

Optimism Propagation*

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Abstract

We document that managerial optimism spreads across firms via customer-supplier networks. We use management earnings forecasts and their realizations to estimate the propagation of optimistic beliefs across firms and find a robust and economically large transmission of biases from customers to suppliers. Indicating causality, we find that supplier forecasts are only affected by recently issued customer forecasts, not by customer forecasts issued in the near future. The effect is stronger when suppliers are less confident about their own forecasts and it increases in the perceived precision and salience of the customer forecast. In addition, we find evidence for real effects of propagated optimism. Taken together, these results suggest that contagious sentiment contributes to fluctuations in business and financing cycles. In a methodological contribution we show how correlation of time-varying optimism between agents can be identified empirically even though the optimism embedded in a forecast is not directly observable, neither before nor after the realization. Conceptually, we argue that propagation of irrational beliefs occurs even if suppliers are perfectly Bayesian; hence the transmission of biased beliefs is not per se irrational.

Keywords: Managerial optimism; Managerial sentiment; Propagation;
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JEL classification: G30; G02

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I. Introduction

The question of how optimism, or more generally 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 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 and focal points for supplier firms in the context of belief formation about future earnings. It is essential for suppliers to incorporate information about the customer's 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.

We use earnings forecasts and their realizations to study optimism propagation.² By studying the dynamic notion of contagion, our analysis necessarily focuses on the *time-varying* component of optimism among managers. This makes the conceptual and

¹ Hirshleifer (2015) reviews the literature on behavioral finance, 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)

² Forecasts or forecast errors have been used as measures of optimism in previous studies, but not in the context of optimism propagation (see, e.g., Landier and Thesmar (2009), Ben-David, Graham, and Harvey (2013), Hribar and Yang (2013), and Otto (2014)).

empirical analysis of biases considerably more complicated. The reason is that the bias contained in a specific forecast cannot be discerned in observational data. A forecast, or subjective expectation, is the sum of the true expected value and a (potential) bias. And since the true expected value cannot be observed, the bias cannot be identified either. This indeterminacy remains even after the realization of the predicted quantity has occurred: A commonly used measure of optimism, the forecast error, is the difference between the bias and the unpredictable random component of the realization. The forecast error can be positive either because the forecast was *ex ante* too optimistic or because the unpredictable random component of the realization was negative. But it is precisely this indeterminacy which makes propagation of sentiment in forecasts plausible: Even a perfectly Bayesian supplier seeking to improve his own forecast by incorporating information contained in its customer's forecast necessarily copies part of its customer's bias, because he cannot disentangle the true expectation from the bias contained in the customer's forecast. We show this in a simple model in Section II.A where we also develop additional, more nuanced hypotheses about belief contagion.

The fact that the bias embedded in a forecast cannot directly be observed also complicates the empirical identification of optimism propagation. It creates a particular type of measurement error problem. The observable quantities – the management forecast and the forecast error – are the sum of the bias and a “nuisance”, or measurement error, variable. In the case of the 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 real shocks between the firms.³ A method-

³ Equivalently, the correlation of customer and supplier forecasts conflates the correlation of biases

ological contribution of this paper is to show that, by regressing suppliers' *forecasts* on their customers' *forecast errors*, bias correlation can be identified. 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. We show this formally and discuss it in detail in section II.B.

We construct a matched customer-supplier sample of U.S. firms between 2003 and 2013 to investigate how optimistic beliefs of managers propagate through customer-supplier networks. As our main result we document a strong positive relationship between customer and supplier optimism. The economic magnitude of this effect is large: a one percentage point increase in the forecast optimism of a customer representing 100% of supplier sales leads to a 0.41 percentage point increase in supplier optimism in our most conservative specification. Given the magnitude of this “optimism pass-through rate” and the fact that customers often have many suppliers – both proximate ones as well as more distant ones in the supply chain – an initial shock to the beliefs of a management of a large firm may generate significant aggregate effects.

To provide causal evidence on optimism propagation, we exploit the precise timing and sequence of forecast issuance. Specifically, we find that supplier forecasts are only affected by *recently issued* customer forecasts, but not by customer forecasts that are issued in the near future. This is consistent with the spreading of optimistic beliefs, because 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 observable by both firms, with the correlation of the true earnings expectations.

e.g. an optimistic report in a relevant trade journal.⁴

We provide a number of additional results that are consistent with optimism propagation. First, we find that belief 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 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.

Second, our results indicate that contagion is stronger for more salient customer forecasts. More recently issued customer forecasts have stronger contagion effects, and so do forecasts by customers with a greater economic importance – measured by the percentage of the supplier’s total sales going to that customer, or by the correlation of the suppliers’ stock price with that of its customer. Contagion is also stronger the larger is the perceived signal 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 more precise customer forecasts should be more likely to influence suppliers’ beliefs.

Third, 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 for a given firm or customer-supplier relationship. 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 add quarter or quarter-customer industry fixed effects. This ensures that our results are not due to market-wide

⁴ We thank David Hirshleifer for pointing out this example.

or industry-wide waves of sentiment.⁵

Fourth, we run falsification tests in which we randomly draw same-industry (alternatively, same-product market) 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 managerial optimism. Relating time-varying optimism of a firm's management to *its own* corporate policies, we find that investment, inventories, and leverage, increase, while stock issuance decreases. This complements earlier findings of the effects of permanent, person-specific attitudes on firm policies (Malmendier and Tate, 2005; Malmendier, Tate, and Yan, 2011; Ben-David, Graham, and Harvey, 2013; Graham, Harvey, and Puri, 2013)). Importantly, we find similar results for the effects of *propagated* optimism on a firm's corporate policies, where we estimate propagated optimism as the component of a supplier's optimism that is predicted by its customers' optimism.

Taken together, our findings show that optimism spreads along supply chains, and that these propagated beliefs prompt changes in corporate policies of connected firms. A large initial shock to the beliefs of the managers of only a few large corporations could thus have significant ripple effects on the amount and structure of investment and financing in the economy.

⁵ We also document that the direction of learning is crucial to our findings: while suppliers learn from their customers' forecasts, customers do not seem to learn from their suppliers' forecasts. This is further inconsistent with a sentiment wave that is common to supplier and customer firms in some shared but unobservable dimension, such as a shared product market.

This paper is inspired by the large literature in social psychology that investigates the conditions under which communication leads to attitude or opinion change in individuals.⁶ Psychology research in this field does not, however, focus on the specific “opinions” or expectations relevant to economists, such as expected corporate earnings or stock prices, 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 lack of data, he cites anecdotal and suggestive evidence rather than large-scale empirical studies.

In financial economics, this paper relates to three sets of literature. First, it relates to a 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, and Pool, Stoffman, and Yonker (2015) find that this correlation is higher between managers living in the same neighborhood than between managers that live in the same city but in different neighborhoods. Kaustia and Knüpfer (2012) show that portfolio returns experienced by households influence stock market participation of other households located in geographic proximity. Simon and Heimer (2015) find that traders with good short-term performance are more likely to initiate communications with other traders, who subsequently increase their trading activity. Recently,

⁶ For reviews of the psychology literature on attitude and opinion change, see Petty and Cacioppo (1986, 1996), among others. For a review of the psychology literature on emotional contagion, see Hatfield, Cacioppo, and Rapson (1993).

the peer effect literature has been extended to real estate purchase decisions (see Bayer, Mangum, and Roberts (2016) and Bailey, Cao, Kuchler, and Stroebel (2016)). 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*. By using management forecasts to extract those beliefs, we also add to the growing literature using data on subjective expectations to test economic hypotheses (see Greenwood and Shleifer (2014)).

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. 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. 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 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. Framework and Identification

A. A Simple Model of Optimism Propagation

In this section we present a simple model illustrating how optimistic views spread from one individual to another. We deliberately use a Bayesian framework to show that irrational beliefs held by one individual can spread to another individual even if the latter uses fully rational rules for updating expectations.⁷ 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. The prior distribution is normal,

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

where $\bar{\mu}^S$ is the mean of the prior, and $1/\tau$ is the variance of the distribution. 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, $\bar{\mu}_t^S$. The customer has perfect information about his own expected earnings, but he may issue a biased forecast,

$$\hat{e}_t^C = \mu_t^C + b_t^C, \quad (2)$$

⁷ Cavallo, Cruces, and Perez-Truglia (2016) use a similar framework and apply it to the context of inflation expectations. We build on their model and adapt it to the setting of corporate earnings forecasts.

where b_t^C measures the customer's bias.⁸ Further, μ_t^C is related to μ_t^S , so that the customer's forecast is an informative signal about S 's expected earnings. For simplicity, and without loss of generality, let $\mu_t^C = \mu_t^S$. Because the supplier cannot observe the bias separately, it constitutes noise in the signal. Assuming this noise is normally distributed with mean zero,

$$b_t^C \sim N(0, 1/\kappa), \quad (3)$$

the signal is *on average* perfectly informative but has limited precision κ .

The Bayesian update of S 's expected earnings that optimally incorporates its customer's forecast is given by⁹

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

and hence the bias of S 's forecast is

$$\begin{aligned} b_t^S &= \hat{\mu}_t^S - \mu_t^S = \frac{\tau}{\tau + \kappa} \bar{\mu}_t^S + \frac{\kappa}{\tau + \kappa} (\mu_t^S + b_t^C) - \mu_t^S \\ &= \frac{\tau}{\tau + \kappa} (\bar{\mu}_t^S - \mu_t^S) + \frac{\kappa}{\tau + \kappa} b_t^C. \end{aligned} \quad (5)$$

Equation (5) shows that the bias in firm S 's forecast is greater the larger is the

⁸ The assumption that the supplier does not have perfect information and hence does not know the true earnings expectation while the customer does, is made solely for simplicity of exposition. It does not change the main prediction of this model. In the Appendix, we present a more realistic version of this model in which neither customer nor supplier know the true earnings expectation, and where they can use both internal and external signals to improve on their initial prior.

⁹ See, for instance, DeGroot (1970), p.167.

prior relative to the true earnings expectation at time t , and the greater is the bias of the customer's forecast. The second term shows that, even 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.

The degree of contagion of customer bias to supplier bias is represented by $\frac{\kappa}{\tau+\kappa}$, the ratio of the precisions of the customer's forecast and the supplier's prior. Equation (5) hence predicts that contagion of forecast bias from customer to supplier 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 will test these two predictions in Section IV below.

B. Identifying Optimism Propagation Empirically

In this section we formally show how to empirically identify optimism 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 (superscript “C”) or supplier firm (superscript “S”). Importantly, the supplier’s forecast from which we extract the bias must be issued *after* the customer’s forecast, so that belief propagation from customer to supplier can occur. In contrast to much of the existing empirical literature, we explicitly allow the bias b_{it} to vary across firms and over time.

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

$$\hat{e}_{it}^S = \mu_{it}^S + b_{it}^S, \tag{7a}$$

$$\hat{e}_{it}^C = \mu_{it}^C + b_{it}^C. \tag{7b}$$

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 customer and supplier; so we explicitly allow for $Cov(b_{it}^C, b_{it}^S) \neq 0$ and $Cov(\mu_{it}^C, \mu_{it}^S) \neq 0$. 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 potentially cross-correlations). This is because the measurement errors, or nuisance variables, in the dependent and independent variables, μ^S and μ^C , are 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} :

$$e_{it}^S = \mu_{it}^S + \varepsilon_{it}^S, \tag{8a}$$

$$e_{it}^C = \mu_{it}^C + \varepsilon_{it}^C, \tag{8b}$$

where $\mathbb{E}(\varepsilon^K) = 0$, $Cov(\varepsilon^K, \mu^K) = 0$, $K \in \{C, S\}$. Just as we allow $Cov(\mu_{it}^C, \mu_{it}^S) \neq 0$, we also allow for $Cov(\varepsilon_{it}^C, \varepsilon_{it}^S) \neq 0$ due to the business link between the firms.

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

$$\hat{e}_{it}^S - e_{it}^S = b_{it}^S - \varepsilon_{it}^S, \tag{9a}$$

$$\hat{e}_{it}^C - e_{it}^C = b_{it}^C - \varepsilon_{it}^C. \tag{9b}$$

Forecast errors are intuitive proxies for the bias, and they are used in several studies of op-

timism (e.g. Landier and Thesmar (2009), Ben-David, Graham, and Harvey (2013), Otto (2014)). However, in our setting, forecast errors cannot easily be used as measures of the bias, because the earnings shocks do not simply “average out”. As a result, regressing suppliers’ on customers’ *forecast errors* 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 measurement errors (or nuisance variables) of the dependent and independent variables, ε_{it}^S and ε_{it}^C , are again correlated.

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

$$\begin{aligned}\hat{e}_{it}^S &= \alpha + \beta(\hat{e}_{it}^C - e_{it}^C) + u_{it}, \\ \Leftrightarrow \mu_{it}^S + b_{it}^S &= \alpha + \beta(b_{it}^C - \varepsilon_{it}^C) + u_{it}.\end{aligned}\tag{10}$$

This simple change in the regression specification isolates bias propagation, because the nuisance term, μ_{it}^S , of the dependent variable is an ex-ante expectation while the nuisance term of the independent variable, $-\varepsilon_{it}^C$, is an unpredictable, ex-post shock. By definition, these are uncorrelated.

The only way in which the regression coefficient could be upward biased is if $Cov(\mu_{it}^S, b_{it}^C) > 0$, that is, if the supplier’s true earnings expectation were positively correlated with

the customer's bias. Although we cannot completely rule out this possibility, it seems implausible that a supplier should rationally revise its expectations upwards when its customer is irrationally optimistic about its own earnings. But even if we allow for this possibility, we can reduce or eliminate the influence of this correlation on our coefficient of interest by conditioning on predictors of μ^S . For instance, if suppliers' true earnings expectations are time-invariant, supplier or customer-supplier-pair fixed effects eliminate any bias stemming from $Cov(\mu^S, b^C)$.

What remains is an attenuation bias due to the fact that the dependent variable is measured with (independently distributed) error. This leads to conservative estimates of the effect we are interested in.

Formally, we can write the above problem as a measurement error problem. Starting from equation (6),

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

we replace the dependent variable using equation (7a), i.e. $b_{it}^S = \hat{e}_{it}^S - \mu_{it}^S$, and we replace the independent variable using equation (9b), i.e. $b_{it}^C = \hat{e}_{it}^C - e_{it}^C + \varepsilon_{it}^C$. This yields

$$\begin{aligned} \hat{e}_{it}^S - \mu_{it}^S &= \alpha + \beta(\hat{e}_{it}^C - e_{it}^C + \varepsilon_{it}^C) + u_{it}, \text{ or equivalently} \\ \hat{e}_{it}^S &= \alpha + \beta \underbrace{(\hat{e}_{it}^C - e_{it}^C)}_{b_{it}^C - \varepsilon_{it}^C} + \underbrace{\beta \varepsilon_{it}^C + \mu_{it}^S + u_{it}}_{v_{it}} \end{aligned}$$

where $v_{it} = \beta \varepsilon_{it}^C + \mu_{it}^S + u_{it}$ is the new error term. Under the assumptions stated above, the only type of bias is a standard attenuation bias due to the presence of ε_{it}^C in the independent variable (with negative sign) and in the error term (with positive sign).

Alternative Approach. An alternative approach to identifying management optimism and its propagation is to measure management bias as the difference between the management’s forecast and a plausibly unbiased forecast. Candidates for plausibly unbiased forecasts are statistical forecasts and forecasts of other market observers such as analysts. The management’s relative forecast, e.g. with respect to the consensus analyst forecast,

$$\hat{e}_{it}^{Mgt} - \hat{e}_{it}^{Analysts} = (\mu_{it} + b_{it}^{Mgt}) - (\mu_{it} + b_{it}^{Analysts}) = b_{it}^{Mgt} - b_{it}^{Analysts}, \quad (11)$$

eliminates the nuisance term μ_{it} from the forecast, but it only measures the management bias precisely only if the consensus analyst forecast is indeed unbiased. This is far from obvious. On the one hand, it is well-known that analyst forecasts are themselves biased (see, e.g. Chopra (1998); Michaely and Womack (1999); Lim (2001); Hong and Kacperczyk (2010)). On the other hand it has been documented that, after companies start issuing earnings guidance, analyst forecasts are closely clustered around the company guidance, suggesting that analysts largely adopt the company’s forecast including any bias contained therein. In this case, a relative forecast would severely understate the management bias, and consequently could prevent us from detecting any propagation. For these reasons, we do not use this alternative “relative optimism” approach for our main analysis. Still, we provide some key regression results using relative optimism in Appendix Table A.I and we briefly discuss it in the results section (Section IV).

III. Data

A. Sample Construction

The core of our dataset consists of management forecasts – often called management guidance – of both quarterly and annual earnings per share. Since the passage of Regulation Fair Disclosure (Reg FD) in 2000, issuing management guidance has become the norm for public corporations.¹⁰ Thomson Reuters’ Institutional Brokers’ Estimates System (IBES) starts recording management guidance for all U.S. public firms in 2003, and we use their data for the period 2003 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 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 outstand-

¹⁰ The 2015 National Investor Relations Institute Report states that 86% of publicly listed firms issue EPS guidance.

ing. 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 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.¹¹

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. We thus use a string-distance matching algorithm and manual verification to identify the CRSP PERMNO of publicly listed customer firms. 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 same fiscal period end. We keep only those supplier forecasts for which there is at least one customer with a matched forecast.

¹¹ For details on the variable definitions, see Table IX.

Our final dataset contains 9,797 supplier forecast observations and 9,789 customer-supplier-forecast combinations originating from 1,921 unique suppliers and 570 unique customers.

[Insert Table I here]

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 number is lower than the actual average number of customers since 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, investment), customers and suppliers are similar.

B. Measuring Optimism

As detailed in Section II, we use management earnings forecasts and forecast errors of earnings per share to identify optimism propagation. We scale both variables by the stock price from five trading days prior to the announcement of the forecast, as is standard in the literature (Kothari, 2001).

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&P 500 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 forecast error. All quantities are expressed in percent of the stock price. The average (median) annual earnings forecast is 6.46 (6.16) percent for suppliers. The average realized earnings are slightly lower, resulting in a small positive forecast error, 0.29 percent on average. Quarterly forecasts are slightly lower than actuals, both for suppliers and for customers, on average and at the median. The forecast horizon, which we define as the time between the announcement of a forecast and the announcement of the realized earnings pertaining to that forecast, is between 200 and 230 days for yearly forecasts and 80 and 90 days for forecasts of quarterly earnings.

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 three 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-company 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 error. 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, forecast errors are strongly positively associated with CEOs' net share purchases. In the most conservative specification (column 4), a one percentage point increase in forecast error is associated with net purchases in the amount of \$588,100. 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.

Second, we relate forecast optimism to alternative measures of optimism used in prior literature. Sen and Tumarkin (2015) propose a measure, *ShareRetainer*, that is based on whether a firm's CEO retains some of the shares that the executive receives after exercising stock options in a given year. Panel B of Table III shows a highly significant and positive correlation between their measure and ours (t -statistic of 2.57). Alternatively, the finance literature uses text-based measures of sentiment (e.g., Loughran and McDonald (2011)). We analyze the textual sentiment in 8,577 conference call transcripts that occurred on the same day as the announcement of the EPS forecast, and use Loughran and McDonald's 2014 dictionary of positive and negative financial terms to determine the fraction of positive words.¹² Relating this measure to forecast optimism, we again find a highly significant and positive correlation (t -statistic of 5.85).¹³

¹² We extract the management discussion section of all conference call transcripts available at SeekingAlpha.com, and exclude the Q&A section which also contains analysts' questions and comments. Further details are given in the Variable Appendix.

¹³ 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

Third, we analyze the market reaction around the announcement of realized earnings. If earnings guidance was purely strategic, and the market understood this, then 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.¹⁴ In contrast, Panel C 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, the difference in announcement returns between tercile one and three is 5.49% and 4.87%, for the mean and the median, respectively. 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.

C. Do Suppliers Time their Forecasts to Learn from their Customers?

If supplier managements found their customers' forecasts to be valuable signals for forming their own expectations, one would expect that suppliers would prefer to publish their forecasts only *after* their customers. We examine this in Figure 1. We match forecasts by suppliers to those by their customers while requiring identical forecast peri-

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.

¹⁴ 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 forecast errors and supplier forecasts.

odicity (quarterly or annual) and identical dates/fiscal period ends to which the forecasts pertain. To also match initial forecasts to initial forecasts, and revisions to revisions, we further require a similar distance to the announcement of actual earnings (± 30 days). Despite forecasting for the same date, we find that suppliers file quarterly forecasts on average 4.0 days after their customers (t -statistic of 4.80) and annual forecasts 12.1 days (t -statistic of 8.64) later. This is consistent with suppliers timing their forecasts so to be able to incorporate those of their customers.

[Insert Figure 1 here]

IV. Results

A. Main Results

We proceed by analyzing whether optimism 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 two forecast characteristics, the forecast horizon and a dummy variable indicating a quarterly earnings forecast. Here, we use the sales-weighted customer forecast error as our main independent variable of interest.¹⁵ Therefore, the coefficient is 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 0.706, that is, a pass-through rate of optimism from customers to suppliers of 70.6%.

¹⁵ 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.

We gradually add firm-level controls (column 2), fixed effects for suppliers (column 3) and calendar quarters (column 4). Adding supplier fixed effects removes any potential time-invariant unobservables affecting supplier forecasts while quarter fixed effects control for quarter-specific market-wide waves of sentiment. Column 5 shows a specification which includes supplier as well as quarter fixed effects. The coefficient of interest remains remarkably stable and highly statistically significant across specifications 1 to 5.

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 confounding effect of customer-industry-specific waves of sentiment. In the most stringent specification of column 7, where we also include supplier fixed effects, the coefficient drops to 0.414 but again remains highly statistically significant.

[Insert Table IV here]

Finally, we take an alternative approach in columns 8 and 9. Instead of using the sales-weighted average of customer forecast errors, we keep each customer forecast error as a separate observation and include fixed effects for customer-supplier pairs as well as quarters (column 8) or customer industry-quarters (column 9). Hence, the coefficient of interest is identified off customer-supplier pair specific optimism shocks while controlling for common variation in quarters or in industries and quarters. The coefficient remains highly significant which indicates that optimism 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 0.161 (column 8) and 0.164 (column 9). Crucially, 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.

As expected, we 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.¹⁶

In Table A.I, we show results using an alternative approach to estimating optimism propagation. Following equation (11), we define *Relative optimism*, both for the customer and the supplier, as the difference between the management’s forecast and analysts’ consensus forecast for the same fiscal period’s earnings. As discussed in Section II.B, this has the advantage of eliminating the nuisance term μ_{it} in managements’ forecasts, leaving only biases on both sides of the regression equation. The downside of the relative optimism measure is that it may understate actual management optimism if analysts exhibit similar biases as management. Consequently, the magnitude of bias propagation estimated via regression (11) may be understated. Repeating the specifications of Table IV while using this alternative approach, we still find a highly significant relative bias correlation in all our specifications, though, as expected, the coefficients’ magnitudes are roughly half the size of those in Table IV.

To further corroborate the customer-supplier link as the main channel through which

¹⁶ We control for these variables in all our regressions, but do not show them in subsequent tables to conserve space.

the propagation of optimism occurs, Table V provides regressions in which we repeat the specification shown in Table IV, column 7, but in addition investigate the cross-sectional variation in propagation. Columns 1 to 6 of Table V test the key predictions of the model laid out in Section II.A, namely that first, contagion of forecast bias from customer to supplier is more pronounced the less certain or confident the supplier is about its forecast, and second, the more precise he 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 alternative 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 more volatile historically. Following the model’s predictions, contagion of forecast optimism from customer to supplier should be stronger 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 V 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 optimism propagation is stronger when suppliers are less certain about future profits. Comparing column 1

with column 2 shows that the belief propagation documented in Table IV is concentrated among firms whose management is 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. Motivated by this finding, we run the regressions in columns 4 to 8 only on the subsample with strictly positive supplier forecast range. (Results are slightly weaker if we run those regression on the full sample.) In column 4 we use the ratio of the supplier's to the customer's forecast range as an interaction variable. Optimism contagion should increase with the supplier's own uncertainty only if the customer's forecast is considered to be 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 regressions from columns 2 and 3, 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 volatility. We obtain similar but statistically somewhat weaker results compared to those using the forecast range, i.e. a positive coefficient for the interaction term in each case.

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 the propagation of optimism from customer to supplier. In column 8 we take an alternative approach to measuring customer importance by using the correlation of excess 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. We estimate the correlation of excess stock returns between customer and supplier by running a time-series regression of the supplier’s on the customer’s monthly excess stock returns, separately for each customer-supplier pair. Consistent with the results on sales share, we find that customer optimism impacts supplier optimism significantly more when the stock return correlation is higher.

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, the bias propagation coefficient steadily declines and becomes insignificant for window $t-3$. We include several customer forecasts simultaneously in columns 4 and 5: in column 4, the

largest and only significant customer forecast is the most recent one while older and stale customer forecasts are insignificant. Finally, in column 6 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 optimism. Here, only the lagged customer forecast error remains statistically significant and its coefficient is very similar in magnitude to that in column 1. Taken together, the results in Table VI indicate a Granger-type causality for optimism 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 customer-supplier setting. 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 major customers, the reverse – customers learning from their suppliers’ forecasts – seems economically less plausible. Thus optimism trickling down the supply chain induces correlation between supplier forecasts and lagged customer forecast errors. If instead our results were driven by unobserved shared characteristics or a signal observed by both the customer and the supplier but not by the econometrician, we should also find a significant correlation between *customer* forecasts and lagged *supplier* forecast errors. We provide these results in Appendix Table A.II. Our key coefficients on *Supplier forecast error* are now substantially smaller and are insignificant in all specifications.

[Insert Figure 2 here]

Figure 2 provides a third falsification test to rule out spurious correlation between customer and supplier optimism and to rule out contagion that is due to reasons other than

those related to the specific customer-supplier pair. We run placebo regressions using the most conservative specification of Table IV, that of column 7. Specifically, we run this specification using randomly drawn same-industry (alternatively, same-product market) pseudo-customers instead of the actual customers, repeat this procedure 10,000 times, and plot a histogram of the 10,000 coefficients on the sales-weighted customer forecast variable. If the correlation between customer and supplier optimism 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 0.414 from Table IV, column 7, 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%.

The top graph of Figure 2 shows the distribution of pseudo-customer regression coefficients when industries are defined using the Fama-French 48-industry classification and the Hoberg-Phillips text-based network industry classification. The bottom graph shows the corresponding distributions of t -statistics for those coefficients. Our estimated coefficient of 0.414 lies far above even the highest pseudo-customer coefficient out of 10,000 draws, regardless of which industry classification we use while the estimated t -statistic of 3.22 from Table IV lies in the top 1%. This confirms that the optimism spillover that we document is specific to customer-supplier pairs.

C. Real Effects

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 return relative to the average forecast error in the same survey wave (Ben-David, Graham, and Harvey, 2013), and using psychometric tests (Graham, Harvey, and Puri, 2013). In a first step, we investigate whether forecast optimism, as expressed in companies' earnings forecasts, is also correlated with corporate policies. In a second step, we test whether *propagated* forecast optimism also entails 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 optimism, and directly relate it to various firm policies. Hence, we run regressions of the type

$$y_{it} = \alpha + \beta(\hat{e}_{it} - e_{it}) + \gamma'X_{it} + \lambda_{it} + u_{it}, \quad (12)$$

where y_{it} is a policy variable of firm i , $\hat{e}_{it} - e_{it}$ is the EPS forecast error of firm i , X_{it} is a vector of control variables, λ_{it} is a set of fixed effects, and u_{it} is a mean-zero error term.

We test for changes in investment, inventories, book leverage, and equity issuance. As forecast optimism indicates an expectation of greater revenues and lower financial risk, we expect investment, inventories and leverage to increase with optimism. In contrast, we expect stock issuance to decrease with optimism, because (over)optimism indicates that management views the stock as undervalued by the market and hence should be more reluctant to issue equity (Heaton, 2002; Malmendier, Tate, and Yan, 2011).

In these tests, we match forecasts, realizations, and the policy variable 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. We further ignore any revisions during this period and keep only the earliest forecast for a given fiscal period. 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 VII here]

Table VII presents the results. For each of the four policies, we show results with firm fixed effects only and with firm and year fixed effects combined. In line with the above predictions, we find that optimistic forecasts are associated with greater corporate investment, more inventory, greater book leverage and decreased stock issuance. Notably, the effect of optimism is highly significant for all corporate policies, even after including firm and time fixed effects. In columns 1 to 4, a one percentage point higher forecast error is associated with a 0.05 percentage points greater investment ratio and a 0.10 percentage point increase in inventories. In other words, a one standard deviation increase in forecast optimism (2.2 percentage points) increases investments and inventories by 0.11 and 0.22 percentage points respectively, which compares to average within-firm standard deviations in both variables of 1.8 and 1.5 percentage points. In columns 5 and 6, leverage increases by about 0.3 percentage points with a one percentage point increase in forecast optimism.

Alternatively, one standard deviation in forecast optimism increases leverage by 0.66 percentage points, which relates to a within-firm standard deviation of 5.9 percentage points. Finally, the dependent variable in columns 7 and 8 is an indicator that is equal to one (which we scale to 100 to ease interpretation) if the firm has an equity issue recorded in the Thomson One database in a given year, and zero otherwise. The results show that a one percentage point higher forecast error is associated with a 0.5-0.6 percentage points lower likelihood of stock issuance in a given year. Given that the average probability of stock issuance per year is only 6.4 percent in our sample, this represents an almost 10 percent decline in the likelihood to issue equity. These results are consistent with and corroborate the findings of the above-mentioned earlier studies on the real effects of optimism.

In the single-stage regression of equation (12) it is possible that the effect of the forecast error on firm policies is not only driven by the management's bias, b_{it} , but also by the earnings shock ε_{it} . For example, the effect of the forecast error on leverage could be positive either because optimism causes management to actively increase debt or because a negative earnings shock decreases the book asset value (while debt obligations remain unchanged).¹⁷ Alternatively, a positive earnings shock (and hence a lower forecast error) may lead the management to pay down some of its outstanding liabilities, reducing the debt-to-asset ratio and thereby causing a downward bias for our coefficient. As a result we cannot rule out the possibility that the earnings shock confounds the effect of optimism on firm policy in regression (12). Our regressions of firm policies on *propagated* optimism, to which we turn next, are less affected by this channel as we explain below.

Our final tests are designed to detect real effects of propagated optimism. Specifically,

¹⁷ The potential confounding effect of the earnings shock depends on the policy of interest. In the case of investment, the earnings shock would likely have an effect that is opposite to the effect of optimism: optimism should increase investment while a negative earnings shock should decrease investment.

we estimate propagated optimism in a first-stage regression as the component of a supplier's forecast that is predicted by its customers' optimism. Here, we use the customer's forecast error as an instrument for the supplier's forecast optimism. Thus the first stage of this instrumental variables regression is identical to equation (10) and to the single-stage regression we use in our main table (Table IV). We then use the predicted supplier forecast as an independent variable in regressions of various firm policies:

$$\hat{e}_{it}^S = \alpha_1 + \beta_1(\hat{e}_{it}^C - e_{it}^C) + \gamma_1' X_{it}^S + \lambda_{1it} + u_{it} \quad (\text{First stage}) \quad (13)$$

$$y_{it}^S = \alpha_2 + \beta_2 \hat{e}_{it}^S + \gamma_2' X_{it}^S + \lambda_{2it} + \nu_{it} \quad (\text{Second stage}) \quad (14)$$

In this two-stage specification, the earnings shock contained in the forecast error of the first-stage independent variable ($\hat{e}_{it}^C - e_{it}^C = b_{it}^C - \epsilon_{it}^C$) is less likely to confound the effect of optimism on the supplier's firm policies, because the predicted value from the first stage contains the earnings shock of the customer firm, not the supplier firm. So any real shock to a customer can affect the supplier's policy only to the extent that it trickles down to the supplier.

As in our previous tests of real effects, and for the same reasons, we 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 substantially compared to Table VII. Still, with values consistently above 10, our first-stage F -statistics indicate that there are no weak instrument concerns.¹⁸

[Insert Table VIII here]

¹⁸ The first stage of this regression (available upon request) corresponds to Table IV except that it uses a smaller sample.

As in Table VII above, we show two regressions for each corporate policy, one with firm fixed effects only and one with firm and year fixed effects. Columns 1 and 2 do not reveal statistically significant effects of propagated optimism for investment. A one percentage point increase in customer optimism increases investment by a statistically insignificant 0.04 to 0.07 percentage points. We however find statistically significant effects for inventories, leverage, and equity issuance. Inventories increase by 0.78 to 1.06 percentage points with a one percentage point increase in propagated optimism while book leverage increases by 2.1 to 2.3 percentage points. These are economically large effects given that average inventories and average book leverage are 10 percent and 21 percent respectively in our sample, and within-firm standard deviation are only 1.9 percent and 5.9 percent. Finally, the probability of equity issuance in columns 7 and 8 decreases by 6.7 to 7.6 percentage points with a one percentage point increase in propagated optimism.¹⁹ Taken together, the results in Table VIII reveal that propagated optimism has only modest effects on investment but strong effects on corporate financial decisions. We note that our focus on the effects of time-varying, within-firm variation in optimism is per se quite demanding since corporate policies are known to be highly persistent, and hence determinants of changes in these policies are typically more difficult to identify than determinants of cross-sectional variation.

V. Conclusion

We study how optimism spreads across firms via customer-supplier relationships. We use firms' EPS forecasts to measure fluctuations in managerial optimism and devise a

¹⁹ The magnitude of the effect in column (8) declines to -4.3 percentage points (t -statistic of -3.16) when restricting the sample to significant equity issuances that exceed 10 percent of outstanding shares.

regression framework that separates the propagation of biases in beliefs from the propagation of real shocks along the supply chain. Our main contribution is to document a strong positive relationship between customer and supplier optimism: a one percentage point increase in forecast optimism of a hypothetical customer representing 100% of the supplier's sales, leads to a 0.40 to 0.70 percentage point increase in supplier optimism. This result holds in univariate as well as multivariate tests controlling for a range of company and forecast characteristics and numerous fixed effects. Subsample tests further document that optimism propagation strengthens the less confidence suppliers have in their own forecasts, the greater is the perceived precision of the customer forecast signal, and it also strengthens when customers are more important or salient to the supplier.

Several falsification tests address causality concerns. First, we run placebo regressions replacing actual customers' forecasts with forecasts of pseudo-customers (non-customers from the same industry or same product market); our actual-customer coefficient consistently lies in the top 0.1% of the empirical distribution of pseudo-customer coefficients. Second, we show that optimism spillover only occurs 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. These timing results establish a Granger-type causality between customer and supplier forecast optimism. Third, we show that biases propagate from customers to suppliers, but not the reverse, indicating that propagation is not due to some unobserved shared characteristic of suppliers and customers.

We also investigate the real effects of propagated managerial optimism and find significant effects on leverage, equity issuance, and inventories. These results are important, because they show not only that beliefs propagate between management teams that ob-

serve each other's profit forecasts, but that these propagated beliefs lead managers 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 production 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 supply 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 optimism propagates 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 further contribute to our understanding of belief propagation in economic networks.

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Appendix.

A Simple Framework for Optimism Propagation: Extension

In this Appendix we present an extended version of the simple Bayesian framework laid out in Section II.A. In this extension, we relax the assumption that the customer knows the true earnings expectation; instead, both customer and supplier make use of internal and external signals to generate their respective forecasts.

True expected earnings of the supplier, μ_t^S , are time-varying and cannot be known with certainty, because the process determining earnings is not fully known. Rather, earnings expectations are normally distributed,

$$\mu_t^S \sim N(\bar{\mu}^S, 1/\tau). \quad (\text{A-1})$$

$\bar{\mu}_t^S$ is the initial prior for expected earnings and can be thought of as the long-run average of earnings. $1/\tau$ is the variance of expected earnings, and we refer to τ the precision of the initial prior. Assume that the management of firm S seeks to incorporate internal and external information in order to generate a more accurate prediction of earnings than the long-run average, $\bar{\mu}_t^S$. In particular, management aims to use the most recent information available, information that enables it to make a time- t specific prediction of its earnings. We first consider the use of internal information such as projections of orders by the firm's own sales people, internal projections about the industry's growth, estimates from process engineers about potential efficiency improvements in production, and so on. Assume such information can be subsumed into a single signal s_t , where

$$s_t = \mu_t^S + \eta_t, \quad (\text{A-2})$$

and $\eta_t \sim N(0, 1/\kappa_1)$. Thus the signal is unbiased for the true expected earnings, but contains noise η_t with variance $1/\kappa_1$ (or precision κ_1). The Bayesian update of firm S 's expected earnings solely based on the internal signal is given by

$$\hat{\mu}_t^S = \frac{\tau}{\tau + \kappa_1} \bar{\mu}^S + \frac{\kappa_1}{\tau + \kappa_1} s_t. \quad (\text{A-3})$$

The update of expected earnings is a weighted sum of the initial prior, $\bar{\mu}^S$, and the signal, s_t , where the weights are determined by the relative precision of the two terms. The update has variance $1/(\tau + \kappa_1)$ (or precision $\hat{\tau} \equiv \tau + \kappa_1$).²⁰

Because this forecast is not based on perfect but only limited information, it can deviate from the true expected earnings. That is, the supplier makes the ex-ante forecast error

$$\begin{aligned} \hat{\mu}_t^S - \mu_t^S &= \frac{\tau}{\tau + \kappa_1} \bar{\mu}^S + \frac{\kappa_1}{\tau + \kappa_1} s_t - \mu_t^S \\ &= \frac{\tau}{\tau + \kappa_1} \bar{\mu}^S + \frac{\kappa_1}{\tau + \kappa_1} (\mu_t^S + \eta_t) - \mu_t^S \\ &= \frac{\tau}{\tau + \kappa_1} (\bar{\mu}^S - \mu_t^S) + \frac{\kappa_1}{\tau + \kappa_1} \eta_t. \end{aligned} \quad (\text{A-4})$$

The forecast is not perfect, because the long-run prior may deviate from the true expected earnings and the signal is not perfectly precise. It is important to distinguish this type of forecast error from the more commonly used definition of forecast error. The forecast error given in equation (A-4) is an *ex-ante* imprecision in expectation formation that is due to the lack of complete information. We therefore call it *ex-ante forecast error*. In contrast, the more common definition of forecast error is the difference between the forecast and the realized earnings. The latter type of forecast error is driven by both the *ex-ante forecast error* and the unpredictable random component of the earnings realization. We therefore refer to the latter

²⁰ See, for instance, DeGroot (1970), p.167.

definition as the *ex-post forecast error*.

Symmetrically, the customer uses his internal signal, $s_t^C = \mu_t^C + \eta_t^C$, to also form a time- t specific forecast:

$$\hat{\mu}_t^C = \frac{\tau^C}{\tau^C + \kappa_1^C} \bar{\mu}^C + \frac{\kappa_1^C}{\tau^C + \kappa_1^C} s_t^C. \quad (\text{A-5})$$

The publicly issued forecast, \hat{e}_t^C , may however include a random, *iid* normally distributed bias, b_t^C :

$$\begin{aligned} \hat{e}_t^C &= \hat{\mu}_t^C + b_t^C \\ &= \mu_t^C + \nu_t + b_t^C, \end{aligned} \quad (\text{A-6})$$

where for the second line, we define ν_t as the difference between $\hat{\mu}_t^C$ and μ_t^C . Note that ν_t is also normally distributed.

We further assume that μ_t^C is related to 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 $\mu_t^C = \mu_t^S$. Hence, $\hat{e}_t^C \sim N(\mu_t^S, 1/\kappa_2)$, where $1/\kappa_2 = \sigma^2(\nu_t) + \sigma^2(b_t^C)$ is the variance of the external signal (or κ_2 is its precision). Because the customer's forecast is an informative signal about the supplier's expected earnings, it is rational for the supplier to incorporate it into its own forecast despite it being noisy due to imprecision in its rational component, $\mu_t^C + \nu_t$, as well as potential bias b_t^C .

The Bayesian update of firm S 's expected earnings based on both the internal and external signal is given by

$$\begin{aligned} \hat{\mu}_t^S &= \frac{\hat{\tau}}{\hat{\tau} + \kappa_2} \hat{\mu}_t^S + \frac{\kappa_2}{\hat{\tau} + \kappa_2} \hat{e}_t^C \\ &= \frac{\hat{\tau}}{\hat{\tau} + \kappa_2} \hat{\mu}_t^S + \frac{\kappa_2}{\hat{\tau} + \kappa_2} (\mu_t^S + \nu_t + b_t^C), \end{aligned} \quad (\text{A-7})$$

and hence the ex-ante forecast error of firm S 's forecast is

$$\begin{aligned}
\hat{\mu}_t^S - \mu_t^S &= \frac{\hat{\tau}}{\hat{\tau} + \kappa_2} \hat{\mu}_t^S + \frac{\kappa_2}{\hat{\tau} + \kappa_2} (\mu_t^S + \nu_t + b_t^C) - \mu_t^S \\
&= \frac{\hat{\tau}}{\hat{\tau} + \kappa_2} (\hat{\mu}_t^S - \mu_t^S) + \frac{\kappa_2}{\hat{\tau} + \kappa_2} \nu_t + \frac{\kappa_2}{\hat{\tau} + \kappa_2} b_t^C \\
&= \frac{\hat{\tau}}{\hat{\tau} + \kappa_2} (\hat{\mu}_t^S - \mu_t^S) + \frac{\kappa_2}{\hat{\tau} + \kappa_2} (\hat{\mu}_t^C - \mu_t^C) + \frac{\kappa_2}{\hat{\tau} + \kappa_2} b_t^C. \tag{A-8}
\end{aligned}$$

Equation (A-8) shows that the ex-ante forecast error of firms S is greater (1) the larger is its forecast based on solely internal information relative to the true earnings expectation, (2) the greater is the customer's rational forecast based solely on his internal information, and (3) the greater is the customer's forecast bias.

The last term shows that even 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 customer's bias 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. The degree of contagion of customer bias to supplier bias is represented by $\frac{\kappa_2}{\hat{\tau} + \kappa_2}$, the ratio of the precisions of the customer's forecast and the supplier's internal forecast, or in other words, the ratio of the precision of external and the internal signals. Hence, equation (A-8) predicts that contagion of forecast bias from customer to supplier is more pronounced (1) the less certain the supplier is about its future earnings based on internal information, and (2) the more precise he believes the customer's forecast to be.

Figures and Tables

Figure 1

Days between Announcement of Supplier and Customer Forecasts

The two histograms show the difference in calendar days between the annual (quarterly) EPS forecast announcement dates by suppliers and their customers. Forecasts are matched to have identical periodicity (quarterly or annual), an identical forecast date/fiscal period end to which the forecast pertains and to have similar distances to the announcement of actual earnings. Positive differences imply that suppliers issued their forecasts after their customers did.

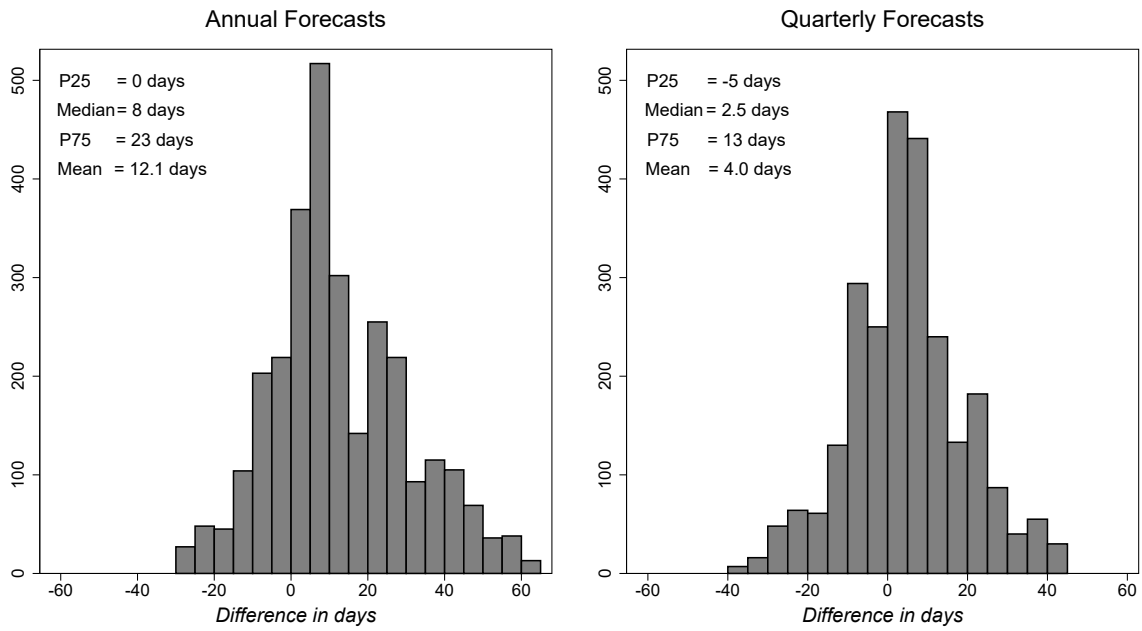


Figure 2
Distribution of Coefficients using Bootstrapped Pseudo-Customers

We re-run our main specification (Table IV, column 7) 10,000 times and replace in each run the suppliers' actual customers with pseudo-customers that are randomly drawn from the same Fama-French 48 industry (same Hoberg Philipps TNIC industry). The upper (lower) panel shows the empirical distribution of the 10,000 coefficients (t -statistics) on *Customer forecast error*. The arrows indicates the coefficient and t -statistic from Table IV, column 7.

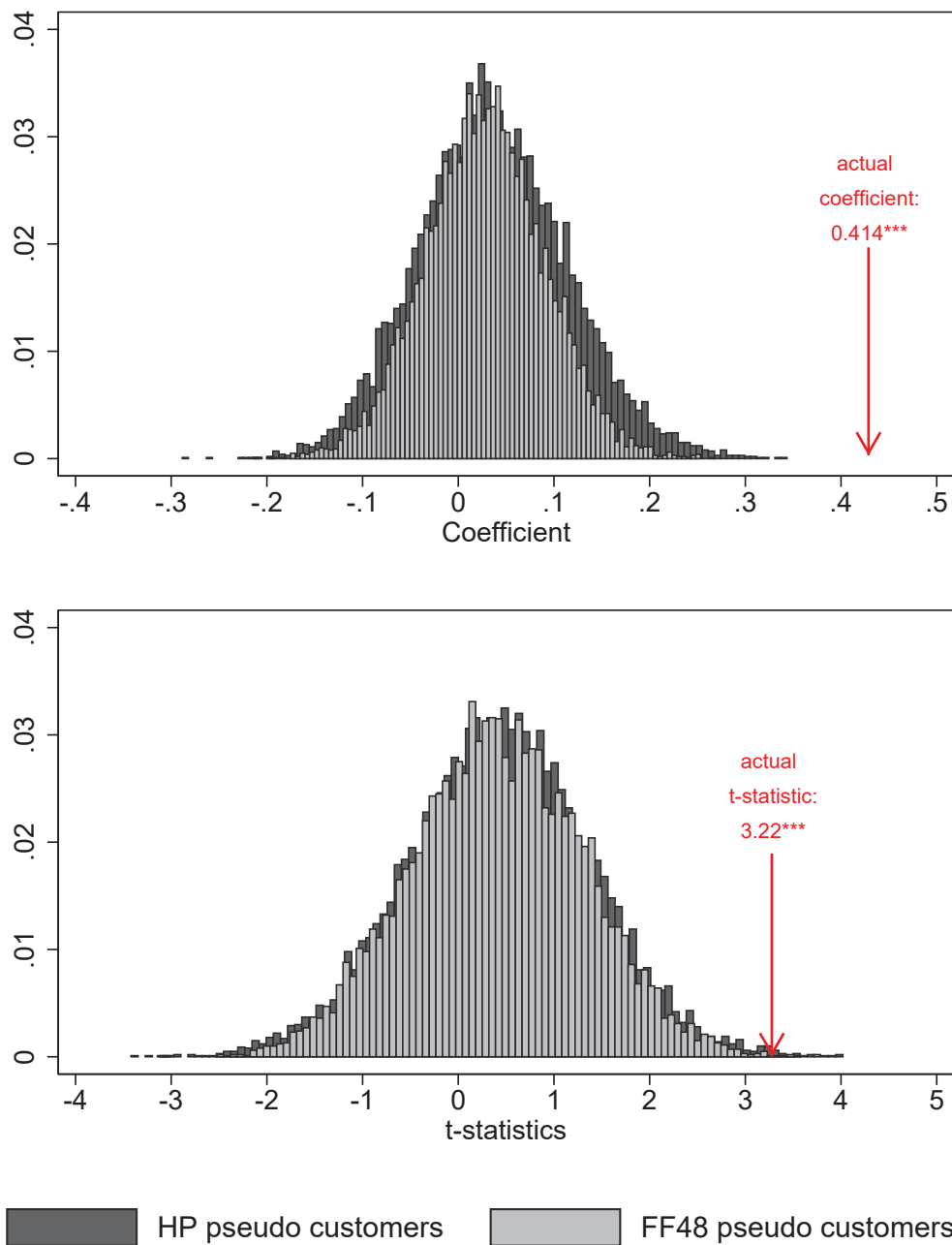


Table I
Descriptive Statistics

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 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	
<i>Pct. of sales to customer</i>	0.00	0.08	0.11	0.15	0.17	0.20	0.29	0.91	0.11	
<i>C/S beta (stock return correl.)</i>	-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	
<i>Total assets</i> [\$bn]	0.89	5.05	15.91	1,921		18.54	44.56	95.28	572	
<i>Sales</i> [\$bn]	0.83	4.43	11.47	1,921		19.96	40.30	60.98	572	
<i>Market value</i> [\$bn]	1.56	9.48	29.12	1,921		29.22	72.31	126.87	572	
<i>Market-to-book</i>	1.60	1.99	1.23	1,921		1.64	1.90	0.91	572	
<i>PP&E</i>	0.13	0.16	0.13	1,921		0.19	0.25	0.19	572	
<i>Profitability</i>	0.12	0.11	0.12	1,921		0.15	0.15	0.06	572	
<i>Book leverage</i>	0.17	0.20	0.18	1,921		0.23	0.24	0.15	572	
<i>Net book leverage</i>	0.02	-0.02	0.32	1,921		0.13	0.13	0.21	572	
<i>Investment</i>	0.03	0.03	0.03	1,921		0.03	0.04	0.03	572	
<i>Inventory</i>	0.10	0.13	0.11	1,917		0.11	0.15	0.12	572	
<i>Stock Issuance</i>	0.00	0.07	0.25	1,917		0.00	0.02	0.14	563	

Table II
Management Forecasts: Descriptive Statistics

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

	Mean	Median	SD	N
Panel A: Suppliers				
<i>Annual forecast</i> [%]	6.46	6.16	3.39	6,243
<i>Annual forecast error</i> [%]	0.29	-0.09	2.01	6,243
<i>Quarterly forecast</i> [%]	0.95	1.09	1.59	3,547
<i>Quarterly forecast error</i> [%]	-0.11	-0.10	0.63	3,546
<i>Annual forecast horizon</i> [days]	231.56	217.00	105.55	6,243
<i>Quarterly forecast horizon</i> [days]	80.54	91.00	27.68	3,546
Panel B: Customers				
<i>Annual forecast</i> [%]	6.70	6.87	2.15	6,385
<i>Annual forecast error</i> [%]	-0.08	-0.04	1.01	6,385
<i>Quarterly forecast</i> [%]	1.52	1.65	1.25	3,551
<i>Quarterly forecast error</i> [%]	-0.06	-0.11	0.44	3,551
<i>Annual forecast horizon</i> [days]	203.00	230.65	110.57	6,385
<i>Quarterly forecast horizon</i> [days]	90.00	77.71	29.68	3,551

Table III
Management Forecasts and Alternative Optimism Measures

Panel A shows regressions of net share purchases by the CEO on the management's EPS forecast error. All own-firm 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 2014. Panel B shows the correlation between management EPS forecast errors and *ShareRetainer* (Sen and Tumarkin (2015)) and a text-based sentiment measure of managerial discussions from same-day conference call transcripts. Both measures are explained in detail in the Variable Definitions. The regressions control for the above firm-level controls, *Firm FEs* and *Customer industry* \times *Year FEs* or *Firm* \times *FPE FEs* respectively. Panel C shows the buy-and-hold abnormal returns for 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 forecast error and CEO net share purchases				
Dept. variable:	<i>Net share purchases (in thousand dollars)</i>			
	(1)	(2)	(3)	(4)
<i>Forecast error</i>	902.5*** (7.51)	621.9*** (5.74)	625.7*** (5.49)	588.1*** (4.87)
Firm-level controls	No	Yes	Yes	Yes
Firm FEs:	No	No	Yes	Yes
Year FEs:	No	No	No	Yes
Observations	13,260	12,987	12,987	12,987
R-squared	0.00	0.04	0.68	0.69

Panel B: Management forecast error and alternative optimism measures				
Shares Retained upon Stock Option Exercise (<i>ShareRetainer</i> by Sen and Tumarkin (2015)):			0.007*** (2.57)	
Sentiment of Management Discussion in same-day Conference Call Transcripts:				0.015*** (5.85)

Panel C: Market Reaction to earnings surprises relative to guidance				
Event window [days]:	Mean difference test		Median difference test	
	[-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
<i>t</i> -statistic/ <i>z</i> -statistic	-36.99	-31.80	-36.40	-32.89

Table IV
Optimism Propagation: Main Results

This table shows the correlation between supplier and customer forecast optimism controlling for firm characteristics and a set of fixed effects. Columns 1 to 7 use the sales-weighted customer forecast error when a supplier has multiple customers. In those columns, the coefficient is interpreted as the effect on supplier optimism of a one-unit increase in optimism of a customer representing 100% of supplier sales. In columns 8 and 9 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 supplier optimism of a one-unit increase in optimism of the average customer (who represents on average 17% of supplier sales). *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. *Quarterly earnings forecast* is an indicator variable which equals one for quarterly forecasts and zero for annual forecasts. Customer industry fixed effects are based on 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)
<i>Customer forecast error</i>	0.706** (2.26)	0.779*** (2.99)	0.799*** (4.47)	0.746*** (2.98)	0.765*** (5.06)	0.482** (2.35)	0.414*** (3.22)	0.161*** (2.65)	0.164*** (3.02)
<i>Forecast horizon</i>	0.002*** (5.79)	0.002*** (6.51)	0.002*** (7.19)	0.003*** (7.10)	0.003*** (7.99)	0.003*** (6.54)	0.003*** (6.96)	0.002*** (6.90)	0.003*** (6.96)
<i>Quarterly earnings forecast</i>	-5.059*** (-28.54)	-4.821*** (-28.50)	-4.703*** (-21.31)	-4.726*** (-28.12)	-4.615*** (-20.45)	-4.687*** (-25.08)	-4.646*** (-18.96)	-4.714*** (-21.98)	-4.641*** (-20.61)
<i>Log assets</i>		0.386*** (5.82)	0.554*** (3.90)	0.376*** (5.53)	0.536*** (3.00)	0.320*** (4.16)	0.530*** (2.72)		0.695*** (3.29)
<i>Tobin's Q</i>		-0.584*** (-7.75)	-0.254*** (-3.12)	-0.565*** (-7.25)	-0.108 (-1.45)	-0.529*** (-6.02)	-0.099 (-1.24)		-0.140* (-1.82)
<i>PP&E</i>		-1.195 (-1.61)	0.306 (0.21)	-1.142 (-1.57)	0.339 (0.23)	-1.245 (-1.45)	-0.209 (-0.12)		1.845 (1.02)
Observations	7,631	7,563	7,563	7,563	7,563	7,563	7,563	9,789	9,701
R-squared	0.494	0.571	0.797	0.586	0.812	0.646	0.839	0.799	0.820
Supplier FEs:	No	No	Yes	No	Yes	No	Yes	No	No
Quarter FEs:	No	No	No	Yes	Yes	No	No	No	Yes
Customer industry x quarter FEs:	No	No	No	No	No	Yes	Yes	No	No
Customer-supplier FEs:	No	No	No	No	No	No	No	Yes	Yes

Table V
Optimism Propagation: Cross-sectional Variation

This table documents cross-sectional variation in the propagation of optimism. Column 1 (column 2) shows results for 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 optimism 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. Columns 7 and 8 show cross-sectional variation in propagation with respect to more important (or more salient) customers. Column 4 interacts a customer's forecast error with the supplier-to-customer ratio of forecast ranges. Column 5 interacts the customer's forecast error with the supplier's earnings volatility, while column 6 repeats the column 5 analysis using the supplier-to-customer ratio of earnings volatility. Column 7 adds an interaction of the customer forecast 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 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 the same in all columns and identical with those shown in Table IV. Customer industry fixed effects are based on the customers' Fama-French 48 industry classification. All results include standard errors that are clustered at the supplier level.

Dept. variable:	<i>Supplier forecast</i>							
	Zero range (1)	Non-zero range (2)	Full (3)	Non-zero (4)	Non-zero (5)	Non-zero (6)	Non-zero (7)	Non-zero (8)
<i>Customer forecast error (FE)</i>	0.455 (1.18)	0.556*** (6.51)	0.212 (1.01)					
<i>Supplier range</i> × <i>Customer FE</i>			0.402*** (3.35)					
<i>Supplier-to-customer range</i> × <i>Customer FE</i>				0.064** (2.50)				
<i>Supplier earnings variance</i> × <i>Customer FE</i>					0.025*** (2.15)			
<i>S-C earnings variance ratio</i> × <i>Customer FE</i>						0.045* (1.74)		
<i>Supplier's sales share</i> × <i>Customer FE</i>							0.443*** (2.93)	0.431* (1.71)
<i>Customer-supplier beta</i> × <i>Customer FE</i>								-1.103*** (-1.98)
<i>Direct effect of interaction term</i>			0.355* (1.91)	-0.042*** (-2.94)	-0.000 (-0.01)	-0.064*** (-2.78)	-0.490 (-0.93)	
Observations	1,276	6,286	6,617	1,607	7,092	7,470	7,092	6,498
R-squared	0.964	0.930	0.930	0.950	0.931	0.932	0.931	0.937
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 VI
Optimism Propagation: Leads and Lags

This table documents the propagation of optimism 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 EPS forecast error pertaining to the earliest forecast issued in the four-month window following the issuance of the supplier's forecast. *Customer forecast error [t-1]* is the EPS forecast error pertaining to the latest customer forecast issued in the four months preceding the supplier's forecast. Similarly, periods *[t-2]* and *[t-3]* reference further lagged four-month windows. Firm-level controls are identical with those shown in Table IV. Customer industry \times quarter fixed effects are based on the customers' Fama-French 48 industry classification. All results include standard errors that are clustered at the supplier level.

	(1)	(2)	(3)	(4)	(5)	(6)
	<i>Supplier forecast</i>					
Dept. variable:						
<i>Customer forecast error [t+1]</i>						0.085 (0.27)
<i>Customer forecast error [t-1]</i>	0.695*** (4.05)			0.582** (2.46)	0.608*** (3.09)	0.630** (2.12)
<i>Customer forecast error [t-2]</i>		0.615*** (4.54)		0.278 (1.46)	0.271* (1.80)	
<i>Customer forecast error [t-3]</i>			0.207 (1.14)	-0.004 (-0.02)		
Observations	4,128	4,081	3,933	3,325	3,694	3,544
R-squared	0.933	0.931	0.933	0.935	0.933	0.933
Control variables included:	Yes	Yes	Yes	Yes	Yes	Yes
Supplier FEs:	Yes	Yes	Yes	Yes	Yes	Yes
Customer industry \times quarter FEs:	Yes	Yes	Yes	Yes	Yes	Yes

Table VII
Real Effects of Managerial Optimism

This table shows regressions of various corporate policies on a firm's *own* EPS forecast error – a measure of management's optimism – and standard determinants of these policies. We use annual forecasts with a remaining forecast horizon between 180 and 365 days only. The dependent variables *Investments*, *Inventory* and *Book leverage* are expressed in percent of book assets. *Stock Issuance* is an indicator variable that is zero if the firm did not issue new stock, and – for ease of interpretation of coefficients – 100 if the firm did issue new stock. Variable definitions are in Table IX.

Dept. variable:	<i>Investment</i>		<i>Inventory</i>		<i>Book leverage</i>		<i>Stock issuance</i>	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Forecast error</i>	0.056*** (3.04)	0.038** (2.07)	0.103*** (3.36)	0.089*** (2.91)	0.337*** (5.32)	0.298*** (4.62)	-0.597*** (-4.15)	-0.531*** (-3.60)
<i>Ln(total assets)</i>	-0.308** (-2.42)	-0.230 (-1.54)	-1.197*** (-6.33)	-1.536*** (-6.10)	4.404*** (7.93)	5.039*** (7.01)	-2.070* (-1.96)	1.454 (1.15)
<i>Tobin's Q</i>	0.005*** (6.93)	0.005*** (6.32)	-0.001* (-1.92)	-0.001 (-1.63)	-0.009*** (-3.16)	-0.009*** (-2.69)	0.025*** (5.03)	0.024*** (4.51)
<i>Profitability</i>	0.039*** (3.69)	0.036*** (3.37)	0.057*** (3.99)	0.053*** (3.63)	-0.199*** (-3.28)	-0.207*** (-3.33)	-0.227** (-2.46)	-0.192** (-2.08)
<i>PP&E</i>	0.169*** (6.51)	0.167*** (6.48)	0.005 (1.05)	0.006 (1.34)	0.100*** (5.71)	0.094*** (5.48)	0.240*** (3.81)	0.222*** (3.55)
Observations	8,617	8,617	8,551	8,551	8,605	8,605	8,614	8,614
R-squared	0.816	0.821	0.974	0.975	0.854	0.856	0.303	0.309
Firm FEs:	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs:	No	Yes	No	Yes	No	Yes	No	Yes

Table VIII
Real Effects of Propagated Managerial Optimism

This table shows second-stage instrumental variables regressions of various corporate policies on *propagated* optimism. 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 optimism, which is similar to column 5 of Table IV. The first stage results are omitted for space reasons but available upon request. The last row reports *F*-statistics from the first stage regressions. The dependent variables *Investments*, *Inventory* and *Book leverage* are expressed in percent of book assets. *Stock Issuance* is an indicator variable that is zero if the firm did not issue new stock, and – for ease of interpretation of coefficients – 100 if the firm did issue new stock. All results include standard errors that are clustered at the firm level.

Dept. variable:	<i>Capex</i>		<i>Inventory</i>		<i>Book leverage</i>		<i>Stock issuance</i>	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Forecast (instrumented)</i>	0.039 (0.26)	0.073 (0.39)	0.774** (2.27)	1.059** (2.52)	2.315* (1.67)	2.121* (1.71)	-6.683*** (-2.93)	-7.601*** (-3.07)
<i>Ln(total assets)</i>	-0.224 (-0.88)	-0.177 (-0.61)	-2.245*** (-2.77)	-2.302** (-2.28)	5.093** (2.35)	6.464*** (2.74)	9.910*** (2.64)	9.262** (2.15)
<i>Tobin's Q</i>	0.007 (1.63)	0.007* (1.70)	0.001 (0.47)	0.002 (0.50)	0.027* (1.95)	0.020 (1.48)	-0.026 (-1.11)	-0.022 (-1.05)
<i>Profitability</i>	-0.007 (-0.17)	-0.010 (-0.21)	-0.008 (-0.16)	-0.019 (-0.33)	-0.923*** (-3.79)	-0.837*** (-3.87)	0.816** (2.06)	0.814** (2.07)
<i>PP&E</i>	0.161*** (7.27)	0.152*** (7.17)	0.046 (1.47)	0.027 (0.86)	0.326*** (3.03)	0.262*** (2.89)	0.561* (1.75)	0.717** (2.21)
Observations	1,522	1,522	1,522	1,522	1,522	1,522	1,521	1,521
R-squared	0.828	0.830	0.939	0.933	0.841	0.859	0.086	0.062
Firm FEs:	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs:	No	Yes	No	Yes	No	Yes	No	Yes
<i>F</i> -stat of excl. instrument	10.79	13.62	10.79	13.62	10.79	13.62	10.79	13.62

Table IX
Variable Definitions

Variable name	Definition	Data source
<i>Earnings forecast data</i> $Forecast_{it}$	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: $Forecast_{it} = \frac{\hat{e}_{it}}{P_{it}}$. 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
<i>Customer forecast</i> $_{it}$, <i>sales-weighted</i>	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
<i>Forecast error</i> $_{it}$	The forecast error of quarterly and annual EPS guidance issued by the management of company i at time t : $Forecast\ error_{it} = \frac{\hat{e}_{it} - e_{it}}{P_{it}}$. EPS guidance data (\hat{e}_{it}) and the respective realized EPS (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. P_{it} is the closing stock price of company i five trading days prior to the announcement of the forecast at time t . We use WRDS's algorithm to link IBES (IBES ticker) to CRSP (permno). 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
<i>Forecast horizon</i> $_{it}$	The number of calendar days between the issuance of an EPS forecast at time t by company i and the announcement of realized earnings for the fiscal period end date to which the forecast applies.	IBES
<i>Forecast range</i> $_{it}$	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
<i>Quarterly earnings forecast</i> $_{it}$ <i>Customer actual</i> $_{it}$	Indicator variable that equals 1 if company i 's forecast issued at t is a quarterly forecast, else 0.	IBES
<i>Customer actual</i> $_{it}$, <i>sales-weighted</i>	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. 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		
$C/S\ beta_{i,j}$	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 $_{i,t}$	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		
$Ln(assets)_{i,t}$	The natural logarithm of 1 plus company i 's total assets (AT) in millions of USD at the end of fiscal year t .	COMPUSTAT
$Market\ value\ of\ assets_{i,t}$	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
$Sales_{i,t}$	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
$Tobin's\ Q_{i,t}$	Ratio of market value of assets to book value of company i at time t .	COMPUSTAT
$PP\&E_{i,t}$	Total net value of property, plants and equipment (PPENT) divided by total assets (AT) for company i at time t .	COMPUSTAT
$Profitability_{i,t}$	Operating income before depreciation (OIBDP) divided by total assets (AT) for company i at time t .	COMPUSTAT
$Book\ leverage_{i,t}$	Debt in current liabilities (DLC) plus long term debt (DLTT) divided by total assets (AT) for company i at time t .	COMPUSTAT
$Stock\ issuance_{i,t}$	Indicator variable whether the firm issued new stock in the 12 preceding months in an SEO. We scale it by 100 to ease the interpretation of coefficients. That is, the variable is 0 if no new stock was issued and 100 if new stock was issued.	Thomson Reuters' SDC
$Inventory_{i,t}$	Total inventories (INVT) divided by total assets (AT) for company i at time t .	COMPUSTAT
$Investment_{i,t}$	Capital expenditures (CAPX) divided by total assets (AT) for company i at time t .	COMPUSTAT
Alternative Optimism Measures		
$ShareRetainer_{i,t}$	Based on Sen and Tumarkin (2015) and obtained from Robert Tumarkin's webpage. An indicator variable that is 1 (optimistic) if the cumulative shares retained by the CEO of firm i on days with option exercise during fiscal year t exceeds 1% and 0 (not optimistic) otherwise.	Robert Tumarkin's webpage
$Transcript\ Sentiment_{i,t}$	The sentiment of the managerial discussion of management's conference call with analysts that was held the same day as the announcement of the earnings forecast. We exclude the Q&A section that contains comments and questions by analysts. Sentiment is computed as the number of positive words divided by the sum of positive and negative words, where positive and negative words are identified from Loughran and McDonald's 2014 Master Dictionary on financial terms (downloaded from Bill McDonald's webpage). Transcript data is obtained from SeekingAlpha.com with coverage starting in 2005.	SeekingAlpha .com

Table A.I
Optimism Propagation: Relative Bias

This table presents regressions of supplier managements' relative forecast optimism on its customers' relative forecast optimism, where relative optimism is measured via the difference between management's forecast and analysts' consensus forecast for the same fiscal period's earnings. Columns 1 to 7 use sales-weighted customer forecasts when a supplier has multiple customers. In those columns, the coefficient is interpreted as the effect on (relative) supplier optimism of a one-unit increase in (relative) optimism of a customer representing 100% of supplier sales. In columns 8 and 9 each customer-supplier pair is a separate observation and hence forecasts for each individual customer and fiscal period are used. In these columns, the coefficient is interpreted as the effect on (relative) supplier optimism of a one-unit increase in (relative) optimism of the average customer (who represents on average 17% of supplier sales). *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. *Quarterly earnings forecast* is an indicator variable which equals one for quarterly forecasts and zero for annual forecasts. Customer industry fixed effects are based on the customer's Fama-French 48 industry classification. All results include standard errors that are clustered at the supplier level.

Dept. variable:	<i>Relative supplier optimism</i>								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>Relative customer optimism</i>	0.342*** (3.66)	0.309*** (3.25)	0.396*** (3.55)	0.254*** (2.64)	0.342*** (3.07)	0.281*** (2.71)	0.361*** (2.83)	0.065*** (2.88)	0.050*** (2.21)
<i>Forecast horizon</i>	-0.000 (-0.65)	-0.000 (-0.49)	-0.000 (-1.58)	-0.000 (-0.02)	-0.000 (-1.33)	-0.000 (-0.09)	-0.000 (-0.74)	-0.000* (-1.84)	-0.000 (-1.30)
<i>Quarterly earnings forecast</i>	-0.150*** (-6.04)	-0.121*** (-5.11)	-0.166*** (-6.76)	-0.111*** (-4.64)	-0.158*** (-6.37)	-0.125*** (-4.62)	-0.143*** (-5.22)	-0.187*** (-6.98)	-0.178*** (-6.64)
<i>Ln(assets)</i>		0.043*** (6.03)	-0.086*** (-3.24)	0.043*** (5.94)	-0.078** (-2.44)	0.050*** (5.89)	-0.094*** (-2.87)		-0.079** (-2.16)
<i>Tobin's Q</i>		0.032*** (4.38)	0.001 (0.04)	0.036*** (4.93)	0.005 (0.41)	0.027*** (3.45)	0.000 (0.01)		-0.003 (-0.17)
<i>PPE</i>		-0.094 (-0.80)	-0.212 (-0.82)	-0.101 (-0.86)	-0.246 (-0.97)	-0.030 (-0.22)	-0.192 (-0.78)		-0.001 (-0.00)
Observations	7,456	7,393	7,393	7,393	7,393	7,393	7,393	9,541	9,458
R-squared	0.014	0.029	0.239	0.044	0.252	0.193	0.371	0.265	0.283
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
C-S FEs:	No	No	No	No	No	No	No	Yes	Yes

Table A.II
Direction of Propagation

This table shows the correlation between customer and supplier forecast optimism controlling for firm characteristics and a set of fixed effects. Similar to Table IV, the dependent variable (*Customer forecast*) occurs after the forecast used in the key independent variable (*Supplier forecast error*). Columns 1 to 7 use the sales-weighted supplier forecast error when a supplier has multiple customers. In columns 8 and 9 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. *Quarterly earnings forecast* is an indicator variable which equals one for quarterly forecasts and zero for annual forecasts. Customer industry fixed effects are based on the customer's Fama-French 48 industry classification. All results include standard errors that are clustered at the customer level.

Dept. variable:	<i>Customer forecast</i>								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>Supplier forecast error</i>	0.347 (0.90)	0.188 (0.56)	0.329 (1.00)	0.251 (0.82)	0.280 (1.06)	0.313 (0.73)	0.419 (0.91)	0.033 (1.18)	0.028 (1.17)
<i>Forecast horizon</i>	0.001** (2.06)	0.001*** (2.70)	0.001*** (3.63)	0.002*** (3.89)	0.002*** (4.67)	0.002*** (3.21)	0.002*** (3.93)	0.002*** (3.85)	0.002*** (5.46)
<i>Quarterly earnings forecast</i>	-5.123*** (-25.85)	-5.019*** (-28.57)	-5.195*** (-22.13)	-4.852*** (-29.89)	-5.130*** (-22.91)	-4.704*** (-23.51)	-5.034*** (-18.99)	-5.014*** (-18.10)	-4.928*** (-16.18)
<i>Log assets</i>		0.290*** (3.21)	1.153*** (5.02)	0.260*** (3.11)	0.698** (1.99)	0.372*** (4.25)	0.370*** (2.77)	1.483*** (3.82)	0.983 (1.57)
<i>Tobin's Q</i>		-0.728*** (-7.22)	-0.521*** (-4.24)	-0.593*** (-5.76)	-0.308** (-2.27)	-0.659*** (-4.81)	-0.284** (-2.28)	-0.531*** (-2.98)	-0.285 (-1.48)
<i>PPE</i>		-0.650 (-1.20)	-0.034 (-0.02)	-0.644 (-1.28)	-1.242 (-0.71)	-1.583 (-1.14)	-3.342** (-1.97)	1.754 (0.47)	-1.375 (-0.44)
Observations	2,971	2,957	2,957	2,957	2,957	2,957	2,957	10,393	10,393
R-squared	0.579	0.638	0.803	0.678	0.828	0.785	0.888	0.824	0.848
Supplier FEs:	No	No	Yes	No	Yes	No	Yes	No	No
Quarter FEs:	No	No	No	Yes	Yes	No	No	No	Yes
Customer industry x quarter FEs:	No	No	No	No	No	Yes	Yes	No	No
Customer-supplier FEs:	No	No	No	No	No	No	No	Yes	Yes