Optimism Propagation*

Torsten Jochem and Florian S. Peters

November 2017

Abstract

We develop an empirical framework for identifying bias correlation between agents using subjective expectations. We apply this framework to corporate managers and document that optimism spreads across firms along supply chains. Corroborating a causal mechanism of belief contagion, we find that biases in supplier forecasts are only affected by previously issued customer forecasts, not by those issued in the near future. Belief propagation increases when suppliers have less confidence in their own views and when the perceived precision and salience of customer forecasts increase. Propagated optimism causes changes in the financial policies of suppliers, suggesting that contagious sentiment contributes to fluctuations of business and credit cycles via production networks.

Keywords: Managerial optimism; Belief propagation; Expectation formation; Networks

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

* We thank Dion Bongaerts, Robert Durand, David Hirshleifer, Simas Kucinscas, Tomislav Ladika, Ulrike Malmendier, Michaela Pagel, Zacharias Sautner, Paul Schempp, Alexander Wagner, Toni Whited, Jeffrey Wurgler, and Scott Yonker (EFA discussant), seminar participants at Columbia University, Dutch National Bank, Norwegian School of Economics, University of Amsterdam, University of Bonn, University of Michigan, and participants at the 2016 European Finance Association, 2016 FMA Annual Meeting, 2016 Research in Behavioral Finance Conference, and the 2015 Australasian Finance and Banking Conference for valuable comments. Torsten Jochem: University of Amsterdam. Email: t.jochem@uva.nl. Florian Peters: University of Amsterdam. Email: f.s.peters@uva.nl.

I. Introduction

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

However, there is little evidence of how exactly sentiment propagates among economic agents.[1] This is likely due to the fact that there is limited data available on individuals' beliefs, and maybe more importantly, that the various channels of propagation are difficult to identify. In general, sentiment spreads through social interaction within peer groups. But peer groups are often hard to identify empirically.

In this paper, we investigate one specific channel through which the beliefs of corporate managers spread across firms: customer-supplier networks. Customer firms are natural peers for supplier managers when they form beliefs about future earnings. It is essential for suppliers to incorporate information about their customers' business prospects into their own forecasts, and it is thus plausible that beliefs about future earnings – both rational and irrational ones – propagate through this channel.

We use earnings forecasts and their realizations to study optimism propagation.[2] Because we study dynamic contagion, our analysis necessarily focuses on the *time-varying* component of optimism among managers. This makes the conceptual and empirical analysis of biases considerably more complicated. The reason is that the bias contained

[1] Hirshleifer (2015) reviews the behavioral finance literature, noting the limited evidence on how opinions propagate from person to person, and concluding: "the time has come to move beyond behavioral finance to social finance, which studies the structure of social interactions, how financial ideas spread and evolve, and how social processes affect financial outcomes." (Hirshleifer, 2015, p.215)

[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; Otto, 2014; Hribar and Yang, 2016).

in a specific forecast cannot be discerned in observational data. A forecast, or subjective expectation, equals 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: Optimism is often measured using forecast errors, which can be affected by both an ex-ante bias and an ex-post earnings shock. In other words, the forecast error can be positive either because the forecast was ex ante too optimistic or because the earnings shock was negative. It is precisely this indeterminacy which makes propagation of sentiment in forecasts plausible: Because he cannot disentangle the true expectation from the bias in the customer's forecast, even a perfectly Bayesian supplier seeking to improve his own forecast necessarily copies part of the customer's bias. 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 be directly 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 – both contain the bias and a "nuisance" variable, or measurement error. 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 earnings shocks between the firms.[3] In a methodological contribution we show that bias correlation can be identified by regressing suppliers' *forecasts* on

[3] Equivalently, the correlation of customer and supplier forecasts conflates the correlation of biases with the correlation of the true earnings expectations.

their customers' *forecast errors*. The reason is that in this specification, both the dependent and independent variables contain the bias, but their respective nuisance variables are no longer correlated. We show this formally and discuss it in detail in section II.B.

To investigate empirically how optimistic beliefs of managers propagate through production networks we construct a matched customer-supplier sample of U.S. firms between 2003 and 2013. Our main result is to 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 that represents 100% of a supplier's sales leads to a 0.45 percentage point increase in supplier optimism.

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, and not by customer forecasts that are issued in the near future. This is consistent with propagation of optimistic beliefs since beliefs can only propagate from customer to supplier after the customer's beliefs become known. It is inconsistent with mechanisms by which customers and suppliers update their beliefs simultaneously based on an outside signal observable by both firms, e.g., an optimistic report in a relevant trade journal.[4]

We provide a number of additional results. First, we find that 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 or when the forecast range is wider. This is consistent with 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 fore-

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

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

Third, our results hold with a broad set of fixed effects, including supplier or customer-supplier-pair fixed effects. These fixed effects isolate the time-varying component of 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 led by similarly optimistic managers. Our results also hold when we add quarter or quarter-industry fixed effects. This ensures that our results are not due to market-wide or industry-wide sentiment waves.

Fourth, we run falsification tests in which we randomly draw pseudo-customers from the same industry as the actual customer and use the pseudo-customer's forecast error as our independent variable. We find that the estimated spillover effect using actual customers lies 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.

We also document 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 optimism and overconfidence 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. Hence, the beliefs of over-optimistic managers could snowball across the economy contributing to financing and business cycles as large customers' sentiment spreads to both proximate and distant suppliers.

This paper is inspired by the large literature in social psychology that investigates the conditions under which communication leads to attitude or opinion change in individuals.[5] 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 several strands of literature. First, it relates to the literature on peer effects in financial decisions. For instance, Hong, Kubik, and Stein (2004) and Brown, Ivkovic, Smith, and Weisbenner (2008) find that households who

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

interact more frequently with their neighbors or who live in communities with high stock market participation, are more likely to invest in the stock market. Hong, Kubik, and Stein (2005) and Pool, Stoffman, and Yonker (2015) document that fund managers located in the same city or neighborhood make correlated buying decisions even for non-local stocks. Other papers show that the investment returns experienced by households (Kaustia and Knüpfer, 2012) or traders (Simon and Heimer, 2015) trigger investments by peers. Recently, the peer effect literature has been extended to real estate purchase decisions (see Bayer, Mangum, and Roberts, 2016; Bailey, Cao, Kuchler, and Stroebl, 2017) and to decisions by firms (e.g., Leary and Roberts, 2014; Kaustia and Rantala, 2015). 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 differs from the above papers by studying peer effects in *beliefs* rather than *decisions*.

A second strand of literature relates managerial attitudes to corporate policies. Malmendier and Tate (2005, 2008) and Malmendier, Tate, and Yan (2011) link CEO overconfidence to corporate investment, acquisitions, and financing decisions. Ben-David, Graham, and Harvey (2013) find that firms whose CFOs underestimate risk, tend to invest more and use more leverage, and Graham, Harvey, and Puri (2013) document that optimistic CEOs use more short-term debt. We also assess the effect of managerial attitudes on corporate policies, but our analysis focuses on time-varying optimistic beliefs, and on how their propagation affects real policies.

More broadly, this paper relates to the growing literature exploring how economic agents form subjective expectations. Recent research proposes extrapolative expectations

(Fuster, Laibson, and Mendel, 2010; Greenwood and Shleifer, 2014; Barberis, Greenwood, Jin, and Shleifer, 2017) or diagnostic expectations (Bordalo, Gennaioli, LaPorta, and Shleifer, 2017; Bordalo, Gennaioli, and Shleifer, 2017) to explain leverage and asset price dynamics. As we do, these papers make use of subjective expectations data to motivate or test economic hypotheses.

Finally, our paper contributes to the broader literature on sentiment (Baker and Wurgler, 2007; Baker, Wurgler, and Yuan, 2012; Soo, 2016; 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

To guide our empirical analysis, we present in this section a simple model that illustrates 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.[6] Consider a setting with two firms, a customer (C) and a supplier (S). The management of S does not know its true expected earnings at time t, μ_t^S, and seeks to form expectations about μ_t^S using a prior, and a signal in the form of its customer's earnings forecast. Let

[6] 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.

the prior distribution be normal,

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

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

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

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

We define the customer's bias, b_t^C, as the deviation of the forecast from the true earnings expectation, and do not take a stand on how exactly this deviation arises. Leading behavioral theories posit that biases in expectations can result from irrational models of belief formation (e.g., Kahneman and Tversky, 1982), from limited availability of information (e.g., Daniel, Hirshleifer, and Subrahmanyam, 1998, 2001) or from inattention to available information (e.g., Hong and Stein, 1999; Peng and Xiong, 2006).[7,8]

We assume that μ_t^C is correlated with μ_t^S, so that the customer's forecast is an informative signal about the supplier's expected earnings. For simplicity, and without loss of generality, let $\mu_t^C = \mu_t^S$. Because the supplier cannot distinguish between bias and true expectation in the customer forecast, the bias constitutes noise in the signal. Assuming

[7] For excellent surveys on those theories see Barberis and Thaler (2003) and Hong and Stein (2007).

[8] An extended version of our model that distinguishes between biases arising from limited (attention to) information and irrational expectation formation is available upon request. This extension does not change the main prediction of the model presented in this section.

the bias is i.i.d. normally distributed with mean zero,

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

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 by[9]

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

and hence the bias of S's forecast is

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

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

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

the forecast to the same extent.

While a positive, average correlation between customer and supplier bias is the main prediction of the model, equation (5) also makes the finer predictions that contagion of forecast bias is more pronounced the less certain the supplier is about its future earnings given only its prior, and the more precise he believes the customer's forecast to be. We will test the main as well as these additional 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 (C) or supplier firm (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 on optimism, we explicitly allow the bias b_{it} to vary across firms and over time.

Problem. The problem with the above regression is that biases are not directly observable. What we can observe are management earnings forecasts. But forecasts 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 $Cov(b^C, b^S) \neq 0$ and $Cov(\mu^C, \mu^S) \neq 0$. This implies that simply regressing the suppliers' on the customers' forecasts would conflate the correlation of biases with the correlation of true expectations:

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

In this regression, the estimate of β reflects the sum of the correlation of biases and the correlation of true expectations (and potential cross-correlations). 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 $\mathbb{E}(\varepsilon^K) = 0$, and $Cov(\varepsilon^K, \mu^K) = 0, K \in \{C, S\}$. Just as we allow for $Cov(\mu^C, \mu^S) \neq 0$, we also allow for earnings shocks of customers and suppliers to be correlated, $Cov(\varepsilon^C, \varepsilon^S) \neq 0$, due to the business link between the firms.

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

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

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

Forecast errors are intuitive proxies for the bias, and they are used in several studies of optimism (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*:

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

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 $Cov(\mu^S, b^C)$ > 0, that is, if the supplier's true earnings expectation was positively correlated with the customer's bias. Although we cannot completely rule out this possibility, it seems implausible that a supplier should rationally revise his expectations upwards when his customer is irrationally optimistic about his 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 $Cov(\mu^S, b^C)$. We use these fixed effects in our empirical analysis in Section IV.

What remains is an attenuation bias due to the fact that the independent 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),

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

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

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

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 optimism 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 by other market observers such as analysts. The management's relative forecast, e.g. with respect to analysts' consensus forecast,

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

eliminates the nuisance term μ_{it} from the forecast, but it only measures the management bias precisely if the analysts' consensus 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., 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 could consequently prevent us from detecting any propagation. For these reasons, we do not use this alternative 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 quarterly and annual earnings per share (EPS). Since the passage of Regulation Fair Disclosure (Reg FD) in 2000, issuing management guidance has become the norm for public corporations.[10] Thomson Reuters' Institutional Brokers' Estimates System (I/B/E/S) starts recording management guidance for 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

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

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 I/B/E/S company identifier (I/B/E/S ticker). Most companies provide a forecast range instead of a single point estimate of earnings. In these cases, we define the point estimate as the midpoint between the lower and upper bound of the range. We add to this the reported realized EPS for the respective fiscal period from the I/B/E/S Actuals database along with the announcement date of the actual.

We then link each I/B/E/S ticker with its respective CRSP Permno using the CRSP-I/B/E/S 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 I/B/E/S guidance and actuals data are continuously split-adjusted to reflect earnings per share on the basis of the most current number of shares outstanding. We scale all guidance and actuals numbers by the stock price, and therefore split-adjust historical stock prices using CRSP's historical split adjustment factor.

We supplement our dataset with accounting data from the CRSP/COMPUSTAT Merged Database (CCM). From annual CCM data, we construct several firm-level control variables. We measure firm size as the logarithm of total assets. We compute Tobin's Q as the ratio of market value of assets to book value of assets. We measure asset tangibility as property, plant and equipment scaled by total assets. We also report two other measures of firm size, total sales and market value, as well as profitability, book leverage, investment, inventories and stock issuance.[11]

Finally, for every I/B/E/S company with non-missing guidance data, we identify all officially disclosed customer firms using COMPUSTAT's customer segment files. Regu-

[11] For details on variable definitions, see Table IX.

lation 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 but no company identifier. 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 period and with the same periodicity (quarterly or annual). We keep only those supplier forecasts for which there is at least one customer with a matched forecast.

Our final dataset contains 9,789 customer-supplier-forecast combinations originating from 1,921 unique suppliers and 572 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 244. 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 1.55. This number is lower that 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 accounted for by that customer. The second measure is the correlation between the excess stock returns of the customer and the supplier, a stock market-based measure of the importance of a customer.

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

B. Measuring Optimism

As detailed in Section II, we use management's earnings per share forecasts and forecast errors to identify optimism propagation. Using forecasted and realized values of uncertain quantities to gauge the optimism of individuals has precedents in the literature (Ben-David, Graham, and Harvey, 2013; Landier and Thesmar, 2009).

[Insert Table II here]

As is standard in the literature (Kothari, 2001), we scale forecasts and forecast errors by the stock price from five trading days prior to the announcement of the forecast. 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 6.45 (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 respective realized earnings, 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 is 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. Thus, management forecasts could mainly reflect strategic considerations rather than actual expectations, and our measure could 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 management 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 forecast errors.

[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 on the forecast error. In all specifications, forecast errors are strongly positively associated with CEOs' net share purchases. In the most conservative specification in column 4, a one percentage point increase in forecast error is associated with net purchases in the amount of \$588,200. 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 *ShareRetainer*, an optimism measure proposed by Sen and Tumarkin (2015) that is based on whether a firm's CEO retains some of the shares that the executive receives after exercising stock options. Panel B of Table III shows a highly significant and positive correlation between their measure and our forecast-based measure (t-statistic of 2.57).

Third, we measure the sentiment in managerial language in conference calls and relate it to our measure of forecast optimism. Specifically, we extract the management discussion section of all conference call transcripts available at SeekingAlpha.com and construct a textual sentiment measure following Loughran and McDonald (2011) for 8,577 conference calls that occurred on the same day as the announcement of the EPS forecast. We again find a highly significant and positive correlation (t-statistic of 5.85). Taken together, these correlations support the validity of forecast-based measures as proxies of managerial optimism.[12]

[12] One could also think of relating forecast optimism to the overconfidence measures proposed by Malmendier and Tate (2005). One important difference is that Malmendier and Tate aim at identifying overconfidence as a *permanent* managerial attribute while our approach seeks to quantify the *time-varying* component of optimism. Thus, the measures are not directly comparable. However, one can construct a time-varying *Holder67* measure by classifying a manager as overconfident in a given year if, in that year, he fails to exercise deep in-the-money options. Using this time-varying proxy for overconfidence, we find a significant negative correlation with the forecast range (t-statistic of -2.84). This has also been shown by Hribar and Yang (2016). However, we do not find a correlation between *Holder67* and the forecast error. In other words, narrower forecast ranges (which indicate less confidence in the forecast) are associated with late option exercise, but large forecast errors are not.

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

If suppliers' managers found their customers' forecasts to be valuable signals for forming their own expectations, one would expect that suppliers prefer to publish their forecasts only *after* their customers. We examine this in Figure 1. We match forecasts for the same fiscal period by suppliers to those of their customers. 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 and fiscal period, we find that suppliers file quarterly forecasts on average four days after their customers (t-statistic of 4.80) and annual forecasts twelve days (t-statistic of 8.64) later. This is consistent with suppliers timing their forecasts to be able to incorporate those of their customers.

[Insert Figure 1 here]

IV. Does Optimism Propagate?

A. Main Results

We proceed by analyzing whether optimism is contagious across the supply chain. In Table IV we estimate our main regression specification, equation (10), which identifies optimism propagation. 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.[13] We use one observation per

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

supplier forecast, and in case of multiple customers we take the sales-weighted average of the customers' forecast errors as our main independent variable.[14] The coefficient is therefore 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 0.690, that is, a pass-through rate of optimism from customers to suppliers of 69.0%.

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 sentiment waves. 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 sentiment waves. In the most stringent specification of column 7 the coefficient drops to 0.451 but again remains highly statistically significant.

[Insert Table IV here]

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

[14] 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.

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 0.150 (column 8) and 0.093 (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 with an average sales share of 17%.

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 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 investigate whether propagation occurs because suppliers seek to learn from their customers' forecasts, we exploit cross-sectional variation in signal importance or precision in Table V. Columns 1 to 6 of Table V test the key predictions of the model laid out in Section II.A: First, contagion of forecast bias from customer to supplier is more pronounced the less certain the supplier is about his 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 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 corroborates these results using a continuous interaction term: 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 only 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 propagation should increase with the supplier's own uncertainty only if the customer's forecast is considered to be relatively more precise and hence informative. Column 4, showing a positive and significant interaction term, confirms this prediction. In columns 5 and 6 we re-run the regression from column 4, replacing the forecast range with past EPS volatility. Column 5 reports the regression using only the supplier's EPS volatility while column 6 uses the ratio of supplier to customer EPS volatility. We obtain similar but statistically weaker results compared to those using the forecast range.

In columns 7 and 8 we separate customers by their importance to their suppliers. In column 7, we use the sales share as a measure of customer importance, and investigate whether customers with larger sales shares are more influential in affecting suppliers' beliefs. We expect more important customers to have more influence on their suppliers' forecasts, and this is indeed what we find: a larger sales share increases the propagation of optimism from customer to supplier. In column 8 we use a market-based measure of customer importance, the correlation of excess stock returns between customers and suppliers. For each customer-supplier pair we run a regression of the supplier's daily stock return on the customer's daily return, controlling for the market. Consistent with the results on sales share, we find that customer 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 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]. 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: 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. Only the lagged customer forecast error remains statistically significant and its coefficient is very similar in magnitude to that in column 1 while the coefficient of the leading forecast is close to zero. Taken together, the results in Table 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 substantially smaller and insignificant in all specifications.

[Insert Figure 2 here]

Figure 2 provides a third falsification test to rule out the concern that our results are driven by industry unobservables. We run placebo regressions based on Table IV, column 7 in which we replace actual customers with randomly drawn same-industry pseudo-customers. We 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 one would expect a similar coefficient in the pseudo-customer regressions.

The top chart in Figure 2 shows the distributions of pseudo-customer regression coefficients when industries are either defined using the Fama-French 48-industry classification or the Hoberg-Phillips text-based network industry classification. The bottom chart shows the corresponding distributions of t-statistics for those coefficients. Our estimated coefficient of 0.451 lies far above even the highest pseudo-customer coefficient out of 10,000 draws, regardless of which industry classification we use. Similarly, the estimated t-statistic of 3.61 from Table IV lies in the top 1% in the bottom chart. This confirms that the optimism propagation that we document is customer-supplier specific and not driven by industry unobservables.

V. Does Propagated Optimism Affect Corporate Decisions?

Existing literature documents that managerial optimism and overconfidence affect corporate policies. In these studies, belief distortions are measured in various ways: using late option exercise and press portrayals of CEOs (Malmendier and Tate, 2005; Malmendier, Tate, and Yan, 2011), using forecast errors of CFOs for the S&P 500 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

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

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_i are firm fixed effects, ϕ_t are time 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 (excessive) 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 policy variables such that they all pertain to the same fiscal year. That is, $\hat{e}_{it}$ is the earnings forecast for fiscal year t, e_{it} are the reported earnings for the same period, and y_{it} is the policy variable measured at the end of fiscal year t. We use only annual forecasts with a remaining forecast horizon between 180 and 365 days. 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. In columns 2 and 4, a one percentage point higher forecast error is associated with a 0.04 percentage points greater investment ratio and a 0.09 percentage point increase in inventories. In economic terms, a one standard deviation increase in forecast optimism (2.2 percentage points) increases investments and inventories by 0.10 and 0.20 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 time-invariant 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).[15] 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, we estimate propagated optimism in a first-stage regression as the component of a supplier's forecast that is predicted by its customers' optimism, that is, 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 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:

$$\hat{e}^S_{it} = \alpha_1 + \beta_1(\hat{e}^C_{it} - e^C_{it}) + \gamma_1' X^S_{it} + \lambda_{1it} + u_{it} \qquad \text{(First stage)} \qquad (13)$$

$$y^S_{it} = \alpha_2 + \beta_2 \hat{\hat{e}}^S_{it} + \gamma_2' X^S_{it} + \lambda_{2it} + \nu_{it} \qquad \text{(Second stage)} \qquad (14)$$

[15] 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.

In this two-stage specification, the earnings shock contained in the forecast error of the first-stage independent variable ($\hat{e}^C_{it} - e^C_{it} = b^C_{it} - \epsilon^C_{it}$) 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 earnings shock to a customer can affect the supplier's policy only to the extent that it trickles down to the supplier.

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.[16]

[Insert Table VIII here]

We again 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 0.77 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 1.9 percent and 5.9 percent. Finally,

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

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.[17] 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 demanding since corporate policies are known to be relatively persistent, and hence determinants of changes in these policies are more difficult to identify than determinants of cross-sectional variation (Fama and French, 2002; Lemmon, Roberts, and Zender, 2008).

VI. Conclusion

We study how optimism spreads across firms in production networks. We use firms' EPS forecasts as a measure of subjective expectations, and devise a 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 that represents 100% of a supplier's sales leads to a 0.45 percentage point increase in supplier optimism. Subsample tests further show that optimism propagation is stronger when suppliers have less confidence in their own forecasts, the perceived relative precision of the customer forecast is greater, and when customers are more important or salient to the supplier. Several falsification tests address causality concerns.

We also investigate the real effects of propagated managerial optimism and find sig-

[17] 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.

nificant effects on leverage, equity issuance, and inventories. These results are important, because they show not only that beliefs propagate, but that 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 output and financing in the greater economy. One reason is that initial shocks to beliefs in large firms can spread across many firms – to all proximate suppliers as well as to the suppliers of suppliers across the entire supply chain. Furthermore 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 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. In light of the broader relevance of belief contagion in economics, our methodological approach to identifying correlation in biases using subjective expectations may be applied to a variety of questions regarding herd behavior and information cascades.

References

Bailey, Michael C., Ruiqing Cao, Theresa Kuchler, and Johannes Stroebl, 2017, The Economic Effects of Social Networks: Evidence from the Housing Market, *Journal of Political Economy* forthcoming.

Baker, Malcolm, and Jeffrey Wurgler, 2007, Investor Sentiment in the Stock Market, *Journal of Economic Perspectives* 21, 129–151.

Baker, Malcom, Jeffrey Wurgler, and Yu Yuan, 2012, Global, Local and Contagious Investor Sentiment, *Journal of Financial Economics* 104, 272–287.

Barberis, Nicolas, Robin Greenwood, Lawrence Jin, and Andrei Shleifer, 2017, Extrapolation and Bubbles, *Journal of Financial Economics* forthcoming.

Barberis, Nicholas, and Richard Thaler, 2003, A Survey of Behavioral Finance, in George Constantinides, Milton Harris, and Rene Stulz, ed.: *Handbook of the Economics of Finance* . pp. 1052–1090 (North-Holland: Elsevier).

Bayer, Patrick, Kyle Mangum, and James W. Roberts, 2016, Speculative Fever: Investor Contagion in the Housing Boom, *NBER Working Paper No. 22065.*

Ben-David, Itzhak, John R. Graham, and Campbell R. Harvey, 2013, Managerial Miscalibration, *Quarterly Journal of Economics* 128, 1547–1584.

Bordalo, Pedro, Nicola Gennaioli, Rafael LaPorta, and Andrei Shleifer, 2017, Diagnostic Expectations and Stock Returns, *Working Paper.*

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, 2017, Diagnostic Expectations and Credit Cycles, *Journal of Finance* forthcoming.

Brown, Jeffrey R., Zoran Ivkovic, Paul A. Smith, and Scott Weisbenner, 2008, Neighbors Matter: Causal Community Effects and Stock Market Participation, *Journal of Finance* 63, 1509–1531.

Cavallo, Alberto, Guillermo Cruces, and Ricardo Perez-Truglia, 2016, Learning from Potentially Biased Statistics, *Brookings Papers on Economic Activity* pp. 59–108.

Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam, 1998, Investor Psychology and Security Market Under- and Overreactions, *Journal of Finance* 53, 1839–1885.

——— , 2001, Overconfidence, Arbitrage and Equilbrium Asset Pricing, *Journal of Finance* 56, 921–965.

DeGroot, Morris H., 1970, *Optimal Statistical Decisions* (Wiley, New Jersey) 1st edn.

Fama, Eugene F., and Kenneth R. French, 2002, Testing Trade-off and Pecking Order Predictions about Dividends and Debt, *The Review of Financial Studies* 15, 1–33.

Fuster, Andreas, David Laibson, and Brock Mendel, 2010, Natural Expectations and Macroeconomic Fluctuations, *Journal of Economic Perspectives* 24, 67–84.

Graham, John R., Campbell R. Harvey, and Manju Puri, 2013, Managerial Attitudes and Corporate Actions, *Journal of Financial Economics* 109, 103–121.

Greenwood, Robin, and Andrei Shleifer, 2014, Expectations of Returns and Expected Returns, *Review of Financial Studies* 27, 714–746.

Hatfield, Elaine, John T. Cacioppo, and Richard L. Rapson, 1993, *Emotional Contagion* (Cambridge, UK: Cambridge University Press).

Heaton, J.B., 2002, Managerial Optimism and Corporate Finance, *Financial Management* 31, 33–45.

Hirshleifer, David, 2015, Behavioral Finance, *Annual Review of Finance* 7, 133–59.

Hong, Harrison, and Marcin Kacperczyk, 2010, Competition and Bias, *Quarterly Journal of Economics* 125, 1683–1725.

Hong, Harrison, Jeffrey D. Kubik, and Jeremy C. Stein, 2004, Social Interaction and Stock-Market Participation, *Journal of Finance* 59, 137–163.

——— , 2005, Thy Neighbor's Portfolio: Word-of-Mouth Effects in the Holdings and Trades of Money Managers, *Journal of Finance* 60, 2801–2824.

Hong, Harrison, and Jeremy C. Stein, 1999, A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets, *Journal of Finance* 54, 2143–2184.

——— , 2007, Disagreement and the Stock Market, *The Journal of Economic Perspectives* 21, 109–128.

Hribar, Paul, and Holly Yang, 2016, CEO Overconfidence and Management Forecasting, *Contemporary Accounting Research* 33, 204–227.

Kahneman, Daniel, and Amos Tversky, 1982, On the Psychology of Prediction, in Daniel Kahneman, Paul Slovic, and Amos Tversky, ed.: *Judgement under Uncertainty: Heuristics and Biases* . pp. 48–68 (Cambridge, UK: Cambridge University Press).

Kaustia, Markku, and Samuli Knüpfer, 2012, Peer Performance and Stock Market Entry, *Journal of Financial Economics* 104, 321–338.

Kaustia, Markku, and Ville Rantala, 2015, Social Learning and Corporate Peer Effects, *Journal of Financial Economics* 117, 653–669.

Kothari, S.P., 2001, Capital Markets Research in Accounting, *Journal of Accounting and Economics* 31, 105–231.

Landier, Augustin, and David Thesmar, 2009, Financial Contracting with Optimistic Entrepreneurs, *The Review of Financial Studies* 22, 117–150.

Leary, Mark T., and Michael R. Roberts, 2014, Do Peer Firms Affect Corporate Financial Policy?, *Journal of Finance* 69, 139–178.

Lemmon, Michael L., Michael R. Roberts, and Jaime F. Zender, 2008, Back to the Beginning: Persistence and the Cross-section of Corporate Capital Structure, *Journal of Finance* 63, 1575–1608.

Lim, Terence, 2001, Rationality and Analysts' Forecast Bias, *Journal of Finance* 56, 369–385.

Loughran, Tim, and Bill McDonald, 2011, When is a Liability not a Liability? Textual Analysis, Dictionaries, and 10-Ks, *Journal of Finance* 66, 35–75.

Malmendier, Ulrike, and Geoffrey Tate, 2005, CEO Overconfidence and Corporate Investment, *Journal of Finance* 60, 2661–2700.

———, 2008, Who makes Acquisitions? CEO Overconfidence and the Market's Reaction, *Journal of Financial Economics* 89, 20–43.

———, and Jon Yan, 2011, Overconfidence and Early-Life Experiences: The Effect of Managerial Traits on Corporate Financial Policies, *Journal of Finance* 66, 1687–1733.

Michaely, Roni, and Kent L. Womack, 1999, Conflict of Interest and the Credibility of Underwriter Analyst Recommendations, *Review of Financial Studies* 12, 653–686.

Otto, Clemens, 2014, CEO Optimism and Incentive Compensation, *Journal of Financial Economics* 114, 366–404.

Peng, Lin, and Wei Xiong, 2006, Investor Attention, Overconfidence and Category Learning, *Journal of Financial Economics* 80, 563–602.

Petty, Richard E., and John T. Cacioppo, 1986, *Communication and Persuasion: Central and Peripheral Routes to Attitude Change* . Springer Series in Social Psychology (New York, NY: Springer).

———, 1996, *Attitudes and Persuasion: Classic and Contemporary Approaches* (Boulder, CO: Westview Press).

Pool, Veronika K., Noah Stoffman, and Scott E. Yonker, 2015, The People in Your Neighborhood: Social Interactions and Mutual Fund Portfolios, *Journal of Finance* 70, 2679–2732.

Sen, Rik, and Robert Tumarkin, 2015, Stocking Up: Executive Optimism, Option Exercise, and Share Retention, *Journal of Financial Economics* 118, 399–430.

Shiller, Robert J., 1984, Stock Prices and Social Dynamics, *Brookings Papers on Economic Activity* 2, 457–498.

——— , 2000, *Irrational Exuberance* (Princeton, NJ: Princeton University Press) 1st edn.

Simon, David, and Rawley Heimer, 2015, Facebook Finance: How Social Interaction Propagates Active Investing, *Working Paper No. 15-22.*

Soo, Cindy, 2016, Quantifying Animal Spirits: News Media and Sentiment in the Housing Market, *Working Paper.*

Stambaugh, Robert F., Jianfeng Yu, and Yu Yuan, 2012, The Short of it: Investor Sentiment and Anomalies, *Journal of Financial Economics* 104, 288–302.

Figures and Tables

Figure 1
Timing of Forecast Announcements

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

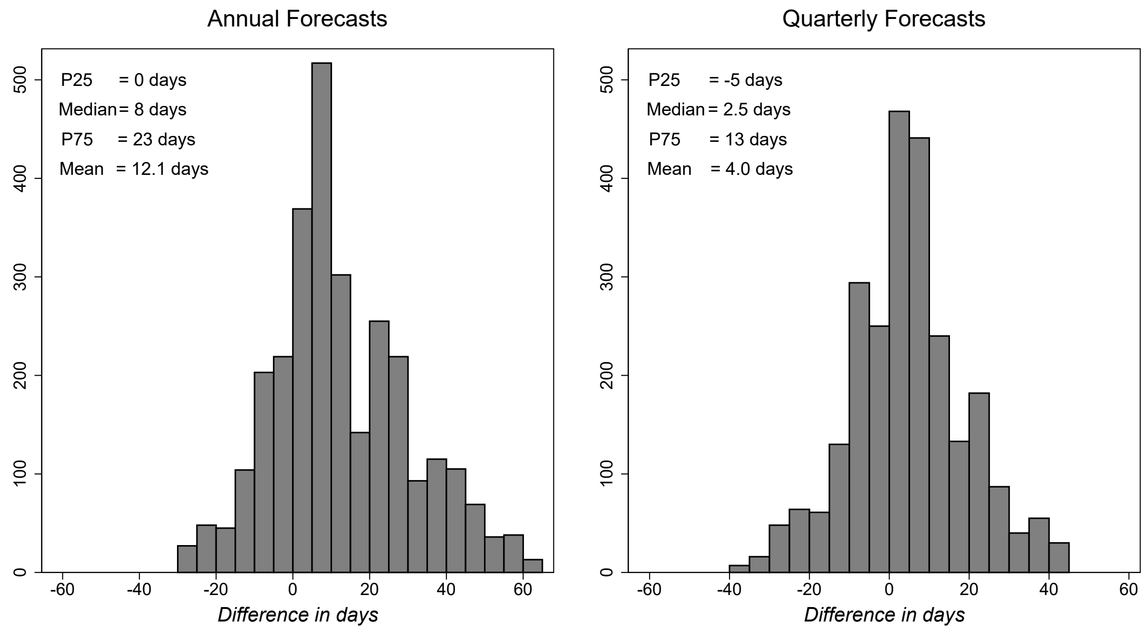

Figure 2
Distribution of Coefficients using Bootstrapped Pseudo-Customers

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 (alternatively, same Hoberg Philipps TNIC industry). The upper (lower) chart shows the empirical distribution of the 10,000 coefficients (t-statistics) of *Customer forecast error*. The arrows indicate the coefficient and t-statistic from Table IV, column 7.

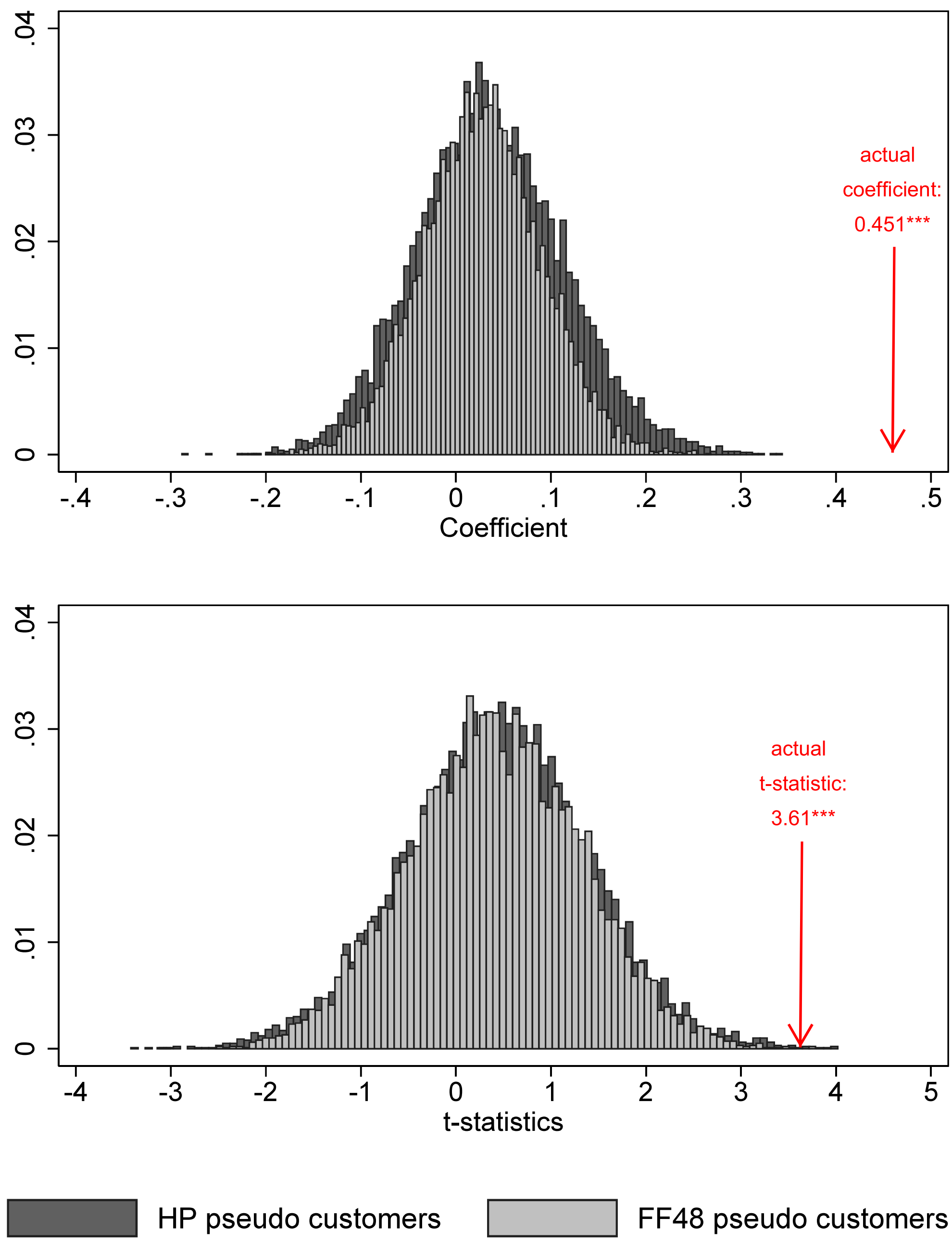

Table I
Descriptive Statistics

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 I/B/E/S as well as stock price information in CRSP. Panel B shows supplier and customer firm characteristics as obtained from COMPUSTAT. All variable definitions are given in Table IX.

Panel A: Basic statistics									
	Min	P10	P25	Median	Mean	P75	P90	Max	SD
# suppliers per year	56.00	136.00	139.00	150.50	162.83	200.00	220.00	244.00	49.37
# customers per year	24.00	54.00	63.00	70.00	73.00	89.50	103.00	104.00	22.51
# customers per supplier	1.00	1.00	1.00	1.00	1.55	2.00	3.00	5.00	0.77
Pct. of sales to customer	0.00	0.08	0.11	0.15	0.17	0.20	0.29	0.91	0.11
C/S beta (stock return correl.)	-0.50	-0.05	0.03	0.10	0.10	0.16	0.25	0.83	0.13

Panel B: Customer and supplier firm characteristics								
	Suppliers				Customers			
	Median	Mean	SD	N	Median	Mean	SD	N
Total assets [$bn]	0.89	5.05	15.91	1,921	18.54	44.56	95.28	572
Sales [$bn]	0.83	4.43	11.47	1,921	19.96	40.30	60.98	572
Market value [$bn]	1.56	9.48	29.12	1,921	29.22	72.31	126.87	572
Market-to-book	1.60	1.99	1.23	1,921	1.64	1.90	0.91	572
PP&E	0.13	0.16	0.13	1,921	0.19	0.25	0.19	572
Profitability	0.12	0.11	0.12	1,921	0.15	0.15	0.06	572
Book leverage	0.17	0.20	0.18	1,921	0.23	0.24	0.15	572
Net book leverage	0.02	-0.02	0.32	1,921	0.13	0.13	0.21	572
Investment	0.03	0.03	0.03	1,921	0.03	0.04	0.03	572
Inventory	0.10	0.13	0.11	1,917	0.11	0.15	0.12	572
Stock Issuance	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 management EPS forecasts, separately for suppliers (Panel A) and customers (Panel B) and separately for annual and quarterly earnings. Forecasts and forecast errors are scaled by the stock price five days prior to the forecast announcement. *Forecast horizon* is the number of days between guidance issuance and the announcement of realized earnings to which the guidance refers.

	Mean	Median	SD	N
Panel A: Suppliers				
Annual forecast [%]	6.45	6.16	3.39	6,243
Annual forecast error [%]	0.29	-0.09	2.01	6,243
Quarterly forecast [%]	0.95	1.09	1.59	3,546
Quarterly forecast error [%]	-0.11	-0.10	0.63	3,546
Annual forecast horizon [days]	231.50	217.00	105.51	6,243
Quarterly forecast horizon [days]	80.51	91.00	27.66	3,546
Panel B: Customers				
Annual forecast [%]	6.70	6.87	2.15	6,385
Annual forecast error [%]	-0.08	-0.04	1.01	6,385
Quarterly forecast [%]	1.52	1.65	1.25	3,551
Quarterly forecast error [%]	-0.06	-0.11	0.44	3,551
Annual forecast horizon [days]	203.00	230.59	110.51	6,385
Quarterly forecast horizon [days]	90.00	77.71	29.68	3,551

Table III
Management Forecasts and Alternative Optimism Measures

Panel A shows regressions of net, own-firm share purchases by the CEO on the management's EPS forecast error. All net share purchases made by the CEO in the 12 months prior to the issuance of a management forecast are cumulated to construct the dependent variable. Firm-level controls include *Log assets*, *Tobin's Q*, *Profitability* and *PP&E*. The data come from Thomson Reuters' Insider Filings database for the period between 2003 and 2014. Panel B shows coefficients from regressions of management EPS forecast errors on *ShareRetainer* (Sen and Tumarkin, 2015) as well as a text-based sentiment measure of managerial discussions derived from conference call transcripts. Both measures are explained in detail in Table IX (Variable Definitions). The regressions control for the above mentioned firm-level controls, firm fixed effects and customer industry-year or firm-fiscal period fixed effects. t-statistics, reported in parentheses, are based on standard errors clustered at the firm level.

Panel A: Management forecast error and CEO net share purchases

Dept. variable:	*Net share purchases (in thousands of dollars)*			
	(1)	(2)	(3)	(4)
Forecast error	902.4***	621.7***	625.5***	588.2***
	(7.51)	(5.74)	(5.49)	(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	0.007**	
(*ShareRetainer* by Sen and Tumarkin (2015)):	(2.56)	
Sentiment of Management Discussion in same-day		0.015***
Conference Call Transcripts:		(5.85)

Table IV
Optimism Propagation: Main Results

This table shows regressions of supplier forecasts on their customers' forecast errors that isolate correlation in forecast optimism between the linked firms. 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 forecast issuance and the announcement of the respective realized earnings. *Quarterly earnings forecast* is an indicator variable which equals one for quarterly forecasts and zero for annual forecasts. All other control variables are defined in Table IX. Customer industry fixed effects are based on the customer's Fama-French 48 industry classification. t-statistics, reported in parentheses, are based on standard errors clustered at the supplier level.

Dept. variable:	*Supplier forecast*								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Customer forecast error	0.690**	0.766***	0.773***	0.735***	0.742***	0.504**	0.451***	0.150***	0.093**
	(2.20)	(2.94)	(4.28)	(2.93)	(4.85)	(2.55)	(3.61)	(2.86)	(2.18)
Forecast horizon	0.002***	0.002***	0.002***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(5.69)	(6.43)	(7.09)	(7.00)	(7.88)	(6.58)	(7.04)	(7.42)	(6.14)
Quarterly earnings forecast	-5.065***	-4.825***	-4.708***	-4.730***	-4.621***	-4.679***	-4.641***	-4.596***	-4.675***
	(-28.62)	(-28.57)	(-21.35)	(-28.18)	(-20.49)	(-25.08)	(-18.92)	(-20.69)	(-19.54)
Log assets		0.386***	0.552***	0.376***	0.534***	0.319***	0.517***		0.595**
		(5.82)	(3.88)	(5.53)	(2.98)	(4.17)	(2.64)		(2.47)
Tobin's Q		-0.584***	-0.253***	-0.565***	-0.108	-0.536***	-0.103		-0.106
		(-7.75)	(-3.11)	(-7.25)	(-1.44)	(-6.15)	(-1.30)		(-1.28)
PP&E		-1.191	0.297	-1.140	0.333	-1.186	-0.426		1.535
		(-1.60)	(0.20)	(-1.56)	(0.23)	(-1.39)	(-0.24)		(0.68)
Observations	7,630	7,562	7,562	7,562	7,562	7,562	7,562	9,789	9,701
R-squared	0.493	0.570	0.796	0.585	0.811	0.646	0.840	0.818	0.843
Supplier FEs:	No	No	Yes	No	Yes	No	Yes	No	No
Quarter FEs:	No	No	No	Yes	Yes	No	No	Yes	No
Customer industry × quarter FEs:	No	No	No	No	No	Yes	Yes	No	Yes
Customer-supplier FEs:	No	No	No	No	No	No	No	Yes	Yes

Table V
Optimism Propagation: Cross-Sectional Variation

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

Dept. variable:	*Supplier forecast*							
Sample:	Zero range	Non-zero range	Full	Non-zero	Non-zero	Non-zero	Non-zero	Non-zero
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Customer forecast error (FE)	0.487	0.569***	0.249					
	(1.27)	(6.73)	(1.22)					
Supplier range × *Customer FE*			0.366***					
			(3.36)					
Supplier-to-customer range × *Customer FE*				0.064**				
				(2.48)				
Supplier earnings variance × *Customer FE*					0.025**			
					(2.13)			
S-C earnings variance ratio × *Customer FE*						0.045*		
						(1.73)		
Supplier's sales share × *Customer FE*							0.430***	
							(2.86)	
Customer-supplier beta × *Customer FE*								0.431*
								(1.71)
Direct effect of interaction term			0.297	-0.042***	0.000	-0.064***	-0.508	-1.100**
			(1.59)	(-2.94)	(0.01)	(-2.78)	(-0.96)	(-1.97)
Observations	1,275	6,287	6,620	7,092	7,470	7,159	7,092	6,498
R-squared	0.964	0.930	0.930	0.931	0.932	0.931	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 error of the earliest EPS forecast issued in the four-month window following the issuance of the supplier's forecast. *Customer forecast error [t-1]* is the error of the latest customer forecast issued in the four month period preceding the supplier's forecast. Similarly, periods *[t-2]* and *[t-3]* reference deeper lags of four-month windows. Control variables are the same as in Table V. t-statistics, reported in parentheses, are based on standard errors clustered at the supplier level.

Dept. variable:			*Supplier forecast*			
	(1)	(2)	(3)	(4)	(5)	(6)
Customer forecast error [t+1]						0.063
						(0.19)
Customer forecast error [t-1]	0.641***			0.658***	0.678***	0.592*
	(3.69)			(2.76)	(3.49)	(1.86)
Customer forecast error [t-2]		0.533***		0.168	0.146	
		(3.96)		(0.96)	(1.07)	
Customer forecast error [t-3]			0.138	-0.057		
			(0.81)	(-0.30)		
Observations	4,128	4,080	3,947	3,330	3,692	3,537
R-squared	0.933	0.931	0.933	0.936	0.933	0.934
Control variables included:	Yes	Yes	Yes	Yes	Yes	Yes
Supplier FEs:	Yes	Yes	Yes	Yes	Yes	Yes
Customer industry × quarter FEs:	Yes	Yes	Yes	Yes	Yes	Yes

Table 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 *Investment*, *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; t-statistics, reported in parentheses, are based on standard errors clustered at the firm level.

Dept. variable:	*Investment*		*Inventory*		*Book leverage*		*Stock issuance*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Forecast error	0.056***	0.038**	0.103***	0.089***	0.337***	0.298***	-0.597***	-0.531***
	(3.04)	(2.07)	(3.36)	(2.91)	(5.32)	(4.62)	(-4.15)	(-3.60)
Ln(total assets)	-0.308**	-0.230	-1.197***	-1.536***	4.404***	5.039***	-2.070*	1.454
	(-2.42)	(-1.54)	(-6.33)	(-6.10)	(7.93)	(7.01)	(-1.96)	(1.15)
Tobin's Q	0.005***	0.005***	-0.001*	-0.001	-0.009***	-0.009***	0.025***	0.024***
	(6.93)	(6.32)	(-1.92)	(-1.63)	(-3.16)	(-2.69)	(5.03)	(4.51)
Profitability	0.039***	0.036***	0.057***	0.053***	-0.199***	-0.207***	-0.227**	-0.192**
	(3.69)	(3.37)	(3.99)	(3.63)	(-3.28)	(-3.33)	(-2.46)	(-2.08)
PP&E	0.169***	0.167***	0.005	0.006	0.100***	0.094***	0.240***	0.222***
	(6.51)	(6.48)	(1.05)	(1.34)	(5.71)	(5.48)	(3.81)	(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 to conserve space but available upon request. The last row reports F-statistics from the first-stage regressions. The dependent variables *Investment*, *Inventory* and *Book leverage* are expressed in percent of book assets. *Stock Issuance* 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; t-statistics, reported in parentheses, are based on standard errors clustered at the supplier level.

Dept. variable:	*Investment*		*Inventory*		*Book leverage*		*Stock issuance*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Forecast (instrumented)	0.039	0.073	0.774**	1.059**	2.315*	2.121*	-6.683***	-7.601***
	(0.26)	(0.39)	(2.27)	(2.52)	(1.67)	(1.71)	(-2.93)	(-3.07)
Ln(total assets)	-0.224	-0.177	-2.245***	-2.302**	5.093**	6.464***	9.910***	9.262**
	(-0.88)	(-0.61)	(-2.77)	(-2.28)	(2.35)	(2.74)	(2.64)	(2.15)
Tobin's Q	0.007	0.007*	0.001	0.002	0.027*	0.020	-0.026	-0.022
	(1.63)	(1.70)	(0.47)	(0.50)	(1.95)	(1.48)	(-1.11)	(-1.05)
Profitability	-0.007	-0.010	-0.008	-0.019	-0.923***	-0.837***	0.816**	0.814**
	(-0.17)	(-0.21)	(-0.16)	(-0.33)	(-3.79)	(-3.87)	(2.06)	(2.07)
PP&E	0.161***	0.152***	0.046	0.027	0.326***	0.262***	0.561*	0.717**
	(7.27)	(7.17)	(1.47)	(0.86)	(3.03)	(2.89)	(1.75)	(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
F-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
Earnings forecast data		
Forecast$_{it}$	The forecast of quarterly and annual EPS issued by the management of company i at time t scaled by the stock price five trading days before the forecast announcement: Forecast$_{it}$ = $\frac{\hat{e}_{its}}{P_{it}}$. EPS guidance data ($\hat{e}_{it}$) are obtained from Thomson Reuters's I/B/E/S database. We undo the historical split-adjustment by I/B/E/S 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.	I/B/E/S, CRSP
Customer forecast$_{it}$*, sales-weighted*	The average forecast of company i's customers at time t, with each customer weighted by its sales share with company i. For each forecast by a supplier, only the most recent forecast with the same periodicity (quarterly or annual) of each of its customers is used. Customer-supplier pairs are obtained from COMPUSTAT's customer segment files for a given time t. Since COMPUSTAT's customer segment files does not provide firm identifiers, we string-match customer names to company names in COMPUSTAT's fundamental annual file. Company i's disclosed sales to his customer are scaled by i's total sales as obtained from COMPUSTAT to calculate sales shares. As-is (i.e., non-rescaled) sales shares at time t are then used as weights to average all customers' optimism for any given supplier at time t. When no sales share is given, we assume the minimum threshold (10%) that triggers following SFAS No. 131 mandatory customer disclosure. We drop a few observations where sales share is negative or exceeds 100% or where the sum of reported sales shares to all customers at a given time t exceeds 100%.	I/B/E/S, CRSP, COMPUSTAT, COMPUSTAT customer segment file
Forecast error$_{it}$	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 I/B/E/S database. We undo the historical split-adjustment by I/B/E/S 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 I/B/E/S (I/B/E/S 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.	I/B/E/S, CRSP
Forecast horizon$_{it}$	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.	I/B/E/S
Forecast range$_{it}$	The difference between the upper and the lower bound of the EPS forecast as issued by company i at time t. We truncate quarterly and annual ranges separately at the 99th percentile.	I/B/E/S
Quarterly earnings forecast$_{it}$	Indicator variable that equals 1 if company i's forecast issued at t is a quarterly forecast, else 0.	I/B/E/S
Customer actual$_{it}$	The realized earnings per share announced by customer i for fiscal period s, price-adjusted using the closing price of customer i's stock five trading days before the announcement date. We truncate the scaled customer actuals (separately for quarterly and annual forecasts) at the 1st and 99th percentile.	I/B/E/S, CRSP
Customer actual$_{it}$*, sales-weighted*	The average optimism of company i's customers at time t, with each customer optimism value weighted by the sales share from i to that customer. The sales share to any given customer is determined by dividing the disclosed sales to that customer in COMPUSTAT's customer segment file by i's total sales in that year.	I/B/E/S, CRSP, COMPUSTAT, COMPUSTAT customer segment file

Table IX - Continued

Variable name	Definition	Data source
Customer-Supplier link data		
C/S $beta_{ij}$	The coefficient β_{ij} from a time-series regression of daily excess stock returns of supplier i on excess stock returns of its customer j and the excess market return: $r_{it} - r_{ft} = \alpha_{ij} + \beta_{ij}(r_{jt} - r_{ft}) + \gamma_{ij}(r_{mt} - r_{ft})$. Computed from stock return data available for at least 200 trading days between one year before the earliest disclosed date of a customer-supplier relationship and the latest disclosed date of a relationship. Winsorized at the 0.5th and 99.5th percentile.	COMPUSTAT, COMPUSTAT customer segment file
Sales share$_{ijt}$	The sales share of supplier i at the time of a forecast t to his customer j. When no sales share is given, we assume the minimum threshold (10%) that triggers following SFAS No. 131 mandatory customer disclosure. We drop a few observations where sales share is negative or exceeds 100% or where the sum of reported sales shares to all customers at a given time t exceeds 100%.	COMPUSTAT, COMPUSTAT customer segment file
Balance sheet / control variables		
Ln(assets)$_{it}$	The natural logarithm of 1 plus company i's total assets (AT) in millions of USD at the end of fiscal year t.	COMPUSTAT
Market value of assets$_{it}$	Market value of assets of company i in millions of USD at the end of fiscal year t. Calculated as book value of assets (AT) plus market value of equity (CSHO*PRCC_F) minus book value of equity (SEQ + TXDITC - PSTKRV).	COMPUSTAT
Sales$_{it}$	Gross sales and the amount of actual millions to customers for regular sales of company i in billions of USD completed during fiscal year t (COMPUSTAT item SALE).	COMPUSTAT
Tobin's Q$_{it}$	Ratio of market value of assets to book value of assets for company i at time t.	COMPUSTAT
PP&E$_{it}$	Total net value of property, plants and equipment (PPENT) divided by total assets (AT) for company i at time t.	COMPUSTAT
Profitability$_{it}$	Operating income before depreciation (OIBDP) divided by total assets (AT) for company i at time t.	COMPUSTAT
Book leverage$_{it}$	Debt in current liabilities (DLC) plus long term debt (DLTT) divided by total assets (AT) for company i at time t.	COMPUSTAT
Stock issuance$_{it}$	Indicator variable whether the firm issued new stock in the 12 preceeding 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$_{it}$	Total inventories (INVT) divided by total assets (AT) for company i at time t.	COMPUSTAT
Investment$_{it}$	Capital expenditures (CAPX) divided by total assets (AT) for company i at time t.	COMPUSTAT
Alternative Optimism Measures		
ShareRetainer$_{it}$	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$_{it}$	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 management's relative forecast optimism on its customers' relative forecast optimism, where relative optimism is measured as the difference between the 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 forecast issuance and the announcement of the respective realized earnings. *Quarterly earnings forecast* is an indicator variable which equals one for quarterly forecasts and zero for annual forecasts. All other control variables are defined in Table IX. Customer industry fixed effects are based on the customer's Fama-French 48 industry classification. t-statistics, reported in parentheses, are based on standard errors clustered at the supplier level.

Dept. variable:	*Relative supplier optimism*								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Relative customer optimism	0.342***	0.309***	0.397***	0.254***	0.343***	0.248**	0.334***	0.048**	0.060**
	(3.66)	(3.25)	(3.56)	(2.65)	(3.07)	(2.42)	(2.63)	(2.13)	(2.45)
Forecast horizon	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-0.67)	(-0.51)	(-1.59)	(-0.04)	(-1.35)	(-0.22)	(-0.87)	(-1.53)	(-0.64)
Quarterly earnings forecast	-0.151***	-0.122***	-0.166***	-0.111***	-0.158***	-0.127***	-0.146***	-0.179***	-0.158***
	(-6.05)	(-5.13)	(-6.77)	(-4.65)	(-6.37)	(-4.68)	(-5.38)	(-6.75)	(-5.51)
Ln(assets)		0.043***	-0.086***	0.043***	-0.078**	0.051***	-0.088***		-0.120***
		(6.03)	(-3.24)	(5.94)	(-2.44)	(5.99)	(-2.70)		(-2.99)
Tobin's Q		0.032***	0.001	0.036***	0.006	0.026***	-0.002		-0.001
		(4.39)	(0.07)	(4.93)	(0.43)	(3.30)	(-0.16)		(-0.09)
PP&E		-0.094	-0.214	-0.100	-0.247	-0.026	-0.137		-0.037
		(-0.80)	(-0.82)	(-0.86)	(-0.97)	(-0.20)	(-0.56)		(-0.12)
Observations	7,455	7,392	7,392	7,392	7,392	7,392	7,392	9,540	9,457
R-squared	0.014	0.029	0.239	0.044	0.252	0.190	0.369	0.280	0.380
Supplier FEs:	No	No	Yes	No	Yes	No	Yes	No	No
Quarter FEs:	No	No	No	Yes	Yes	No	No	Yes	No
Customer industry × 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 regressions of the customer's forecast on the supplier's forecast error, thus switching the dependent and independent variables of Table IV. Observations for the dependent and independent variables are matched such that the issuance of the customer forecast occurs after that of the supplier. 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. *Forecast horizon* is the number of days between the forecast issuance and the announcement of the respective realized earnings. *Quarterly earnings forecast* is an indicator variable which equals one for quarterly forecasts and zero for annual forecasts. All other control variables are defined in Table IX. Customer industry fixed effects are based on the customer's Fama-French 48 industry classification. t-statistics, reported in parentheses, are based on standard errors clustered at the supplier level.

Dept. variable:					*Customer forecast*				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Supplier forecast error	0.330	0.181	0.295	0.247	0.246	0.287	0.238	0.028	0.027
	(0.89)	(0.56)	(1.00)	(0.83)	(1.03)	(0.70)	(0.70)	(1.17)	(1.12)
Forecast horizon	0.001**	0.001***	0.001***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(2.05)	(2.71)	(3.66)	(3.88)	(4.72)	(3.20)	(3.99)	(5.44)	(4.79)
Quarterly earnings forecast	-5.142***	-5.018***	-5.188***	-4.851***	-5.123***	-4.704***	-5.027***	-4.926***	-4.903***
	(-25.65)	(-28.63)	(-22.12)	(-30.02)	(-22.90)	(-23.61)	(-19.13)	(-16.20)	(-15.15)
Log assets		0.289***	1.150***	0.259***	0.695**	0.372***	0.415***	0.982	1.971***
		(3.21)	(4.98)	(3.10)	(1.97)	(4.22)	(2.72)	(1.57)	(3.14)
Tobin's Q		-0.729***	-0.521***	-0.594***	-0.308**	-0.661***	-0.321**	-0.285	-0.203
		(-7.21)	(-4.25)	(-5.76)	(-2.27)	(-4.81)	(-2.24)	(-1.48)	(-1.23)
PP&E		-0.650	-0.105	-0.645	-1.310	-1.589	-3.607**	-1.395	0.415
		(-1.19)	(-0.06)	(-1.28)	(-0.76)	(-1.14)	(-2.41)	(-0.44)	(0.10)
Observations	2,978	2,957	2,957	2,957	2,957	2,957	2,957	10,393	10,393
R-squared	0.579	0.637	0.803	0.678	0.828	0.784	0.887	0.848	0.901
Supplier FEs:	No	No	Yes	No	Yes	No	Yes	No	No
Quarter FEs:	No	No	No	Yes	Yes	No	No	Yes	No
Customer industry × quarter FEs:	No	No	No	No	No	Yes	Yes	No	Yes
Customer-supplier FEs:	No	No	No	No	No	No	No	Yes	Yes