Bias Propagation in Economically Linked Firms*

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Abstract

We document that managerial biases spread across firms along supply chains. Supporting a causal interpretation, we show that beliefs trickle up the supply chain, not down, and that biases in supplier forecasts are only affected by customer forecasts issued before, not after, the supplier's forecast. We further find that bias propagation increases when suppliers have less confidence in their own views and when the perceived precision and importance of customer forecasts increase. Biases cause changes in the corporate policies of suppliers, suggesting that contagious beliefs in production networks contribute to fluctuations of business and financing cycles.

Keywords: Bias propagation; Managerial optimism; Production networks

JEL Codes: G4, D8, D9, G3, D2

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1. Introduction

The question of how biases in expectations originate and spread across individuals, investors, and firms has long been of interest to academics and practitioners. 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 evidence of how exactly sentiment propagates among economic agents.[1] 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 for supplying firms' managers when forming beliefs about future earnings. It is essential for suppliers to incorporate information about their customers' business prospects into their own forecasts, and 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 biases in expectations – which is also referred to as sentiment in the finance literature.[2] We use management earn-

[1] Hirshleifer (2015) reviews the behavioral finance literature, noting the limited evidence on how opinions propagate from person to person, and concluding: "the time has come to move beyond behavioral finance to social finance, which studies the structure of social interactions, how financial ideas spread and evolve, and how social processes affect financial outcomes." (Hirshleifer, 2015, p.215) For a recent example of this emerging literature see Hvide and Östberg (2015) examining how investment ideas spread among co-workers.

[2] We use the terms bias, biased beliefs, and sentiment interchangeably in this paper to refer to the variable component of optimism. The psychology literature distinguishes between a stable or dispositional

ings forecasts and their realizations to measure changes in managerial bias and their propagation along the supply chain.[3] Measuring the time-varying component of bias is considerably more challenging than measuring its persistent, trait-like component. The reason is that the bias contained in a specific forecast cannot typically be discerned in observational data. A forecast, or subjective expectation, equals the sum of the true expectation and a potential bias; and if the true expectation cannot be observed, the bias cannot be identified either. This indeterminacy remains even after the realization of the predicted variable has occurred: the forecast error, often used as a measure of optimism, contains both the ex-ante bias and an unpredictable ex-post shock. While persistent bias can be estimated simply by averaging forecast errors, the time-varying component cannot easily be measured.

From a theoretical perspective, the difficulty to disentangle the bias from the rational component of a forecast is precisely the reason why propagation of sentiment in forecasts is plausible: even a perfectly Bayesian supplier seeking to improve its own forecast necessarily copies part of its customer's bias, because its manager cannot disentangle the true expectation from the bias in the customer's forecast. We show this in a simple model in section 2.1 where we also develop additional, more nuanced hypotheses about bias contagion.

From an empirical perspective, this indeterminacy creates a particular type of measurement error problem. The observable quantities – the management forecast and the forecast error – both contain the bias but also a "nuisance" variable. In the case of the

component of optimism, and a situational component which can be influenced by experience or interaction and is specific to a particular context. See, e.g., Carver and Scheier (2014) for dispositional optimism and Petty and Cacioppo (1986) or Seligman (1998) for the latter type of optimism. We do not use the word optimism as this is typically associated with dispositional optimism in the finance literature.

[3] Forecasts or forecast errors have been used as measures of optimistic beliefs in previous studies, but not in the context of propagation (see, e.g., Landier and Thesmar, 2009; Otto, 2014; Hribar and Yang, 2016).

forecast error, the nuisance variable is the unpredictable ex-post earnings shock. Hence, one cannot identify correlation in biases simply by regressing supplier forecast errors on customer forecast errors, as this would conflate the correlation of biases with the correlation of earnings shocks between the firms. Equivalently, the correlation of customer and supplier forecasts would conflate the correlation of biases with the correlation of the true earnings expectations. We show formally and discuss in detail in section 2.2 that bias correlation can instead be identified by regressing suppliers' *forecasts* on their customers' *forecast errors*. The reason is that in this specification, both the dependent and independent variables contain the bias, but their respective nuisance variables are no longer correlated.

To investigate empirically how biased beliefs of managers propagate through production networks we construct a matched customer-supplier sample of U.S. firms between 2003 and 2016. Our main contribution is to document a strong positive relationship between customer and supplier biases. The economic magnitude of this effect is large: a one percentage point increase in the forecast bias of a customer that represents 100% of a supplier's sales leads to a 0.41 percentage point increase in the supplier's bias.

To provide causal evidence on bias propagation, we first show that beliefs trickle up the supply chain, not down. Given this direction, we exploit the precise timing and sequence of forecast issuance. We find that supplier forecasts are only affected by customer forecasts issued before the supplier's forecast, not after. This is consistent with propagation of optimistic beliefs since beliefs can only propagate from customer to supplier after the customer's beliefs become known. It is inconsistent with mechanisms by which customers and suppliers update their beliefs simultaneously based on an outside signal observed by both firms, e.g., an optimistic report in a relevant trade journal.[4]

We provide a number of additional results. First, we find that propagation is more pronounced when suppliers are less confident about their earnings forecast, that is, when they issue a forecast range instead of a point estimate or when the forecast range is wider. This is in line with a Bayesian model of updating as we show in section 2.1: less confident suppliers should be more eager to incorporate outside signals into their own forecasts.

Second, our results indicate that more recently issued customer forecasts have stronger contagion effects, and so do forecasts by economically more important customers – measured by the percentage of the supplier's sales accounted for by that customer, or by the correlation of the suppliers' and customers' stock prices. Contagion is also increasing in the precision of the customer forecast relative to that of the supplier, measured by relative earnings volatility or by relative forecast ranges. This further supports bias propagation because more salient and precise customer forecasts should be more likely to influence suppliers' beliefs.

Third, our results hold with a broad set of fixed effects, including supplier or customer-supplier-pair fixed effects. These fixed effects isolate the time-varying component of bias for a given firm or customer-supplier pair. Thus, our results are not driven by a tendency of optimistic managers to form business links with firms led by similarly optimistic managers. Our results continue to hold when we add quarter or quarter $\times$ industry fixed effects. This ensures that our results are not due to shared information that could manifest in market-wide or industry-wide sentiment waves.[5]

Fourth, we run a number of falsification tests. In one of them, we randomly draw

[4] We thank David Hirshleifer for pointing out this example.

[5] Note that this does not preclude market or industry-wide propagation of biases. Rather, by controlling for such aggregate effects, we aim to isolate customer-supplier-pair specific propagation.

pseudo-customers from the same industry as the actual customer and use the pseudo-customer's forecast error as our independent variable. We find that the estimated spillover effect using actual customers lies far above the maximum 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 managerial biases. Relating optimistic forecasts of a firm's management to its own corporate policies, we find that investments, inventories, leverage and stock repurchases increase, while stock issuance decreases. This complements earlier findings of the effects of optimism and overconfidence on firm policies (Malmendier and Tate, 2005; Malmendier, Tate, and Yan, 2011; Graham, Harvey, and Puri, 2013). We find similar results for the effects of propagated beliefs on firm policies, where we estimate propagated bias as the component of a supplier's bias that is predicted by its customers' biases.

Taken together, our findings show that biased beliefs spread along supply chains, and that these propagated biases prompt changes in corporate policies of connected firms. Hence, the beliefs of optimistic or pessimistic managers could ripple across the economy contributing to financing and business cycles as customer sentiment spreads to both proximate and distant suppliers.

This paper is inspired by the large literature in social psychology that investigates the conditions under which communication leads to opinion or attitude change in individuals.[6] Psychology research in this field does not, however, focus on the specific "opinions" relevant to economists, such as expectations about corporate earnings or stock prices,

[6] For reviews of the social psychology literature on attitude and opinion change, see Petty and Cacioppo (1986), among others. For a review of the literature on emotional contagion, see Hatfield, Cacioppo, and Rapson (1993).

and we extend the literature in this direction. In a pioneering article relating social psychology to economics, Shiller (1984) argues that social interaction contributes to the spreading and amplification of irrational beliefs among investors. But due to the limited data available at the time, Shiller cites anecdotal and suggestive evidence rather than large-scale empirical studies.

In financial economics, this paper relates to several strands of literature. First, it relates to the literature on peer effects in financial decisions. Several papers show that people are influenced by geographical or professional peers in their stock market investment decisions.[7] Recently, the peer effect literature has been extended to real estate purchase decisions and to decisions by firms.[8] Our paper is related to these studies as customers are natural peers for suppliers, and hence may influence their suppliers' views about future earnings. Our analysis differs from the above papers by studying peer effects in *beliefs* rather than *actions*.

There is also a growing literature investigating the propagation of real and financial shocks across firms. Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) and Carvalho (2014) analyze how shocks to individual firms in interconnected production networks can cause aggregate fluctuations. Cohen and Frazzini (2008) show that propagated real shocks are only slowly incorporated into stock prices of suppliers leading to return predictability.[9] These studies are related to ours because real linkages between firms are

[7] See Hong, Kubik, and Stein (2004), Brown, Ivkovic, Smith, and Weisbenner (2008) and Kaustia and Knüpfer (2012) for households; Hong, Kubik, and Stein (2005) and Pool, Stoffman, and Yonker (2015) for mutual fund managers; Hvide and Östberg (2015) for workers; Simon and Heimer (2015) for traders.

[8] See Bayer, Mangum, and Roberts (2016) and Bailey, Cao, Kuchler, and Stroebl (2018) for real estate purchase decisions, and Leary and Roberts (2014) and Kaustia and Rantala (2015) for firm decisions.

[9] In supply chain management, the finding that small order fluctuations in downstream retailers can cause large order fluctuations in upstream suppliers – a phenomenon labeled the "bullwhip" effect – has spawned a large literature (see, e.g. Lee, Padmanabhan, and Whang (1997)). In the bullwhip effect the amplification of order fluctuations along the supply chain occurs when temporary demand shocks

the reason why the beliefs of managers should be linked as well. Understanding belief propagation in economic networks is relevant in its own right, as (distorted) beliefs can trigger actions and thus have real effects in addition to and independently from primary economic shocks.

Another strand of literature relates managerial attitudes to various corporate policies such as investment, mergers and acquisitions, and financing choices.[10] We also assess the effect of managerial attitudes on corporate policies, but our analysis focuses on time-varying biases, and on how their propagation affects corporate policies.

Finally, our paper contributes to the literature on investor sentiment.[11] These studies are mostly concerned with the effect of investor sentiment on asset prices and use aggregate, market-wide sentiment indicators. Our analysis focuses on beliefs of management teams of individual firms, and how the propagation of those beliefs affects their actions.

2. Framework and Identification

2.1. A simple model of bias propagation

To guide our empirical analysis, we provide a simple model that illustrates how biased views spread from one individual to another. We deliberately use a Bayesian framework to show that biased beliefs held by one individual can spread to another individual even

are interpreted as permanent and firms fail to communicate what part of the orders are meant to fill backlogs. In other words, demand shocks propagate through the supply chain. In contrast, our empirical setup (see section 2.1) explicitly removes the impact of such shocks, and analyzes how beliefs embedded in forecasts propagate along the supply chain.

[10] See Malmendier and Tate (2005, 2008); Malmendier, Tate, and Yan (2011); Graham, Harvey, and Puri (2013); Landier and Thesmar (2009); Gennaioli, Ma, and Shleifer (2016).

[11] See Baker and Wurgler (2007); Baker, Wurgler, and Yuan (2012); Soo (2018); Stambaugh, Yu, and Yuan (2012).

if the latter is fully rational when updating expectations.[12]

Consider a setting with two firms, a customer (C) and a supplier (S). The management of S does not know its true expected earnings at time t, μ_t^S, and seeks to form expectations about μ_t^S using a prior, and a signal in the form of its customer's earnings forecast. Let the prior distribution be normal,

$$\mu_t^S \sim N(\overline{\mu}^S, 1/\tau), \tag{1}$$

with mean $\overline{\mu}^S$ and variance $1/\tau$. We refer to τ as the precision of the prior.

Firm S's management seeks to incorporate the earnings forecast of its customer in order to generate a more accurate prediction of its own earnings than the initial prior, $\overline{\mu}^S$. The customer's forecast contains its true expected earnings, μ_t^C, but it may be biased:

$$\hat{e}_t^C = \mu_t^C + b_t^C. \tag{2}$$

We define the customer's bias, b_t^C, as the deviation of the forecast from the true expectation. This notion of bias is a statistical one, and includes behavioral as well as strategic reasons. Strategic motives include an aversion to missing earnings forecasts therefore resulting in conservative, negatively biased, forecasts (Hui, Matsunaga, and Morse, 2009). We do not take a stand on how exactly the customer's bias arises.[13]

[12] Cavallo, Cruces, and Perez-Truglia (2016) use a similar framework and apply it to inflation expectations. We build on their model and adapt it to the setting of corporate earnings forecasts.

[13] Leading behavioral theories posit that biases in expectations can result from irrational models of belief formation (e.g., Kahneman and Tversky, 1982), from limited availability of information (e.g., Daniel, Hirshleifer, and Subrahmanyam, 1998, 2001) or from inattention to available information (e.g., Hong and Stein, 1999; Peng and Xiong, 2006). For excellent surveys see Barberis and Thaler (2003) and Hong and Stein (2007). An extended version of our model that distinguishes between biases arising from limited (attention to) information and irrational expectation formation is available upon request. This extension does not change the main prediction of the model presented in this section.

We assume that μ_t^C is correlated with μ_t^S, so that the customer's forecast is an informative signal about the supplier's earnings. For simplicity, and without loss of generality, let $\mu_t^C = \mu_t^S$. Because the supplier cannot distinguish between bias and true expectation in the customer forecast, the bias constitutes noise in the signal. We assume the bias is *i.i.d.* normally distributed with mean zero,[14]

$$b_t^C \sim N(0, 1/\kappa). \tag{3}$$

The Bayesian update of S's expected earnings that optimally incorporates its customer's forecast is given by[15]

$$\begin{aligned} \hat{\mu}_t^S &= \frac{\tau}{\tau+\kappa}\overline{\mu}^S + \frac{\kappa}{\tau+\kappa}\hat{e}_t^C \\ &= \frac{\tau}{\tau+\kappa}\overline{\mu}^S + \frac{\kappa}{\tau+\kappa}(\mu_t^S + b_t^C), \end{aligned} \tag{4}$$

where the second line makes use of equation (2) and the assumption that $\mu_t^C = \mu_t^S$. Hence the bias of S's forecast is

$$b_t^S = \hat{\mu}_t^S - \mu_t^S = \frac{\tau}{\tau+\kappa}(\overline{\mu}^S - \mu_t^S) + \frac{\kappa}{\tau+\kappa}b_t^C. \tag{5}$$

Equation (5) shows that the bias in S's forecast increases with the bias in its customer's forecast. The degree of bias contagion from customer to supplier is given by $\frac{\kappa}{\tau+\kappa}$, the relative precision of the customer's forecast to the supplier's prior. Hence, even

[14] The assumption of a mean-zero bias serves to isolate the time-varying dimension. A non-zero persistent bias can be learned, making it less likely to propagate. Empirically, we remove persistent biases via firm fixed effects.

[15] See, for instance, DeGroot (1970), p.167.

if a firm's management is completely rational in using outside signals to form earnings expectations, any bias in the customer's forecast will seep into its own forecast. The reason for this is that the signal's noise cannot be separately observed, and thus both the informative component of the signal, μ_t^S, as well as the bias, b_t^C, are incorporated into the forecast to the same extent.

While a positive correlation between customer and supplier bias is the main prediction of the model, equation (5) also makes the finer predictions that contagion of forecast bias is more pronounced the less certain the supplier is about its future earnings given only its prior, and the more precise he believes the customer's forecast to be. We test the main as well as these additional predictions in section 4 below.

2.2. Identifying bias propagation empirically

In this section we show how to empirically identify bias propagation in customer-supplier networks using management earnings forecasts and their realizations. We start by showing how regressing supplier forecasts (or forecast errors) on their customers' forecasts (or forecast errors) leads to biased estimates of propagation. We then present our solution which consists of regressing supplier *forecasts* on customer *forecast errors*.

Our goal is to estimate the following equation:

$$b_{it}^S = \alpha + \beta b_{it}^C + u_{it}, \tag{6}$$

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. In this equation, subscript i references a customer-supplier pair, t indexes the fiscal period to which the forecast pertains, and the superscript indicates the customer (C) or supplier firm (S). Importantly, the supplier's forecast must be issued *after* the customer's forecast, so that belief propagation from customer to supplier can occur. We explicitly allow the bias b_{it} to vary across firms and over time.

Problem. The problem with the above regression is that biases are not directly observable. What we can observe are management earnings forecasts. But forecasts, $\hat{e}$, are the sum of the true earnings expectation, μ_t, and the bias, b_t:

$$\hat{e}_{it}^{K} = \mu_{it}^{K} + b_{it}^{K}, \; K \in (C, S). \tag{7}$$

This creates a specific type of measurement error problem with the challenge of separating propagation of biases from propagation of true earnings expectations. In our setting, propagation (or correlation) of true earnings expectations is just as plausible as propagation of biases because of the business link between customers and suppliers; so we explicitly allow for $Cov(\mu^C, \mu^S) \neq 0$. This implies that simply regressing the suppliers' on the customers' forecasts would conflate the correlation of biases with the correlation of true expectations:

$$\begin{aligned} \hat{e}_{it}^{S} &= \alpha + \beta \hat{e}_{it}^{C} + u_{it} \\ \Leftrightarrow \mu_{it}^{S} + b_{it}^{S} &= \alpha + \beta(\mu_{it}^{C} + b_{it}^{C}) + u_{it}. \end{aligned}$$

In this regression, the estimate of β reflects the sum of the correlation of biases and the correlation of true expectations (and potential cross-correlations). The reason is that the nuisance terms in the dependent and independent variables, μ^S and μ^C, are likely correlated.

Another quantity useful for identifying the bias are realized earnings. Realized earnings, e_{it}, are the sum of the true expectation and a mean-zero, unpredictable earnings shock, ε_{it}:

$$e_{it}^K = \mu_{it}^K + \varepsilon_{it}^K, \ K \in (C, S) \tag{8}$$

where $\mathbb{E}(\varepsilon^K) = 0$, and $Cov(\varepsilon^K, \mu^K) = 0, K \in \{C, S\}$. Just as we allow for $Cov(\mu^C, \mu^S) \neq 0$, we also allow for earnings shocks of customers and suppliers to be correlated, $Cov(\varepsilon^C, \varepsilon^S) \neq 0$, due to the business link between the firms.

From earnings forecasts and realized earnings, we can compute the forecast error:

$$\hat{e}_{it}^K - e_{it}^K = b_{it}^K - \varepsilon_{it}^K, \ K \in (C, S). \tag{9}$$

Forecast errors are intuitive proxies for biases in expectations, and they are used in several studies of optimism (e.g., Landier and Thesmar, 2009; Otto, 2014; Hribar and Yang, 2016). However, for measuring propagation of biases, one cannot simply correlate forecast errors as this would conflate the correlation of biases with the correlation of earnings shocks:

$$\begin{aligned} \hat{e}_{it}^S - e_{it}^S &= \alpha + \beta(\hat{e}_{it}^C - e_{it}^C) + u_{it} \\ \Leftrightarrow b_{it}^S - \varepsilon_{it}^S &= \alpha + \beta(b_{it}^C - \varepsilon_{it}^C) + u_{it}. \end{aligned}$$

In this regression, the estimate of β reflects the sum of the correlation of biases and the correlation of earnings shocks – because the nuisance terms of the dependent and independent variables, ε^S and ε^C, are again correlated.

Solution. The solution we propose is to regress supplier *forecasts* on customer *forecast errors*:

$$\begin{aligned} \hat{e}^S_{it} &= \alpha + \beta(\hat{e}^C_{it} - e^C_{it}) + u_{it}, \\ \Leftrightarrow \mu^S_{it} + b^S_{it} &= \alpha + \beta(b^C_{it} - \varepsilon^C_{it}) + u_{it}. \end{aligned} \tag{10}$$

This simple change in the regression specification isolates bias propagation, because the nuisance term, μ^S, of the dependent variable is an ex-ante expectation while the nuisance term of the independent variable, $-\varepsilon^C$, is an unpredictable, ex-post shock. By definition, these are uncorrelated. Because the nuisance term of the independent variable is *i.i.d.*, it represents classic measurement error, attenuating (i.e. providing a conservative estimate of) β relative to the true effect.[16]

A concern with this specification could be that our estimate overstates the true magnitude of bias propagation if $Cov(\mu^S, b^C) > 0$. This could be the case if customers become optimistic after seeing a high supplier forecast and interpreting it mostly as fundamentally driven (i.e. high μ^S). However, this would require that customers see their supplier's forecast before issuing their own forecast. As explained above (page 11), our timing convention precludes this: we match supplier forecasts issued at time t with customer forecasts that are issued before time t. We also show in Table 6, column 6, that customer bias is not correlated with previously issued supplier forecasts. Alternatively,

[16] One may wonder how bias propagation can occur if the independent variable, the customer's forecast error, cannot be observed at the time the supplier's management makes its forecast. It is important to note that management's observing the forecast *error* is not necessary for estimating the propagation coefficient β, only the *forecast* needs to be observed as we discuss in section 2.1. Using the forecast error as an independent variable is just a statistical technique to address the identification problem.

a supplier's fundamental may increase when its customer becomes too optimistic, if the customer follows up on his optimism by placing more orders. This would imply that the supplier's inventories decrease with customer bias. However, we find (Table 9) that suppliers' inventories increase rather than decrease with customer bias. This is consistent with biases propagating, and inconsistent with customer biases affecting the supplier's fundamentals.

3. Data

3.1. Sample construction

The core of our dataset consists of management forecasts – also called management guidance – of quarterly and annual earnings per share (EPS). Since the passage of Regulation Fair Disclosure (Reg FD) in 2000, issuing management guidance has become the norm for public corporations.[17] Thomson Reuters' Institutional Brokers' Estimates System (IBES) starts recording management guidance for U.S. public firms in 2003, and we use their data for the period 2003 to 2016.

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 issued, and the IBES company identifier (IBES ticker). Most companies 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 lower and upper bounds of the range. We add to this the reported realized EPS for

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

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 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 also split-adjust historical stock prices using CRSP's historical split adjustment factor.

We 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 property, plant and equipment scaled by total assets. We also report two other measures of firm size, sales and market value, as well as profitability, net book leverage, investment, inventories, stock issuance and repurchases. For details on variable definitions, see Table A1.

Finally, for every 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 sales in interim financial reports. 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 but no company identifier. We use a string-distance matching algorithm and manual verification to identify the CRSP Permno of publicly listed customer firms. For each supplier forecast, we then merge in the *most recently issued* customer forecast for the same fiscal period and periodicity (quarterly or annual). We keep only those supplier forecasts for which there is at least one customer with a matched forecast.

Our final dataset contains 13,541 customer-supplier-forecast combinations originating from 692 unique suppliers and 237 unique customers.

[Insert Table 1 here]

Table 1 shows descriptive statistics of customers and suppliers. Panel A contains basic statistics on customer-supplier relationships. The average number of unique suppliers in our sample is 180 per year but varies across years from 81 to 264. There are, on average, 94 customers per year, varying from a minimum of 42 to a maximum of 160 per year. The average number of customers per supplier is 1.86. This number is lower than the actual number of customers since we cannot identify all customers of a given firm, but only those which are disclosed in Compustat 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 accounted for by 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 customer is about ten times larger than the average supplier. On most other dimensions (Tobin's Q, leverage, profitability, investment, inventories), customers and suppliers are similar.

3.2. Key variables

As is standard in the literature (Kothari, 2001), we scale forecasts and forecast errors by the stock price five trading days prior to the announcement of the forecast. Table 2 reports some basic forecast statistics. We split these statistics by suppliers and customers as well as by whether the forecast is for quarterly or annual earnings. We report both the management forecast and the forecast error. All quantities are expressed in percent of the stock price. The average annual earnings forecast is 6.17 percent for suppliers. The average realized earnings are slightly lower, resulting in a small positive forecast error, 0.21 percent on average. Quarterly forecasts are slightly lower than actuals, both for suppliers and for customers. The forecast horizon, defined as the time between the announcement of a forecast and the announcement of the respective realized earnings, is around 230 days for annual earnings and around 90 days for quarterly earnings.

[Insert Table 2 here]

3.3. Do forecast errors reveal managerial bias?

In this section we corroborate the use of management forecast errors as measures of managerial bias. We do so by relating forecast errors to managerial actions that are consistent with optimistic beliefs. First, we examine CEO insider trading behavior in the months prior to the issuance of a forecast. If management holds excessively optimistic 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-company stock by top managers to be positively correlated with management forecast errors.

[Insert Table 3 here]

Panel A of Table 3 confirms the insider trading prediction for CEOs. The table reports regressions of net purchases by CEOs on the forecast error. In all specifications, forecast errors are strongly positively associated with CEOs' net share purchases. In the most conservative specification in column 4, a one percentage point increase in forecast error is associated with net purchases in the amount of $725,000 in the year leading up to the optimistic forecast (t-statistic of 5.91). 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.

Second, we relate the forecast error to *Share Retainer*, a managerial optimism measure proposed by Sen and Tumarkin (2015) that is based on whether a firm's CEO retains some of the shares that the executive receives after exercising stock options. Panel B of Table 3 shows a significant and positive correlation between their measure and our forecast-based measure (t-statistic of 2.56).

Third, we measure the sentiment in managerial language in conference calls and relate it to the forecast error. Specifically, we extract the management discussion section of all conference call transcripts available at SeekingAlpha.com and construct a textual sentiment measure following Loughran and McDonald (2011) for 8,577 conference calls that occurred on the same day as the announcement of the EPS forecast. We again find a highly significant and positive correlation (t-statistic of 5.85).

A fourth way to validate that management forecasts reveal actual beliefs is to relate them to the overconfidence measures proposed by Malmendier and Tate (2005). We relate *Forecast range* to Malmendier and Tate's *Holder67* measure. A wider forecast range indicates less confidence in the forecast. We thus expect forecast range to be negatively correlated with *Holder67*. This is also what we find: a wider forecast range is associated with a significantly lower probability of the CEO being classified as overconfident (t-statistic of -2.84). This has also been shown by Hribar and Yang (2016) in a different sample and time period.[18] Taken together, the above results support the use of forecast-based measures as proxies for managerial bias.

3.4. Does the sequence of forecast issuance allow suppliers to learn from their customers forecasts?

The key premise of this paper is that suppliers learn from their customers' forecasts and incorporate this information into their own forecasts. If managers find their customers' forecasts to be valuable signals, then suppliers may want to wait to issue their forecasts until after their customers do. We examine this idea in Figure 1. We match forecasts for the same fiscal period by suppliers to those of their customers and find that suppliers file quarterly forecasts on average three days after their customers (t-statistic of 5.10) and annual forecasts ten days later (t-statistic of 8.86). This means that the majority of suppliers in our sample are able to learn from their customers' forecasts.

[Insert Figure 1 here]

[18] We construct a time-varying *Holder67* measure by classifying a manager as overconfident in a given year if, in that year, the manager fails to exercise deep in-the-money options.

4. Do Biases Propagate?

4.1. Main results

We proceed by analyzing whether biases are contagious across the supply chain. In Table 4 we estimate our main regression specification, equation (10). Column 1 shows the correlation between customer and supplier bias, controlling for two forecast characteristics, the forecast horizon and a dummy variable indicating a quarterly earnings forecast, as well as firm-level variables.[19] We use one observation per supplier forecast, and in case a supplier has multiple customers we take the sales-weighted average of the customers' forecast errors as our main independent variable. The coefficient is therefore interpreted as the increase in a supplier's bias corresponding to a one-unit increase in the bias of a customer with a hypothetical sales share of 100%. We obtain a highly significant and economically sizable coefficient of 0.623, that is, a pass-through rate from customers to suppliers of 62.3%.

We gradually add fixed effects for suppliers (columns 2 and 4) and calendar quarters (columns 3 and 4). Adding supplier fixed effects removes any confounding effect due to time-invariant unobservables, including persistent biases, while quarter fixed effects control for quarter-specific market-wide sentiment waves. Column 4 shows a specification which includes supplier as well as quarter fixed effects. The coefficient of interest remains stable and highly statistically significant across specifications 1 to 4.

Next, in column 5, we replace quarter fixed effects with customer industry $\times$ quarter fixed effects, thereby only relying on variation in customer bias that is not shared by its industry peers in a given quarter. This specification eliminates the potential confounding

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

effect of customer industry-specific sentiment waves. In this most stringent specification the coefficient declines to 0.410 but remains highly significant (t-statistic of 3.00).

[Insert Table 4 here]

We take an alternative approach in columns 6 and 7. Instead of collapsing multiple customer observations and using the sales-weighted average of customer forecast errors, we now keep each customer forecast error as a separate observation and include fixed effects for customer-supplier pairs as well as quarters (column 6) or customer industry × quarters (column 7). Hence, the coefficient of interest is identified off customer-supplier pair specific sentiment shocks while controlling for common variation in quarters or in industries and quarters. The coefficient remains highly significant (t-statistic of 2.87). Compared with columns 1 to 5, the coefficient drops to 0.151 (column 6) and 0.105 (column 7). The decline in the coefficient is a mechanical consequence of using each individual customer forecast error instead of the sales-weighted average of customer forecast errors. 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 with an average sales share of 16%.

In Table A2 we investigate asymmetries in bias propagation. A literature in psychology shows that people process positive and negative news differently when updating beliefs. Bénabou (2015) reviews this literature and concludes that people systematically underreact to negative news and update more strongly to positive news. In our setting, this would imply greater propagation for high forecasts (where the bias and hence the forecast error tend to be positive) than for low forecasts. Accordingly, we separate our sample into subsamples of positive or negative customer forecast errors. We caution that this classification is imperfect as forecast errors are noisy measures of the bias. Still, we find positive coefficients for the sample of positive customer forecast errors, similar in magnitude to those in Table 4. In contrast, for the sample of negative customer forecast errors, magnitudes are much smaller and none of the coefficients are significant.

4.2. Cross-sectional tests

In this section we test the cross-sectional predictions of our model. Contagion of forecast bias from customer to supplier should be more pronounced the less certain the supplier is about his forecast, and second, the more precise the supplier believes the customer's forecast to be (see equation 5).

We measure the certainty or confidence with which a firm makes a forecast in two ways. First, we use the forecast range that the firm itself provides for its forecast. The forecast range is comparable with a confidence interval: While a narrow range or a point estimate signals management's confidence or certainty about future earnings, a wide interval suggests that management is less certain about how earnings will eventually turn out. Second, we compute the volatility of a firm's historical EPS. A firm's future EPS should be harder to predict if its EPS was historically more volatile. Thus we expect more propagation the wider is the supplier's forecast range relative to the customer's and the greater is its EPS volatility relative to that of its customer.

[Insert Table 5 here]

In columns 1 and 2, we build on this notion and run separate regressions on the subsamples with zero and strictly positive ranges of supplier forecasts. Alternatively, in column 3 we use the full sample and include an interaction term of the supplier's forecast range with the customer forecast error. All three regressions show that bias propagation is stronger when suppliers are less certain about future profits. Comparing column 1 with column 2 shows that the bias propagation documented in Table 4 is concentrated among firms whose management is less certain about future profits. Column 3 corroborates these results using a continuous interaction term: the greater the supplier's uncertainty about future profits, the larger is the bias propagation from its customers. We continue to use the full sample in columns 4 to 8. (Results are stronger if we run those regressions on the subsample of forecasts with strictly positive forecast range.) In column 4 we use the ratio of the supplier's to the customer's forecast range as an interaction variable. Bias propagation should increase with the supplier's own uncertainty only if the customer's forecast is considered to be relatively more precise and hence informative. Column 4, showing a positive and significant interaction term, confirms this prediction. In columns 5 and 6 we re-run the regression from column 4, replacing the forecast range with past EPS volatility. Column 5 reports the regression using only the supplier's EPS volatility while column 6 uses the ratio of supplier to customer EPS volatility. We obtain similar but statistically weaker results compared to those using the forecast range.

In columns 7 and 8 we separate customers by their importance to their suppliers. In column 7, 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. We expect more important customers to have more influence on their suppliers' forecasts, and this is indeed what we find: a larger sales share increases bias propagation from customer to supplier. In column 8 we use a market-based measure of customer importance, the correlation of excess stock returns between customers and suppliers. For each customer-supplier pair we run a regression of the supplier's daily stock return on the customer's daily return, controlling for the market. Consistent with the results on sales share, we find that customer bias impacts supplier bias significantly more when the stock return correlation is higher.

4.3. Falsification tests

Table 6 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 customer forecasts issued in different time intervals. Specifically, period *t-1* spans the six months prior to the issuance of the supplier's forecast, that is, calendar days [-1, -180] relative to the announcement of the supplier's forecast. Likewise, periods *t-2* and *t-3* correspond to the windows [-181, -360] and [-361, -540] while *t+1* references the window [1, 180]. 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 6 here]

Columns 1 to 5 of Table 6 show that more recent forecasts by customers have indeed more influence on supplier forecasts: moving from column 1 to column 3, the bias propagation coefficient steadily declines and becomes insignificant for windows *t-2* and *t-3*. We include several customer forecasts simultaneously in columns 4 and 5: The largest and only significantly positive customer forecast coefficient is the one for the most recent customer forecast while older and stale forecasts tend not to affect supplier forecasts. Finally, in column 6 we add the earliest 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 its forecast announcement, it should not affect supplier bias. Indeed, only the lagged customer forecast error remains statistically significant and its coefficient is very similar in magnitude to that in column 1 while the coefficient of the leading forecast is close to zero. Taken together, the results in Table 6 indicate a Granger-type causality for bias propagation: Suppliers respond to the most recent customer forecasts, but not to those made in the near future.

A second falsification test makes use of the expected direction of learning in the supply chain. While there is a strong economic rationale for suppliers to learn about the future demand for their goods and services from the forecasts of their customers, the reverse – customers learning from their suppliers' sales or earnings forecasts – is economically less important. Thus biases should trickle up the supply chain, not down. We test for the reverse direction of propagation in Table 7 by switching customer and supplier in regression equation (10). That is, we regress the customer's forecast on the supplier's forecast error, using supplier forecasts that are issued before those of the customers. Our key coefficients on *Supplier forecast error* are substantially smaller and insignificant in all specifications. This confirms that biases do not trickle down the supply chain. It also implies that our main results are not driven by unobserved shared characteristics or signals observed by customers and suppliers but not by the econometrician.

[Insert Table 7 here]

Figure 2 provides a third falsification test. We run placebo regressions based on the specification in Table 4, column 5, in which we replace actual customers with randomly drawn same-industry pseudo-customers using the Fama-French 48-industry classification or the Hoberg-Phillips product market peers. We repeat this procedure 10,000 times, and plot a histogram of the 10,000 coefficients on the sales-weighted customer forecast variable. Note that this regression specification includes customer industry $\times$ quarter fixed effects; hence it is expected that the distribution is centered on zero even in the presence of industry sentiment waves. Our actual-customer coefficient of 0.410 lies more than 6.5 standard deviations above the mean of the counterfactual distributions, regardless of which industry classification we use, and none of the 10,000 placebo estimates is greater than the actual-customer coefficient.

The takeaway from the three falsification tests is that the actual production network (and thus the actual customers' forecasts), the precise relative timing of supplier and customer forecasts, and the directional nature of the supply-chain relationship are all crucial for generating our key results.

[Insert Figure 2 here]

5. Do Biases Affect Corporate Decisions?

Existing literature documents that managerial optimism and overconfidence affect corporate policies. In these studies, belief distortions are measured in various ways: using late option exercise and press portrayals of CEOs (Malmendier and Tate, 2005; Malmendier, Tate, and Yan, 2011), using forecast errors of CFOs for the S&P 500 (Ben-David, Graham, and Harvey, 2013), and using psychometric tests (Graham, Harvey, and Puri, 2013). Similar to these previous studies we investigate whether time-varying optimistic beliefs, as expressed in companies' earnings forecasts, are also correlated with corporate policies. Furthermore, we test whether propagated biases entail such real effects.

We start by investigating whether optimistic beliefs about future earnings are associated with firms' own corporate policies. If management is optimistic about the firm's earnings prospects, it should take actions in line with those expectations. As in our main regression (equation 10), we use the forecast error as a proxy for optimistic beliefs, and replace the dependent variable with various firm policies.

We test for changes in investment, inventories, leverage, equity repurchases and issuance. As a positively biased forecast indicates an expectation of greater revenues and lower financial risk, we expect investment, inventories and leverage to increase with optimistic bias. We also expect stock issuance (stock repurchase) to decrease (increase), because optimistic beliefs indicate that management views the stock as undervalued by the market (Heaton, 2002; Malmendier, Tate, and Yan, 2011).

In these tests, we match forecasts, realizations and policy variables such that they all pertain to the same fiscal year. That is, $\hat{e}_{it}$ is the earnings forecast for fiscal year t, e_{it} are the reported earnings for the same period, and y_{it} is the policy variable measured at the end of fiscal year t. We use only annual forecasts with a remaining forecast horizon between 180 and 365 days, keep only the earliest forecast for a given fiscal period and ignore any revisions. 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 there is enough time for firms to implement changes to corporate policy.

[Insert Table 8 here]

Table 8 presents the results. For each of the five policies, we show results with both firm and year fixed effects. In line with the above predictions, we find that optimistic forecasts are associated with greater corporate investment, more inventory, greater book leverage, greater stock repurchases and decreased stock issuance. Notably, the effect of optimistic beliefs is highly significant for all corporate policies. In columns 1 and 2, a one percentage point higher forecast error is associated with a 0.09 percentage points greater investment ratio and a 0.09 percentage point increase in inventories. In economic terms, a one standard deviation increase in forecast error (2.1 percentage points in this sample) increases investments and inventories by 0.19 percentage points, which compares to average within-firm standard deviations in both variables of 1.49 and 1.59 percentage points respectively. In column 3, net book leverage increases by 0.80 percentage points with a one percentage point increase in forecast error. Alternatively, one standard deviation in forecast error increases leverage by 1.68 percentage points, which relates to a within-firm standard deviation of 10.1 percentage points. Finally, the dependent variables in columns 4 and 5 are indicator variables which are equal to one (and which we scale to 100 to ease interpretation) if the firm has a share repurchase or an equity issue recorded in CRSP or Thomson One in a given year, and zero otherwise. The results show that a one percentage point higher forecast error is associated with a 1.29 percentage points increased likelihood to repurchase shares and a 0.42 percentage points lower likelihood of issuing stock. This compares to an average frequency of a repurchase (issuance) of 68.1 (6.2) percent in our sample. These results on time-varying beliefs are consistent with and complement the findings of the above-mentioned studies on the real effects of persistent optimism.

Our final tests are designed to detect real effects of propagated biases. Specifically, we estimate propagated bias in a first-stage regression as the component of a supplier's forecast that is predicted by its customers' forecast error, that is, we use the customer's forecast error as an instrument for the supplier's forecast bias. The first stage of this instrumental variables regression is identical to the single-stage regression we use in our main table (Table 4). We then use the predicted supplier forecast as an independent variable in regressions of various firm policies. As we now require matched customer forecasts for each supplier forecast in the first stage, the sample size drops substantially from about 11,000 observations in Table 8 to about 1,300 observations. Still, the first-stage F-statistics are large enough to allow for examination of the second stage.[20]

[Insert Table 9 here]

Table 9 again contains one regression for each corporate policy with both firm and year fixed effects. Columns 1 and 3 do not reveal statistically significant effects of propagated bias for investment and leverage. We however find statistically significant effects for inventories, equity repurchases and issuance. Inventories increase by 1.5 percentage points with a one percentage point increase in propagated bias, which is economically large given that the within-firm standard deviation in our sample is 2.1 percent. Further, the probability of equity repurchases in column 4 increases by 17.3 percentage points, and the probability of an equity issuance in column 5 decreases by 8.7 percentage points

[20] The first stage of this regression corresponds to Table 4 except that it uses a smaller sample.

with a one percentage point increase in propagated bias. This compares to an average probability to repurchase (issue) equity in any given year of 69 percent (4.5 percent) in this sample.

In summary, the evidence on the direct real effects of biases in Table 8 is in line with those of earlier studies. In connection with our main results (Table 4) on bias propagation this suggests that transmitted, distorted beliefs have real effects that manifest themselves in upstream suppliers. Although it is challenging to identify such indirect effects with a two-stage IV regression in a small sample with firm and time fixed effects, we are able to document significant effects on some relevant corporate policies (Table 9).

6. Conclusion

We study how managerial biases spread across firms in production networks. Using EPS forecasts as a measure of subjective expectations and a regression framework that separates the propagation of biases in beliefs from the propagation of real shocks along the supply chain, we document a strong positive effect of customer on supplier biases. A one percentage point increase in the forecast bias of a hypothetical customer that represents 100% of a supplier's sales leads to a 0.41 percentage point increase in the supplier's bias. Subsample tests further show that bias propagation is stronger when suppliers have less confidence in their own forecasts, the perceived relative precision of the customer forecast is greater, and when customers are more important to the supplier. Several falsification tests address causality concerns.

We also investigate the real implications of time-varying optimistic biases and find significant effects on investment, inventories, leverage, stock repurchases and issuance.

This complements previous studies showing that managers' dispositional optimism affects corporate actions. Combined with our main result of optimistic beliefs propagating along the supply chain, this indicates that contagious beliefs can have important real effects in upstream suppliers. Hence, shocks to the beliefs of downstream firm managers may have significant aggregate effects on output and financing in the greater economy due to the pyramidal structure of supply chains.

Our findings document one specific channel through which biases propagate among a specific group of economic agents: corporate managers. Of course, contagion of beliefs is a 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 further contribute to our understanding of belief propagation in economic networks.

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Figures and Tables

Figure 1
Timing of Forecast Announcements

The graphs show frequency distributions of the difference in calendar days between the EPS forecast issuance dates of customers and suppliers. Forecasts for annual earnings are on the left, those for quarterly earnings on the right. Customer and supplier forecasts are matched to have identical fiscal period ends. Positive differences imply that suppliers issued their forecasts after their customers did.

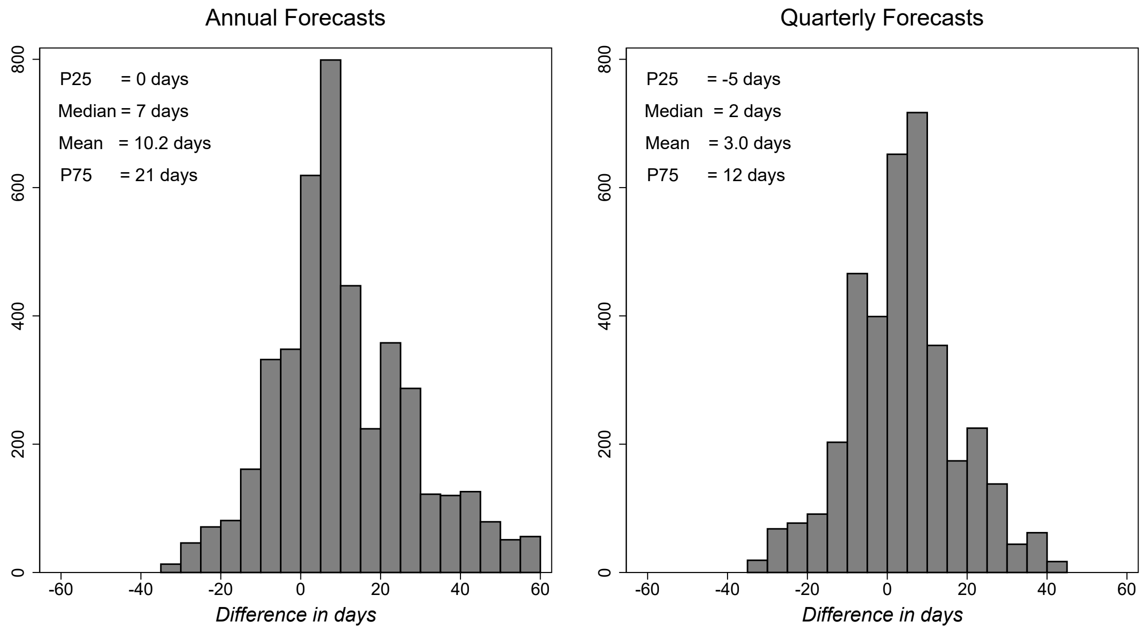

Figure 2
Distribution of Coefficients using Bootstrapped Pseudo-Customers

We re-run our main specification (Table 4, column 5) 10,000 times and replace in each run suppliers' actual customers with pseudo-customers that are randomly drawn from the same Fama-French 48 industry (alternatively, same Hoberg Philipps TNIC industry). The graphs show the empirical distribution of the 10,000 coefficients of *Customer forecast error*. The arrows indicate the coefficient from Table 4, column 5.

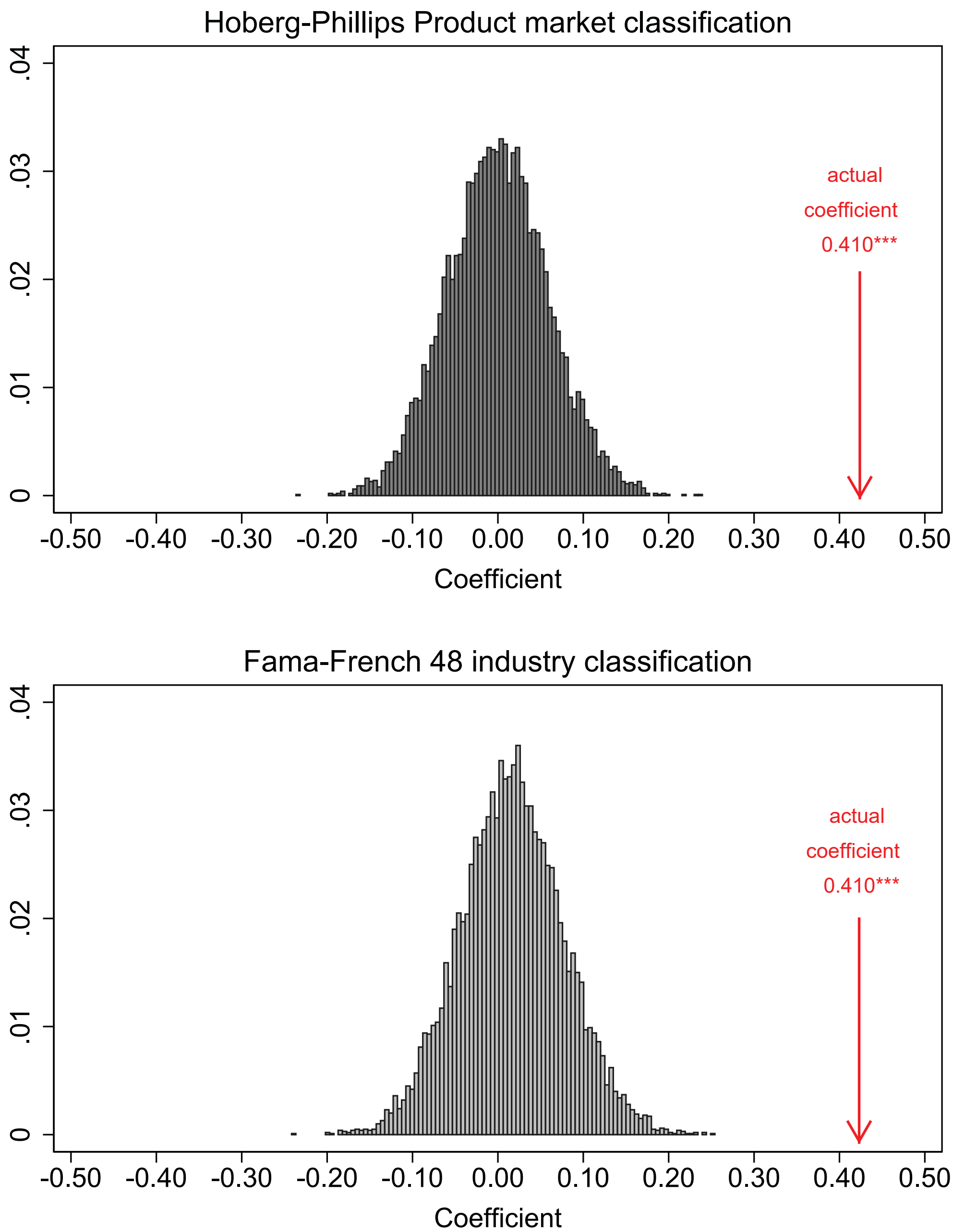

Table 1
Descriptive Statistics

Panel A shows descriptive statistics for our sample of matched customer-supplier pairs. Customer-supplier links are identified using Compustat's customer segment files. We only include suppliers and customers with management guidance data in Thomson Reuters' IBES and stock price information in CRSP. Panel B shows supplier and customer firm characteristics as obtained from Compustat, CRSP and Thomson One. All variables are defined in Table A1.

Panel A: Basic statistics							
	P5	P25	Median	Mean	P75	P95	SD
# suppliers per year	81.00	158.00	168.00	179.73	210.00	264.00	45.59
# customers per year	42.00	78.00	85.00	94.40	112.00	160.00	28.79
# customers per supplier	1.00	1.00	1.00	1.86	2.00	4.00	1.53
Pct of sales to customer	0.02	0.10	0.14	0.16	0.20	0.37	0.11
C/S beta	-0.08	0.04	0.11	0.12	0.20	0.34	0.14

Panel B: Customer and supplier firm characteristics						
	Supplier (N=692)			Customers (N=237)		
	Median	Mean	SD	Median	Mean	SD
Total assets [$bn]	1.13	5.66	17.08	13.57	38.02	84.09
Sales [$bn]	0.94	4.92	13.52	14.27	34.90	59.01
Market value [$bn]	1.91	10.66	30.81	20.76	63.01	115.00
Tobin's Q	1.63	1.99	1.17	1.65	1.92	0.95
PP&E	0.13	0.16	0.14	0.21	0.26	0.20
Profitability	0.12	0.11	0.12	0.14	0.15	0.08
Net book leverage	0.07	0.02	0.33	0.13	0.12	0.23
Investment	0.03	0.04	0.04	0.04	0.05	0.04
Inventory	0.10	0.12	0.11	0.13	0.16	0.14
Stock repurchase	1.00	0.57	0.50	1.00	0.80	0.40
Stock issuance	0.00	0.07	0.25	0.00	0.03	0.17

Table 2
Management Forecasts: Descriptive Statistics

This table shows descriptive statistics for management EPS forecasts, separately for suppliers (Panel A) and customers (Panel B) and separately for annual and quarterly earnings. Forecasts and forecast errors are scaled by the split-adjusted stock price five days prior to the forecast announcement. *Forecast horizon* is the number of days between guidance issuance and the announcement of realized earnings to which the guidance refers.

	Mean	Median	SD	N
	Panel A: Suppliers			
Annual forecast [%]	6.17	5.81	3.47	10,006
Annual forecast error [%]	0.21	-0.08	1.83	10,006
Annual forecast horizon [days]	235.56	229.00	105.57	10,006
Quarterly forecast [%]	0.97	1.10	1.57	4,676
Quarterly forecast error [%]	-0.12	-0.10	0.61	4,676
Quarterly forecast horizon [days]	82.24	91.00	26.61	4,676
	Panel B: Customers			
Annual forecast [%]	6.57	6.67	2.06	10,189
Annual forecast error [%]	-0.07	-0.02	0.97	10,189
Annual forecast horizon [days]	202.00	229.87	111.34	10,189
Quarterly forecast [%]	1.56	1.65	1.25	4,695
Quarterly forecast error [%]	-0.06	-0.11	0.43	4,695
Quarterly forecast horizon [days]	91.00	78.78	28.39	4,695

Table 3
Forecast Errors and Alternative Optimism Measures

Panel A shows regressions of own-firm net share purchases by the CEO on the management's EPS forecast error. All net share purchases made by the CEO in the 12 months prior to the issuance of a management forecast are cumulated to construct the dependent variable. Firm-level controls include *Log assets*, *Tobin's Q*, *Profitability* and *PP&E*. The data come from Thomson Reuters' Insider Filings database for the period between 2003 and 2016. Panel B shows coefficients from regressions of management EPS forecast errors on a textual sentiment measure of managerial discussions derived from conference call transcripts that take place the same day as the guidance issuance, on *Share Retainer* (Sen and Tumarkin, 2015) and from a regression of management EPS forecast range on a time-varying version of *Holder67* (Malmendier and Tate, 2005). All variables are defined in Table A1. The regressions control for the above mentioned firm-level controls, firm fixed effects and customer industry-year or firm-fiscal period fixed effects. *t*-statistics, reported in parentheses, are based on standard errors clustered at the firm level.

Panel A: Management forecast error and CEO net share purchases

Dept. variable:	*Net share purchases (in thousands of dollars)*			
	(1)	(2)	(3)	(4)
Forecast error	1,041.3***	655.0***	752.8***	725.0***
	(9.83)	(6.69)	(6.15)	(5.91)
Firm-level controls	No	Yes	Yes	Yes
Firm FEs:	No	No	Yes	Yes
Year FEs:	No	No	No	Yes
Observations	22,326	20,908	20,908	20,908
R-squared	0.00	0.06	0.60	0.60

Panel B: Management forecasts errors and alternative optimism measures

Textual sentiment of management discussions in same-day conference call transcripts	0.015***		
	(5.85)		
Shares retained upon stock option exercise (*Share Retainer* by Sen and Tumarkin (2015))		0.007**	
		(2.56)	
Managerial overconfidence and forecast range (*Holder67* by Malmendier and Tate (2005))			-0.082***
			(-2.84)

Table 4
Bias Propagation: Main Results

This table shows regressions of supplier forecasts on their customers' forecast errors. Columns 1 to 5 use the sales-weighted customer forecast error when a supplier has multiple customers. In those columns, the coefficient is interpreted as the effect on a supplier's bias for a one-unit increase in bias of a customer representing 100% of supplier sales. In columns 6 and 7, each customer-supplier pair is a separate observation and hence each individual customer forecast error is used. In these columns, the coefficient is interpreted as the effect on a supplier's bias of a one-unit increase in bias of the average customer (representing on average 16% of supplier sales). *Forecast horizon* is the number of days between the forecast issuance and the announcement of the respective realized earnings. *Quarterly earnings forecast* is an indicator variable which equals one for quarterly forecasts and zero for annual forecasts. All variables are defined in Table A1. Customer industry fixed effects are based on the customer's Fama-French 48 industry classification (in column 5, when there is only one observation per supplier, on the main customer's industry). t-statistics, reported in parentheses, are based on standard errors clustered at the supplier level.

Dept. variable:	*Supplier forecast*						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Customer forecast error	0.623**	0.638***	0.621***	0.616***	0.410***	0.151***	0.105***
	(2.50)	(3.64)	(2.80)	(4.30)	(3.00)	(3.64)	(2.87)
Forecast horizon	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(5.75)	(6.14)	(6.35)	(5.82)	(5.48)	(4.63)	(4.62)
Quarterly earnings forecast	-4.854***	-4.785***	-4.825***	-4.817***	-4.851***	-4.863***	-4.886***
	(-32.35)	(-23.11)	(-31.01)	(-21.78)	(-19.95)	(-22.20)	(-20.98)
Log assets	0.361***	0.212	0.387***	0.857***	0.909***	0.969***	0.927***
	(5.74)	(1.32)	(5.61)	(3.64)	(3.68)	(4.24)	(3.86)
Tobin's Q	-0.664***	-0.400***	-0.613***	-0.128**	-0.122	-0.176***	-0.139*
	(-9.45)	(-5.28)	(-8.69)	(-1.97)	(-1.57)	(-2.68)	(-1.76)
PP&E	-0.965	-1.914	-1.171*	-1.521	-2.164	-1.057	-1.895
	(-1.60)	(-1.15)	(-1.96)	(-0.98)	(-1.18)	(-0.61)	(-0.89)
Observations	10,283	10,283	10,283	10,283	10,283	13,541	13,541
R-squared	0.544	0.767	0.567	0.788	0.816	0.795	0.817
Supplier FEs:	No	Yes	No	Yes	Yes	No	No
Quarter FEs:	No	No	Yes	Yes	No	Yes	No
Customer industry × quarter FEs:	No	No	No	No	Yes	No	Yes
Customer-supplier FEs:	No	No	No	No	No	Yes	Yes

Table 5
Bias Propagation: Cross-Sectional Variation

This table documents cross-sectional variation in the propagation of biases. Column 1 (column 2) shows regressions on the subsample of supplier forecasts about which suppliers are more (less) confident. We define forecasts with a zero range, i.e. point forecasts, as confident, and forecasts with a positive range as less confident. Column 3 uses the full sample and includes an interaction term with the supplier's forecast range. As columns 1 to 3 are on the supplier level, *Customer forecast error* in those columns is the sales-weighted average forecast error of a supplier's customers. In contrast, columns 4 to 8 make use of customer heterogeneity; hence *Customer forecast error* in those columns represent individual customer's forecast errors. Columns 4 to 6 show how bias propagation varies when the customer's forecast is a relatively more precise signal of earnings, or when the supplier's earnings are more difficult to forecast. Column 4 uses the supplier-to-customer ratio of forecast ranges as a measure of relative signal precision; column 5 uses the supplier's earnings volatility as a measure of forecasting difficulty; column 6 uses the supplier-to-customer ratio of earnings volatility as a measure of relative forecasting difficulty. Columns 7 and 8 show cross-sectional variation in propagation with respect to the importance of customers to a supplier. Column 7 adds an interaction of the customer forecast error with that customer's sales share while column 8 replaces the customer's sales share with the excess stock return correlation between the customer and the supplier. The respective direct effects of the interaction terms (e.g., *Supplier range* in column 3, *Supplier-to-customer range* in column 4) are shown in the last row. Control variables are *Forecast horizon*, *Quarterly earnings forecast*, *Log assets*, *PP&E*, *Supplier actual*, and *Customer actual*. Customer industry fixed effects are based on the customers' Fama-French 48 industry classification. All variables are defined in Table A1. t-statistics, reported in parentheses, are based on standard errors clustered at the supplier level.

Dept. variable:	*Supplier forecast*							
Sample:	Zero range	Non-zero range	Full	Full	Full	Full	Full	Full
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Customer forecast error (FE)	0.419	0.346***	0.013					
	(1.10)	(4.75)	(0.11)					
Supplier range × customer FE			0.499***					
			(4.16)					
Supplier-to-customer range × customer FE				0.061**				
				(2.18)				
Supplier earnings variance × customer FE					0.017**			
					(2.21)			
S-C earnings variance ratio × customer FE						0.038		
						(1.53)		
Supplier's sales share × customer FE							0.377***	
							(2.97)	
Customer-supplier beta × customer FE								0.456***
								(2.81)
Direct effect of interaction term			0.263	-0.050***	-0.055	-0.105***	-0.395	-1.310
			(1.29)	(-2.62)	(-1.29)	(-3.62)	(-1.01)	(-1.63)
Observations	2,045	8,237	10,282	9,463	10,302	9,925	9,463	7,193
R-squared	0.958	0.938	0.934	0.940	0.939	0.938	0.939	0.947
Control variables included:	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Supplier FEs:	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Customer industry × quarter FEs:	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6
Bias Propagation: Leads and Lags

This table documents the propagation of bias for different leads and lags of customer forecasts by making use of the precise timing and sequence of customer forecasts around the issuance of a supplier's forecast. *Customer forecast error [t+1]* is the error of the earliest EPS forecast issued in the six-month window following the issuance of the supplier's forecast. *Customer forecast error [t-1]* is the error of the latest customer forecast issued in the six month period preceding the supplier's forecast. Similarly, periods *[t-2]* and *[t-3]* reference deeper lags of six-month windows. Control variables are the same as in Table 5. All variables are defined in Table A1. t-statistics, reported in parentheses, are based on standard errors clustered at the supplier level.

Dept. variable:	*Supplier forecast*					
	(1)	(2)	(3)	(4)	(5)	(6)
Customer forecast error [t+1]						0.052
						(0.19)
Customer forecast error [t-1]	0.500**			0.543***	0.526***	0.463*
	(2.40)			(3.60)	(3.24)	(1.93)
Customer forecast error [t-2]		0.132		0.299	0.010	
		(0.70)		(1.58)	(0.06)	
Customer forecast error [t-3]			-0.389	-0.653**		
			(-1.39)	(-2.44)		
Observations	8,946	8,662	8,357	7,629	8,159	8,686
R-squared	0.626	0.619	0.622	0.612	0.614	0.623
Control variables included:	Yes	Yes	Yes	Yes	Yes	Yes
Supplier FEs:	Yes	Yes	Yes	Yes	Yes	Yes
Customer industry × quarter FEs:	Yes	Yes	Yes	Yes	Yes	Yes

Table 7
Direction of Propagation

This table shows regressions of the customer's forecast on the supplier's forecast error, thus switching the dependent and independent variables of Table 4. Observations for the dependent and independent variables are now matched such that the issuance of the customer forecast occurs after that of the supplier. Columns 1 to 5 use the sales-weighted supplier forecast error when a supplier has multiple customers. In columns 6 and 7 each customer-supplier pair is a separate observation and hence each individual supplier forecast error is used. *Forecast horizon* is the number of days between the announcement of the forecast and the announcement of realized earnings for the fiscal period end to which the forecast applies. *Forecast horizon* is the number of days between the forecast issuance and the announcement of the respective realized earnings. *Quarterly earnings forecast* is an indicator variable which equals one for quarterly forecasts and zero for annual forecasts. All variables are defined in Table A1. Customer industry fixed effects are based on the customer's Fama-French 48 industry classification. t-statistics, reported in parentheses, are based on standard errors clustered at the supplier level.

Dept. variable:	*Customer forecast*						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Supplier forecast error	0.171	0.247	0.207	0.201	0.179	0.018	0.021
	(0.77)	(0.90)	(0.94)	(0.83)	(0.51)	(0.93)	(1.12)
Forecast horizon	0.001**	0.001***	0.001***	0.001***	0.002***	0.002***	0.002***
	(2.35)	(3.13)	(3.11)	(3.98)	(4.10)	(5.81)	(4.67)
Quarterly earnings forecast	-4.972***	-5.056***	-4.920***	-5.000***	-4.923***	-4.838***	-4.815***
	(-34.41)	(-26.64)	(-34.84)	(-27.76)	(-22.15)	(-20.25)	(-18.97)
Log assets	0.254***	0.235	0.233***	0.195	0.282***	0.376	1.279**
	(3.43)	(1.40)	(3.14)	(0.88)	(3.16)	(0.87)	(2.40)
Tobin's Q	-0.723***	-0.601***	-0.638***	-0.318***	-0.391***	-0.349**	-0.305**
	(-8.83)	(-6.17)	(-7.70)	(-3.13)	(-3.69)	(-2.40)	(-2.22)
PP&E	-0.490	-0.977	-0.515	-1.963	-1.152	0.059	0.242
	(-1.22)	(-0.60)	(-1.31)	(-1.20)	(-1.09)	(0.02)	(0.08)
Observations	4,543	4,543	4,543	4,543	4,543	15,692	15,692
R-squared	0.618	0.797	0.647	0.821	0.882	0.842	0.896
Supplier FEs:	No	Yes	No	Yes	Yes	No	No
Quarter FEs:	No	No	Yes	Yes	No	Yes	No
Customer industry × quarter FEs:	No	No	No	No	Yes	No	Yes
Customer-supplier FEs:	No	No	No	No	No	Yes	Yes

Table 8
Real Effects of Managerial Bias

This table shows regressions of various corporate policies on a firm's *own* EPS forecast error – a measure of management's bias – and standard determinants of these policies. We use annual forecasts with a remaining forecast horizon between 180 and 365 days only. The dependent variables *Investment*, *Inventory* and *Net book leverage* are expressed in percent of book assets. *Stock issuance* (*Stock repurchase*) is an indicator variable that is zero if the firm did not issue new stock (did not repurchase stock), and – for ease of interpretation of coefficients – 100 if the firm did issue new stock (did repurchase outstanding stock). All variables are defined in Table A1. *t*-statistics, reported in parentheses, are based on standard errors clustered at the firm level.

Dept. variable:	*Investment*	*Inventory*	*Net book leverage*	*Stock repurchase*	*Stock issuance*
	(1)	(2)	(3)	(4)	(5)
Forecast error	0.090***	0.091***	0.801***	1.293***	-0.427***
	(5.70)	(3.68)	(7.91)	(5.68)	(-3.07)
Log assets	-0.687***	-1.464***	9.350***	-0.137	2.062**
	(-6.76)	(-7.63)	(10.34)	(-0.08)	(2.06)
Tobin's Q	0.002***	-0.002***	-0.020***	-0.032***	0.028***
	(3.33)	(-2.83)	(-5.02)	(-4.05)	(5.68)
Profitability	0.043***	0.055***	-0.017	0.534***	-0.230***
	(5.47)	(4.50)	(-0.24)	(3.94)	(-3.10)
PP&E	0.052**	0.007**	0.128***	-0.014	0.138**
	(2.49)	(2.06)	(2.76)	(-0.30)	(2.28)
Observations	11,436	11,344	11,399	11,475	10,845
R-squared	0.785	0.971	0.875	0.511	0.303
Firm FEs:	Yes	Yes	Yes	Yes	Yes
Year FEs:	Yes	Yes	Yes	Yes	Yes

Table 9
Real Effects of Propagated Managerial Bias

This table shows second-stage instrumental variables regressions of various corporate policies on *propagated* bias. We use annual forecasts with a remaining forecast horizon between 180 and 365 days only. The first stage uses customer forecast errors as an instrument for suppliers' forecast bias as in the specification shown in column 5 of Table 4. The first-stage results are omitted to conserve space. The last row reports F-statistics from the first-stage regressions. The dependent variables *Investment*, *Inventory* and *Book leverage* are expressed in percent of book assets. *Stock issuance* (*Stock repurchase*) is an indicator variable that is zero if the firm did not issue new stock (did not repurchase stock), and – for ease of interpretation of coefficients – 100 if the firm did issue new stock (did repurchase outstanding stock). Variable definitions are in Table A1; t-statistics, reported in parentheses, are based on standard errors clustered at the supplier level.

Dept. variable:	*Investment*	*Inventory*	*Net book leverage*	*Stock repurchase*	*Stock issuance*
	(1)	(2)	(3)	(4)	(5)
Forecast (instrumented)	-0.026	1.522**	0.487	17.251*	-8.665*
	(-0.12)	(2.36)	(0.28)	(1.69)	(-1.71)
Log assets	-0.588*	-3.708***	8.662***	-20.398*	16.076**
	(-1.84)	(-3.99)	(3.24)	(-1.78)	(2.51)
Tobin's Q	0.001	0.009	-0.033**	0.071	-0.024
	(0.40)	(1.56)	(-2.06)	(0.81)	(-0.66)
Profitability	0.026	-0.165	-0.348	-2.206	1.009
	(0.62)	(-1.51)	(-1.07)	(-1.34)	(1.35)
PP&E	0.094***	0.064*	0.331***	0.879*	0.376
	(4.62)	(1.74)	(2.80)	(1.83)	(1.18)
Observations	1,341	1,342	1,338	1,342	1,277
R-squared	0.667	0.898	0.894	0.165	-0.123
Firm FEs:	Yes	Yes	Yes	Yes	Yes
Year FEs:	Yes	Yes	Yes	Yes	Yes
F-stat of excl. instrument	10.26	9.082	9.153	9.082	9.523

Table A1
Variable Definitions

Variable name	Definition	Data source
I. Earnings forecast data		
Forecast$_{it}$	The forecast of quarterly or annual EPS for fiscal period t, issued by the management of company i, scaled by the split-adjusted stock price five trading days prior to the forecast announcement. EPS guidance data are obtained from Thomson Reuters' IBES database. Stock price and split-adjustment factor are from CRSP. We truncate the variable at the 1st and 99th percentile.	IBES; CRSP
Forecast error$_{it}$	The difference between the EPS forecast by the management and the realized value of company i's quarterly or annual EPS for fiscal period t, scaled by the split-adjusted stock price five trading days prior to the issuance of the forecast. EPS guidance and realized EPS are obtained from Thomson Reuters' IBES database. Stock price and split-adjustment factor are from CRSP. We truncate the variable at the 1st and 99th percentile.	IBES; CRSP
Customer forecast error$_{it}$*, sales-weighted*	The sales-weighted management forecast error of company i's customers for fiscal period t. To each forecast of supplier i we match one forecast of each of i's customers. We use the customer forecast that is made for the same fiscal period and issued prior and closest to the supplier's forecast. Customer-supplier pairs are obtained from Compustat's customer segment files. Since Compustat's customer segment files do not provide firm identifiers, we string-match and manually verify customer names to company names from Compustat's fundamental annual file. Sales shares are defined below.	IBES; CRSP; Compustat; Compustat customer segment files
Forecast horizon$_{it}$	The number of calendar days between the issuance of an EPS forecast and the announcement of realized earnings.	IBES
Forecast range$_{it}$	The difference between the upper and lower bounds of an EPS forecast, scaled by the split-adjusted stock price five trading days prior to the issuance of the forecast. 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 for fiscal period t is for quarterly EPS, else 0.	IBES
Actual$_{it}$	The realized EPS announced by firm i for fiscal period t, scaled by the split-adjusted stock price five trading days before the announcement date. We truncate the variable (separately for quarterly and annual forecasts) at the 1st and 99th percentile.	IBES; CRSP
Customer actual$_{it}$*, sales-weighted*	The sales-weighted average realized EPS of company i's customers for fiscal period t, where actuals are scaled by the split-adjusted stock price five trading days before the announcement date. Sales shares are defined below.	IBES; CRSP; Compustat; Compustat customer segment files
Earnings variance$_{it}$	The annualized variance of realized EPS, computed over the previous four years, and separately for quarterly and annual earnings.	IBES
II. Alternative optimism measures		
Share retainer$_{it}$	Based on Sen and Tumarkin (2015) and obtained from Robert Tumarkin's webpage. It is an indicator variable that equals 1 (optimistic) if the cumulative shares retained by a CEO on days with option exercising exceeds 1% and 0 (not optimistic) otherwise.	Robert Tumarkin's webpage
Holder67$_{it}$	Indicator variable that equals 1 if the CEO of company i fails in fiscal year t to exercise vested stock options that are at least 67% in the money, and 0 otherwise.	ExecuComp

Table A1 - Continued

Variable name	Definition	Data source
Transcript sentiment$_{it}$	Textual sentiment in the managerial discussion section of the analyst conference call held on the same day as the announcement of the EPS forecast. It is computed as the number of positive financial words divided by the sum of positive and negative financial words. Positive and negative financial words are taken from Loughran and McDonald's 2014 Master Dictionary. Conference call transcripts are obtained from SeekingAlpha.com.	SeekingAlpha.com; Bill McDonald's webpage
Net share purchases$_{it}$	Cumulative share purchases (net of share sales) by the CEO in the 12 months prior to the issuance date of a management forecast.	Thomson Reuters' Insider Filings database
III. Customer-supplier link data		
Customer-supplier beta$_{ij}$	The correlation between the excess daily stock returns of supplier i and its customer j after controlling for the excess market return. 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.	CRSP; Compustat customer segment files
Sales share$_{ijt}$	The fraction of supplier i's total sales in fiscal period t going to customer j. When no sales share is given, we assume the minimum threshold by SFAS No. 131 that triggers mandatory customer disclosure (10%). We drop observations where the reported sales share is negative or exceeds 100% or when the sum of reported sales shares to all customers exceeds 100%.	Compustat; Compustat customer segment files
IV. Financial and accounting variables		
Log 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
Tobin's Q$_{it}$	Ratio of market value of assets to book value of assets for company i in fiscal year t.	Compustat
Sales$_{it}$	Net sales (SALE) of company i in billions of USD in fiscal year t.	Compustat
PP&E$_{it}$	Total net value of property, plants and equipment (PPENT) divided by total assets (AT) for company i in fiscal year t.	Compustat
Profitability$_{it}$	Operating income before depreciation (OIBDP) divided by total assets (AT) for company i in fiscal year 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 in fiscal year t.	Compustat
Inventory$_{it}$	Total inventories (INVT) divided by total assets (AT) for company i in fiscal year t.	Compustat
Investment$_{it}$	Capital expenditures (CAPX) divided by total assets (AT) for company i in fiscal year t.	Compustat
Stock issuance$_{it}$	Indicator variable that equals 1 if firm i issues new stock in an SEO during fiscal year t, else 0. We scale it by 100 to ease the interpretation of coefficients.	Thomson One
Stock repurchase$_{it}$	Indicator variable that equals 1 if firm i repurchases stock during fiscal year t, else 0. We follow Stephens and Weisbach (1998) to compute the number of repurchased shares based on the cumulative change in outstanding shares (SHROUT) as recorded in CRSP. The indicator variable equals 1 if the cumulative change is negative, else 0. We scale the indicator by 100 to ease the interpretation of coefficients.	CRSP

Table A2
Bias Propagation: Asymmetric Effects

This table shows regressions of supplier forecasts on their customers' forecast errors, separately for positive and negative customer forecast errors. Columns 1-2 and 5-6 use the sales-weighted customer forecast errors when a supplier has multiple customers. In those columns, the coefficient is interpreted as the effect on a supplier's bias of a one-unit increase in the bias of a customer representing 100% of supplier sales. In columns 3-4 and 7-8, each customer-supplier pair is a separate observation and hence each individual customer forecast error is used. In these columns, the coefficient is interpreted as the effect on a supplier's bias of a one-unit increase in the bias of the average customer (representing on average 16% of supplier sales). *Forecast horizon* is the number of days between the forecast issuance and the announcement of the respective realized earnings. *Quarterly earnings forecast* is an indicator variable which equals one for quarterly forecasts and zero for annual forecasts. All other control variables are defined in Table A1. Customer industry fixed effects are based on the customer's Fama-French 48 industry classification. t-statistics, reported in parentheses, are based on standard errors clustered at the supplier level.

Dept. variable:	*Supplier forecast*							
Sample:	Positive customer forecast error				Negative customer forecast error			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Customer forecast error	0.799***	0.525*	0.119**	0.111*	-0.338	0.240	0.015	0.021
	(2.99)	(1.95)	(2.02)	(1.70)	(-0.72)	(0.54)	(0.20)	(0.25)
Forecast horizon	0.000	0.001	0.000	0.001	0.002***	0.002***	0.002***	0.002***
	(0.81)	(1.14)	(1.00)	(1.26)	(6.81)	(6.28)	(4.93)	(4.42)
Quarterly earnings forecast	-4.712***	-4.735***	-4.807***	-4.901***	-4.783***	-4.800***	-4.827***	-4.900***
	(-22.84)	(-20.95)	(-20.05)	(-19.06)	(-19.14)	(-18.46)	(-19.41)	(-18.27)
Log assets	0.341	1.127**	1.183***	1.226**	0.084	0.674***	0.819***	0.781***
	(1.03)	(2.16)	(2.76)	(2.51)	(0.58)	(3.45)	(3.66)	(3.42)
Tobin's Q	-0.389***	-0.136	-0.128	-0.150	-0.423***	-0.132*	-0.180***	-0.114
	(-2.61)	(-0.89)	(-0.98)	(-0.96)	(-4.77)	(-1.89)	(-2.65)	(-1.46)
PP&E	-4.940*	-4.156	-4.393	-5.724*	-1.117	-0.935	-0.561	-1.575
	(-1.66)	(-1.46)	(-1.57)	(-1.65)	(-0.75)	(-0.67)	(-0.34)	(-0.70)
Observations	3,085	3,085	4,053	4,053	7,035	7,035	9,487	9,487
R-squared	0.753	0.789	0.820	0.846	0.791	0.810	0.813	0.837
Supplier FEs:	Yes	Yes	No	No	Yes	Yes	No	No
Quarter FEs:	No	Yes	Yes	No	No	Yes	Yes	No
Customer industry $\times$ quarter FEs:	No	No	No	Yes	No	No	No	Yes
Customer-supplier FEs:	No	No	Yes	Yes	No	No	Yes	Yes