Business Expectations and Forecast Errors in the Interconnected Economy *

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Abstract

We construct a unique data set that contains information about business expectations, forecast errors, and business transaction relationships to offer a new perspective on mechanisms for the formation of business expectations and the generation and transmission of forecast errors. Our main empirical findings are as follows: Firms' expectations about their growth rates are positively correlated with the number of transaction partners, consistent with firm growth patterns. A longer duration of transaction relationships tends to reduce uncertainty and forecast errors, suggesting the role of information sharing and flexible adjustments in forecasting. A larger forecast variation tends to amplify forecast errors, indicating that uncertainty is a major factor in forecast errors. A firm's forecast error is transmitted to its transaction partners. These forecast error correlations arise from transaction linkages, not more aggregate factors. This study advances our understanding of how firms form business expectations in an interconnected economy and how forecast errors are transmitted between transaction partners.

Keywords: Business Expectations, Forecast Errors, Transaction Relationships

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1 Introduction

Firms look forward and form expectations about their business performances (which we call business expectations), and they, in turn, use such business expectations to make important decisions on their conduct. In fact, production planning and scheduling are based on business expectations, and they are an integral part of supply chain management, especially in the manufacturing sector, to achieve operational efficiency and make profits. However, business expectations are not always accurate due to uncertainty and result in generating forecast errors that come as disturbances to firm performances and consequently affect aggregate outcomes. A sizeable temporary uncertainty shock generates fluctuations in employment, output, and productivity growth (Bloom, 2009), and it can lead to resource misallocation that adversely impacts aggregate productivity (David et al., 2016). The accuracy of a firm's forecast about macro-level economic conditions is positively correlated with firm-level capital investments, sales, and profitability (Tanaka et al., 2019). A firm's business expectation and forecast error vary significantly with its characteristics and phases of a business cycle (Massenot and Pettinicchi, 2018) and firms' inattentiveness distorts their macroeconomic beliefs (Coibion et al., 2018). Business expectations, forecast errors, and uncertainty are thus intertwined to influence resource allocation and economic outcomes at both firm and economy levels. Implicit assumptions often made in this stream of empirical research are that the primary target of a firm's forecasting is macro-economic conditions, that firms form their business expectation independently of other firms, and that firms' own forecast errors, not other firms' forecast errors, are the only influential factors for their conduct and performance. This analytical framework offers many valuable insights, but it remains silent on possible roles played by the interconnectedness of firms in forming business expectations and generating forecast errors. Meanwhile, supply chain linkages have become an increasingly important channel for the propagation of economic shocks (Carvalho et al., 2021) as they are increasingly integrated domestically and globally. Given that the main sources of forecast errors are unanticipated economic shocks and forecast inaccuracy, forecast errors may disturb firm performances and travel within a supply chain. Even though business expectations, forecast errors, and supply chains are fundamental economic issues and are one definite area of concern for firms and policymakers in many countries nowadays, we know very little about how the interconnectedness of firms plays out in forming business expectations and generating and transmitting forecast errors. Especially, empirical evidence is scant mainly because of data limitations.

In this paper, we bring a new element, the interconnectedness of firms, into our empirical analysis and try to offer a new perspective on mechanisms for the formation of business expectations and the generation and transmission of forecast errors. In a similar spirit to the view of the studies by Acemoglu et al. (2012) and Carvalho et al. (2021), we aim to reveal whether a particularity of transaction relationships determines how business expectation is formed and forecast errors are generated and transmitted. In the empirical investigation of this paper, special attention is paid to the number of transaction partners and the duration of transaction relationships. We are interested in investigating whether firms expect to grow when extending a range of transaction partners and building stable transaction relationships. We also attempt to understand whether the law of large numbers applies to minimize uncertainty and forecast errors, whether transaction linkages act as multipliers to amplify them, and whether stable transaction relationships facilitate information sharing and reduce uncertainty and forecast errors. We then examine whether a forecast error of one firm is transmitted to its transaction partners by looking at the correlation of forecast errors between transaction partners. Such interdependencies pose the reflection problem for empirical analysis (Manski, 1993). That is, a forecast error of one firm is partly reflected in that of its transaction partners and vice versa. To deal with this problem, we employ the 2SLS estimation proposed by Bramoullé et al. (2009) and distinguish endogenous, exogenous, and correlated effects (Manski, 1993). The correlation of forecast errors between transaction partners can arise for various reasons. For example, firms in the same industry may have similar information about business conditions and hold similar expectations or be hit by the same industry-specific shocks, causing forecast error correlations. To delve into the source of forecast error correlations, we exploit different layers of the relationship between firms: sector, industry, geographical location, and capital relationships. These layers will likely reflect different natures of forecast biases and economic shocks embedded in forecast errors.

To answer the research questions above, we construct a unique data set containing information about business expectations, forecast errors, and transaction relationships. The data about business expectations come from the Japanese Management and Organizational Practices Survey (JP MOPS, hereafter) conducted in Japan between January 2017 and March 2017, using 2015 as the survey reference year. We use the manufacturing part of JP MOPS that closely follows the survey design and protocol of the US Management and Organizational Practices Survey and includes survey questions regarding business expectations about the value of shipments. The JP MOPS asked Japanese establishments in the manufacturing sector to provide their forecast about shipment value

for 2017. They were also asked to forecast shipment value in 2018 for three scenarios - high, medium, and low realizations - and assign corresponding probabilities. We use the establishment's forecast about the value of shipment for 2017 as our measure of business expectation, while information on establishments' 2018 forecasts and probabilities is used to measure a subjective assessment of uncertainty. The JP MOPS data set is merged with the Japanese Census of Manufacturers, which contains data on realized shipment values for 2017. Our empirical measure of forecast errors is constructed by taking a difference between business expectation in the JP MOPS and a realized shipment value in the Japanese Census of Manufactures. This merged data set is then matched with the firm-level information collected by Teikoku Databank to investigate the effects of transaction relationships on business expectations and forecast errors. In the Teikoku Databank data set, pairs of transaction partners are recorded, which allows us to empirically identify each firm's transaction partners and construct various measures for transaction relationships. To the best of our knowledge, this study is the first to utilize data containing information about a set of business expectations, forecast errors, and transaction relationships and investigate the effects of firms' interdependency on business expectations and forecast errors.

This study reveals several interesting patterns regarding the formation of business expectations, the generation, and the transmission of forecast errors. First, firms' business expectations about their shipment value are positively correlated with the number of transaction partners. This expectation formation pattern aligns with the finding that firms grow by extending a range of transaction partners (Bernard et al., 2021). Second, firms' forecast variation is negatively correlated with the number of transaction partners and the average duration time of transaction relationships. This implies that firms subjectively foresee that the uncertainty of their business performance (i.e., fluctuations in business performance) is low when they have many transaction partners (portfolio effect) and/or when their transaction relationships are stable. Third, we find weak evidence that a firm's forecast error becomes smaller with the number of transaction partners. Fourth, a longer duration of transaction relationships reduces a forecast error. One interpretation of this result is that a long duration of transaction relationships cultivates information sharing and flexible adjustment capabilities, and this reduces forecast errors. Fifth, a larger forecast variation tends to amplify forecast errors, indicating that uncertainty is a major source of forecast errors. Sixth, we find weak evidence that forecast errors are transmitted to transaction partners. Finally, our empirical analysis suggests that forecast error correlations arise from transaction and capital linkages, not more aggregate factors (e.g., sector, industry, and location). In addition, forecast biases are also positively correlated

between firms when they are in transaction relationships. These findings highlight a potentially important mechanism through which the formation of business expectations and the generation of forecast errors depend on a particularity of transaction networks. Thus, how to build transaction relationships affects one's forecast errors and can negatively impact its performance.

This study contributes to the existing research in the following ways. First, this study reveals how firms form business expectations and make forecast errors when they are connected in supply chains. The work by Cobins et al. (2018) examines how firms forecast economic outcomes such as a GDP growth rate. Massenot and Pettinicchi (2018) report that firms' forecasts vary with their characteristics, such as size and age. Bloom et al. (2021) use a data set similar to ours and document that better-managed firms forecast their business performances more accurately. Past empirical studies, including these studies, do not examine whether and how the interdependence of firms through transaction linkages affects expectations and forecast errors. This study advances our understanding of the formation of business expectations and forecast errors in interconnected economies. Second, this study points to the importance of supply chain management under uncertainty. Our empirical analysis indicates that information sharing through a long duration of transaction relationships helps to mitigate forecast errors. This finding provides fresh insights regarding supply chain management since how to build a supply chain is endogenously related to risk management. Finally, the empirical results of this study can be used to obtain several insights into shock propagation mechanisms. As analyzed by Acemoglu et al. (2012) and others, economic shocks propagate in transaction networks, and how shocks propagate depends on a particularity of transaction networks. Theoretical predictions are rich in this research area, but empirical evidence is limited because firm-level data suitable for such analysis have not been available. Economic shocks are embedded partially in forecast errors because forecast errors consist of economic shocks and forecast inaccuracy. Thus, our findings about forecast error correlations between firms give a clue to understanding shock propagation mechanisms.

The rest of the paper is organized as follows. Section 2 describes the data sources and the main research variable used in this study. We also provide the empirical framework to help interpret the estimation results. Our empirical results are presented in Section 3. We first report estimation results about how transaction relationships influence the formation of business expectations. We then present the empirical findings regarding how forecast errors are generated and transmitted in transaction networks. Section 4 concludes.

2 Data and Empirical Framework

2.1 Data

We create a unique data set by combining the following three sources of establishment- and firm-level information: the Japanese Management and Organizational Practices Survey (JP MOPS, *soshiki manegemento ni kansuru chosa*), the Japanese Census of Manufactures and the COSMOS2 database of Teikoku Data Bank. The JP MOPS was conducted as a governmental official statistics between January 2017 and March 2017 by the Economic and Social Research Institute of the Japanese Cabinet Office and its survey questions and methodology closely followed the protocol of the 2015 Management and Organizational Practices Survey administered by the U.S. Census Bureau. The JP MOPS targeted establishments with at least 30 employees in manufacturing, food and drink retail, and information technology service sectors, and these establishments were located in Japan as of July 1st, 2014. In this study, we use the manufacturing part of the JP MOPS because survey questions about business expectations were included in only the manufacturing part. Out of 35,263 surveys delivered to these establishments, 11,405 surveys were returned, and the response rate was 32.3 percent. Establishments in the JP MOPS were asked to forecast the total value of shipment for the entire period of 2017 when they filled in the survey questionnaire between January 2017 and March 2017. The definition of the total value of shipment, the same as the one in the Japanese Census of Manufactures, is provided for this survey question. This forecast is utilized to construct an empirical measure of business expectations.

The Ministry of Economy, Trade and Industry is responsible for conducting the Japanese Census of Manufactures to collect information about establishments in Japan. All establishments with four employees or more located in Japan are subject to the manufacturing census every year, and establishments with at least 30 employees must provide detailed information about their characteristics such as name, location, value-added, the number of employees, a value of shipment, total wage payment, fixed capital, and so forth. Among such variables, the information on the shipment value in the 2017 Census of Manufactures is used as a realized shipment value to compute an establishment's forecast error.

Teikoku Data Bank is a corporate credit reporting company that collects a wide range of information about firms to offer corporate credit reporting and business solution services. In this study, we utilize their COSMOS2 database, which is intended to cover both private and public firms operating in Japan in all industries. The COSMOS2 database contains firm characteristics and

accounting information about 1.4 million firms annually that account for more than 90 percent of the sales in Japan. We also use the database to trace information about transaction relationships. Pairs of a customer and a supplier are recorded as transaction partners in the database when at least one of the firms lists its transaction partner as one of its top five transaction partners. We empirically identify a transaction relationship from this piece of information and construct various measures for transaction relationships. This way of identifying business-to-business transactions is restrictive to a certain extent, but the number of transaction pairs amounts to 4,303,210, and the maximum number of transaction partners is 12,881 for the 2022 database. It captures the majority of actual business-to-business transactions in Japan.

The JP MOPS and the Japanese Census of Manufactures are establishment-level data, whereas the COSMOS2 is a firm-level database. When an establishment in the JP MOPS is one of the multiple establishments belonging to a firm, and the JP MOPS includes at least two such establishments, we aggregate establishment-level variables in the JP MOPS and the Japanese Census of Manufactures into firm-level variables by using relative size, measured by the number of employees, of establishment within a firm as weight and taking a weighted average of each establishment-level variable. Thus, a firm is a unit of analysis in our empirical examination, and the focal firms are firms in the JP MOPS mainly because information on business expectations and forecast error is necessary for the main purpose of this study. The number of focal firms in the merged data is 9,606.

2.2 Main Research Variables

Our key variables in the empirical analysis are business expectations and forecast errors about firms' performance and transaction relationships. Conceptually, a forecast error in the context of this paper is a difference between a forecasted value of business performance and its realized value. Our empirical measure of firms' forecasts is about their business performances and is constructed from survey questions regarding firm's forecasts about the value of shipment. We call this variable business expectation in this paper. Establishments in the JP MOPS were asked to write a realized value of shipment for the entire year of 2016 and forecast a value of their shipment for the entire year of 2017 based on their available information when they answered the JP MOPS questionnaire between January 2017 and March 2017. To minimize the influence of establishment size, we convert this forecast to a growth rate by using firms' survey answers about the value of shipments realized

in the year 2016. Our empirical measure of a business expectation is

$$g_{exp} = \frac{Y_{2017_forecast} - Y_{2016_realized}}{Y_{2016_realized}} \tag{1}$$

where $Y_{2017_forecast}$ and $Y_{2016_realized}$ denote an establishment's forecast about a value of shipment for the year 2017 and a value of shipment realized in the year 2016, respectively.

To construct our measure of a forecast error, we first calculate an actual growth rate of the shipment value for each establishment (i.e., business realization) by using information on realized values of shipment recorded in the Japanese Census of Manufactures. This growth rate is given by $g_{act} = \frac{Y_{2017} - Y_{2016}}{Y_{2016}}$, where Y_{2016} and Y_{2017} denote a realized value of shipment for the years 2016 and 2017, respectively. Then, an establishment's forecast error is empirically defined as

$$f_{err} = g_{exp} - g_{act} \tag{2}$$

We also exploit the information about firms' forecasts in the JP MOPS to construct two important control variables. As explained above, our forecast-related variables are constructed from the survey responses in the JP MOPS. In the nature of survey responses, answering the survey questions about forecasts inaccurately or irresponsibly is a cause for concern. We first winsorize the top and bottom 3 percent of both business expectation and forecast error variables to deal with spurious outliers. Second, we construct a noise control variable that is basically a difference between the values of shipment for the year 2016 recorded in the JP MOPS and in the Japanese Census of Manufactures. More specifically, $noise_control = |\frac{Y_{2016_realized} - Y_{2016}}{0.5(Y_{2016_realized} + Y_{2016})}|$. JP MOPS and the Japanese Census of Manufactures questionnaires were filled in independently at different times. Thus, our noise control variable likely captures a general tendency to answer the JP MOPS survey questions accurately and responsibly, and it indicates that establishments made their best effort to answer more accurately and responsibly as our noise control variable approaches zero.

Another concern is that a degree of uncertainty may differ from establishment to establishment, which may significantly affect the formation of business expectations and the generation of forecast errors. The establishments in the JP MOPS were also asked to forecast the value of their shipment for the year 2018 for three different scenarios (low, medium, and high), and assign a probability to each scenario. We calculate a coefficient variation from the weighted mean and variance of these values of their shipment. This variable, called forecast variation, is intended to capture a degree of uncertainty an establishment subjectively foresees.

As described above, establishment-level measures of business expectation, forecast error, and forecast variation are aggregated into firm-level variables by taking a weighted average of each variable when an establishment in our data is one of the multiple establishments belonging to a firm.

Figure 1 displays the distributions of firm-level business expectations, business realizations, forecast errors, and forecast variation (before winsorize), and Table 1A reports summary statistics on these variables. There are several noteworthy characteristics in these distributions. First, business expectations vary across firms. Although many firms answered zero growth, some foresee positive growth, while others expect negative growth. Second, business realizations (i.e., a realized shipment value) are dispersed around zero. Both positive and negative growth were recorded. More importantly, the distribution of business expectations is similar to that of business realizations. Finally, forecast errors are also dispersed around zero, which looks like a normal distribution. Most firms make forecast errors, but the forecast errors are concentrated around zero. While there are firms whose realized shipment value is less than expected, there are firms that achieved a value of their shipment more than expected. Both optimistic and pessimistic forecasts exist.

[Table 1 and Figure 1 here]

To assess the validity of the forecast error and forecast variation variables, we plot these variables in Figure 2 by a bins scatter where TFP, management scores, the number of employees, and noise control are included as control variables. Note that these two variables are not necessarily correlated mechanically by the way they are constructed. However, it is natural to expect that the absolute value of the forecast error variable is positively correlated with the forecast variation because forecast errors become large in magnitude with a degree of uncertainty surrounding a firm. As we can see from Figure 2, it is indeed the case, which provides reasonable support for the validity of these two empirical measures.

[Figure 2 here]

We focus on two aspects of transaction relationships to capture their characteristics. The first aspect is the interconnectedness of firms. Pairs of transaction partners in the Teikoku Data Bank database allow us to identify a direct link between transaction partners and to capture our focal firms' linkage to other firms by the number of direct transaction partners and page rank. These variables are mainly used to investigate whether firms expect to grow when transacting with many firms and whether their forecast errors are minimized or amplified by a range of transaction partners. The second aspect is the duration of transaction relationships. The Teikoku Data Bank

database traces firms' transaction relationships back to 1993. We identify the number of years two firms have been in transaction relationships in the past, as of the year 2015, and calculate the average years of transaction relationships a firm has with its transaction partners. Our premise is that more information on transactions is shared between transaction partners, which helps reduce information asymmetry and uncertainty when they have longer transaction relationships. A long duration of transaction relationships may also allow firms to make flexible adjustments when some contingencies arise. From these viewpoints, we examine whether transaction duration mitigates forecast errors.

Table 1B reports summary statistics regarding firms' transaction relationships. In the sample of this study, the average number of transaction partners is 55.5, and the median number is 16. The distribution of the number of transaction partners is skewed; most firms have less than 50 transaction partners, and few firms have more than 50 transaction partners. We also observe the number of transaction partners increases with firm size (i.e., sales). Table 1B also presents a change in transaction partners between 2017 and 2018. The average percentage of new transaction partners is 8.7 percent, whereas the average percentage of terminated partners is 6.7 percent. Thus, there are non-negligible changes in the portfolio of transaction partners over time.

Information on the direct links between transaction partners also permits us to examine the effects of forecast errors and transaction partners' characteristics on the formation of business expectations and the generation of forecast errors. To examine this interdependency, we include transaction partners' forecast-related variables (forecast error and forecast variation) in our regression analyses, along with their size, productivity, and number of transaction partners.

2.3 Empirical Framework

2.3.1 Linear-in-mean model

An empirical framework is laid out in this section to help understand our empirical results. We start our regression analysis to understand how firms forecast a growth rate of their shipment value. To conduct this analysis, we employ the following baseline estimation equation:

$$g_{exp_i} = \beta_0 + \beta_1 Own_Ch_i + \beta_2 TR_i + \beta_3 Ptr_Ch_i + u_i \tag{3}$$

where Own_Ch_i is a set of variables that capture firm i's characteristics such as size, age, productivity, and managerial efficiency. These variables are typically used in the regression analyses of

previous studies. The variable TR_i is a set of variables that capture the firm's transaction relationships, such as the number of transaction partners and the duration of transaction relationships. The variable Ptr_Ch_i is a set of transaction partners' characteristics.

Our primary interest is to empirically analyze the determinants of a firm's forecast error when it transacts with other firms. As Manski (1993) categorized, endogenous, exogenous, and correlated effects are likely to be present in our empirical analysis. In the context of this study, endogenous effects are the influence of transaction partners' forecast errors, and exogenous effects relate to transaction partners' characteristics. Correlated effects are factors that lead all firms in the transaction relationships to make forecast errors in a similar fashion.

We employ a standard linear-in-mean model to infer these effects statistically (Bramoullé et al., 2009). Formally, the structural model is given by

$$f_{err_i} = \beta \frac{1}{n_i} \sum_{j \in P_i} f_{err_j} + \gamma x_i + \delta \frac{1}{n_i} \sum_{j \in P_i} x_j + \alpha_l + v_i \tag{4}$$

where P_i is a set of firm i's transaction partners with size n_i and x_i is a set of variables that capture firm i's characteristics and transaction relationships. The parameter β captures the endogenous effects from the transaction partners, whereas the parameter δ reflect their exogenous effects. The α_l captures a fixed factor common to the set of firm i's transaction partners (correlated effects) and ε_i is an error term. In matrix notation,

$$f_{err} = \beta G f_{err} + \gamma X + \delta G X + \sum_{l \in P} \alpha_l \iota + v \tag{5}$$

where G is a matrix that captures direct transaction relationships and $G_{ij} = \frac{1}{n_i}$ if firm j is a direct transaction partner of firm i, and 0 otherwise. The variable ι is a vector of ones.

The simple ordinary least squares (OLS) regression estimates suffer from the well-known reflection problem (Manski, 1993). First, the coefficient β cannot be estimated consistently by the OLS estimation because of simultaneity (Manski, 1993), and, as a result, the estimate cannot be interpreted as a causal effect. If firm i's forecast error is affected by firm j's forecast error and if firm j's forecast error is also affected by firm i's forecast error, f_{err_j} is correlated with v_i in the regression because f_{err_j} contains v_i. This causes the bias in the coefficient estimate.

Second, the OLS estimations do not allow us to distinguish endogenous and correlated effects. More specifically, a partial correlation between one's forecast error and the mean forecast error

of its transaction partners can arise from a common shock or common forecast behaviors in the absence of endogenous effects. For example, a common shock to a pair of transaction partners i and j can cause their forecast errors to move in the same direction even if their forecast errors do not transmit to each other. This common shock can be a network-specific or industry-wide shock, which we will exploit later.

To deal with these problems, we employ the 2SLS estimation proposed by Bramoullé et al. (2009). When the correlated effects are absent, they suggest to use $[X, GX, G^2X]$ as instruments in the first step and use $[E[Gy(\hat{\beta}, \hat{\gamma}, \hat{\delta})|X, G], X, GX]$ as instruments in the second step to gain efficiency further. When the correlated effects are present, the baseline estimating equation needs to be transformed to remove α_l and the instruments are adjusted to be $[(I-G)X, (I-G)GX, (I-G)G^2X]$.

2.3.2 Decomposition of Forecast Errors

As described above, a forecast error consists of g_{exp} (a forecasted growth rate of shipment) and g_{act} (a realized growth rate of shipment). Let X be a vector of controls that econometricians can observe. We first assume that a realized growth rate of shipments can be decomposed into the expected growth conditional on observables $\mathrm{E}[g_{act}|X]$ and an unobservable shock ε:

$$g_{act} = \mathrm{E}[g_{act}|X] + \varepsilon. \tag{6}$$

By definition of the conditional expectation, $\mathrm{E}[\varepsilon|X] = 0$, and ε is not correlated with X. Similarly, we decompose a forecasted growth rate of shipment into the expected growth conditional on observables $\mathrm{E}[g_{act}|X]$ and firm-specific forecast factors u:

$$g_{exp} = \mathrm{E}[g_{act}|X] + u. \tag{7}$$

Firm-specific forecast factors u can reflect private information that firms can observe but econometricians cannot, or/and firm-specific forecast bias. $\mathrm{E}[g_{act}|X]$ is the best forecast given information econometricians can observe, but firms may have more information about predictors for the growth rate and reflect them into their forecast. Thus, there could be a discrepancy between the expectation conditional on observables X and the actual firm's forecast. Alternatively, a firm's forecast can be different from the conditional expectation from the perspective of econometricians because they could have forecast biases. Note that u can be correlated with X, since these biases can be

associated with specific characteristics econometricians can observe. Also, u can be correlated with ε given that u can reflect firm's private information that econometricians cannot observe (u can reflect a part of ε). For simplicity, we assume that u can be linearly decomposed:

$$u = X'\beta + w, \tag{8}$$

where w reflects private information or biases that X cannot explain, and $E[w|X] = 0$. Observables X can contain various influential factors such as firm's own characteristics and transaction relationships, transaction partners' characteristics, and a degree of uncertainty. Then a forecast error is simply characterized as

$$f_{err} = g_{exp} - g_{act} = u - \varepsilon = X'\beta + w - \varepsilon. \tag{9}$$

Conditional on X, the covariance in forecast errors between transaction partners i and j is given by

$$Cov(f_{err_i}, f_{err_j}) = Cov(w_i - \varepsilon_i, w_j - \varepsilon_j) = Cov(\varepsilon_i, \varepsilon_j) + Cov(w_i, w_j) \tag{10}$$

This decomposition shows that a possible correlation between forecast errors comes from two sources. The first source, $Cov(\varepsilon_i, \varepsilon_j)$, is related to an economic shock ε and generates two insights. To gain these insights, decompose ε_i into aggregate shocks ζ_a and idiosyncratic shocks ζ_i; $\varepsilon_i = \zeta_a + \zeta_i$. Then, we obtain

$$Cov(\varepsilon_i, \varepsilon_j) = Var(\zeta_a) + Cov(\zeta_i, \zeta_j) \tag{11}$$

The first insight concerns common economic shocks to firms i and j. The correlation between economic shocks to firms i and j arises when the type of economic shocks is aggregate. The second insight is regarding the transmission of economic shocks between transaction partners. An economic shock of one firm (ε_i) may be transmitted to its transaction partner and be reflected in an economic shock of the transaction partner (ε_j) even if economic shocks are idiosyncratic. This also causes the correlation between economic shocks to firms i and j. A key difference between the first and second insights lies in the interconnectedness of firms in transaction networks. The correlation from

common shocks can arise between firms without any transaction relationships, but the correlation described in the second insight can arise only through direct and indirect transaction relationships.

The second source, $Cov(w_i, w_j)$, is related to a firm's forecast bias w, and this correlation can arise through two channels. Decomposing w_i into common bias z_a and transaction-specific bias z_i yields

$$Cov(w_i, w_j) = Var(z_a) + Cov(z_i, z_j) \tag{12}$$

The correlation arises when firms i and j hold a common view of macro/industry economic conditions that potentially affect each firm's outcomes. The correlation through the second channel arises due to information sharing between transaction partners. A firm may form an expectation about its business by taking the transaction partner's forecast into account. In this case, a transaction partner's forecast bias can enter into a forecast error for the firm.

Our data do not allow us to tell these stories apart cleanly, but we will try to get some insights into them. The main idea to achieve this goal is to utilize the insight that $Cov(\zeta_i, \zeta_j) = 0$ likely holds so that $Cov(\varepsilon_i, \varepsilon_j) = Var(\zeta_a)$ if firms i and j are not in transaction relationships. To implement this idea empirically, we pair firms i and j in our transaction network data that do not transact with each other and estimate $Cov(\varepsilon_i, \varepsilon_j)$. Once we obtain this estimate, we can recover $Cov(z_i, z_j)$ as a residual in Equation (11) by using the full sample.

3 Empirical Results

3.1 Business Expectations, Forecast Variation, and Transaction Relationships

We begin our empirical analysis by examining factors affecting firms' forecasts about their future business performance. We try to understand firms' forecast characteristics by looking at influential factors for future business performances firms subjectively expect (the first moment), and the variation in future business performances firms subjectively foresee (the second moment).

We first examine how business expectation is related to firm's transaction relationships. We conduct the ordinary least squares estimations where the dependent variable is a firm's business expectation, and the main independent variable is the number of direct transaction partners or page rank centrality, a proxy for a degree of interconnectedness to other firms, and the duration

of transaction relationships. Our control variables are the number of employees, sales amount (in millions), firm age, and dummy variables for industry and geographical location. Imani and Ohyama (2023) find that TFP and management scores are positively correlated with the number of direct transaction partners. In addition to these control variables, TFP and management scores are included to control for the firm's growth potential and operational efficiency. We also include a noise control variable to account for respondents' tendency to answer survey questions accurately.

Columns (1) and (2) of Table 2 report the estimation results about the determinants of firms' business expectations. According to our estimation, the number of transaction partners is positively associated with our measure of business expectations. Firms with more transaction partners expect to achieve a higher growth rate of their shipments. This result does not come as a surprise because firms typically grow by extending their range of transaction partners (Bernard et al., 2021). Putting this estimate in perspective, a one percent increase in the number of direct transaction partners is associated with a 0.2 percent increase in an expected rate of firm growth. Column (2) of Table 2 shows a similar positive relationship between business expectation and page rank centrality. Against our prior expectation, the coefficient on the average duration of the transaction relationships is negative and statistically significant. This suggests that firms with unstable transaction relationships are expected to grow.

The effect of firm age on business expectations is negative, indicating that younger firms expect higher growth rates. Management scores are positively correlated with business expectations, whereas TFP is negatively correlated with business expectations. The negative relationship between business expectations and TFP may be hard to interpret, but it may suggest that firms with high TFP are near their optimum scale, so there is little room for growth. Alternatively, this may imply that low-productivity firms overstate their growth potential.

We next use our measure of forecast variation to understand underlying factors for firms' forecasts. For this empirical examination, we regress the firm's forecast variation on the number of direct transaction partners or page rank centrality, along with the set of control variables same as the one in the previous analysis. The estimation results are shown in Columns (3) and (4) of Table 2. Our estimation result shows that the coefficient on the number of direct transaction partners and page rank centrality are negative and are statistically significant at the five percent and one percent significance levels, respectively. Our estimation results indicate "portfolio effects" that forecast variation tends to be low when firms are connected with many firms in the transaction networks.

It is interesting to see that both management scores and TFP are negatively correlated with firms' forecast variation. This may suggest that firms expect that production efficiency and operational efficiency enable them to manufacture their products as planned or deal with unexpected events effectively, which results in mitigating fluctuations in their manufactured product shipment value. The noise control variable is positively correlated with the forecast variation variable. This is anticipated since a large value of the noise control variable is likely to reflect the inaccuracy of survey answers. More importantly, we can control variation from the inaccuracy of survey answers by including this variable in the regression analyses below.

[Table 2 here]

We utilize the information on direct links between transaction partners to examine whether the formation of business expectations of one firm is influenced by the business expectations of its transaction partners. In this empirical investigation, the dependent variable is a firm's business expectation, and the main independent variable is the average value of business expectation of its transaction partners to account for the possibility of multiple transaction partners. A similar exercise is also carried out for forecast variation, where the dependent and main independent variables are replaced by the forecast variation of one firm and the average value of forecast variation of its transaction partners, respectively.

Table 3 reports the estimation results of these empirical exercises. According to the estimation results in (1) and (2) of Table 3, the coefficient on the business expectation of transaction partners is positive, but it is not statistically significant at the conventional significance levels. This implies that firms do not factor in transaction partners' business expectations when they form their own business expectations. We also find that transaction partners' characteristics, such as TFP, management scores, and size, do not affect the formation of one's business expectations.

The estimation results about forecast variation in (3) and (4) of Table 3 offer slightly different perspectives. The coefficient on the average value of forecast variation of its transaction partners is positive and statistically significant at the five or ten percent significance level. This implies that a firm's forecast variation grows with its transaction partners' forecast variation. This may indicate that firms in transaction relationships anticipate network-specific common shocks similarly or some shocks to travel between them. We will consider this issue in the next section when examining forecast error correlations.

[Table 3 here]

3.2 Forecast Errors and Transaction Relationships

3.2.1 Forecast Errors and Transaction Relationships

This section investigates factors contributing to firms' forecast errors. One area of our interest is examining whether a firm's forecast error is affected by its transaction linkage to other firms and, if so, whether a firm's forecast error becomes larger or smaller as it is connected to more firms in transaction relationships. Another area of interest is investigating whether a firm's forecast error is transmitted to its transaction partners. A correlation between forecast errors of different firms can arise from network-specific common shocks or transmissions of forecast errors from one firm to another. Although our data do not allow us to tease out these stories cleanly, we try to get some insight into this issue by exploiting the richness of our data.

We first present estimation results about the relationship between forecast errors and transaction linkages in Table 4. The dependent variable in this estimation is the absolute value of a firm's forecast error, and only the firm's own characteristics are included as independent variables. A firm's forecast variation is included to control for a degree of uncertainty firms face, while firm noise is intended to minimize a contribution to forecast errors arising from the inaccuracy of survey replies. The estimation result in (1) of Table 4 shows that the number of transaction partners is negatively correlated with the absolute value of a firm's forecast error. To understand the nature of forecast errors, we split the sample depending on whether forecast errors are positive or negative. Firms perform worse (better) than expected in the case of positive (negative) forecast errors, and estimation results for this subsample are reported in (2) ((3))of Table 4. A negative correlation holds for positive forecast errors, but the relation disappears for negative forecast errors. Similarly, a negative relationship holds between an absolute value of a firm's forecast error and the average duration of firm's transaction relationships. We observe this relation regardless of the sign of forecast errors (See (5) and (6)). In sum, our estimation results indicate that a firm's forecast error is small when transacting with many firms or when its relationship is stable over time.

The firm's forecast variation is positively correlated with the firm's forecast errors. Given that a firm's forecast error captures its subjective assessment of uncertainty about its business performances, this may reflect that some shock actually hits its business. The firm noise variable is positively correlated with the firm's forecast errors. As expected, forecast errors are large when firms tend to answer survey questions inaccurately. A negative correlation holds between a firm's forecast error and TFP, implying that high-productive firms forecast their future business conditions

more accurately than low-productive firms.

[Table 4 here]

We now add transaction partners' characteristics and their forecast errors to the set of independent variables in the previous estimations to examine each effect of these independent variables on a focal firm's forecast error. We first use the OLS estimation to estimate this relationship and report estimation results in (1) of Table 5. We have results similar to Table 4 regarding the firm's transaction relationships and characteristics, such as transaction duration, forecast variation, TFP, and noise-related variables. According to our OLS estimation, the coefficient on forecast errors of transaction partners is positive and statistically significant at the one percent level, suggesting a positive correlation between a firm's forecast error and its transaction partners' forecast errors. The dependent variable is also correlated negatively with its transaction partners' average transaction duration and positively with their forecast variation.

As explained in Section 2.3, the OLS estimation likely suffers from the reflection problem, and the estimated coefficient on transaction partners' forecast error in (1) of Table 5 would capture the effects of transaction partners' forecast errors as well as those of its own forecast error. To deal with the reflection problem, we conduct 2SLS estimations by employing the estimation method proposed by Bramoullé et al. (2009) (See Section 2.3.1). The estimation results from this 2SLS estimation are reported in (2) and (3) of Table 5. We use $[X, GX, G^2X]$ as instruments in (2) and $[E[Gy(\hat{\beta}, \hat{\gamma}, \hat{\delta})|X, G], X, GX]$ as instruments in (3).

According to the estimation results in (2) of Table 5, the coefficient on its transaction partners' forecast errors is 0.375 and statistically significant at the five percent significance level. Thus, the estimation results show that the positive correlation between these forecast errors remains after dealing with the reflection problem. A firm's forecast variation and noise-related variables are still positively correlated with its forecast errors. While transaction partners' transaction duration is negatively correlated with the dependent variable, we do not see any correlation with transaction partners' forecast variation in this estimation.

The estimation results in (3) of Table 5 show slightly different results. First, the coefficient on a firm's transaction partners' forecast errors is not statistically significant at the conventional significance levels. Second, the coefficients on a firm's TFP and transaction partners' forecast variation become statistically significant. Finally, the estimation results about a firm's transaction duration, its forecast variation, and transaction partners' transaction duration remain qualitatively unchanged.

[Table 5 here]

Based on the estimation results above, we now try to infer what factors are influential in generating forecast errors. As explained in See Section 2.3.1, the potential influential factors can be decomposed into endogenous, exogenous, and correlated effects. The endogenous effects are about whether a firm's forecast error is influenced by its transaction partners' forecast errors and relate to the estimated coefficient on transaction partners' forecast errors in (2) and (3) of Table 5. We have a mixed result here. According to the estimation results in (2), we can infer that a firm's forecast error is influenced by its transaction partners' forecast errors. Especially, the forecast error tends to be larger as its transaction partners' forecast errors are larger. This can be interpreted as forecast errors traveling between direct transaction partners. However, the estimation result in (3) does not support the existence of this endogenous effect.

The exogenous effects relate to a focal firm's characteristics and its transaction partners' characteristics, and we have relatively solid evidence about them across several econometric specifications. The estimation results suggest that a longer duration of transaction relationships tends to reduce a forecast error, whereas a larger forecast variation tends to amplify the forecast error. Firms may be able to exchange information more efficiently, reduce a degree of information asymmetry, and make flexible adjustments for contingencies when they build stable transaction relationships over time. A long duration of transaction relationships enables firms to cope with their forecast errors (direct effect), and they also benefit from reducing their forecast errors when their transaction partners have stable transaction relationships (indirect effect). The forecast variation variable will likely capture the uncertainty of environments in which firms conduct economic activities. It is not difficult to imagine firms committing to a large forecast error when uncertainty looms large. An important point from our perspective is that a forecast error tends to be large when one's transaction partners operate in uncertain environments. Thus, with whom it builds transaction relationships affects one's forecast errors.

3.3 What is the Nature of Forecast Errors?

3.3.1 Forecast Error Correlations

To delve into the nature of forecast errors, we examine forecast error correlations at different layers of the relationship between firms. We start our analysis by randomly paring firms from our full sample and examining whether we observe any correlated relationships between their forecast

errors. This empirical exercise is intended to investigate whether some factor common in the whole manufacturing sector is responsible for generating forecast error correlations between transaction partners since aggregate shocks could enter each firm's forecast error to generate the correlations. The first graph in Figure 3 displays a bin scatter plot that captures a relationship between the focal firm's forecast errors and those of randomly matched firms. The bin scatter plot does not exhibit any relationships. This is also confirmed by our simulation analysis, where firms are repeatedly sampled, and the focal firm's forecast errors are regressed on those of randomly matched firms with the set of control variables used in Table 6A. Only 1.5 percent of the simulations exhibit a statistically significant positive correlation in forecast errors between these pairs of firms. Thus, the sector-level common factors are unlikely to generate the forecast error correlations we observed.

Next, we pair two firms from the same industry in the manufacturing sector and examine whether their forecast errors correlate.[1] We aim to investigate whether industry-level factors such as industry-specific shocks and forecasts contribute to generating forecast error correlations. A statistically significant positive correlation in forecast errors is found in 23.5 percent of the simulations when firms are randomly paired at the industry level (See Table 6A and the second bin scatter plot of Figure 3). Our simulation result does not strongly support that industry-level factors contribute to generating forecast error correlations.

Two firms are now matched from a pool of the same geographical region (10 regions in total) to see whether geographic location is a factor in forecast error correlations. Our simulation analysis confirms that we rarely observe a positive correlation between their forecast errors (See Table 6A and the third scatter plot of Figure 3). These results suggest that region-specific factors are not the main driver of forecast error generation.

[Table 6 here]

[Figure 3 here]

Finally, we examine whether the forecast errors of two firms are positively correlated when being in capital relationships. Instead of conducting simulation analysis, we utilize the information in our data regarding a list of each firm's main shareholders to identify two firms as being in capital relationships. For instance, Toyota is often a major shareholder for its parts suppliers. Table 6B presents the estimation results from the regression analysis, where the dependent variable is a focal firm's forecast error, and the primary independent variable is the average forecast error from firms

[1] An industry is defined by three digits of the Japanese Standard Industry Classification. The chemical industry is an example.

that have capital relationships with the focal firm. The estimation result in column (1) of Table 6B indicates a positive correlation between forecast errors when two firms have capital relationships (See also the first scatter plot in Figure 4). A firm's forecast error tends to be large when the forecast errors of firms in capital relationships are large. Since some firms in capital relationships also establish transaction relationships, we drop firms with tarnation relationships and perform the same regression analysis in column (2) of Table 6B. The estimation result remains unchanged qualitatively and confirms the positive forecast error correlation.[2]

Overall, our analysis suggests that the forecast error correlation between firms arises from transaction and capital linkages, not from more aggregate factors (e.g., industry, geographical location, and economy). What does this result imply? One possibility is that firms share information on business conditions through these linkages and reflect this information in their forecasts of business conditions. This also may suggest that the role of economic shocks is modest in forecast error correlations.

[Figure 4 here]

3.3.2 Expectation Bias Correlations

Forecast errors mainly consist of economic shocks and forecast inaccuracy. In this section, we treat deviations from observables as forecast biases and examine how forecast biases generate forecast errors by using residuals from the expectation regression we conducted above. Our main idea is that the residual from the expectation regression reflects a firm's forecast bias (i.e., the unexplained part by observable factors). This residual may capture a firm's tendency to share information with firms in the same industry or location, which the firm can observe but econometricians do not.

As in the previous section, we first conduct simulation analysis to examine how the patterns of expectation residual correlation vary at the different layers of the relationship between firms. Table 7A presents our simulation results where the dependent variable is a firm's residual from the business expectation regression, and the main independent variable is the average residual of its matched firms. According to the first row of Table 7A, where firms are randomly matched, a firm's expectation residual is not correlated with the expectation residual of its matched firms in most cases (98.5 percent). Similarly, the second and the last rows of Table 7A show no correlation between their expectation residuals when matched at the industry or location level (See also Figure 4, which displays bin scatter plots regarding residual correlations). Overall, these results show that

[2]Many firms are not in the same industry or geographical location when they have capital ties.

their expectation residuals are not correlated with one another when firms are in the same sector, industry, or location.

We next investigate whether their residuals are correlated when firms are in transaction or capital relationships. Table 7B reports estimation results. According to the estimation result in column (1) of Table 7B, expectation residuals are positively correlated between firms in transaction relationships. We also find such a positive correlation when firms are in capital relationships (See column (2) of Table 7B). These results indicate some unobservable factors lead firms to forecast their business conditions similarly when they are in transaction or capital relationships.

Our empirical results above can be interpreted as follows: Common factors at aggregate levels (e.g., sector, industry, and location) are unlikely potential sources of forecast biases, but forecast biases are likely to arise at the transaction linkage level. That is, a firm's forecasting is influenced by unobservable transaction-relation-specific factors such as information sharing and flexible adjustment between firms in transaction relationships, affecting their forecast errors. This interpretation is also consistent with the findings that firms reduce forecast errors when they have long-duration transaction relationships and that firms ' forecast errors are large when their transaction partners' uncertainty is large.

[Table 7 here]

[Figure 5 here]

4 Concluding Remarks

We constructed a unique dataset that includes firms' business expectations, forecast errors, and transaction relationships. This unique dataset allowed us to examine how the interconnectedness of firms through transaction relationships affects the formation of business expectations and the generation of forecast errors, which has been largely understudied due to data limitations. Our empirical results suggest that transaction relationships are one of the key factors that influence the formation of business expectations and the generation of forecast errors. When forming business expectations, firms appear to factor in the growth potential driven by expanding a range of transaction partners. A greater degree of uncertainty, measured by forecast variation, makes firms' forecasts more challenging and less accurate, becoming an important source of forecast errors. Although our evidence is weak and requires further investigation, a forecast error of one firm is affected by its transaction partners' forecast errors, suggesting forecast errors traveling within transaction

relationships. We also find that a long duration of transaction relationships reduces forecast errors and that uncertain business environments amplify them. These effects also arise indirectly through transaction partners. This implies with whom one builds transaction relationships affects forecast errors and, ultimately, firm performance. We also found that forecast error correlations arise from transaction and capital linkages, not sector, industry, and location factors. The novel findings of this study thus advanced our understanding of how firms form business expectations in an interconnected economy and how forecast errors travel among transaction partners.

The empirical examination of this study is largely descriptive. Therefore, we should be cautious when trying to draw any causal inferences from the empirical results of this study. This is the main limitation of this study, and further investigation is required to make causal inferences. Despite the limitation, this study overcome the data limitations past studies faced and offers several novel insights and implications to be tested regarding mechanisms of the formation of business expectations, the generation of forecast errors, and the propagation of economic shocks.

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Tables and Figures

Table 1A: Summary statistics on forecast-related variables

	Mean	Min	1st Quartile	Median	3rd Quartile	Max	No. of obs
Business Expectation	0.025	-0.178	-0.015	0.020	0.066	0.253	8,702
Business Realization	0.045	-0.326	-0.050	0.026	0.117	0.598	6,987
Forecast Error	-0.018	-0.543	-0.097	-0.005	0.075	0.374	6,415
Forecast Variation	0.058	0.009	0.028	0.047	0.077	0.177	7,508

Table 1B: Summary statistics on transaction relationships

	Mean	Std. Dev	Min	Quartile			Max	No. of obs
				1st	Median	3rd		
	(1) Number of transaction partners							
Full sample	55.5	199.4	2	10	16	34	5425	8,460
Small firms	10.7	6	2	7	10	13	89	2,820
Medium firms	19.3	13.4	2	11	16	23	196	2,820
Large firms	136.5	330.5	2	26	50	113	5425	2,820
	(2) Percentage of new transaction partners							
Full sample	8.7	10	0	0	6.7	12	100	3,933
Small firms	8.7	12.1	0	0	5	13.3	100	1,311
Medium firms	8.6	9.3	0	0	6.7	12.5	100	1,311
Large firms	8.9	8.4	0	4.8	7.1	10.8	100	1,311
	(3) Percentage of terminated transaction partners							
Full sample	6.6	7.8	0	0	5.1	9.1	100	3,933
Small firms	6.7	9.9	0	0	0	10.4	100	1,311
Medium firms	6.6	7.6	0	0	5.1	10	100	1,311
Large firms	6.4	5.2	0	3.4	5.7	8.1	100	1,311

Table 2: Determinants of business expectation and forecast variation

	DV: Business Expectation		DV: Forecast Variation	
	(1)	(2)	(3)	(4)
No. of transaction partners	0.002 **		-0.0013 **	
	(0.001)		(0.0006)	
Page rank		0.002 **		-0.002 ***
		(0.001)		(0.001)
Transaction duration	-0.0006 **	-0.0006 **	-0.0005 ***	-0.0005 ***
	(0.0003)	(0.0003)	(0.0001)	(0.0001)
TFP	-0.011 ***	-0.010 ***	-0.005 ***	-0.005 ***
	(0.003)	(0.003)	(0.001)	(0.001)
Management score	0.030 ***	0.030 ***	-0.013 ***	-0.013 ***
	(0.007)	(0.007)	(0.004)	(0.004)
No. of employees (thousand)	-0.0006	-0.0005	0.0003	0.0003
	(0.0007)	(0.0007)	(0.0002)	(0.0002)
Age	-0.0002 ***	-0.0002 ***	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Noise control	0.003		0.002 *	0.002 *
	(0.003)		(0.001)	(0.001)
No of observations	5,816	5,816	5,071	5,071
Adjusted R_squared	0.02	0.02	0.09	0.09

Notes: (i) JP MOPS, Japanese Manufacturing Census, and TDB transaction data are used. (ii) Coefficients are estimated by OLS. (iii) Numbers in parentheses are robust standard errors. (iv) The number of asterisks indicates the significance level in a t-test for coefficients; *<10% , **<5%, and ***<1%.

Table 3: Transaction partner's characteristics as determinants of business expectation and forecast variation

	DV: Business Expectation		DV: Forecast Variation	
Transaction partner's characteristics				
Business expectation	0.017	0.018		0.01
	(0.025)	(0.027)		(0.012)
Forecast variation		-0.019	0.045 *	0.043 **
		(0.058)	(0.026)	(0.026)
TFP	0.003	0.004	-0.002	-0.002
	(0.003)	(0.003)	(0.002)	(0.002)
Management score	0.012	0.008	0.009	0.008
	(0.014)	(0.014)	(0.006)	(0.006)
Size	-0.001	-0.001	0.0003	0.0003
	(0.001)	(0.001)	(0.0003)	(0.0003)
No. transaction partners	0.00001	0.00001	0.00001	0.00001
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
No of observations	3,414	3,252	2892	2,873
Adjusted R_squared	0.018	0.019	0.078	0.078

Notes: (i) JP MOPS, Japanese Manufacturing Census, and TDB transaction data are used. (ii) Coefficients are estimated by OLS. (iii) Numbers in parentheses are robust standard errors. (iv) The number of asterisks indicates the significance level in a t-test for coefficients; *<10% , **<5%, and ***<1%.

Table 4: Forecast errors and transaction relationships

	DV: Forecast Error (absolute value)					
	(1) All	(2) g_act < g_exp	(3) g_act > g_exp	(4) All	(5) g_act < g_exp	(6) g_act > g_exp
No. of transaction partners	-0.003 *	-0.005 **	-0.002			
	(0.002)	(0.002)	(0.003)			
Page rank centrality				-0.006 ***	-0.006 ***	-0.005 ***
				(0.002)	(0.002)	(0.003)
Transaction duration	-0.002 ***	-0.001 ***	-0.002 ***	-0.002 ***	-0.002 ***	-0.002 ***
	(0.0005)	(0.001)	(0.001)	(0.0005)	(0.0005)	(0.001)
Forecast variation	0.0336 ***	0.378 ***	0.314 ***	0.332 ***	0.372 ***	0.310 ***
	(0.046)	(0.054)	(0.068)	(0.046)	(0.055)	(0.068)
TFP	-0.011 ***	-0.013 **	-0.011	-0.010 ***	-0.013 ***	-0.034 *
	(0.004)	(0.005)	(0.007)	(0.004)	(0.005)	(0.018)
Management score	-0.016	0.011	-0.035 *	-0.016	0.011	-0.009
	(0.011)	(0.014)	(0.018)	(0.011)	(0.014)	(0.006)
Noise control	0.070 ***	0.040 ***	0.097 ***	0.070 ***	0.040 ***	0.097 ***
	(0.006)	(0.007)	(0.009)	(0.006)	(0.007)	(0.009)
No of observations	4,982	2,425	2,557	4,982	2,425	2,557
Adjusted R_squared	0.115	0.099	0.137	0.117	0.101	0.138
Controls Included	Yes	Yes	Yes	Yes	Yes	Yes

Notes: (i) JP MOPS, Japanese Manufacturing Census, and TDB transaction data are used. (ii) Coefficients are estimated by OLS. (iii) Numbers in parentheses are robust standard errors. (iv) The number of asterisks indicates the significance level in a t-test for coefficients; *<10% , **<5%, and ***<1%.

Table 5: Transaction partner's characteristics as determinants of forecast errors

	DV: Forecast Error (absolute value)		
	(1)	(2)	(3)
Transaction partners'	0.110 ***	0.375 **	-0.239
Forecast error (absolute value)	(0.023)	(0.187)	(0.197)
Focal firm's transaction relationships			
Number of transaction partners	-0.003	-0.006	-0.003
	(0.002)	(0.005)	(0.002)
Transaction duration	-0.002 ***	-0.002 **	-0.002 ***
	(0.001)	(0.001)	(0.001)
Focal firm's characteristics			
Forecast variation	0.576 ***	0.551 ***	0.629 ***
	(0.056)	(0.067)	(0.064)
TFP	-0.012 ***	-0.008	-0.014 ***
	(0.004)	(0.007)	(0.005)
Management score	0.002	-0.002	0.011
	(0.013)	(0.016)	(0.015)
Size	0.0001	0.0003	0.0001
	(0.0010)	(0.0010)	(0.0010)
Noise control	0.075 ***	0.075 ***	0.076 ***
	(0.007)	(0.007)	(0.007)
Transaction partner's characteristics			
No. transaction partners	-0.001	-0.002	0.001
	(0.001)	(0.002)	(0.002)
Transaction duration	-0.001 **	-0.002 *	-0.002 **
	(0.001)	(0.001)	(0.001)
Forecast variation	0.178 **	0.004	0.414 ***
	(0.073)	(0.131)	(0.154)
TFP	-0.002	-0.005	0.003
	(0.002)	(0.003)	(0.003)
Management score	0.029 *	0.046 **	0.010
	(0.,015)	(0.023)	(0.019)
Size	0.001 ***	0.002 ***	0.0001
	(0.0003)	(0.001)	(0.0010)
Noise control	-0.014	-0.042 *	0.024

	(0.009)	(0.022)	(0.024)
Estimation method	OLS	2SLS	2SLS
No of observations	3723	3723	3723
Adjusted R_squared	0.114	0.065	0.041

Notes: (i) JP MOPS, Japanese Manufacturing Census, and TDB transaction data are used. (ii) Numbers in parentheses are robust standard errors. (iii) The number of asterisks indicates the significance level in a t-test for coefficients; *<10% , **<5%, and ***<1%.

Figure 6A: Forecast error correlations from simulation

	Percentage of significant results	Distribution of coefficients					
		min	25th	50th	Mean	75th	max
Random (Sector)	1.5%	-0.03284	-0.01001	0.00060	0.00040	0. 00932	0. 04763
Industry	23.5%	-0.02185	0.00874	0.01901	0.01957	0.02963	0.06962
Location	3%	-0.04627	-0.01130	0.00017	-0.00100	0.01035	0.04085

Notes: (i) JP MOPS, Japanese Manufacturing Census, and TDB transaction data are used. (ii) For each simulation, forecast error is regressed on the average forecast errors of matched firms. Simulations are conducted for 200 times. (iii) The first column reports the percentage of the cases in which the coefficient on the average forecast errors of matched firms is positive and significant at the ten percent significance level. (iv) The first column reports the distribution of the estimated coefficients on the average forecast errors of matched firms.

Figure 6B: Forecast error correlations in capital ties

	DV: Forecast Error (absolute value)	
	(1) Capital ties	(2) Capital ties only
Partners' Forecast	0.536 ***	0.727 ***
Error (absolute value)	0.040	0.040
No of observations	1,381	1,003
Adjusted R_squared	0.309	0.513

Notes: (i) JP MOPS, Japanese Manufacturing Census, and TDB transaction data are used. (ii) Numbers in parentheses are robust standard errors. (iii) The number of asterisks indicates the significance level in a t-test for coefficients; *<10% , **<5%, and ***<1%.

Figure 7A: Expectation residual correlations from simulation

	Percentage of significant results	Distribution of coefficients					
		min	25th	50th	Mean	75th	max
Random (sector)	1.5%	-0.0739	-0.0195	-0.0016	-0.0006	0.0162	0.0778
Industry	6.0%	-0.0805	-0.0047	0.0126	0.0111	0.0267	0.0970
Location	2.5%	-0.0824	-0.0175	-0.0001	0.0013	0.0179	0.0830

Notes: (i) JP MOPS, Japanese Manufacturing Census, and TDB transaction data are used. (ii) For each simulation, the expectation residual is regressed on the average expectation residual of matched firms. Simulations are conducted for 200 times. (iii) The first column reports the percentage of the cases in which the coefficient on the average expectation residual of matched firms is positive and significant at the ten percent significance level. (iv) The first column reports the distribution of the estimated coefficients on the average expectation residual of matched firms.

Figure 7B: Expectation residual correlations in transaction and capital ties

	DV: Expectation resisual (absolute value)	
	(1) Transaction ties only	(2) Capital ties only
Partners' Expectation	0.074 ***	0.624 ***
Residual (absolute value)	0.028	0.047
No of observations	2,429	596
Adjusted R_squared	0.183	0.438

Notes: (i) JP MOPS, Japanese Manufacturing Census, and TDB transaction data are used. (ii) Numbers in parentheses are robust standard errors. (iii) The number of asterisks indicates the significance level in a t-test for coefficients; *<10% , **<5%, and ***<1%.

Figure 1: Distributions of forecast-related variables

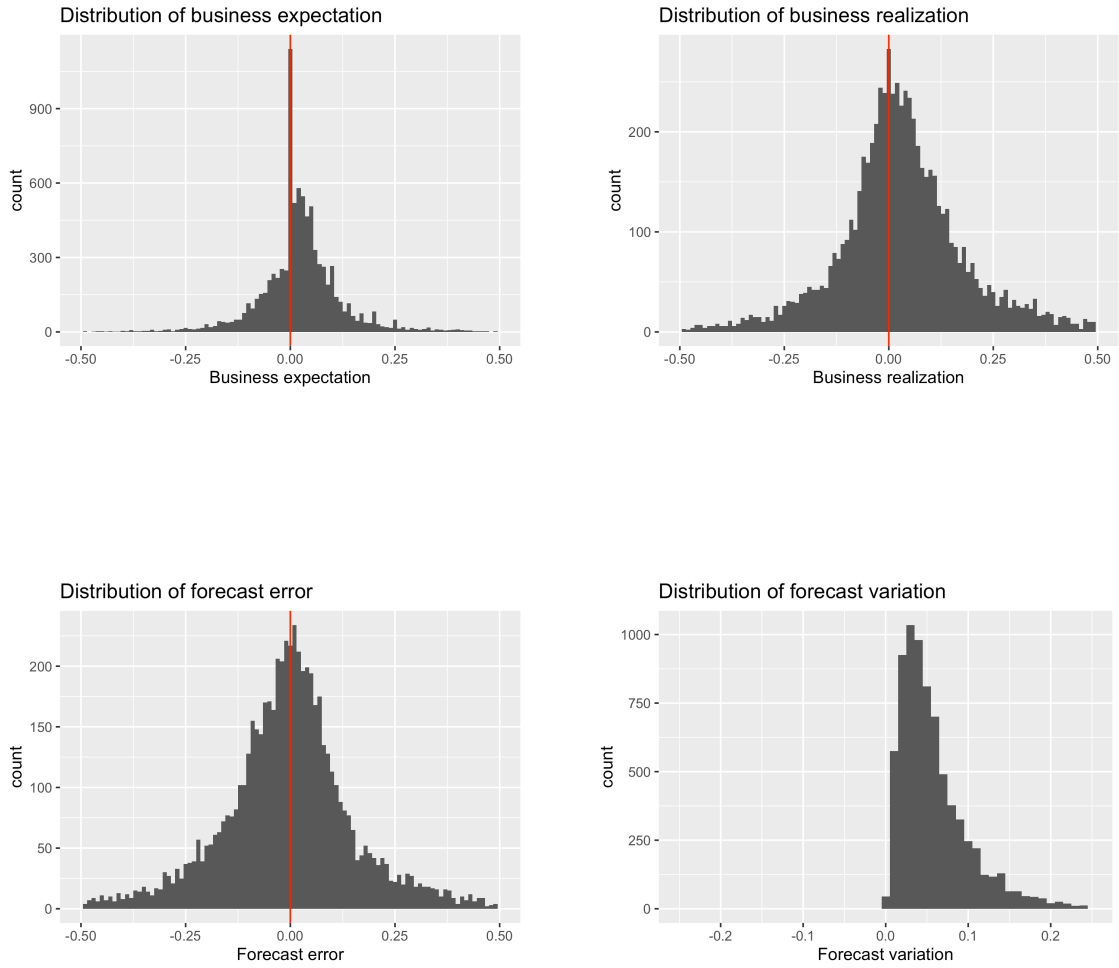


Figure 2: The relationship between forecast variation and forecast errors

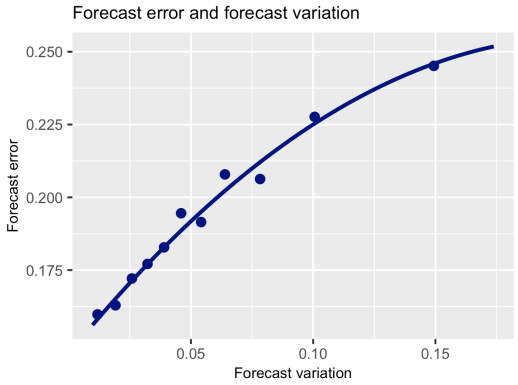


Figure 3: Forecast error correlations

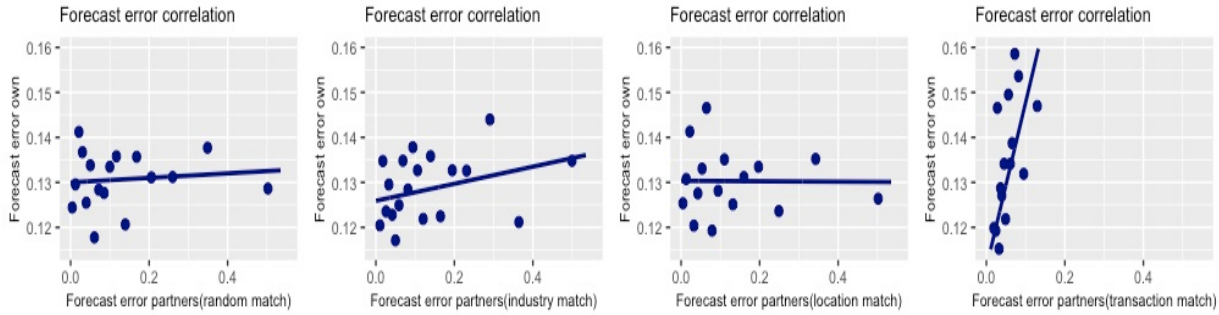


Figure 4: Expectation residual correlations

