both for suppliers and for customers, on average and at the median. The forecast horizon for yearly (quarterly) forecasts is between 200 and 230 (80 and 90) days, on average.

One potential concern with using management forecasts might be that they may not reflect the true views of management, possibly because managers dislike to report a shortfall relative to their own forecast and therefore tend to issue conservative forecasts. In this case, management forecasts could mainly reflect strategic considerations rather than actual expectations, and our measure could thus be a poor measure of beliefs.

We address this concern in two ways. First, we examine CEOs' insider trading behavior in the months prior to the issuance of a forecast. If a management team holds excessively high expectations of future earnings, and the market has more accurate expectations, then the executives will perceive their company's stock as undervalued in the months prior to the issuance of the forecast. Hence we would expect net purchases of own-firm stock by top managers to be positively correlated with management forecasts.

[Insert Table III here]

Panel A of Table III confirms the insider trading prediction for CEOs. The table reports regressions of net purchases by CEOs in the twelve months prior to the forecast issuance. We regress net purchases on the forecast while controlling for realized earnings in order to isolate the effect of biases on trading behavior. Column 1 shows a univariate regression, column 2 adds firm-level controls, column 3 adds firm fixed effects, and column 4 adds year fixed effects. In all specifications, forecasts are strongly positively associated with CEOs' net share purchases. In the most stringent specification (column 4), a one percentage point increase in forecast optimism is associated with net purchases in the amount of $664,000. In untabulated regressions we find similar results for non-CEO executives and the statistical significance of the relationship is as strong for non-CEOs as for CEOs. Quantitatively, the coefficients are about half as large for non-CEOs as for CEOs, consistent with their smaller company-linked wealth.[5]

Second, we analyze the market reaction around the announcement of realized earnings. If earnings guidance was purely strategic, and the market understood this, one should not observe a negative (positive) market reaction to an optimistic (pessimistic) forecast at the announcement of the actual earnings, because investors would not have much trust in the management forecast.[6]

In contrast, Panel B of Table III shows a strong positive reaction to a pessimistic forecast and a negative reaction to an optimistic forecast when realized earnings are announced. Specifically, we split the sample into terciles with respect to the management forecast error, and compute the average and median buy-and-hold abnormal returns (BHARs) around the announcement date within each tercile. The mean difference in the 3-day buy-and-hold abnormal announcement return is 4.63 percent, the median difference is 3.81 percent. Both are highly statistically significant. For the longer 11-day window,

[5] One could also think of relating forecast optimism to the overconfidence measures proposed by Malmendier and Tate (2005). One important difference is that Malmendier and Tate aim at identifying overconfidence as a *permanent* managerial attribute while our approach seeks to quantify the *time-varying* component of optimism. Thus, the measures are not directly comparable. However, one can construct a time-varying *Holder67* measure by classifying a manager as overconfident in a given year if, in that year, he fails to exercise deep in-the-money options. Using this time-varying proxy for overconfidence, we find a significant negative correlation with the forecast range (t-statistic of -2.84) but not with the forecast itself. In other words, wider forecast ranges (which indicate less confidence in the forecast) are associated with earlier option exercise.

[6] By extension, if the market understood the strategic nature of the forecasts, then suppliers should also understand this and thus should not be influenced by their customers' forecasts. This would bias our main results against finding a positive correlation between customer and supplier forecasts.

the difference in announcement returns between tercile one and three is 5.49% and 4.87%, for the mean and the median, respectively. Figure 1a (1b) plots the average BHARs for a 5-day (20-day) window around the announcement. This indicates that, indeed, the market believes the management forecast.

Taken together, the above evidence indicates that management forecasts do reflect the actual beliefs of the management team.

IV. Results

A. Main Results

We proceed by analyzing whether sentiment is contagious across the customer-supplier chain. Table IV contains our main regression results. Column 1 shows the correlation between customer and supplier optimism after controlling for the supplier's and customers' actual earnings as well as forecast characteristics. Here, we use the sales-weighted customer forecast as our main independent variable of interest.[7] Therefore, the coefficient needs to be interpreted as the increase in supplier optimism corresponding to a one-unit increase in the optimism of a customer with a hypothetical sales share of 100%. We obtain a highly significant and economically sizable coefficient of 0.614, that is a pass-through rate of sentiment from customers to suppliers of 61.4%.

We gradually add firm-level controls and fixed effects for suppliers and calendar quarters in the following columns. Adding supplier fixed effects removes any potential time-invariant unobservables affecting supplier forecasts while quarter fixed effects control for

[7]We use the sales weights corresponding to the actual sales, that is, we do not rescale sales weights if the sales of the reported customers do not add up to one.

quarter-specific market-wide waves of sentiment. Column 5 shows our preferred specification, which includes firm-level controls and supplier as well as quarter fixed effects. The coefficient slightly decreases after including supplier fixed effects but remains highly statistically significant and, with a pass-through rate of 54.6%, economically large.

Next, in columns 6 and 7 we replace quarter fixed effects with customer industry-quarter fixed effects thereby only relying on variation in customer optimism that is not shared by its industry peers in a given quarter. This specification eliminates the potential effect of customer-industry-specific waves of sentiment. Again, the coefficient remains largely unchanged.

[Insert Table IV here]

Finally, we take an alternative approach in columns 8 and 9. Instead of using the sales-weighted average of customer forecasts, we keep each customer forecast as a separate observation and include fixed effects for customer-supplier pairs as well as calendar quarters (column 8) or customer industry-calendar quarters (column 9). Hence, the coefficient of interest is identified off customer-supplier pair specific sentiment changes while controlling for common variation in quarters or in industries and quarters. The coefficient remains highly significant which indicates that sentiment contagion is specific to customer-supplier relationships and exists within a given industry and quarter. Compared with columns 1 to 7, the coefficient drops to 0.167 (column 8) and 0.134 (column 9). Crucially, the decline in the coefficient is a mechanical consequence of using each individual customer forecast instead of the sales-weighted average of customer forecasts. As a result, we can no longer interpret the coefficient as the effect of a hypothetical customer representing 100% of the supplier's sales but rather as the effect of the average customer in our sample (which has a mean sales share of 17%).

Unsurprisingly, the supplier's actual is highly correlated with the supplier's forecast. This also explains why the R-squared in column 1 is 86.5% and increases further with additional controls and fixed effects. As expected, we also find a positive coefficient on the forecast horizon and a negative coefficient on the dummy variable for quarterly earnings forecasts, indicating greater optimism for long-range forecasts. This is consistent with Ben-David, Graham, and Harvey (2013) who show that long-range forecasts by CFOs are more optimistic than short-term forecasts.[8]

To further corroborate the customer-supplier link as the main channel through which sentiment contagion occurs, Table V provides regressions in which we repeat the specification shown in Table IV, column 5, but in addition investigate the cross-sectional variation in contagion. Table V makes use of the range of the suppliers' forecasts, that is, the difference between the upper and the lower bound of forecasted earnings. The forecast range is comparable with a confidence interval: while a point estimate by the management signals confidence and certainty about future earnings, a wide interval suggests that the supplier management is less certain about how earnings will eventually turn out. Arguably, in a situation of high uncertainty, customer forecasts become more important reference points for a supplier's management and hence bias propagation should be more pronounced.

[Insert Table V here]

In columns 1 and 2, we build on this notion and run separate regressions on the

[8] We control for these variables in all our regressions, but do not show them in subsequent tables to conserve space.

subsamples with zero and positive ranges of supplier forecasts. Alternatively, in column 3 we use the full sample and include an interaction term of the forecast range with customer optimism. All these regressions show that sentiment propagation is stronger when suppliers are less certain about future profits. Comparing column 1 with column 2 shows that our main results in Table IV are driven by firms whose management are less certain about future profits. Column 3, which uses the interaction term, corroborates these results. The greater the supplier's uncertainty about future profits, the larger is the belief propagation from its customers.

In columns 4 to 7 we separate customers by their importance to their suppliers. In columns 4 and 5, we use the sales share as a measure of customer importance, and investigate whether customers with larger sales shares are more influential in affecting suppliers' beliefs. Motivated by the results from columns 1 to 3, we run these regressions on the subsamples with zero and non-zero ranges; the results are thereby akin to a triple interaction. We would expect more important customers to have more influence on their suppliers' forecasts, but only if those suppliers are uncertain about their forecast. This is indeed what we find: a larger sales share increases the sentiment propagation from customer to supplier, and this effect is concentrated among suppliers who are uncertain about their forecast.

In columns 6 and 7 we take an alternative approach to measuring customer importance by using the excess correlation of stock returns between customers and suppliers. The correlation between a customer's and a supplier's stock return is a market-based measure of how important a signal from the customer might be to the supplier. Similar to before, we find that customer sentiment impacts supplier sentiment significantly more when the stock return correlation is higher; and this effect is again concentrated among suppliers that exhibit greater uncertainty in their forecast.

B. Falsification Tests

Table VI serves as our first falsification test. If suppliers made use of their customers' forecasts to produce their own forecast, they should only be using the most recent rather than older, stale customer forecasts. For each supplier, we therefore obtain the most recent customer forecast (or revision thereof) for several time intervals. Specifically, period *t-1* spans the four months prior to the issuance of the supplier's forecast, that is, calendar days [-1, -120] relative to the announcement of the supplier's forecast. Likewise, periods *t-2* and *t-3* correspond to the windows [-121, -240] and [-241, -360] while *t+1* references the window [1, 120]. Importantly, in each interval, we use the customer forecast that is issued the *closest* to the supplier's forecast, that is, we use the latest one within any time period before the supplier's forecast announcement, and the earliest one within period *t+1.*

[Insert Table VI here]

Columns 1 to 5 of Table VI show that more recent forecasts by customers have indeed more influence on supplier forecasts: moving from column 1 to column 3, significance levels steadily decline and the coefficient is smallest for window *t-3.* We include several customer forecasts simultaneously in columns 4 and 5: the largest and the only signficant customer forecast is the most recent one while older and stale customer forecasts are insignificant. Finally, in columns 6 and 7 we add the customer forecast issued in the time window that succeeds the supplier's forecast date. As this is information which is not yet available to the supplier at the time of his forecast announcement, it should not affect supplier sentiment. In column 6 we use the leading, period *t+1*, customer forecast only. It remains weakly significant. This may be due to autocorrelation in the forecasts, so that the future forecast may proxy for the current forecast. In column 7, we therefore include both the lagged and leading customer forecast. Now, only the lagged customer forecast remains statistically significant. Taken together, the results in Table VI indicate that the supplier uses primarily the most recent rather than stale or future information from the customer when generating a forecast.

[Insert Figure 2 here]

Figure 2 provides a second falsification test to rule out spurious correlation between customer and supplier sentiment and to rule out contagion that is due to reasons other than those related to the specific customer-supplier pair. We run placebo regressions of our preferred specification of Table IV, column 5. Specifically, we run this specification using randomly drawn same-industry pseudo-customers instead of the actual customers, repeat this procedure 1,000 times, and plot a histogram of the 1,000 coefficients on the sales-weighted customer forecast variable. If the correlation between customer and supplier sentiment that we document in Table IV was driven by factors common to the customer or supplier industries at the time the forecasts were issued, and were not specific to the customer-supplier link, one would expect a similar coefficient in the pseudo-customer regressions. If, however, the coefficient of 0.546 from Table IV, column 5, is in the 99th percentile of the distribution of pseudo-customer regression coefficients, the probability that our results are due to industry effects as opposed to customer-supplier-specific belief spillovers is less than 1%.

Figure 2(a) shows the distribution of pseudo-customer regression coefficients when industries are defined using the Fama-French 48-industry classification. Figure 2(b) shows the same distribution of coefficients when we use Hoberg-Phillips text-based network industry classifications. Our estimated coefficient of 0.546 lies far above even the highest pseudo-customer coefficient out of 1,000 draws, regardless of which industry classification we use. This confirms that the sentiment spillover that we document is specific to customer-supplier pairs.

C. Real Effects

Existing literature documents that managerial optimism and overconfidence affect corporate policies (Malmendier and Tate (2005); Malmendier, Tate, and Yan (2011); Ben-David, Graham, and Harvey (2013); Graham, Harvey, and Puri (2013)). In this section, we investigate whether sentiment, as expressed in companies' earnings forecasts, affects corporate policies, and, more importantly, whether propagated sentiment also entails such real effects.

[Insert Table VII here]

We start by investigating whether management sentiment is associated with the firm's own corporate policies. If management is optimistic about the firm's earnings prospects, it may take actions in line with those expectations. In Table VII we test for changes in net book leverage, cash, inventories and capital expenditures. Importantly, we again control for realized earnings to isolate the effect of the management's bias on corporate decisions. As optimism indicates an expectation for greater sales, we expect capital expenditures and inventories to increase, cash holdings to decrease and net book leverage to increase.[9]

In our tests, we use only annual forecasts with a remaining forecast horizon between 180 and 365 days. We further ignore any revisions during this period and keep only the earliest forecast. We use relatively long-horizon forecasts for two reasons: First, this allows for significant time to pass before the realized earnings become known. Biased expectations should have a greater effect on corporate decisions the further in the future the error in the forecast is revealed. Second, it ensures that enough time passes for firms to implement changes to corporate policy, given that typically policy changes occur infrequently. This timing convention biases us against finding significant real effects of sentiment, as the management may obtain more precise information about the later realized earnings in the months following the forecast issuance and cancel planned decisions. We thus view the estimated effects as a lower bound of the true effects.

For each of the four policies we show the results without fixed effects, with year fixed effects, and with industry and year fixed effects combined. In line with expectations, we find that sentiment is associated with higher book leverage and lower cash holdings as well as with higher inventories and more capital expenditures. For net book leverage, cash and inventory, the coefficients are highly significant with t-statistics above 5. For capital expenditures, the coefficient is positive but becomes insignificant after including industry fixed effects.

[9] We use book leverage instead of market leverage as forecast optimism is scaled by the stock price, which might lead to a mechanical correlation with market leverage.

[Insert Table VIII here]

In our final tests we analyze whether there are also real effects of *propagated* sentiment on the suppliers' policies. Specifically, we estimate propagated sentiment as the component of a supplier's sentiment that is predicted by its customers' sentiment by using the customers' sales-weighted forecast as an instrument for the supplier's forecast. As in our previous tests, and for the same reasons, we again use only annual forecasts with a forecast horizon of 180 to 365 days. As we now require matched customer forecasts for each supplier forecast in the first stage, the sample size drops by more than half compared to Table VII. With values of about 40, our first-stage F-statistics indicate that there are no weak instrument issues.[10] As in the previous table, we show three regressions for each corporate policy, one without fixed effects, one with year fixed effects, and one with industry and year fixed effects combined. For instance, column 1 shows that, net book leverage increases by 5.257 percentage points with a one-unit increase in optimism. In our most stringent specification using both industry and year fixed effects, the coefficient drops to 1.799 and remains significant at the ten percent level. Similarly, cash holdings decrease by 1.610 percentage points, while inventory and capital expenditures increase by 0.795 and 0.155, respectively. These effects are economically large: A one standard deviation increase in propagated sentiment leads to a 0.38 standard deviation increase in net book leverage, a 0.34 standard deviation decrease in cash holdings, and a 0.31 and 0.22 standard deviation increase in inventories and capital expenditures, respectively.

[10] The first stage of this regression corresponds to Table IV, except that it uses a smaller sample. The lowest t-statistic of the sales-weighted customer forecast in the first stage regressions is 6.5.

V. Conclusion

We study how sentiment spreads across firms via customer-supplier relationships. We use the beliefs embedded in firms' EPS forecasts to measure fluctuations in management sentiment and use a regression framework that is able to separate the propagation of biases in expectations from the propagation of rational expectations. Our main contribution is to document a strong positive relationship between customer and supplier sentiment: a one-unit increase in sentiment of a hypothetical customer representing 100% of the supplier's sales, leads to a 0.40 to 0.60 unit increase in supplier sentiment, or a 40% to 60% sentiment pass-through rate. This result holds in univariate as well as multivariate tests controlling for a range of company and forecast characteristics and numerous fixed effects.

Several falsification tests address causality concerns. First, we repeatedly replace actual customers' forecasts with the forecasts of pseudo-customers (non-customers from the same industry); our actual-customer coefficient consistently lies in the top 0.1% of the empirical distribution of pseudo-customer coefficients. This shows that sentiment contagion is specific to the customer-supplier relationship and is not driven by market-wide or industry-specific sentiment waves. We also show that sentiment spillovers only occur for customer forecasts that are issued *before* a supplier's forecast, and not (shortly) after, and that the effect is stronger for more recent customer forecasts.

Subsample tests document that sentiment contagion is more pronounced among suppliers that are less confident about their forecast, in other words, when they issue a forecast range instead of a point estimate and, conditional on issuing a range, when the forecast range is wider. The spillover effect also strengthens when customers are more important or more salient, such as when they have a greater sales share or exhibit greater correlation with their supplier's stock return.

Finally, we investigate the real effects of sentiment. When examining the direct effects of management optimism on its own firm's policies, we find a strong effect on book leverage, inventory, investment and cash holdings. Importantly, we also find similar effects on suppliers' firm policies when using propagated sentiment, estimated as the component of a supplier's sentiment that is predicted by its customers' sentiment.

The results on real effects are important because they show not only that beliefs propagate between individuals or groups that communicate with each other, but that these propagated beliefs lead management teams to make decisions that they would not have made otherwise. It is hence conceivable that initial shocks to the beliefs of managers of large corporations could have significant aggregate effects on the amount and structure of investment and financing in the greater economy. First, because initial shocks to beliefs in large firms spread across many firms – to all proximate suppliers as well as to the suppliers of suppliers across the entire value chain. And second, because those beliefs would affect corporate decisions in all of these firms. Such effects could be regarded as the corporate analogue to the sentiment-driven stock market bubbles described by Shiller (2000, Ch. 8).

Our findings document one specific channel through which sentiment spreads among a specific group of economic agents: corporate managers. Of course, contagion of beliefs is likely to be a much more general phenomenon, occurring between different types of economic agents, operating through different channels and affecting various types of decisions. Identifying other channels of transmission and other effects of that transmission could contribute to our understanding of belief propagation in economic networks.

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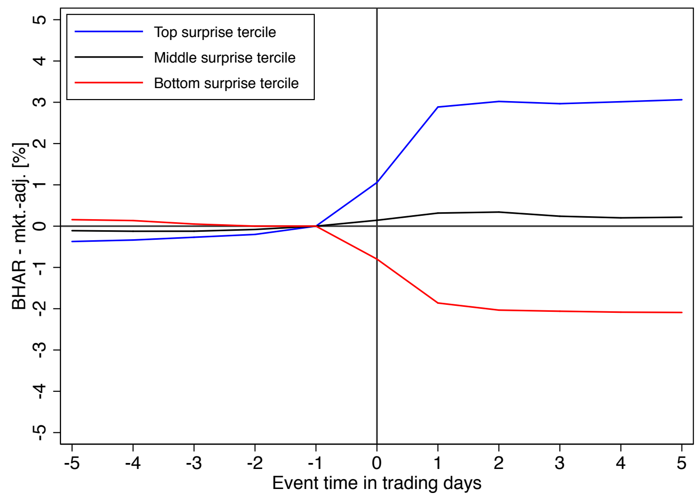
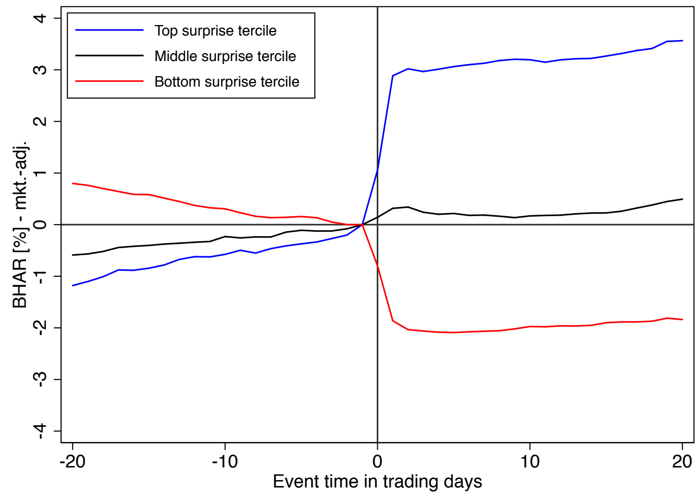
Figures and Tables

Figure 1
Market reaction to earnings announcements of optimistic, neutral and pessimistic forecasts



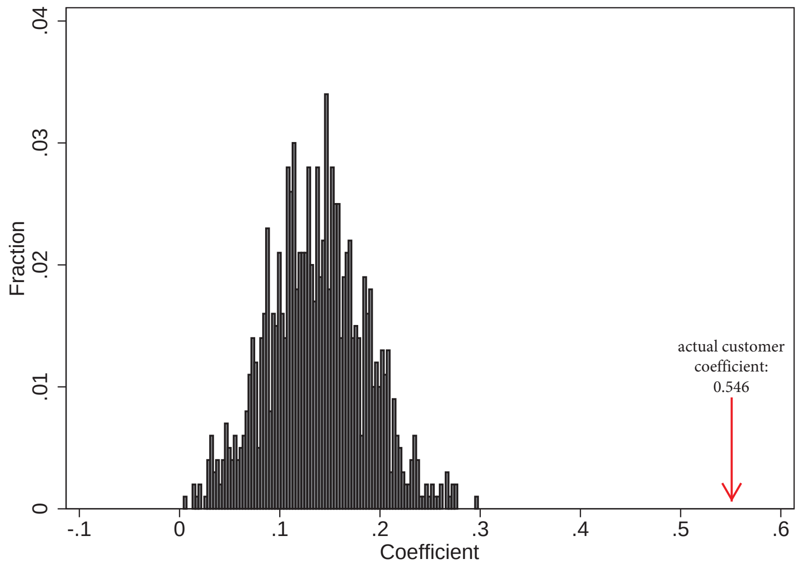
(a) Event window: ± 5 trading days



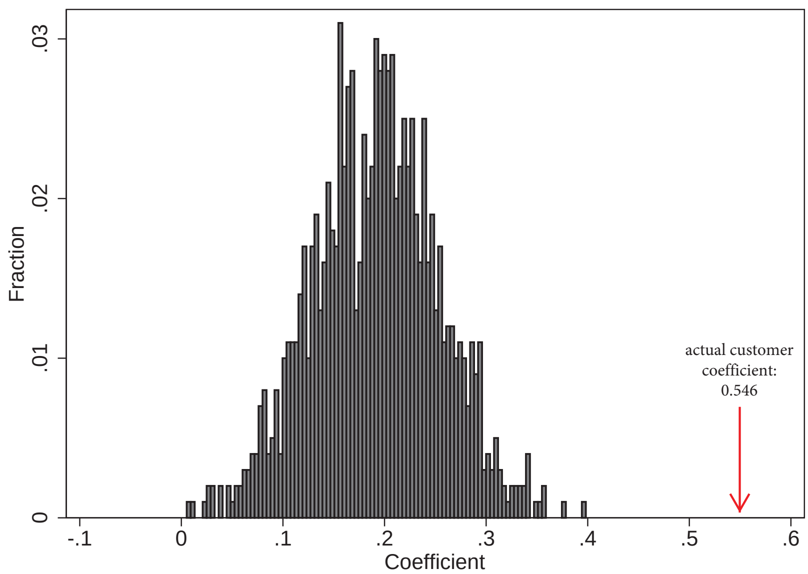
(b) Event window: ± 20 trading days

Figure 2
Distribution of coefficients using bootstrapped pseudo-customers

We re-run our main specification (Table IV, column 5) 1,000 times and replace in each run the suppliers' actual customers with pseudo-customers that are randomly drawn from the same industry. Figure (a) [(b)] shows the empirical distribution of the pseudo-customers' forecast optimism coefficient when randomly drawing pseudo-customers from the same Fama-French 48 industry [Hoberg Phillips TNIC industry]. If a common customer or supplier industry factor (e.g., an aggregate optimism wave) was leading to the optimism spillover, we would expect the empirical distributions of the pseudo-customers to be overlapping with the coefficient from the actual customer. We display the coefficient from Table IV, which lies above the maximum value of both empirical distributions.



(a) Pseudo-customers drawn from Fama-French 48 industries



(b) Pseudo-customers drawn from Hoberg-Phillips TNIC industries

Table I
Descriptive Statistics

Panel A shows descriptive statistics on our customer-supplier matched sample. The data originates from COMPUSTAT's customer segment files; as the segment files do not provide any firm identifiers, a string-matching algorithm was used to obtain CRSP PERMNO identifiers. We include suppliers and customers with management guidance data in Thomson Reuter's IBES as well as stock price information in CRSP. Panel B shows supplier and customer firm characteristics as obtained from COMPUSTAT.

Panel A: Basic statistics

	Min	P10	P25	Median	Mean	P75	P90	Max	SD
# suppliers per year	56.00	136.00	139.00	150.50	162.92	200.00	220.00	245.00	49.52
# customers per year	24.00	54.00	63.00	70.00	73.17	89.50	104.00	104.00	22.69
# customers per supplier	1.00	1.00	1.00	1.00	1.57	2.00	3.00	5.00	0.79
Pct. of sales to customer	0.00	0.08	0.11	0.15	0.17	0.20	0.29	0.91	0.11
C/S beta (stock return correl.)	-0.50	-0.05	0.03	0.10	0.10	0.16	0.25	0.83	0.13

Panel B: Customer and supplier firm characteristics

	Suppliers				Customers			
	Median	Mean	SD	N	Median	Mean	SD	N
Total assets [$bn]	0.89	5.05	15.91	1,921	18.42	44.61	95.44	570
Sales [$bn]	0.83	4.43	11.47	1,921	20.27	40.41	61.06	570
Market value [$bn]	1.56	9.48	29.12	1,921	29.12	72.35	127.08	570
Market-to-book	1.60	1.99	1.23	1,921	1.64	1.90	0.91	570
PP&E	0.13	0.16	0.13	1,921	0.19	0.25	0.19	570
Profitability	0.12	0.11	0.12	1,921	0.15	0.15	0.06	570
Book leverage	0.17	0.20	0.18	1,921	0.23	0.24	0.15	570
Net book leverage	0.02	-0.02	0.32	1,921	0.13	0.13	0.21	570
Capex	0.03	0.03	0.03	1,921	0.03	0.04	0.03	570
Inventory	0.10	0.13	0.11	1,918	0.11	0.15	0.12	570
Cash	0.14	0.21	0.20	1,921	0.08	0.11	0.11	570

Table II
Management Forecasts: Descriptive Statistics

The table shows descriptive statistics for our sample of management forecasts, separated by suppliers and customers and separated by whether the guidance applies to an annual or quarterly report. Forecasts and realized earnings (actuals) are scaled by the stock price five days prior to forecast announcement. *Forecast horizon* is the number of days between the date of guidance issuance and the fiscal period end to which the guidance applies.

	Mean	Median	SD	N
	Panel A: Suppliers			
Annual forecast [%]	6.46	6.16	3.39	6,250
Annual actual [%]	6.16	6.10	3.78	6,250
Quarterly forecast [%]	0.95	1.09	1.59	3,547
Quarterly actual [%]	1.06	1.17	1.68	3,547
Annual forecast horizon [days]	231.72	217.00	105.51	6,250
Quarterly forecast horizon [days]	80.55	91.00	27.68	3,547
	Panel B: Customers			
Annual forecast [%]	6.70	6.87	2.15	6,392
Annual actual [%]	6.80	6.91	2.23	6,392
Quarterly forecast [%]	1.52	1.65	1.25	3,553
Quarterly actual [%]	1.61	1.76	1.30	3,553
Annual forecast horizon [days]	203.00	230.90	110.78	6,392
Quarterly forecast horizon [days]	90.00	77.71	29.68	3,553

Table III
Management Forecasts: Insider Trading and Market Reaction

Panel A shows net purchases of own-firm shares by management in the 12 months *prior to the issuance* of an optimistic management forecast between 2003 and 2014 while controlling for the realization of earnings (*actual*). Firm-level controls include *Log assets*, *Tobin's Q*, *Profitability* and *PP&E*. The data originates from Thomson Reuters' Insider Filings database. Panel B shows the buy-and-hold abnormal returns between the top and bottom tercile of earnings surprises in either a 3-day or 11-day event window around the announcement of the actual EPS.

Panel A: Management optimism and CEO net share purchases

Dept. variable:	Net share purchases (in dollars)			
	(1)	(2)	(3)	(4)
Forecast	875,206***	767,299***	704,631***	663,889***
	(7.06)	(7.15)	(7.45)	(6.98)
Observations	13,036	12,773	12,773	12,773
R-squared	0.017	0.150	0.578	0.584
Firm-level controls	No	Yes	Yes	Yes
Firm FEs:	No	No	Yes	Yes
Year FEs:	No	No	No	Yes

Panel B: Market Reaction to earnings surprises relative to guidance

	Mean difference test		Median difference test	
Event window [days]:	[-1,+1]	[-5,+5]	[-1,+1]	[-5,+5]
Mean/median in top tercile	2.69	3.23	2.30	2.70
Mean/median in bottom tercile	-1.94	-2.26	-1.51	-2.17
Difference	-4.63	-5.49	-3.81	-4.87
t-statistic/z-statistic	-36.99	-31.80	-36.40	-32.89

Table IV
Sentiment Propagation: Main Results

The table shows the correlation between supplier and customer optimism controlling for firm characteristics and a set of fixed effects. Columns 1 to 7 use unscaled, sales-weighted customer forecasts so that the coefficient is interpreted as the effect of a one-unit increase in optimism of a customer representing 100% of supplier sales. *Customer actual* and *Supplier actual* are the customer's and supplier's realized EPS, respectively. *Forecast horizon* is the number of days between the announcement of the forecast and the fiscal period end to which the forecast applies. *Quarterly earnings forecast* is an indicator variable which equals 1 for quarterly forecasts and 0 for annual forecasts. Customer industry fixed effects use the customer's Fama-French 48 industry classification. All results include standard errors that are clustered at the supplier level.

Dept. variable:					*Supplier forecast*				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Customer forecast, sales-weighted	0.614***	0.657***	0.582***	0.636***	0.546***	0.568***	0.416***		
	(5.89)	(6.48)	(6.61)	(6.26)	(6.80)	(5.14)	(4.77)		
Customer actual, sales-weighted	-0.511***	-0.534***	-0.460***	-0.510***	-0.443***	-0.407***	-0.348***		
	(-4.96)	(-5.20)	(-4.95)	(-5.21)	(-5.19)	(-3.61)	(-3.74)		
Supplier actual	0.772***	0.745***	0.676***	0.745***	0.662***	0.735***	0.648***	0.642***	0.627***
	(30.73)	(29.51)	(27.01)	(28.70)	(25.97)	(26.82)	(22.77)	(21.82)	(19.70)
Forecast horizon	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(5.29)	(5.36)	(5.06)	(5.47)	(5.41)	(5.36)	(5.26)	(4.78)	(4.65)
Quarterly earnings forecast	-1.110***	-1.232***	-1.578***	-1.228***	-1.630***	-1.184***	-1.721***	-1.708***	-1.823***
	(-8.52)	(-9.32)	(-11.54)	(-9.12)	(-11.76)	(-8.30)	(-11.26)	(-9.84)	(-9.68)
Log assets		0.013	0.382***	0.016	0.367***	-0.017	0.340***	0.484***	0.444***
		(0.60)	(5.08)	(0.75)	(4.04)	(-0.60)	(3.27)	(4.31)	(3.48)
Tobin's Q		-0.239***	-0.015	-0.248***	-0.006	-0.222***	-0.033	0.007	-0.009
		(-7.07)	(-0.53)	(-7.22)	(-0.23)	(-6.21)	(-1.03)	(0.21)	(-0.22)
PP&E		-0.463*	-0.214	-0.486*	-0.232	-0.655*	-0.491	0.428	0.438
		(-1.68)	(-0.31)	(-1.79)	(-0.33)	(-1.86)	(-0.55)	(0.56)	(0.45)
Customer forecast								0.167***	0.134***
								(4.35)	(3.03)
Customer actual								-0.138***	-0.114**
								(-3.55)	(-2.57)
Observations	7,586	7,518	7,518	7,518	7,518	7,518	7,518	9,653	9,653
R-squared	0.865	0.870	0.923	0.873	0.925	0.890	0.933	0.926	0.933
Supplier FEs:	No	No	Yes	No	Yes	No	Yes	No	No
Quarter FEs:	No	No	No	Yes	Yes	No	No	Yes	No
Customer industry x quarter FEs:	No	No	No	No	No	Yes	Yes	No	Yes
Customer-Supplier FEs:	No	No	No	No	No	No	No	Yes	Yes

Table V
Sentiment Propagation: Cross-sectional Variation

The table documents a strengthening correlation between customer and supplier optimism when the customer is more likely to be a focal point to the supplier management. Columns 1 and 2 divide the sample into supplier forecasts where suppliers are confident about their forecast (zero range and point estimates only) and supplier forecasts where suppliers have less confidence in their forecast (non-zero range). Column 3 shows that the correlation strengthens as the supplier's level of confidence declines as evidenced by a rising forecast range. Columns 4 and 5 show a stronger propagation of sentiment for customers that represent larger sales shares, but again only when the supplier has less confidence about its own forecast (column 5). Columns 6 and 7 document that the sentiment propagation strengthens with an increasing correlation between customer and supplier stock returns, but again only when the supplier has less confidence about its own forecast (column 7). Included firm-level controls are identical with those shown in Table IV and include *Customer actual*, *Supplier actual*, *Forecast horizon* and *Quarterly earnings forecast*. Customer industry fixed effects use the customer's Fama-French 48 industry classification. All results include standard errors that are clustered at the supplier level.

Dept. variable:				*Supplier forecast*			
Sample:	Zero range	Non-zero range	Full	Zero range	Non-zero range	Zero range	Non-zero range
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Customer forecast, sales-weighted	0.255	0.401***	0.001				
	(0.44)	(4.93)	(0.01)				
Forecast range			0.472*				
			(1.79)				
Forecast range × *customer forecast*			0.475***				
			(3.02)				
Sales share				0.599	-0.372		
				(0.41)	(-0.75)		
Sales share × *customer forecast*				-0.224	0.397***		
				(-0.47)	(3.47)		
C/S-beta						1.640	-0.994*
						(0.93)	(-1.91)
C/S-beta × *customer forecast*						-0.257	0.578**
						(-0.36)	(2.20)
Customer forecast				0.113	0.032	0.047	-0.010
				(0.88)	(0.67)	(0.44)	(-0.25)
Observations	1,269	6,249	6,249	1,615	8,038	1,427	7,362
R-squared	0.969	0.934	0.935	0.962	0.936	0.964	0.940
Firm-level controls:	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Supplier FEs:	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Customer industry × quarter FEs:	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table VI
Sentiment Propagation: Leads and Lags

The table documents that timing is crucial for the propagation of sentiment from the customer to the supplier. Each time period represents a 4 month window such that $t+1$ ($t-1$) are the 4 calendar months just following (just prior to) the day of the supplier's forecast announcement. Likewise, $t-2$ ($t-3$) represents the months 5-8 (9-12) prior to the supplier's forecast announcement. In each window, we use customers' *closest* forecasts, that means the most recent ones (the earliest ones) in time periods before (after) the supplier's forecast announcement. The set of control variables included are identical with those shown in Table IV and include the *Customer actual*, *Supplier actual*, *Forecast horizon* and *Quarterly earnings forecast*. Customer industry × quarter fixed effects use the customer's Fama-French 48 industry classification. All results include standard errors that are clustered at the supplier level.

Dept. variable:				*Supplier forecast*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Customer forecast [t+1]						0.386*	-0.099
						(1.89)	(-0.35)
Customer forecast [t-1]	0.534***			0.640***	0.547***		0.552**
	(3.67)			(3.70)	(3.61)		(2.11)
Customer forecast [t-2]		0.578***		0.322	0.295		
		(2.94)		(1.60)	(1.62)		
Customer forecast [t-3]			0.337	0.132			
			(1.35)	(0.47)			
Log assets	0.358***	0.427***	0.483***	0.502***	0.414***	0.348***	0.363***
	(2.71)	(2.98)	(3.13)	(3.35)	(3.02)	(2.84)	(2.92)
Tobin's Q	-0.006	-0.012	0.010	0.027	0.011	-0.005	0.004
	(-0.15)	(-0.25)	(0.21)	(0.50)	(0.22)	(-0.11)	(0.09)
PP&E	-0.693	-0.485	-0.597	-0.200	-0.531	-0.544	-0.738
	(-0.59)	(-0.38)	(-0.42)	(-0.12)	(-0.38)	(-0.41)	(-0.52)
Observations	4,123	4,082	3,941	3,319	3,689	3,784	3,530
R-squared	0.937	0.935	0.937	0.941	0.938	0.936	0.938
Supplier FEs:	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Customer industry × quarter FEs:	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table VII
Real Effects of Sentiment

The table shows the correlation between the optimism of a firm's management and its *own* corporate policies. To allow for sufficient time for firm characteristics to change and to avoid a quick realization of an overly optimistic forecast, we exclude quarterly forecasts and retain only annual forecasts with a remaining forecast horizon between 180 and 365 days. We further ignore any revisions and only keep the earliest forecast. *Actual* is the firm's realized EPS. The corresponding balance sheet information of firms is obtained from COMPUSTAT's annual fundamental file; the dependent variables have been scaled by 100. Industry fixed effects are based on Fama-French 48 industry classification. All results include standard errors that are clustered at the firm level.

Dept. variable:	*Net book leverage*			*Cash*			*Inventory*			*Capital expenditures*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Forecast	2.012***	2.130***	2.246***	-0.970***	-1.052***	-1.013***	0.922***	0.991***	0.558***	0.040*	0.046**	0.023
	(9.53)	(9.79)	(10.86)	(-8.31)	(-8.81)	(-8.77)	(6.80)	(7.07)	(5.69)	(1.79)	(2.02)	(1.03)
Actual	-0.830***	-0.787***	-0.777***	0.441***	0.423***	0.412***	-0.421***	-0.399***	-0.102	-0.133***	-0.114***	-0.087***
	(-4.94)	(-4.67)	(-4.72)	(4.88)	(4.65)	(4.65)	(-4.01)	(-3.79)	(-1.39)	(-6.13)	(-5.23)	(-4.24)
Ln(total assets)	4.258***	4.265***	4.229***	-1.927***	-1.939***	-1.940***	-1.034***	-1.056***	-1.022***	-0.354***	-0.367***	-0.274***
	(13.32)	(13.11)	(12.96)	(-11.77)	(-11.63)	(-11.16)	(-5.71)	(-5.82)	(-7.11)	(-8.81)	(-9.20)	(-5.86)
Tobin's Q	-0.068***	-0.069***	-0.061***	0.052***	0.053***	0.046***	-0.014***	-0.015***	-0.005***	0.002***	0.002***	0.003***
	(-13.66)	(-13.20)	(-12.15)	(16.40)	(15.86)	(14.29)	(-5.96)	(-5.92)	(-3.09)	(3.10)	(3.51)	(4.89)
Profitability	0.351***	0.354***	0.263***	-0.317***	-0.322***	-0.272***	0.317***	0.313***	0.055**	0.092***	0.087***	0.063***
	(4.44)	(4.44)	(3.23)	(-7.11)	(-7.10)	(-5.81)	(7.80)	(7.75)	(2.27)	(8.32)	(7.93)	(5.45)
PP&E	0.371***	0.371***	0.289***	-0.179***	-0.179***	-0.148***	-0.047***	-0.046***	-0.019	0.132***	0.133***	0.148***
	(17.35)	(17.30)	(8.01)	(-16.84)	(-16.75)	(-8.69)	(-3.73)	(-3.70)	(-1.21)	(27.96)	(28.00)	(16.48)
Observations	9,014	9,014	9,014	9,014	9,014	9,014	8,911	8,911	8,911	9,016	9,016	9,016
R-squared	0.374	0.381	0.447	0.362	0.371	0.431	0.073	0.089	0.566	0.494	0.500	0.543
Industry FEs:	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Year FEs:	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes

Table VIII
Real Effects of Propagated Sentiment

The table shows the correlation between a supplier's *propagated* optimism and its corporate policies, where the supplier's forecast is instrumented by its customers' forecasts. To allow for sufficient time for firm characteristics to change and to avoid a quick realization of an overly optimistic forecast, we again only retain forecasts with a horizon of between 180-365 days to allow for sufficient time; among revisions, we only keep each customer's earliest forecast. *Actual* is the firm's realized EPS. The corresponding annual balance sheet information of suppliers is obtained from COMPUSTAT's annual fundamental file; the dependent variables have been scaled by 100. Industry fixed effects are based on suppliers' Fama-French 48 industry classification. All results include standard errors that are clustered at the firm level.

Dept. variable:	*Net book leverage*			*Cash*			*Inventory*			*Capital expenditures*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Forecast	5.257***	5.026***	1.799*	-3.443***	-3.386***	-1.610***	1.201**	1.193**	0.795**	-0.073	-0.083	0.155*
	(4.09)	(3.91)	(1.80)	(-4.72)	(-4.69)	(-2.70)	(2.35)	(2.30)	(2.12)	(-0.90)	(-1.01)	(1.93)
Actual	-2.734**	-2.466**	-0.429	1.886***	1.814***	0.712	-0.664	-0.650	-0.565*	0.008	0.022	-0.133*
	(-2.44)	(-2.20)	(-0.48)	(3.02)	(2.92)	(1.43)	(-1.42)	(-1.35)	(-1.80)	(0.12)	(0.33)	(-1.92)
Customer actual, sales-weighted	-2.614**	-2.406**	-1.022	2.216***	2.189***	1.123*	-0.604	-0.601	0.292	0.052	0.045	-0.024
	(-2.45)	(-2.22)	(-1.01)	(3.58)	(3.51)	(1.87)	(-1.00)	(-1.02)	(0.65)	(0.79)	(0.74)	(-0.42)
Ln(total assets)	5.106***	5.104***	2.524***	-2.145***	-2.111***	-1.093***	-1.338***	-1.339***	-1.343***	-0.265***	-0.276***	-0.110**
	(7.02)	(6.98)	(3.24)	(-5.00)	(-4.86)	(-2.58)	(-4.24)	(-4.22)	(-3.68)	(-6.23)	(-6.28)	(-2.36)
Tobin's Q	-0.058***	-0.061***	-0.061***	0.046***	0.047***	0.044***	-0.018***	-0.018***	-0.009**	0.002*	0.002*	0.003***
	(-4.68)	(-4.86)	(-5.56)	(5.50)	(5.60)	(5.56)	(-3.85)	(-3.87)	(-2.55)	(1.65)	(1.80)	(3.24)
Profitability	0.091	0.110	0.017	-0.165	-0.174	-0.068	0.113	0.112	0.005	0.020	0.019	0.013
	(0.44)	(0.54)	(0.10)	(-1.45)	(-1.52)	(-0.71)	(1.58)	(1.55)	(0.12)	(1.35)	(1.31)	(0.98)
PP&E	0.727***	0.728***	0.382***	-0.418***	-0.425***	-0.292***	0.002	0.004	0.007	0.160***	0.161***	0.190***
	(7.35)	(7.38)	(3.33)	(-7.71)	(-7.72)	(-5.20)	(0.05)	(0.09)	(0.15)	(12.85)	(12.84)	(12.05)
Observations	3,657	3,657	3,657	3,657	3,657	3,657	3,657	3,657	3,657	3,657	3,657	3,657
R-squared	0.394	0.406	0.556	0.388	0.400	0.536	0.112	0.117	0.444	0.489	0.497	0.578
Industry FEs:	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Year FEs:	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
F-stat of excl. instrument	42.58	41.51	43.59	42.58	41.51	43.59	42.58	41.51	43.59	42.58	41.51	43.59

Table IX
Variable Definitions

Variable name	Definition	Data source
Earnings forecast data		
Forecast$_{it}$	The forecast of quarterly and annual EPS issued by the management of company i at time t scaled by the stock price five trading days before the forecast announcement: Forecast$_{it} = \frac{\hat{e}_{its}}{P_{it}}$. EPS guidance data ($\hat{e}_{it}$) are obtained from Thomson Reuters's IBES database. We undo the historical split-adjustment by IBES using CRSP's historical split adjustment factor. We truncate the variable at the 1st and 99th percentile. We also drop a few observations where the forecast has a negative horizon or where a quarterly (annual) forecast has a horizon exceeding 8 (18) months.	IBES, CRSP
Customer forecast$_{it}$*, sales-weighted*	The average forecast of company i's customers at time t, with each customer weighted by its sales share with company i. For each forecast by a supplier, only the most recent forecast with the same periodicity (quarterly or annual) of each of its customers is used. Customer-supplier pairs are obtained from COMPUSTAT's customer segment files for a given time t. Since COMPUSTAT's customer segment files does not provide firm identifiers, we string-match customer names to company names in COMPUSTAT's fundamental annual file. Company i's disclosed sales to his customer are scaled by i's total sales as obtained from COMPUSTAT to calculate sales shares. As-is (i.e., non-rescaled) sales shares at time t are then used as weights to average all customers' optimism for any given supplier at time t. When no sales share is given, we assume the minimum threshold (10%) that triggers following SFAS No. 131 mandatory customer disclosure. We drop a few observations where sales share is negative or exceeds 100% or where the sum of reported sales shares to all customers at a given time t exceeds 100%.	IBES, CRSP, COMPUSTAT, COMPUSTAT customer segment file
Forecast horizon$_{it}$	The number of calendar days between the issuance of an EPS forecast at time t by company i and the fiscal period end date to which the forecast applies.	IBES
Forecast range$_{it}$	The difference between the upper and the lower bound of the EPS forecast as issued by company i at time t. We truncate quarterly and annual ranges separately at the 99th percentile.	IBES
Quarterly earnings forecast$_{it}$	Indicator variable that equals 1 if company i's forecast issued at t is a quarterly forecast, else 0.	IBES
Customer actual$_{it}$	The realized earnings per share announced by customer i for fiscal period s, price-adjusted using the closing price of customer i's stock five trading days before the announcement date. We truncate the scaled customer actuals (separately for quarterly and annual forecasts) at the 1st and 99th percentile.	IBES, CRSP
Customer actual$_{it}$*, sales-weighted*	The average optimism of company i's customers at time t, with each customer optimism value weighted by the sales share from i to that customer. The sales share to any given customer is determined by dividing the disclosed sales to that customer in COMPUSTAT's customer segment file by i's total sales in that year.	IBES, CRSP, COMPUSTAT, COMPUSTAT customer segment file

Table IX - Continued

Variable name	Definition	Data source
Customer-Supplier link data		
C/S beta$_{ij}$	The correlation between the excess daily stock returns of supplier i and the excess daily stock returns of its customer j after controlling for the market risk premium. Computed from stock price data for at least 200 trading days between one year before the earliest date of a disclosed customer-supplier relationship and the latest date of a disclosed relationship. Winsorized at the 0.5th and 99.5th percentile.	COMPUSTAT, COMPUSTAT customer segment file
Sales share$_{ijt}$	The sales share of supplier i at the time of a forecast t to his customer j. When no sales share is given, we assume the minimum threshold (10%) that triggers following SFAS No. 131 mandatory customer disclosure. We drop a few observations where sales share is negative or exceeds 100% or where the sum of reported sales shares to all customers at a given time t exceeds 100%.	COMPUSTAT, COMPUSTAT customer segment file
Balance sheet / control variables		
Ln(assets)$_{it}$	The natural logarithm of 1 plus company i's total assets (AT) in millions of USD at the end of fiscal year t.	COMPUSTAT
Market value of assets$_{it}$	Market value of assets of company i in millions of USD at the end of fiscal year t. Calculated as book value of assets (AT) plus market value of equity (CSHO*PRCC_F) minus book value of equity (SEQ + TXDITC - PSTKRV).	COMPUSTAT
Sales$_{it}$	Gross sales and the amount of actual millions to customers for regular sales of company i in billions of USD completed during fiscal year t (COMPUSTAT item SALE).	COMPUSTAT
Tobin's Q$_{it}$	Ratio of market value of assets to book value of assets for company i at time t.	COMPUSTAT
PP&E$_{it}$	Total net value of property, plants and equipment (PPENT) divided by total assets (AT) for company i at time t.	COMPUSTAT
Profitability$_{it}$	Operating income before depreciation (OIBDP) divided by total assets (AT) for company i at time t.	COMPUSTAT
Net book leverage$_{it}$	Debt in current liabilities (DLC) plus long term debt (DLTT) minus cash and short-term investments (CHE) divided by total assets (AT) for company i at time t.	COMPUSTAT
Cash$_{it}$	Cash and short-term investments (CHE) divided by total assets (AT) for company i at time t.	COMPUSTAT
Inventory$_{it}$	Total inventories (INVT) divided by total assets (AT) for company i at time t.	COMPUSTAT
Capex$_{it}$	Capital expenditures (CAPX) divided by total assets (AT) for company i at time t.	COMPUSTAT