Business Expectations, Forecast Errors, and Dynamics of Transaction Relationships *

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Abstract

We construct a unique data set that contains information about a set of business expectations, forecast errors, and business transaction relationships to examine the nature of uncertainty and mechanisms on the formation of business expectations and the generation of forecast errors when firms are connected in supply chains. Firms' business expectations about their growth rates are positively correlated with the number of transaction partners, which is consistent with firm growth patterns. We find weak evidence that a firm's forecast error transmits to its transaction partners. A longer duration of transaction relationships tends to reduce a forecast error, whereas a larger forecast variation tends to amplify the forecast error. This effect also arises from transaction partners. Our empirical analysis suggests with whom one builds transaction relationships affects one's forecast errors and, ultimately, its performances. This study advances our understanding of how firms form business expectations in an interconnected economy and how forecast errors propagate among 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, 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 may come as disturbances to firm performances and consequently affect aggregate outcomes. A large 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), and a firm's business expectation and forecast error vary significantly with its characteristics and phases of a business cycle (Massenot and Pettinicchi, 2018). Business expectation, forecast error, and uncertainty are thus intertwined with each other 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 error, are only influential factors for their conduct and performance. This analytical framework offers many useful 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. Supply chain disruptions are one definite area of concern for firms and policymakers in many countries nowadays. Despite the fact that business expectations, forecast errors, and supply chains are fundamental economic issues, we have known very little about whether and how the formation of one firm's business expectations is affected by its transaction relationships with other firms, whether and how forecast errors of one firm are affected by its transaction partners in supply chains and transmit to them, and whether and how decisions and performances of one firm are influenced by forecast errors of its transaction partners. Especially, empirical evidence is scant in this dimension 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 of forecast errors as well as dynamics of transaction relationships. More specifically, we first treat firms' transaction relationships as given and investigate how firms' business expectations and forecast errors depend on their transaction relationships. Our particular focus in this empirical investigation is on the interdependence of business expectations, the transmission of forecast errors, and the portfolio/propagation effects of transaction relationships on 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 firm's transaction relationships determines how business expectation is formed and forecast errors travel between transaction partners. Such interdependencies pose the reflection problem for empirical analysis (Manski, 1993). To deal with this problem, we distinguish endogenous, exogenous, and correlated effects (Manski, 1993) and employ the 2SLS estimation proposed by Bramoullé et al. (2009). In the context of this study, endogenous effects are the influence of transaction partners' forecast errors, and exogenous effects relate to a focal firm's and its transaction partners' characteristics. Correlated effects are factors that lead all firms in the transaction relationships to make forecast errors in a similar fashion. We then treat firms' forecast errors as given and shed light on the dynamics of their transaction relationships through a lens of forecast errors. We basically ask whether firm's forecast errors can be an important driver of the evolution of business transaction networks by examining how they play out in maintaining and building firms' future transaction relationships. Although transaction network structures are often treated as given when examining the effects of firms' interdependency on their conduct and resource allocation, forecast errors may significantly impact the dynamics of transaction relationships as firms adjust their resource allocation after their own and transaction partners' forecast errors are revealed.

To answer the research questions above, we construct a unique data set containing information about business expectations, forecast errors, and business transaction relationships. The data about business expectations come from the Japanese Management and Organizational Practices Survey (JP MOPS, hereafter) that was 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 shipment. In the JP MOPS, Japanese establishments in the manufacturing sector were asked to provide their forecast about the value of shipment for 2017 and assign corresponding probabilities to three scenarios - high, medium, and low realizations - for the 2018 forecast. 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 value of shipment 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 so that we can empirically identify each firm's transaction partners and a transaction network structure. To the best of our knowledge, this study is the first study that has utilized data containing information about a set of business expectations, forecast errors, and transaction relationships, and investigated the effects of firms' interdependency on business expectations and forecast errors as well as the dynamics of transaction relationships.

This study reveals several interesting patterns regarding the formation of business expectations, the generation of forecast errors, and the propagation of forecast errors. First, firms' business expectations about their shipment value are positively correlated with the number of transaction partners and negatively correlated with the average duration time of transaction relationships. 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 and/or when their transaction relationships are stable. Third, the formation of business expectations is unaffected by transaction partners' characteristics, but the firm's forecast variations are correlated with each other between transaction partners. Fourth, we find very weak evidence that a firm's forecast error is influenced by its transaction partners' forecast errors (endogenous effects). Fifth, we have relatively solid evidence about exogenous effects. A longer duration of transaction relationships tends to reduce a forecast error, whereas a larger forecast variation tends to amplify the forecast error. One interpretation of the former result is that a long duration of transaction relationships cultivates information sharing and flexible adjustment capabilities, and this mitigates forecast errors. Notably, 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 transaction errors. Finally, forecast errors have impacts on the dynamics of transaction relationships. When firms perform better than expected, this is considered favorable forecast errors. In such cases, they restructure their transaction partners by adding and deleting them. On the other hand, when firms perform worse than expected, they struggle with reorganizing their transaction partners.

This study contributes to the existing research in three ways. First, this study reveals how firms form business expectations and make forecast errors in interconnected economies. An empirical measure of firms' forecast is regarding macroeconomic indicators such as a GDP growth rate in past studies. Even when firms' forecasts are about their own performances, past empirical studies assume that firms do not consider their relationship with other firms when forming business expectations. As a result, we know little about how the interdependence of firms through transaction relationships affects the expectations regarding firm performance. This study advances our understanding of the formation of business expectations and forecast errors in interconnected economies. Second, this study offers 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 business transaction networks. Theoretical predictions are rich in this research area, but empirical evidence is limited because firm-level data containing forecasts and transaction networks have not been available. This study overcomes this data limitation and argues that a residual component of forecast errors partly reflects economic shocks. The empirical results of this study indicate that having many transaction relationships helps to absorb economic shocks and that economic shocks travel between transaction partners, though further analyses are required to back up these findings. Finally, this study empirically examines the roles of forecast errors in the dynamics of transaction relationships. Transaction relationships are typically treated as exogenous when studying the propagation mechanisms of economic shocks. Characteristics of firm and transaction relationships are typically studied as determinants for changing transaction partners, and forecast errors are not considered determinants. This study treats forecast errors as an important determinant for the endogenous formation of transaction relationships and offers a fresh perspective to this literature.

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 of this study. Our empirical results are presented in Section 3. We first report estimation results about how transaction relationships influence the formation of business expectations. We next show the empirical findings of this paper regarding how forecast errors are generated and propagated in business transaction networks. Finally, the estimation results are presented regarding how forecast errors impact the dynamics of transaction relationships. 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 their transactional 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 result in affecting the formation of business expectations and the generation of forecast errors in a significant way. 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 is called forecast variation and 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 among firms. Although many firms answered zero growth, some firms foresee positive growth, and other firms 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, and its distribution looks like a normal distribution. The majority of 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 allows us to trace firms' transaction relationships back to the year 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 on the variables 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.

A piece of information on the direct links between transaction partners also permits us to examine the effects of forecast errors and characteristics of transaction partners on the formation of business expectations and the generation of forecast errors. To examine this interdependency, transaction partners' forecast-related variables (forecast error and forecast variation) are included 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:

$$g_{exp_i} = \beta_0 + \beta_1 Own\_Ch_i + \beta_2 TR_i + \beta_3 Ptr\_Ch_i + \varepsilon_i \tag{3}$$

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

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

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,

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

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 firm j's forecast error is also affected by firm i's forecast error, f_{err_j} contains ε_i and thus is correlated with ε_i in the regression, which 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 (Incomplete)

On the other hand, when $Cov(\varepsilon_i, \varepsilon_j) \neq 0$, a forecast error of one firm transmits to its transaction partners directly through v_j when forecast characteristics of transaction partners are controlled for. This part of the forecast error would not be transmitted to other firms unless it has transaction relationships with them.

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 v:

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

By definition of the conditional expectation, $\mathrm{E}[v|X] = 0$, and v 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 v given that u can reflect firm's private information that econometricians cannot observe (u can reflect a part of v). 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. The richness of our data allows us to analyze determinants of firms' business expectations at a more granular level than previous studies by including such variables in our regression analysis below.

Then a forecast error is simply characterized as

$$f_{err} = u - v = X'\beta + w - v. \tag{9}$$

Caution is needed when interpreting γ_1, the coefficient on the average forecast error of transaction partners. For the sake of argument, assume that $\varepsilon_j = w_j - v_j$ is only a random component in a forecast error after controlling for Ptr_Ch_i. Then, the covariance in forecast errors between transaction partners i and j is given by

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

Our data do not allow us to tell these stories apart cleanly, but we will try to get some insights into it. The main idea of this investigation is to ask whether the effect of forecast errors of transaction partners on one's forecast error would remain if their transaction relationships were shut down. A common shock is likely to generate a forecast error correlation between transaction partners if the effect remains in such a situation. On the other hand, the shock component of a forecast error made by one firm is likely to be transmitted to transaction partners if we observe that the effects are absent. To implement this test empirically, we use our transaction network data to conduct counterfactual analyses by paring transaction partners counterfactually. The fact that economic shocks are not observable prevents us from examining how they travel from one firm to another. This empirical method allows us to track how economic shocks travel within a transaction network with a reasonable degree of accuracy.

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. The coefficient on the average duration of the transaction relationships is negative and statistically significant. This suggests that firms with stable transaction relationships are expected to grow. Column (2) of Table 2 shows a similar positive relationship between business expectation and page rank centrality.

Regarding the control variables, the effect of firm age is negative. One interpretation is that old firms forecast their business performances conservatively. Management scores are positively correlated with business expectations, whereas TFP is negatively correlated with business expectations. The negative relationship between business expectation 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 in a similar fashion or that they anticipate some shocks to travel between them. We will consider this issue in the next section when examining forecast errors.

[Table 3 here]

3.2 Forecasting Errors and Transaction Relationships

3.2.1 Forecasting Errors and Transaction Relationships without correlated effects

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 our interest is investigating whether a firm's forecast error is affected by transaction partners' forecast errors. 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 using 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. The 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.

Regarding the control variables, 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 its 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 is likely to 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 Impacts of Forecasting Errors on Future Transaction Relationships

Do forecast errors impact firm behaviors? We first take a similar approach to past studies to answer this question by examining how output and input measures change with forecast errors. Our output measure is a growth rate of the value of shipments between 2017 and 2018. We also look at a change in inventory growth rate between 2017 and 2018. Similarly, our input measures are a growth rate of capital between 2017 and 2018, that of new machines, and that of the number of employees. Note that our forecast errors are regarding a growth rate of the value of shipments between 2016 and 2017. Thus, we intend to investigate how forecast errors affect immediate future outcomes.

Table 6A presents estimation results where either a growth rate of the value of shipments or a growth rate of inventory is the dependent variable. The main independent variable is the absolute value of a forecast error, and the control variables we used in Table 5 are included in this estimation. According to Column (1) of Table 6A, the coefficient on the absolute value of a forecast error is negative, but it is not statistically significant at the conventional significance levels. To examine further, we split our sample into two, depending on whether a forecast error is positive or negative. Column (2) of Table 6A shows estimation results in the positive error case where a firm's forecast about the value of shipments is larger than its realized value, whereas column (3) of Table 6A reports estimation results in the negative error case where a firm's forecast about the value of shipments is smaller than its realized value. In the sample of positive forecast errors, the coefficient on the absolute value of a forecast error is positive and statistically significant at the one percent significance level. Thus, the future growth rate of the value of shipments is high when a firm's business expectation exceeds its realization to a large extent. On the other hand, in the sample of negative forecast errors, the coefficient on the absolute value of a forecast error is negative and statistically significant at the one percent significance level. Although we do not report, we do not find these relationships when we look at a longer-term effect by replacing the dependent variable with the value of shipment growth rate between 2017 and 2020. One interpretation of these results is that reversion to the mean is at work. When a firm's performance is worse than expected in a given year, its performance bounces back in the following year. The opposite occurs when firms perform better than expected in a given year. It is likely that a forecast error largely in the regression analysis reflects a stochastic shock to the value of shipments because a firm's forecast-related characteristics are controlled for. If this is indeed the case, we observe reversion to the mean. The estimation results about inventory changes also support this interpretation. According to our estimation in column (6) of Table 6A, the coefficient on the forecast error is positive and statistically significant, implying an increase in inventory in the following year when firms perform better than expected in a given year. We basically find that the growth rates of the value of shipments and inventory move with forecast errors in the opposite direction.

Table 6B reports estimation results about the relationship between inputs and forecast errors. Our estimation results in columns (2) and (3) of Table 6B suggest that the effect of forecast errors on capital depends on whether the forecast errors are positive or negative. While capital growth rates are negatively correlated with forecast errors when firms perform worse than expected in a given year, capital growth rates are positively correlated with forecast errors when firms perform better than expected. Furthermore, we find similar results regarding the growth rate of new machines (See columns (5) and (6) of Table 6B). Overall, our estimation results indicate that firms make adjustments to increase capital stock when their performance exceeds their expectation and to decrease capital stock when their performance fall short of their expectation. We do not find such adjustments regarding the amount of labor employed (See columns (8) and (9) of Table 6B).

[Table 6 here]

We next examine how firms restructure their set of transaction partners in response to forecast errors. In this examination, we use information on a change in the transaction partners of focal firms between 2017 and 2018, the period just after forecast errors are realized. Table 7 reports three estimation results where we use the number of added transaction partners, the number of dropped transaction partners, and a net change in the number of transaction partners as the dependent variable separately. As in the previous analysis, we split our sample according to the sign of forecast errors (i.e., positive or negative forecast errors).

As in the case of Table 6, we observe different impacts of forecast errors on the number of added transaction partners by the sign of forecast errors. When firms perform worse than expected (i.e., positive forecast error case, see column (2) of Table 7), the coefficient on forecast error is negative and statistically significant at the one percent significance level. Thus, firms tend to struggle to add new transaction partners after they make a large positive forecast error. On the other hand, when a firm's business performance exceeds its expectation (i.e., positive forecast error case, see column (3) of Table 7), the coefficient on forecast error is positive and statistically significant at the one percent significance level. This suggests that firms add more transaction partners as they outperform their expectations.

Regarding the effects of forecast errors on the number of dropped transaction partners, our estimation results show that the number of dropped partners positively correlates with forecast errors when firms perform better than expected (i.e., positive forecast error case, see column (3) of Table 7). Thus, firms are led to drop transaction partners after they find that their business performance is better than expected. Although it is not statistically significant, the estimated effect is negative when firms perform worse than expected (i.e., negative forecast error case, see column (2) of Table 7). Our estimation results about a net change in the number of transaction partners are basically a combination of the results regarding the addition and deletion of transaction partners.

Overall, our estimation results indicate that firms restructure their set of transaction partners in response to forecast errors. More specifically, when firms perform worse than expected to a large extent, they face the challenge of reorganizing the set of transaction partners by adding and deleting them, and it results in reducing the number of their transaction partners. We see a different story when firms perform better than expected. In this case, firms tend to both add and drop their transaction partners in response to large favorable forecast errors.

[Table 7 here]

Our next empirical question is what type of transaction partners firms add to or drop from the set of their transaction partners in response to the forecast errors they make. We focus on labor productivity and firm size as the main characteristics of transaction partners and examine how these characteristics of added or dropped transaction partners differ from those of incumbent transaction partners.

Table 8 reports the estimation results of this examination in which the sample is split into positive and negative forecast error cases. The dependent variable in this estimation is either the labor productivity of a focal firm's transaction partners or the transaction partners' firm size. The control variables include focal firms' characteristics such as productivity, management scores, size, location, and industry dummies. A variable of interest in this estimation is the forecast error variable interacted with the dummy variable for an added transaction partner. We intend to examine how firms select their new transaction partners or terminate current transaction partners after observing forecast errors.

According to Table 8A, the dummy for an added transaction partner is negative and statistically significant at the one percent significance level in all the specifications. Thus, the labor productivity of transaction partners newly added is lower than that of the incumbent transaction partners. We also find that the firm size of transaction partners newly added is smaller than that of the incumbent transaction partners. Regarding the interaction term of the added transaction partner dummy with forecast error, Column (4) of Table 8A shows that the interaction term is positively correlated with firm size for the subsample of firms that perform better than expected. This can be interpreted as follows: The firm size of newly added transaction partners is generally smaller than that of incumbent transaction partners, but firms start transacting with relatively larger firms, similar to the incumbent transaction partners, after observing their performance is better than expected.

In Table 8B, we observe similar patterns regarding the characteristics of dropped transaction partners. Compared with the transaction partners the focal firms keep over time in their portfolio, the labor productivity and firm size of dropped transaction partners are both lower. However, the coefficient on the interaction term with forecast errors is positive for the subsample of firms that perform better than expected (See (2) and (4) of Table 8B). It implies that the focal firms drop transaction partners similar to the remaining transaction partners regarding labor productivity and firm size.

In sum, firms keep high-productive and large firms as their core transaction partners and add or drop low-productive and small firms. Firms' forecast errors affect this pattern when firms outperform their expectations. In this case, the labor productivity and size of added or dropped transaction partners become similar to those of core transaction partners. This result suggests the possibility that a favorable realization of a shock enables firms to drastically restructure their portfolio of transaction partners, although our data allow us to test this possibility.

[Table 8 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 relationships. 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 a long duration of transaction relationships reduces a forecast error and uncertain business environments amplify it. These effects also arise indirectly through transaction partners. This implies with whom one builds transaction relationships affects one's forecast errors and, ultimately, its performance. This study thus advanced our understanding of how firms form business expectations in an interconnected economy and how forecast errors propagate among transaction partners.

Our empirical investigation also suggests that firms change their transaction partners in response to their forecast errors. We found different responses depending on whether firms performed better or worse than expected. When firms perform better than expected, they restructure the portfolio of transaction partners drastically by adding and dropping them. On the other hand, when firms underperform, they struggle to change transaction partners. Thus, it is not the case that transaction relationships are stable over time even after firms make forecast errors.

The empirical examination of this study is largely descriptive in nature. 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 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 * (0.002)	-0.005 ** (0.002)	-0.002 (0.003)			
Page rank centrality				-0.006 *** (0.002)	-0.006 *** (0.002)	-0.005 *** (0.003)
Transaction duration	-0.002 *** (0.0005)	-0.001 *** (0.001)	-0.002 *** (0.001)	-0.002 *** (0.0005)	-0.002 *** (0.0005)	-0.002 *** (0.001)
Forecast variation	0.0336 *** (0.046)	0.378 *** (0.054)	0.314 *** (0.068)	0.332 *** (0.046)	0.372 *** (0.055)	0.310 *** (0.068)
TFP	-0.011 *** (0.004)	-0.013 ** (0.005)	-0.011 (0.007)	-0.010 *** (0.004)	-0.013 *** (0.005)	-0.034 * (0.018)
Management score	-0.016 (0.011)	0.011 (0.014)	-0.035 * (0.018)	-0.016 (0.011)	0.011 (0.014)	-0.009 (0.006)
Noise control	0.070 *** (0.006)	0.040 *** (0.007)	0.097 *** (0.009)	0.070 *** (0.006)	0.040 *** (0.007)	0.097 *** (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%.

Table 6A: Forecast errors and output growth

	DV: Shipment value growth		
	(1) All	(2) g_act < g_exp	(3) g_act > g_exp
Forecast Error (absolute value)	-0.032	0.178 ***	-0.137 ***
	(0.037)	(0.062)	(0.038)
No of observations	4,958	2,410	2,548
Adjusted R_squared	0.025	0.039	0.032
	DV: Inventory growth		
	(1) All	(2) g_act < g_exp	(3) g_act > g_exp
Forecast Error (absolute value)	0.113 ***	-0.056	0.186 ***
	(0.053)	(0.114)	(0.059)
No of observations	4,505	2,166	2,339
Adjusted R_squared	0.031	0.011	0.066

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 6B: Forecast errors and input growth

	DV: Capital growth		
	(1) All	(2) g_act < g_exp	(3) g_act > g_exp
Forecast Error (absolute value)	0.029	-0.234 ***	0.183 ***
	(0.059)	(0.114)	(0.071)
No of observations	4,523	2,176	2,347
R_squared	0.04	0.043	0.044
	DV: New machine growth		
	(1) All	(2) g_act < g_exp	(3) g_act > g_exp
Forecast Error (absolute value)	-0.020	-0.651 *	0.135
	(0.178)	(0.35)	(0.214)
No of observations	3,570	1,677	1,893
R_squared	0.242	0.247	0.256
	DV: Labor growth		
	(1) All	(2) g_act < g_exp	(3) g_act > g_exp
Forecast Error (absolute value)	-0.008	-0.040	0.004
	(0.02)	(0.04)	(0.024)
No of observations	4,958	2,410	2,548
R_squared	0.013	0.011	0.009

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 7: Forecast errors and changes in transaction partners

Panel A	DV: No. of added transaction partners		
	(1) All	(2) g_a < g_f	(3) g_a > g_f
Forecast Error (absolute value)	0.075	-0.608 ***	0.433 ***
	(0.053)	(0.097)	(0.065)
No of observations	4,993	2,453	2,558
Loglikelihood	-20,761	-9,986	-10,220
Panel B	**DV: No. of dropped transaction partners**		
	(1) All	(2) g_a < g_f	(3) g_a > g_f
Forecast Error (absolute value)	0.182 ***	-0.167	0.386 ***
	(0.065)	(0.115)	(0.080)
No of observations	4,993	2,435	2,558
Log Likelihood	-12,908,580	-6,311.12	-6,453.889
Panel C	**DV: Net change**		
	(1) All	(2) g_a < g_f	(3) g_a > g_f
Forecast Error (absolute value)	0.225	-1.400	0.784
	(0.857)	(1.319)	(1.068)
No of observations	4,993	2,435	2,558
R_squared	0.26	0.24	0.33

Notes: (i) JP MOPS, Japanese Manufacturing Census, and TDB transaction data are used. (ii) Coefficients are estimated by Poisson Model for Panels A and B and OLS for Panel C. (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 8: Forecast errors and characteristics of added and dropped transaction partners

	DV: Labor productivity				DV: Firm size			
	(1) g_act < g_exp		(2) g_act > g_exp		(3) g_act < g_exp		(4) g_act > g_exp	
Add dummy	-0.339	***	-0.323	***	-1.189	***	-1.325	***
	(0.026)		(0.025)		(0.064)		(0.060)	
Forecast error x add dummy	0.234		0.151		0.445		0.694	***
	(0.151)		(0.105)		(0.386)		(0.268)	
No of observations	5,327		5,606		5,328		5,606	
R_squared	0.164		0.152		0.138		0.15	
Controls Included	Yes		Yes		Yes		Yes	
	DV: Labor productivity				DV: Firm size			
	(1) g_act < g_exp		(2) g_act > g_exp		(3) g_act < g_exp		(4) g_act > g_exp	
Drop dummy	-0.277	***	-0.274	***	-1.005	***	-1.171	***
	(0.028)		(0.026)		(0.067)		(0.064)	
Forecast error x drop dummy	0.205		0.227	*	-0.09		0.785	***
	(0.161)		(0.116)		(0.384)		(0.300)	
No of observations	5,231		5,444		5,231		5,444	
R_squared	0.138		0.131		0.116		0.126	
Controls Included	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%.

Figure 1: Distributions of forecast-related variables

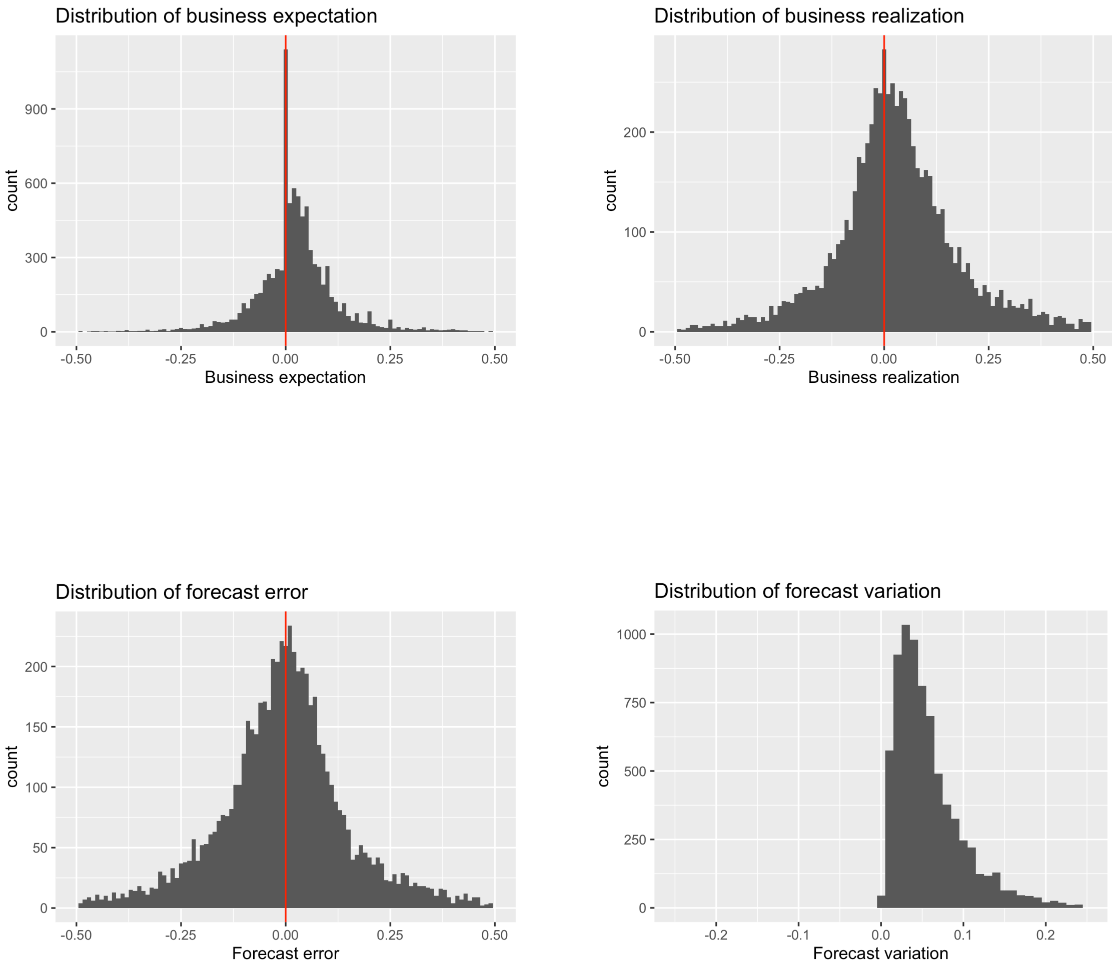

Figure 2: The relationship between forecast variation and forecast errors