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Uncertainty over Production Forecasts: An Empirical Analysis Using Monthly Firm Survey Data

Masayuki Morikawa*

Abstract

This study, using monthly micro data on firms' forecasted and realized production quantities, presents new evidence of the uncertainty of production forecasts. We make a number of novel findings that contribute to the literature on this topic. Forecast errors are heterogeneous among individual manufacturers, while firms operating in the information and communications technology-related industries, firms producing investment goods, and smaller firms exhibit greater forecast uncertainty. Moreover, forecast uncertainty is greater in the contractionary phases of the business cycle and the uncertainty measures calculated from the micro data are able to predict macroeconomic fluctuations. Finally, the forecast uncertainty of Japanese manufacturing firms is associated with overseas policy uncertainty in addition to Japan's own economic policy uncertainty.

Keywords: production, uncertainty, forecast error, manufacturing, volatility

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* Research Institute of Economy, Trade and Industry (RIETI). 1-3-1 Kasumigaseki, Chiyoda-ku, Tokyo 100-8901, Japan. E-mail address: morikawa-masayuki@rieti.go.jp; BXZ00354@nifty.ne.jp. Tel.: +81-3-3501-1362. I would like to thank Haruhiko Ando, Yasuo Goto, Seiichiro Inoue, Arata Ito, Keisuke Kondo, Atsushi Nakajima, Norio Nakazawa, Yukiko Saito, Makoto Yano, Hiroyuki Yoshiya, and the seminar participants at RIETI for their valuable comments and suggestions. Any errors are my own. I am grateful to the Ministry of Economy, Trade and Industry for providing the micro data of the Survey of Production Forecast used in this study. This research is supported by JSPS Grants-in-Aid for Scientific Research (26285063, 26590043).

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1. Introduction

Uncertainty and its impacts on economic activities attract attention from policy practitioners and economic researchers. Uncertainty, which arises from financial crises, unexpected policy developments in major countries following changes of political power, and natural disasters, among other factors, negatively affects firm behavior over the course of the economy, particularly impacting on long-term investments including innovation and recruitment (see Carruth *et al*., 2000 and Bloom, 2014 for surveys).

Since uncertainty is subjective in nature and not directly observable from statistical data, various proxy variables have been proposed to capture the uncertainty faced by economic agents.[1] Representative uncertainty measures include the (1) volatility of stock prices (Bloom *et al*., 2007; Bloom, 2009), (2) cross-sectional disagreement of forecasts by professional economists (Driver and Moreton, 1991; Dovern *et al*., 2012), (3) unexplained portion of macroeconomic variables derived from econometric models (Jurado *et al*., 2015), (4) ex post forecast errors in firms' business outlook (Bachmann *et al*., 2013; Arslan *et al*., 2015; Morikawa, 2016a), (5) survey-based firms' subjective uncertainty (Guiso and Parigi, 1999; Bontempi, 2016; Morikawa, 2016b), and (6) frequency of newspaper articles on policy uncertainty (Baker *et al*., 2016).

The measure of uncertainty adopted in this study is the ex post errors in the production forecasts of manufacturing firms. Although firms' forecast errors have been used as proxy of uncertainty in the literature, empirical studies have generally depended on the qualitative outlook of business conditions (e.g., improving, unchanging, or deteriorating) available from business surveys (Bachmann et al., 2013; Arslan et al.,

[1] The ideal measure to capture the uncertainty faced by economic agents is the point forecast and its probability distribution of individual firms or households (Pesaran and Weale, 2006); however, such data for individual companies or households are rarely available.

2015; Morikawa, 2016a). By contrast, this study uses quantitative data on ex ante production forecasts and ex post realized production at the firm- and product-levels taken from a monthly survey of Japanese manufacturers conducted by the Ministry of Economy, Trade and Industry (METI), namely the Survey of Production Forecast (SPF).

A small number of studies analyze quantitative forecast errors at the firm-level. For example, Bachmann and Elstner (2015), using quarterly survey data on manufacturing firms in Germany (i.e., the IFO Business Climate Survey), quantify and analyze production errors. However, since production quantities are not directly available from the survey data, they construct quantitative expectation errors for firms' production growth from the expectation of capacity utilization rates based on several assumptions, such as production capacity remaining constant. Bachmann *et al*. (2017) present a quantitative analysis of a firm-level investment expectation error termed investment surprise for a 40-year panel of German manufacturing firms (i.e., the IFO Investment Survey). Although the availability of a long panel is an advantage, the investment data used in their study have only an annual frequency.

By contrast, the SPF captures the cyclical movements of Japanese manufacturers' production on a monthly basis. The survey specifically asks firms for their production forecasts for the next month, estimated production for the current month, and realized production for the previous month. Because no analyses of forecast errors using monthly frequency quantitative firm- and product-level production have thus far been carried out, this study contributes to the literature on uncertainty in two main ways.[2] First, when only data on qualitative forecasts and realizations are available, unexpected improvements (or deteriorations) in business conditions are treated equally. However, in practice, the economic impacts of forecast errors of 5% and 50%, for example, are very different. Second, adopting firm- and product-level micro data enables us to analyze not only the time-series properties of uncertainty but also its cross-sectional heterogeneity by industry or product type. While production uncertainty is naturally heterogeneous

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[2] Bachmann and Elstner (2015), who analyze firms' forecast errors using micro data from German manufacturers, state that "ideally, researchers would need high-frequency quantitative expectation and realization data on firm-specific variables," but that "such information is not available for under-yearly frequencies and for long time horizons in any business survey we know of."

and rest heavily on the characteristics of the industries or products in question, such an analysis has been hampered by data limitations.

By using these novel data, we make seven important findings about production uncertainty at the firm- and product-levels. First, forecast errors differ by firms. Indeed, even when realized production at the aggregate-level is corrected downward from the forecast (i.e., overpredicted), many firms' realized production amounts are corrected upward from their forecasted amounts (i.e., underpredicted). Second, while realized production tends to be slightly less (about 2% on average) than forecasted production, the average absolute forecast error is larger than 10%. Third, firms operating in information and communications technology (ICT)-related industries, firms producing investment goods, and smaller firms exhibit greater production uncertainty. Fourth, the higher the volatility of actual production in the recent past, the greater forecast uncertainty will be, suggesting that past production volatility can be used as a proxy of uncertainty. Fifth, forecast uncertainty heightens in contractionary phases of the business cycle. In particular, production uncertainty rises at the time of large exogenous shocks such as the global financial crisis (2008–2009) and Great East Japan Earthquake (2011). Sixth, the uncertainty measures calculated from the firm-level micro data are able to predict macroeconomic fluctuations that cannot be detected from the measures constructed from publicly available aggregated data, indicating the value of firm-level production forecast data. Seventh, the production uncertainty of Japanese manufacturing firms is associated with overseas policy uncertainty in addition to Japan's own economic policy uncertainty (EPU).

The remainder of this paper is structured as follows. Section 2 explains the data used in this study, the procedure for calculating the forecast errors and uncertainty measures, and the method of analysis. Section 3 reports the results, including (1) descriptive observations on the time-series movements of forecast uncertainty; (2) differences in uncertainty by industry, product type, and firm size; (3) the relationship between forecast uncertainty and production volatility; (4) the cyclical characteristics of forecast uncertainty; and (5) the relationship between the production uncertainty and EPU indices constructed from the frequency of newspaper articles. Section 4 concludes, presenting the policy implications, limitations of the study, and issues to be addressed in future work.

2. Data and Method of Analysis

A. *The SPF*

This study uses monthly firm- and product-level micro data taken from the SPF from January 2006 to March 2015. The SPF collects information on firms' forecasts of the following month's production quantity, estimated production quantity for the current month, and realized production quantity for the previous month. For example, the February survey asks for the production forecast for March, estimated production for February, and realized production for January. **Table 1** summarizes the time structure of the survey. The survey is carried out at the end of each month and the deadline for reporting is the 10th of the following month.[3]

The survey data are used to construct the Indices of Production Forecast (IPF), which show the forecasted manufacturing production relative to the base year (currently 2010).[4] IPF is an important macroeconomic statistic for judging business cycle phases. In particular, the "realization ratio," namely the gap between the realized production of the current month's survey and estimated production of the previous month's survey, and the "amendment ratio," the gap between the estimated production of the current month's survey and forecasted production of the previous month's survey, are regarded as useful measures for judging the turning points of business cycles. For example, unexpected negative (positive) figures of these ratios may signal that the business cycle is approaching its peak (trough).

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[3] The details of the survey including the survey form are available at the website of the METI (http://www.meti.go.jp/statistics/tyo/yosoku/).

[4] The IPF is published monthly at the same time as the release of the Indices of Industrial Production (IIP), which are similar to the Industrial Production and Capacity Utilization (constructed by the Federal Reserve Bank) in the United States.

The SPF surveys 195 manufacturing products and approximately 700 firms. Sample firms are chosen on a product-by-product basis to cover approximately 80% of the domestic production of each product, as determined from the annual Current Survey of Production (conducted by the METI).[5] The resampling of firms is conducted every five years to retain the 80% coverage of the production of each product. However, about 60% of these firms were surveyed throughout the sample period used in this study. Moreover, as forecasted and realized monthly productions of more than 90% of the surveyed products are expressed as quantities (rather than as monetary values) such as tonnage or the number of products, most production data are real figures unaffected by price changes. For example, the unit of quantities of iron and steel products and chemicals is expressed in tonnage, while that of vehicles and household electronic appliances is expressed in the number of products manufactured.[6]

The SPF classifies industries into (1) iron and steel, (2) non-ferrous metals, (3) fabricated metals, (4) general machinery, (5) electronic parts and devices, (6) electrical machinery, (7) information and communication electronics equipment, (8) transport equipment, (9) chemicals, (10) pulp, paper, and paper products, and (11) other manufacturing. In addition, the products are, based on their major use, categorized into (1) capital goods, (2) construction goods, (3) durable consumer goods, (4) non-durable consumer goods, (5) producer goods for manufacturing, and (6) producer goods for non-manufacturing. Unfortunately, firm characteristics other than industry and product category, such as the number of employees and firm age, are not included in the SPF.[7]

In this study, we define the production forecast error as the gap between realized production and forecasted production. For example, the difference between the forecasted production for March in the February survey and the realized production for March in the April survey is the forecast error. The size of the forecast error can be

[5] The Current Survey of Production is similar to the Annual Survey of Manufacturers in the United States.

[6] Since the units of quantity measure differs by product, it is not possible to aggregate production quantity across different products.

[7] As the micro data of the SPF is highly confidential, the names of the firms surveyed are unavailable to researchers. Therefore, it is impossible to link the data with other firm surveys to obtain firm characteristics.

interpreted as the degree of production forecast uncertainty at the time of the survey (February, in this case).

It is possible to calculate the forecast errors at the aggregate-level from the published series of the IPF. **Figure 1** depicts the movements of the forecast errors for the whole manufacturing sector,[8] showing two huge negative surprises (forecasted production > realized production) during the global financial crisis (2008–2009) and Great East Japan Earthquake (2011) periods. In normal times, small negative surprises are frequent, but positive surprises (forecasted production < realized production) can occur. The absolute sizes of both positive and negative surprises proxy for the degree of macro-level production uncertainty at the time of forecasting.

However, even when realized production underperforms forecasted production at the aggregate-level, some firms underperform and other firms overperform (relative to their forecasts) at the micro-level. In other words, there are large gross forecast errors behind the relatively small net forecast errors.[9] These aggregated net forecast errors conceal the heterogeneous movements of individual firms. For example, when the overperformed production amount is the same as the underperformed production amount, the net forecast error (or production uncertainty) calculated from the aggregate indices will be zero. However, it is natural to think that uncertainty is greater when large positive and negative forecast errors co-exist than when both positive and negative errors are small. It is for this reason that we use firm- and product-level micro data derived from the SPF to present new empirical evidence on the production forecast uncertainty of Japanese manufacturers.[10]

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[8] Data on aggregated IPF is available from the website of the METI (http://www.meti.go.jp/statistics/tyo/iip/).

[9] Research using qualitative business survey data indicates that many positive and negative surprises co-exist at the firm-level, even when the forecast error at the aggregate level is small (Morikawa, 2016a).

[10] Although the currently available data period is limited to about 10 years between January 2006 and March 2015, the total number of observations is more than 100,000. As the Survey of Production Forecast is regarded as containing highly confidential information about firms' production forecast, more recent data are unavailable for researchers.

B. *Method of Analysis*

By using the data set explained above, we first calculate simple forecast errors at the firm- and product-levels. The production quantity of firm i in month t (q_{it}) is converted into the logarithmic form and the difference between forecasted production ($\ln(E(q_{it}))$) and realized production ($\ln(q_{it})$) is defined as the "forecast error" of production ($error_{it}$), which is the measure of production uncertainty at the firm- and product-levels adopted in this study:

$$error_{it} = \ln(q_{it}) - \ln(E(q_{it})) \tag{1}$$

A positive $error_{it}$ indicates that the firm's production forecast was underpredicted (or a positive surprise), whereas a negative $error_{it}$ means overprediction (or a negative surprise). To avoid the confounding effects of extremely large positive/negative values, we remove the observations when the absolute value of $error_{it}$ exceeds unity as outliers.[11] Because the figures are expressed in logarithmic form, when either forecasted or realized production is zero, the forecast error is treated as a missing value.[12]

Next, we calculate the absolute forecast error ($absfe_{it}$) as the absolute value of $error_{it}$, which is an alternative measure of production uncertainty at the firm- and product-levels:

$$absfe_{it} = |\, error_{it} \,| \tag{2}$$

Based upon these micro-level production uncertainty measures, we then construct time-series data on aggregate production uncertainty. Specifically, following studies that

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[11] In total, 1,922 observations (1.8%) are dropped. As the standard deviation of $error_{it}$ before removing outliers is 0.324, removing observations of $error_{it}$ that exceed unity is similar to removing observations that are either three standard deviations larger or smaller than the sample mean.

[12] Zero production (about 4% of the observations) sometimes occurs in cases when a factory either goes into periodic maintenance or stops operation following an accident.

have used qualitative business survey data (Bachmann *et al*., 2013; Morikawa, 2016a), we define the (1) mean absolute forecast error (denoted as $MEANABSFE_t$) and (2) forecast error dispersion (denoted as $FEDISP_t$) as measures of production uncertainty at time t. $MEANABSFE_t$ is the means of the individual absolute forecast errors ($absfe_{it}$) at time t. $FEDISP_t$ is the cross-sectional dispersion of the individual forecast errors ($error_{it}$) at time t calculated as the standard deviation. We calculate these uncertainty measures ($MEANABSFE_t$ and $FEDISP_t$) by industry and product type in addition to for the whole manufacturing sector to detect differences at a more fine-grained level.

These two aggregated measures serve as our proxies of production uncertainty even though they are conceptually different. For example, when all firms overpredicted their production in the next month (downward correction ex post) by the same magnitude, $MEANABSFE_t$ takes a positive value, whereas $FEDISP_t$ is zero by definition. However, according to studies using qualitative business survey data (Bachmann *et al*., 2013; Morikawa, 2016a), $MEANABSFE_t$ and $FEDISP_t$ generally exhibit similar time-series movements.

By using these firm-level and aggregated measures of production uncertainty, we first document their headline time-series properties and the differences by industry and product type. We then analyze the differences by producer size by dividing the sample into large and small producers, as the qualitative forecast errors of large firms are less than those of small firms (Bachmann and Elstner, 2015; Morikawa, 2016a). Because the SPF does not contain information about firm characteristics, as noted above, we divide the sample into large and small producers based upon the mean production quantity of each producer during the sample period. Specifically, the production quantity of firm i ($\overline{\mathrm{qi}}$) averaged in the sample period is calculated, and a large (small) producer is defined as a firm whose production quantity is larger (smaller) than the mean quantity ($\overline{\mathbf{q}}$) of the product. We then test the statistical differences of $error_{it}$ and $absfe_{it}$ by producer size.

Next, we analyze the relationships between production volatility and the production uncertainty measures at the firm-level. While past volatility is frequently used as a proxy of economic uncertainty, it does not necessarily represent the future uncertainty faced by firms. Our main interest here is whether greater volatility in the past is positively associated with greater forecast uncertainty in the future. In this analysis, we thus measure a firm's production volatility as the coefficient of variation (standard deviation divided by the mean) of production in the 12 months before the time of forecasting.

Uncertainty measures have a countercyclical property in that uncertainty heightens during recessions and declines during booms (Bloom, 2014; Jurado *et al*., 2015). To verify this property at the firm-level, we divide the sample period into expansionary and contractionary phases and test the statistical differences of $error_{it}$ and $absfe_{it}$ by these cyclical phases.[13] In addition, we analyze the relationships between the aggregated uncertainty measures ($MEANABSFE_t$ and $FEDISP_t$) and macroeconomic fluctuations, such as the lead–lag relationships. Although it is natural to use GDP as a representative macroeconomic time series, GDP data are available only at a quarterly frequency. Therefore, we use the monthly Indices of All Industry Activity (IAA) to analyze the relationships with the measures of production forecast uncertainty.[14]

Finally, we analyze the relationship between the production uncertainty measures calculated from the SPF and the EPU indices constructed from the frequency of newspaper articles (Baker *et al*., 2016). The global EPU index (EPU–Global) and index for the United States (EPU–US), in addition to the EPU index for Japan (EPU–Japan), are available on a monthly basis.[15] We analyze the correlations and lead–lag relationships of our measure of forecast uncertainty with the EPU indices.

3. Results

A. *Forecast Errors at the Firm-Level*

[13] In Japan, the reference dates of the business cycle are discussed in the Investigation Committee for Business Cycle Indicators and determined by the Economic and Social Research Institute of the Cabinet Office.

[14] The IAA is constructed by weight-averaging the indices of various industries with the added value weights of the base year. The IAA data are available at the website of METI (http://www.meti.go.jp/statistics/tyo/zenkatu/).

[15] The outline of the global EPU index is explained by Davis (2016).

Table 2 reports the summary statistics of the forecast errors ($error_{it}$) and absolute forecast errors ($absfe_{it}$) throughout the sample period (2006–2015). The means of $error_{it}$ and $absfe_{it}$ are -0.024 and 0.133, respectively. During the sample period, realized production falls short of the forecast by 2.4% and the absolute forecast error is more than 10% on average. However, the medians are -0.007 and 0.074, respectively, which are smaller in absolute terms than the mean figures. **Figure 2-A** illustrates the distribution of the forecast errors ($error_{it}$). Although those calculated from the IPF tend to show downward corrections (see **Figure 1**), the firm-level forecast errors are concentrated around zero and distributed evenly on both the positive and the negative sides. However, at the same time, the tails of the distribution are long, indicating that firms sometimes experience either large positive or large negative forecast errors.

Table 2 reports the summary statistics for selected subperiods and the whole sample period. The mean forecast errors show greater negative values at times of large exogenous shocks and the standard deviations are greater in these periods, too. The means and dispersions of the absolute forecast errors are larger in the years of large shocks than in normal years. **Figure 2-B** depicts the distribution of the forecast errors by subperiod, confirming that the forecast errors are greater in these extraordinary periods than in normal times.

To visualize the time-series movements of the forecast error distribution, **Figure 3** depicts the composition of firms with positive errors (underprediction), no errors, and negative errors (overprediction). Although the percentages of negative errors are sometimes large, both positive and negative errors can co-exist at any time. For example, just after the collapse of Lehman Brothers (November 2008 to February 2009), the percentages of firms with negative errors exceeded 70%; however, even in this period, more than 20% of firms experienced an upward correction. It might be that these firms were either too cautious (making an underprediction) about their businesses or that their performance improved unexpectedly, or both. On average, 42.6%, 4.3%, and 53.1% of firms had positive, no, and negative errors, respectively. Although the percentage of firms with negative forecast errors is higher than that of positive errors, in some months, the percentage of firms with a positive surprise exceeds 50%.

Instead of the composition of firms, **Figure 4** depicts the separate sample means of the positive and negative errors. For comparison purposes, the forecast errors calculated from publicly available aggregated data (the same as those in **Figure 1**) are also illustrated. During the global financial crisis (2008–2009) and Great East Japan Earthquake (2011), not only the absolute error sizes of underperformers but also those of overperformers are larger than in normal times, indicating that a non-negligible number of firms performed better than their overly pessimistic forecasts. This observation suggests that the absolute forecast error, namely production forecast uncertainty, heightens during huge exogenous macroeconomic shocks. Further, although the global financial crisis and Great East Japan Earthquake are different shocks in nature, the overall reactions of the forecast errors resemble each other.

Figure 4 also shows that even in normal times, the means of both the positive and the negative errors (12.8% and -14.5%, respectively) exceed 10% in absolute terms. Therefore, positive and negative surprises are frequent and co-exist. The sizes of the forecast errors are, quantitatively, not small. Although these are simple observations, they are new findings that cannot be detected from qualitative business surveys or the aggregated series of the IPF.

B. *Production Uncertainty by Industry and Product Type*

By using data on the firm-level forecast errors ($error_{it}$) and absolute forecast errors ($absfe_{it}$), we construct aggregated uncertainty measures ($MEANABSFE_t$ and $FEDISP_t$) for the whole manufacturing sector. As explained in the previous section, $MEANABSFE_t$ is the mean of $absfe_{it}$ and $FEDISP_t$ is the standard deviation of $error_{it}$. **Figure 5** depicts the time-series movements of $MEANABSFE_t$ and $FEDISP_t$. Although the two measures are conceptually different, the series show a similar time-series pattern: both measures indicate heightened uncertainty during the global financial crisis and Great East Japan Earthquake.

We next calculate these uncertainty measures by industry and product type. **Table 3** summarizes the means of $MEANABSFE_t$ and $FEDISP_t$ during the sample period. By industry, the information and communication electronics equipment industry shows the highest figures for both uncertainty measures, followed by the general machinery, electronic parts and devices, and electrical machinery industries. Conversely, the uncertainty measures are relatively low in fabricated metals, transport equipment, chemicals, and pulp, paper, and paper products. By product type, capital goods show the highest uncertainty in $MEANABSFE_t$ and $FEDISP_t$. As capital goods are, by definition, strongly related to equipment investment, the higher uncertainty of these products reflects the large and unpredictable movements of investment at the macro-level. The production forecast uncertainties are heterogeneous by industry and product type.

C. *Comparison of Forecast Error by Producer Size*

Table 4 indicates the differences in forecast errors ($error_{it}$) and absolute forecast errors ($absfe_{it}$) by producer size. As explained in the previous section, since the SPF does not capture information on firm size, we define small (large) producers as firms whose average production during the study period is smaller (larger) than the mean of firms producing the same product and test the statistical difference of their forecast errors. According to the results for the whole manufacturing sector, the sample means of the forecast errors ($error_{it}$) of large and small producers are -2.1% and -2.6%, respectively. While the difference is quantitatively small, it is statistically significant at the 1% level (Panel A, **Table 4**), suggesting that small producers tend to overpredict their production relative to large producers.

However, the results are different by industry and product type. While large producers in three industries (general machinery, electrical machinery, and pulp, paper, and paper products) exhibit smaller negative surprises, the opposite is true for another three industries (non-ferrous metals, fabricated metals, and information and communication electronics equipment), and there are no significant differences in five industries (iron and steel, electronic parts and devices, transport equipment, chemicals, and other manufacturing). By product type, large producers exhibit smaller negative surprises in four product categories (capital goods, durable consumer goods, non-durable consumer goods, and producer goods for manufacturing), but the result for construction goods is the opposite. Small producers' tendency to overpredict is not common across either industry or product type.

By contrast, the results for the absolute forecast errors ($absfe_{it}$) indicate clearly that the forecasts of smaller producers are less accurate (Panel B, **Table 4**). In the whole manufacturing sector, the figures for large and small producers are 11.9% and 15.0%, respectively. These differences are statistically significant at the 1% level in every industry and product category. By industry, the gaps by producer size are remarkable among firms in the information and communication electronics equipment, iron and steel, non-ferrous metals, and electronic parts and devices industries.

Instead of dividing the sample into large and small subsamples, we run a simple regression, where producer size (the log of the production quantity relative to the product mean) is used as a continuous explanatory variable and the forecast errors and absolute forecast errors are used as the dependent variables. Product dummies and time (month) dummies are also used as control variables. In the regressions, as both producer size and forecast errors are expressed in logarithmic form, the estimated coefficients for producer size can be interpreted as the elasticity of forecast errors with respect to producer size. The finding that small producers tend to face greater production uncertainty, or, in other words, that the forecasts of large producers are relatively accurate, is confirmed from the regression analysis using the continuous producer size variable (**Table 5**). The difference by size is pronounced in the case of using absolute forecast errors as the dependent variable (column (2), **Table 5**), indicating that doubling the size of a producer reduces the absolute forecast error by 1.5% on average.

Our inference is that the absolute forecast error ($absfe_{it}$), which shows the accuracy of the production forecast irrespective of the sign, is a better measure of uncertainty of the production forecast than is the simple forecast error ($error_{it}$), which reflects optimism and pessimism in addition to pure (non-directional) uncertainty. In short, the production forecasts of large producers are either more accurate than those of small producers or small producers face greater forecast uncertainty in their production. This result is consistent with the findings of studies using quarterly qualitative business survey data (Bachmann and Elstner, 2015; Morikawa, 2016a). Our interpretation of this result is that the costs of gathering and processing information to make production forecasts are somewhat fixed and that large producers strive to forecast accurately by investing in such information activities.

D. *Production Volatility and Forecast Errors*

Table 6 reports the panel estimation results of the relationship between the volatility of realized production and forecast error at the firm-level. In these regressions, the dependent variables are the forecast errors ($error_{it}$) and absolute forecast errors ($absfe_{it}$) alternatively. The explanatory variable is production volatility over the past 12 months, calculated as the coefficient of variation. Time fixed-effects are used to control for the macroeconomic conditions common across firms. We conduct two estimation patterns where firm fixed-effects are either included or omitted.

Columns (1) and (2) of **Table 6** presents the regression results using the simple forecast error ($error_{it}$) as the dependent variable. The coefficients of past production volatility are negative and significant when firm fixed-effects are not included, meaning that firms with more volatile production in the recent past tend to show greater negative surprises (column (1)). However, the signs of the coefficients turn positive when firm fixed-effects are included (column (2)), meaning that after accounting for unobservable firm characteristics, greater volatility in recent past production is associated with a larger positive surprise (or a smaller negative surprise) in the near future. This result suggests that firms tend to make cautious production forecasts after experiencing large production fluctuations, resulting in an underprediction.

When the absolute forecast error ($absfe_{it}$) is used as the dependent variable, the volatility coefficients are found to be positive and highly significant irrespective of the inclusion of firm fixed-effects (columns (3) and (4), **Table 6**). The greater the production volatility in the recent past, the more uncertain the forecasts of future production will be. From the viewpoint of empirical research on uncertainty, this result suggests that production volatility can be used as a practical proxy of uncertainty about production in the near future.

If we reverse the variables, namely using realized production volatility during the *future* 12 months as the dependent variable and either $error_{it}$ or $absfe_{it}$ as the explanatory variable, the estimated coefficients for $error_{it}$ are negative and those for $absfe_{it}$ are positive, with both statistically significant at the 1% level (**Appendix Table A1**). These results hold irrespective of including firm fixed-effects, indicating that greater forecast uncertainty is associated with volatile production in the near future.

E. *Business Cycles and Production Uncertainty*

Many studies of macroeconomic uncertainty have indicated that uncertainty rises in recessions and falls in booms (Bloom, 2014). In this subsection, we first examine the differences in the firm-level forecast errors by phases of the business cycle. **Table 7** summarizes the comparisons by the business cycle phases with statistical significance. According to the results of the forecast errors ($error_{it}$) for the whole manufacturing sector, the means of negative surprises in expansionary and contractionary phases are -1.5% and -5.3%, respectively (Panel A, **Table 7**). Obviously, the statistical difference is highly significant. By industry, the negative surprise (or overprediction) is larger in contractionary phases in every industry, and the differences are statistically significant in nine of 11 industries, with the exception of the electrical machinery and transport equipment industries. While the mean size of overprediction (downward correction) stands out in industries such as electrical machinery, general machinery, and information and communication electronics equipment, the differences by cyclical phases are large in electronic parts and devices and chemicals.

By product type, a significantly larger negative surprise in contractionary phases is observed in capital goods, construction goods, producer goods for manufacturing, and production goods for non-manufacturing. The difference by cyclical phases is prominent in firms/products belonging to producer goods for manufacturing: the means of negative surprises in the expansionary and contractionary phases are -0.9% and -6.6%, respectively. As most products classified in electronic parts and devices and chemicals industries belong to producer goods, the results by industry and product type are consistent.

Panel B of **Table 7** compares the absolute forecast errors ($absfe_{it}$). For the whole manufacturing sector, these errors in the expansionary and contractionary phases are 12.8% and 15.2%, respectively. While the difference is not large, it is statistically significant at the 1% level. By industry, the absolute forecast errors in the contractionary phase are larger than those in the expansionary phase for the majority of industries, with the exception of transport equipment, and the differences are statistically significant in eight industries. By product type, larger absolute forecast errors are found in capital goods, construction goods, and producer goods for manufacturing. The production forecasts of these product categories become inaccurate in contractionary phases.

As the above observations are based on the dichotomic division of cyclical phases, the magnitude of the strength or weakness of overall economic activity is not considered. To quantify the degree of macroeconomic conditions, we compare the relationships between the measures of production uncertainty ($MEANABSFE_t$ and $FEDISP_t$) and the IAA. The horizontal axis in **Figure 6** is the seasonally adjusted IAA and the vertical axis is the production uncertainty measures for the whole manufacturing sector. As can be seen, uncertainty for both $MEANABSFE_t$ and $FEDISP_t$ is lower when macroeconomic activity level is higher and vice versa. The correlation coefficients with the IAA are -0.574 for $MEANABSFE_t$ and -0.672 for $FEDISP_t$.

While this figure plots the simultaneous relationships between the IAA and production uncertainty measures, there may be lead–lag relationships. In this respect, we estimate simple vector autoregressive (VAR) models to detect the Granger causality running from the uncertainty measures to IAA. The lag lengths in these VAR models are one and two months.[16] We find that both uncertainty measures (*$MEANABSFE_t$* and *$FEDISP_t$*) have significant Granger causality to the IAA at the 1% level (Panel A, **Table 8**). On the contrary, the reverse causality from the IAA to the uncertainty measures is insignificant for both *$MEANABSFE_t$* and *$FEDISP_t$* (p-values are 0.825 and 0.359; not reported in the table).

However, these results may reflect the lead–lag relationship between the economic activity of the manufacturing sector and the whole economy (IAA). To check this possibility, we conduct VAR models with three variables, including the IIP as an additional variable.[17] Even if we include the IIP in the model, both uncertainty measures still Granger cause the IAA (Panel B, **Table 8**). On the contrary, we do not find significant causality running from the IIP to IAA. The results of these exercises suggest that macroeconomic activity tends to decline shortly after production uncertainty calculated from the firm-level forecast errors rises.

On the contrary, when we use the absolute forecast error of production calculated from the publicly available aggregated IPF (denoted as *AGG_ABSFE_t*), we cannot detect Granger causality from this measure to the IAA (see the lower parts of Panels A and B, **Table 8**). This result indicates that the uncertainty measures calculated from the firm- and product-level micro data contain valuable information for judging the development of business cycles, which is not obtainable from the publicly available aggregated series of the IPF. Indeed, when we estimate the same models excluding the years of the global financial crisis (2008–2009) and Great East Japan Earthquake (2011), we still detect that *$MEANABSFE_t$* and *$FEDISP_t$* Granger cause the IAA, but that *AGG_ABSFE_t* does not.

Furthermore, we estimate the VAR models of the same specifications by using the monthly Indices of Business Conditions constructed by the Cabinet Office as an alternative measure of macroeconomic activity. The results are consistent with those obtained by using the IAA. *$MEANABSFE_t$*, and *$FEDISP_t$* Granger cause these indices

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[16] Even when longer lags (e.g., three months and four months) are added into the VAR models, the results are essentially unchanged.
[17] Seasonally adjusted series of the IIP are used.

(p-values are 0.000), whereas AGG_ABSFE_t does not show Granger causality (p-value is 0.693). In summary, the results that the uncertainty measures calculated from firm-level data have Granger causality to macroeconomic activity and that the causality cannot be detected from the measure derived from publicly available aggregated data are robust.

F. *Production Forecast Uncertainty and EPU*

In this subsection, we present evidence of the relationships between our measures of production forecast uncertainty (*MEANABSFE* and *FEDISP*) and the EPU indices. The newspaper-based EPU indices developed by Baker *et al*. (2016) have frequently been used in recent empirical studies of policy uncertainty.[18] Currently, the monthly EPU indices for the United States, the European Union, Japan, and other countries are available to researchers. More recently, the Global EPU index (EPU–Global), which is the weighted average of the EPU indices of individual countries, has also been released.

As we are interested in the extent to which domestic and overseas policy uncertainties affect Japanese manufacturing firms, this study uses the EPU index for Japan (EPU–Japan) as well as EPU–Global or, alternatively, the index for the United States (EPU–US).[19] We adopt EPU–US as an alternative to EPU–Global because the latter, by construction, contains information about EPU–Japan, which may not represent pure overseas policy uncertainty.

Table 9 presents the correlation coefficients between our measures of production uncertainty and the EPU indices. *MEANABSFE* and *FEDISP* have positive correlations with both EPU–Japan and EPU–Global, indicating that production uncertainty is

[18] Recent studies using EPU indices include Bernal *et al*. (2016), Gulen and Ion (2016), Caggiano *et al*. (2017), and Meinen and Roehe (2017).
[19] The data on EPU–Japan used in this study are the latest series at the time of writing; they were provided by Dr. Arata Ito, a co-author of Arbatli *et al*. (2017). The other series were downloaded from the Economic Policy Uncertainty website.

associated with uncertain policy developments.[20] Unexpectedly, the correlations with EPU–US are slightly stronger than those with EPU–Japan, possibly because the production forecasts of Japanese manufacturing firms depend heavily on policy developments in the United States. These observations are consistent with studies based on firm surveys (Morikawa, 2016b, 2016c) that indicate that Japanese firms, particularly manufacturing firms, are concerned about policy uncertainty related to international trade.

Table 10 reports the results from a simple panel regression analysis, where the absolute forecast error at the firm-level ($absfe_{it}$) is treated as the dependent variable and the EPU indices are used as explanatory variables. In these estimations, firm fixed-effects are controlled for. When the policy uncertainty indices are included separately, the coefficients for EPU–Japan, EPU–Global, and EPU–US are all positive and significant at the 1% level and the sizes of the coefficients are similar (columns (1)–(3)), suggesting that firms' production forecasts become inaccurate when domestic and overseas policy uncertainty heightens.

When EPU–Japan and EPU–Global are simultaneously used as the explanatory variables, both coefficients are positive and statistically significant, whereas the size of the coefficient for EPU–Japan is about five times greater than that for EPU–Global (column (4)). As EPU–Global contains information about EPU–Japan, we re-estimate by replacing EPU–Global with EPU–US (column (5)). Interestingly, in this specification, the coefficient for EPU–US is slightly larger than that for EPU–Japan, confirming that the accuracy of Japanese manufacturing firms' production forecasts is heavily affected by EPU in the United States. Even when we estimate the same models excluding the years of the global financial crisis (2008–2009) and Great East Japan Earthquake (2011), the sizes of the coefficients for the EPU indices reduced, but they are still statistically significant.

Finally, **Appendix Table A3** reports the correlation coefficients with the EPU indices

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[20] When testing Granger causality between our measures of production uncertainty and the EPU Indices, EPU–Japan, EPU–Global, and EPU–US weakly Granger cause *MEANABSFE* and *FEDISP* (**Appendix Table A2**).

by industry and product type. Similar to the findings for the whole manufacturing sector, the production uncertainties of most industries correlate with, in descending order, EPU–US, EPU–Japan, and EPU–Global. However, the electronic parts and devices industry is an important exception. In this industry, both *MEANABSFE* and *FEDISP* have higher correlations with EPU–Global and EPU–US than with EPU–Japan. Unexpectedly, the correlations of the production uncertainty of the transport equipment industry with the EPU indices are generally low, possibly reflecting the accuracy of production forecasts in this industry indicated before. By product type, the production uncertainty of construction goods has higher correlations with EPU–Japan than the overseas EPU indices, as expected from the domestic nature of this industry. On the contrary, the production uncertainty of capital and producer goods for manufacturing has the highest correlations with EPU–US.

To summarize, these results suggest that Japanese manufacturing firms, particularly those producing parts, components, and materials, are involved in the deepening global value chain. As a result, these firms' production forecasts are affected by the development of overseas policy uncertainty.

4. Conclusion

This study, using monthly micro data on Japanese manufacturing firms' forecasted and realized production taken from the SPF, presents new findings on the uncertainty of production forecasts. The major results and the implications of the first empirical study adopting monthly-frequency quantitative production forecast data at the firm- and product-levels are as follows. First, forecast errors at the firm-level often differ from those derived from publicly available aggregated data. Even when realized production at the aggregate level is downward corrected from the forecast (i.e., overpredicted), a non-negligible number of firms' realized productions exceed their forecasts (i.e., underpredicted) and vice versa. Second, during the sample period, realized production tends to be less than the forecasted amounts (approximately 2% downward correction on average). More importantly, however, the size of the absolute forecast error is large (more than 10% on average).

Third, firms operating in ICT-related manufacturing industries, firms producing investment goods, and smaller producers exhibit greater production forecast uncertainty. Fourth, the higher the volatility of actual production in the recent past, the greater future production uncertainty will be, suggesting that production volatility, which is frequently used as a measure in the literature, is a good proxy of uncertainty. Fifth, production uncertainty is greater in contractionary phases of the business cycle than in expansionary phases. This finding is in line with past empirical studies of uncertainty. Further, production uncertainty rises at times of large exogenous shocks, such as the global financial crisis (2008–2009) and Great East Japan Earthquake (2011) despite the different nature of these shocks.

Sixth, the uncertainty measures calculated from firm-level data have Granger causality to macroeconomic activity represented by the IAA. This causality cannot be detected from the measure derived from publicly available aggregated data, indicating the practical usefulness of firm-level forecast data. In this respect, it is desirable for government agencies in charge of macroeconomic policy to pay attention not only to the aggregate figures of the IPF but also to the movements and dispersion of the firm-level production forecast errors.

Finally, the forecast uncertainty of Japanese manufacturing firms is associated with the movements of newspaper-based indices of policy uncertainty (EPU). Relationships are found not only with Japan's own policy uncertainty (EPU–Japan) but also with overseas policy uncertainty (EPU–Global and EPU–US). In particular, production uncertainty in industries such as the electronic parts and devices industry has a strong association with overseas policy development.

Although this study makes a novel contribution because its use of high-frequency firm- and product-level quantitative data on production forecasts and realizations, there are many limitations. The period of analysis is limited to about 10 years because of data availability. The period also includes extraordinary shocks such as the global financial crisis and Great East Japan Earthquake, which is, in some senses, desirable when analyzing production uncertainty. However, the results may be partly driven by these special events. Analysis using longer time series is therefore left for future research. In addition, the industry coverage of this study is limited to the manufacturing sector; however, it would be desirable to cover the non-manufacturing sector (e.g., wholesale and retail industries) given the trend toward the service economy. In this respect, governments' statistical agencies ought to develop and conduct monthly surveys on the production forecasts of service firms.

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TABLE 1. FORECASTED, ESTIMATED, AND REALIZED PRODUCTION QUANTITIES IN THE SPF

Months of Production	Months of Surveys				
	February survey	March survey	April survey	May survey	· · ·
January	January realized				
February	February estimate	February realized			
March	**March forecast**	March estimate	**March realized**		
April		April forecast	April estimate	April realized	
May			May forecast	May estimate	
June				June forecast	· · ·
·					
·					
·					

TABLE 2. SUMMARY STATISTICS OF FIRM-LEVEL FORECAST ERRORS

	Periods	Nobs.	Mean	Std. Dev.	Median
$error_{it}$	Whole period	102,051	-0.0235	0.2105	-0.0069
	2008-2009	24,165	-0.0374	0.2349	-0.0173
	2011	11,392	-0.0374	0.2304	-0.0112
	Normal times	66,494	-0.0161	0.1968	-0.0037
$absfe_{it}$	Whole period	102,051	0.1332	0.1647	0.0742
	2008-2009	24,165	0.1569	0.1788	0.0934
	2011	11,392	0.1486	0.1800	0.0836
	Normal times	66,494	0.1220	0.1552	0.0665

Note: $error_{it}$ and $absfe_{it}$ denote the forecast errors and absolute forecast errors calculated from the forecasted and realized productions at the firm-level. The sample period runs from January 2006 to March 2015. "Normal times" are the years excluding 2008–2009 and 2011.

TABLE 3. PRODUCTION FORECAST UNCERTAINTY AGGREGATED BY INDUSTRY AND PRODUCT TYPE

	(1) *MEANABSFE*	(2) *FEDISP*	(3) Nobs.
All manufacturing	0.1331	0.2104	102,281
1 Iron and steel	0.1178	0.1938	6,914
2 Non-ferrous metals	0.1203	0.1849	4,931
3 Fabricated metals	0.0985	0.1541	5,780
4 General machinery	0.1624	0.2487	14,861
5 Electronic parts and devices	0.1617	0.2367	8,016
6 Electrical machinery	0.1650	0.2404	9,339
7 Information and communication electronics	0.1941	0.2795	6,204
8 Transport equipment	0.0958	0.1769	4,856
9 Chemicals	0.1008	0.1640	20,342
10 Pulp, paper, and paper products	0.0724	0.1258	5,117
11 Other manufacturing	0.1443	0.2203	15,921
1 Capital goods	0.1883	0.2745	18,665
2 Construction goods	0.1227	0.1898	4,966
3 Durable consumer goods	0.1306	0.2096	8,495
4 Non-durable consumer goods	0.1175	0.1704	439
5 Producer goods for manufacturing	0.1127	0.1827	54,505
6 Producer goods for non-manufacturing	0.1446	0.2072	1,767

Note: Since some products are not classified into any type, the sum of the observations by product type (1 to 6 in the lower part of this table) falls short of the observations in whole manufacturing.

TABLE 4. PRODUCTION FORECAST ERRORS BY PRODUCER SIZE

Panel A. Forecast Error ($error_{it}$)

	(1) Small	(2) Large	(3) (2)-(1)	
All manufacturing	-0.026	-0.021	0.005	***
1 Iron and steel	-0.020	-0.015	0.005	
2 Non-ferrous metals	0.016	-0.003	-0.019	***
3 Fabricated metals	-0.005	-0.022	-0.016	***
4 General machinery	-0.051	-0.031	0.020	***
5 Electronic parts and devices	-0.023	-0.021	0.001	
6 Electrical machinery	-0.060	-0.024	0.036	***
7 Information and communication electronics	-0.026	-0.043	-0.017	**
8 Transport equipment	-0.018	-0.011	0.007	
9 Chemicals	-0.026	-0.027	-0.002	
10 Pulp, paper, and paper products	-0.034	-0.024	0.010	***
11 Other manufacturing	-0.009	-0.003	0.005	
1 Capital goods	-0.045	-0.028	0.017	***
2 Construction goods	-0.006	-0.020	-0.013	**
3 Durable consumer goods	-0.047	-0.040	0.008	*
4 Non-durable consumer goods	-0.137	0.023	0.160	***
5 Producer goods for manufacturing	-0.024	-0.020	0.004	***
6 Producer goods for non-manufacturing	-0.035	-0.021	0.014	

Panel B. Absolute Forecast Error ($absfe_{it}$)

	(1) Small	(2) Large	(3) (2)-(1)	
All manufacturing	0.150	0.119	-0.030	***
1 Iron and steel	0.146	0.094	-0.053	***
2 Non-ferrous metals	0.152	0.102	-0.050	***
3 Fabricated metals	0.120	0.082	-0.038	***
4 General machinery	0.177	0.149	-0.028	***
5 Electronic parts and devices	0.186	0.140	-0.046	***
6 Electrical machinery	0.179	0.152	-0.027	***
7 Information and communication electronics	0.231	0.161	-0.070	***
8 Transport equipment	0.105	0.085	-0.019	***
9 Chemicals	0.104	0.099	-0.005	***
10 Pulp, paper, and paper products	0.094	0.055	-0.038	***
11 Other manufacturing	0.156	0.132	-0.024	***
1 Capital goods	0.214	0.166	-0.048	***
2 Construction goods	0.160	0.094	-0.066	***
3 Durable consumer goods	0.150	0.115	-0.035	***
4 Non-durable consumer goods	0.204	0.089	-0.115	***
5 Producer goods for manufacturing	0.123	0.104	-0.019	***
6 Producer goods for non-manufacturing	0.174	0.117	-0.057	***

Notes: Small (large) producers are firms designated by their production quantity during the period of analysis being smaller (larger) than the mean of the firms in the same product. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 5. ELASTICITIES OF THE FORECAST ERRORS WITH RESPECT TO PRODUCER SIZE

	(1) *error* $_{it}$	(2) *absfe* $_{it}$
SIZE	0.0045 ***	-0.0214 ***
	(0.0006)	(0.0004)
Product dummies	yes	yes
Time dummies	yes	yes
Nobs.	102,051	102,051
Adjusted R^2	0.0435	0.1519

Notes: OLS estimations with standard errors in parentheses. *** $p < 0.01$. Producer size (SIZE) is the difference between a firm's production quantity and the mean quantity of the firms producing the same product (both expressed in natural logarithms).

TABLE 6. PRODUCTION VOLATILITY AND FORECAST ERRORS (PANEL ESTIMATION RESULTS)

	(1) *error* $_{it}$	(2) *error* $_{it}$	(3) *absfe* $_{it}$	(4) *absfe* $_{it}$
Volatility	-0.0071 ***	0.0092 ***	0.0659 ***	0.0148 ***
	(0.0011)	(0.0018)	(0.0008)	(0.0013)
Firm FE	no	yes	no	yes
Time FE	yes	yes	yes	yes
Nobs.	88,821	88,821	88,821	88,821
R^2	0.0223	0.0253	0.0908	0.0336

Notes: OLS and fixed-effects estimations with standard errors in parentheses. *** $p < 0.01$. The R^2 of the firm fixed-effects estimations is the within R^2. Volatility is calculated as the coefficient of variation (standard error divided by the mean) of production quantity during the past 12 months.

TABLE 7. PRODUCTION FORECAST ERRORS BY BUSINESS CYCLE PHASE

Panel A. Forecast Error (*error$_{it}$*)

	(1) Expansion	(2) Contraction	(3) (2)-(1)	
All manufacturing	-0.015	-0.053	-0.038	***
1 Iron and steel	-0.006	-0.055	-0.049	***
2 Non-ferrous metals	0.014	-0.033	-0.047	***
3 Fabricated metals	-0.006	-0.043	-0.037	***
4 General machinery	-0.033	-0.063	-0.030	***
5 Electronic parts and devices	-0.005	-0.076	-0.072	***
6 Electrical machinery	-0.039	-0.048	-0.009	
7 Information and communication electronics	-0.030	-0.053	-0.023	***
8 Transport equipment	-0.014	-0.018	-0.004	
9 Chemicals	-0.015	-0.071	-0.056	***
10 Pulp, paper, and paper products	-0.019	-0.064	-0.045	***
11 Other manufacturing	0.000	-0.026	-0.026	***
1 Capital goods	-0.032	-0.050	-0.018	***
2 Construction goods	-0.009	-0.031	-0.022	***
3 Durable consumer goods	-0.041	-0.048	-0.007	
4 Non-durable consumer goods	-0.016	-0.021	-0.006	
5 Producer goods for manufacturing	-0.009	-0.066	-0.057	***
6 Producer goods for non-manufacturing	-0.021	-0.048	-0.027	**

Panel B. Absolute Forecast Error (*absfe$_{it}$*)

	(1) Expansion	(2) Contraction	(3) (2)-(1)	
All manufacturing	0.128	0.152	0.024	***
1 Iron and steel	0.112	0.139	0.027	***
2 Non-ferrous metals	0.116	0.135	0.018	***
3 Fabricated metals	0.095	0.111	0.017	***
4 General machinery	0.157	0.175	0.018	***
5 Electronic parts and devices	0.151	0.196	0.045	***
6 Electrical machinery	0.163	0.170	0.007	
7 Information and communication electronics	0.192	0.200	0.008	
8 Transport equipment	0.096	0.090	-0.006	
9 Chemicals	0.092	0.133	0.041	***
10 Pulp, paper, and paper products	0.067	0.093	0.027	***
11 Other manufacturing	0.141	0.157	0.016	***
1 Capital goods	0.187	0.194	0.008	**
2 Construction goods	0.120	0.131	0.010	**
3 Durable consumer goods	0.130	0.132	0.002	
4 Non-durable consumer goods	0.113	0.135	0.022	
5 Producer goods for manufacturing	0.105	0.141	0.036	***
6 Producer goods for non-manufacturing	0.145	0.144	-0.001	

Note: The phases of business cycles are based on the Reference Dates of the Business Cycle (Cabinet Office). ** $p < 0.05$, *** $p < 0.01$.

TABLE 8. GRANGER CAUSALITY TEST FROM PRODUCTION FORECAST UNCERTAINTY TO THE IAA

Panel A. Two-variable VARs

Uncertainty measures		p-value	
Micro data	*MEANABSFE*	0.000	***
	FEDISP	0.000	***
Aggregated data	*AGG_ABSFE*	0.422	

Panel B. Three-variable VARs (including IIP)

Uncertainty measures and IIP		p-value	
Micro data	*MEANABSFE*	0.000	***
	IIP	0.604	
	FEDISP	0.000	***
	IIP	0.682	
Aggregated data	*AGG_ABSFE*	0.954	
	IIP	0.040	**

Notes: *AGG_ABSFE* is the absolute forecast error calculated from the publicly available aggregated series of the PFI. The IAA and IIP are seasonally adjusted series. The lag lengths in the VAR models are one and two months. ** $p < 0.05$, *** $p < 0.01$.

TABLE 9. CORRELATION COEFFICIENTS BETWEEN PRODUCTION UNCERTAINTY AND THE EPU INDICES

	(1) *MEANABSFE*	(2) *FEDISP*
EPU-Japan	0.436	0.427
EPU-Global	0.349	0.317
EPU-US	0.458	0.465

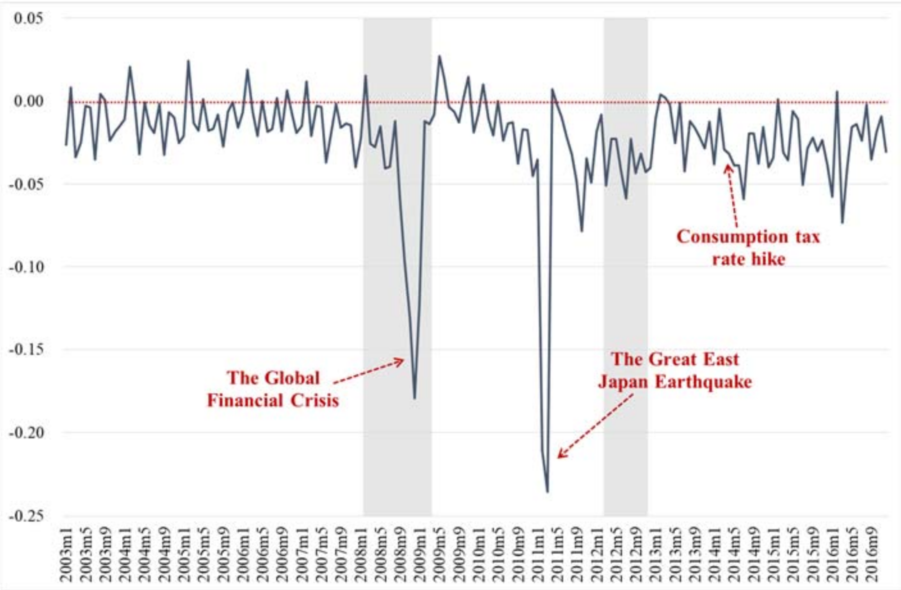
Note: The EPU indices are constructed by Baker *et al*. (2016).

TABLE 10. THE EPU INDICES AND ABSOLUTE FORECAST ERRORS (PANEL ESTIMATION RESULTS)

	(1)	(2)	(3)	(4)	(5)
EPU-Japan	0.00034 ***			0.00029 ***	0.00016 ***
	(0.00001)			(0.00002)	(0.00002)
EPU-Global		0.00025 ***		0.00006 ***	
		(0.00001)		(0.00002)	
EPU-US			0.00030 ***		0.00020 ***
			(0.00001)		(0.00002)
Firm FE	yes	yes	yes	yes	yes
Nobs.	102,051	102,051	102,051	102,281	102,281
R^2 (within)	0.0062	0.0044	0.0071	0.0063	0.0077

Notes: Fixed-effects estimation results with standard errors in parentheses. *** $p < 0.01$. The dependent variable is the firm-level absolute forecast errors ($absfe_{it}$). The EPU indices are constructed by Baker *et al*. (2016).

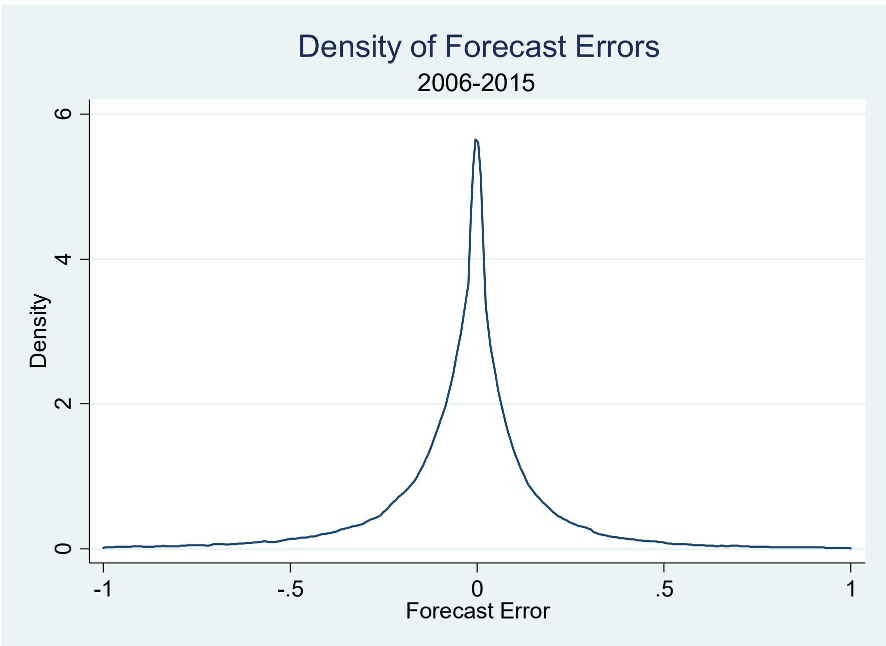
FIGURE 1. PRODUCTION FORECAST ERRORS AT THE AGGREGATE LEVEL



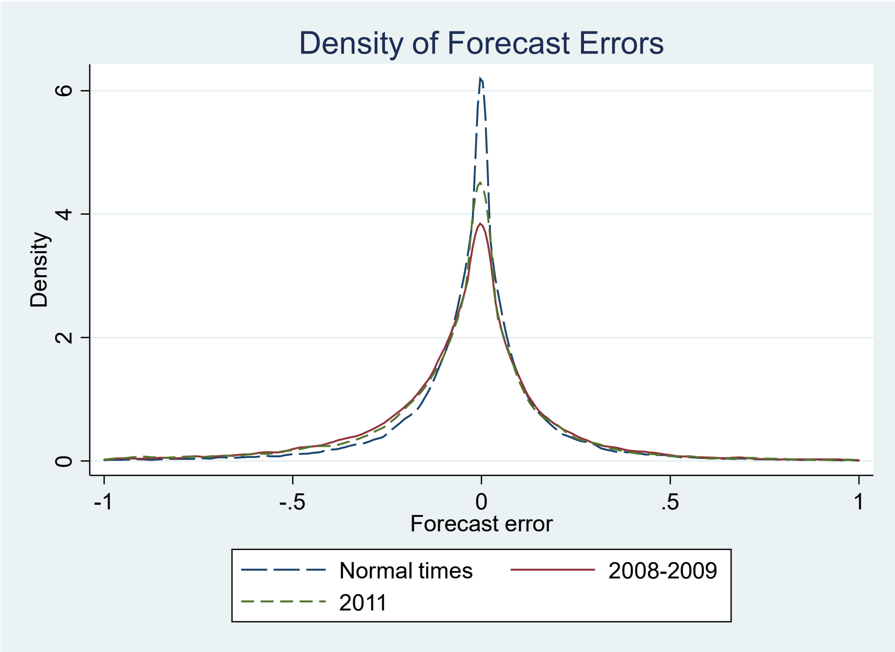
Note: The figure is constructed from the publicly available aggregated series of the IPF. Shaded areas indicate contractionary periods.

FIGURE 2. DISTRIBUTION OF THE FORECAST ERRORS (*$error_{it}$*)

A. Whole Sample Period

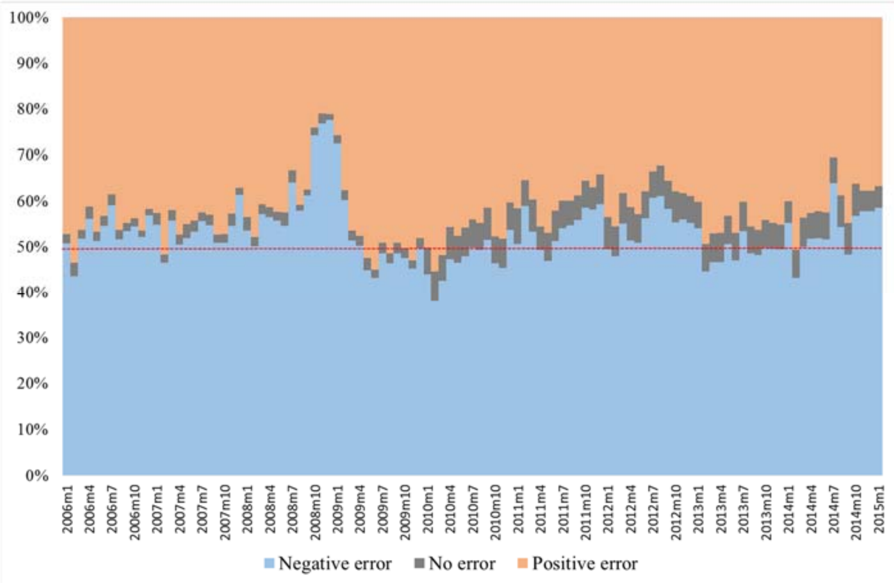


B. By Subperiod



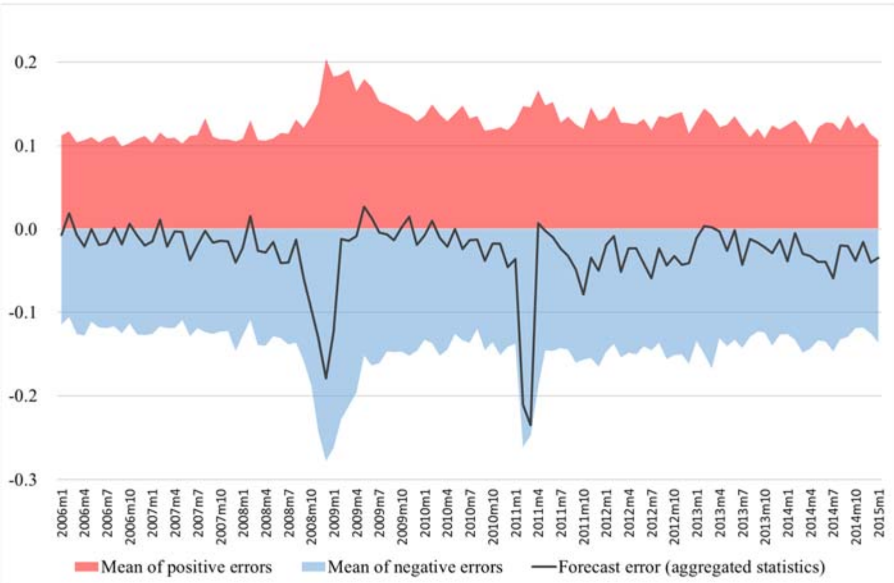
Notes: The figure is drawn from the micro data of the SPF. Firm-level forecast errors (*error*$_{it}$) are calculated as ln(q_{it}) - ln(E(q_{it})). The observations with an absolute value of *error*$_{it}$ that exceeds unity are treated as outliers and removed from the sample. “Normal times” are the years excluding 2008–2009 and 2011.

FIGURE 3. COMPOSITION OF FIRMS WITH POSITIVE, NO, AND NEGATIVE ERRORS



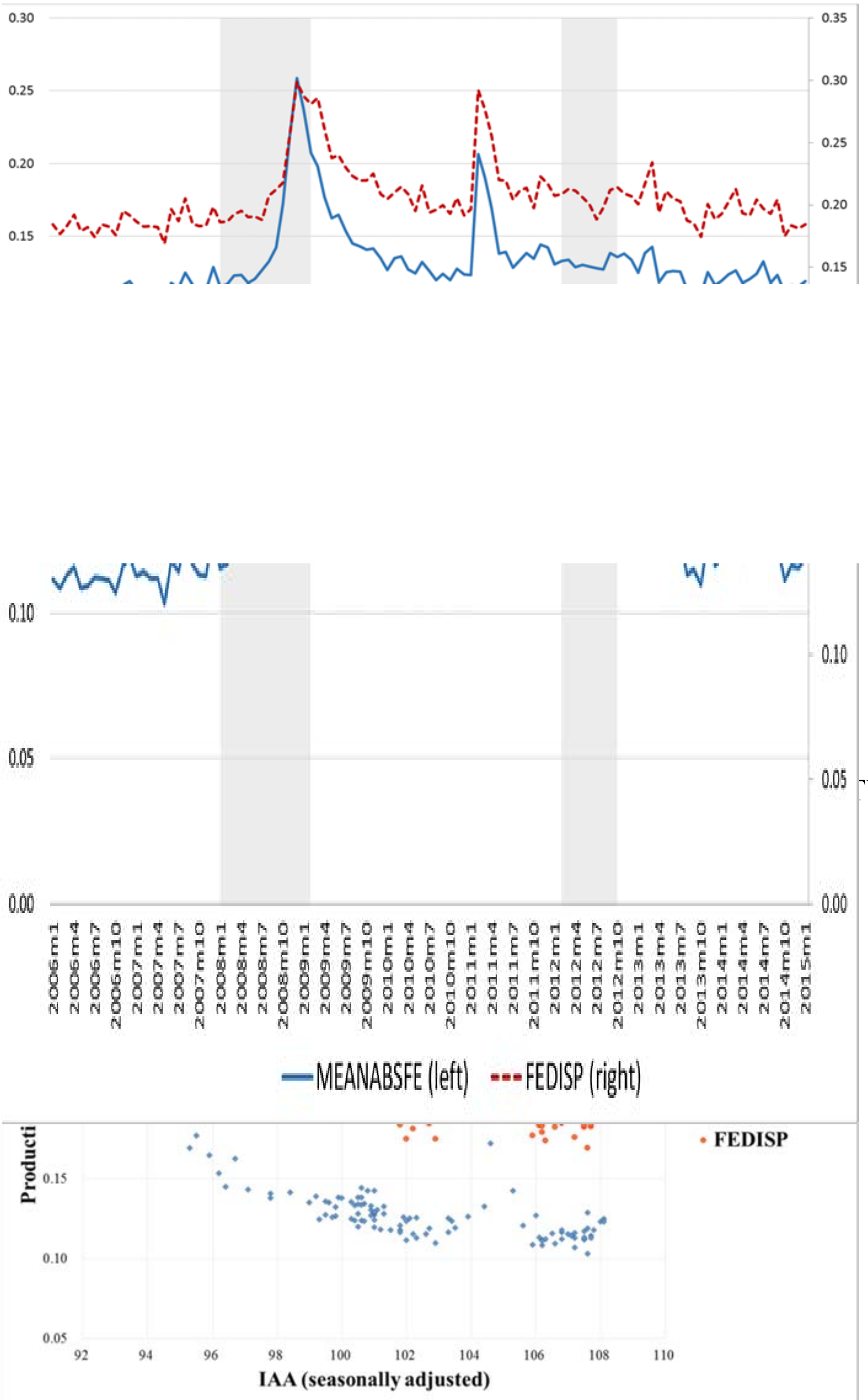
Note: Positive (negative) error means realized production quantity larger (smaller) than the forecasted quantity.

FIGURE 4. MEAN FORECAST ERRORS AT THE MICRO AND MACRO LEVELS



Note: The means of positive errors (in red) and negative errors (in blue) are calculated separately.

FIGURE 5. MOVEMENTS OF THE PRODUCTION UNCERTAINTY MEASURES FOR THE WHOLE MANUFACTURING SECTOR



Note: The IAA is the seasonally adjusted series.

APPENDIX TABLE A1. FORECAST ERRORS AND PRODUCTION VOLATILITY (PANEL ESTIMATION RESULTS)

	(1) Volatility	(2) Volatility	(3) Volatility	(4) Volatility
$error_{it}$	-0.2148 ***	-0.1145 ***		
	(0.0102)	(0.0065)		
$absfe_{it}$			1.2203 ***	0.3294 ***
			(0.0125)	(0.0090)
Firm FE	no	yes	no	yes
Time FE	yes	yes	yes	yes
Nobs.	92,618	92,618	92,618	92,618
R^2	0.0407	0.0996	0.1265	0.1096

Notes: OLS and fixed-effects estimations with standard errors in parentheses. *** p < 0.01. Volatility, the dependent variable, is calculated as the coefficient of variation (standard error divided by the mean) of production quantity during the past 12 months.

APPENDIX TABLE A2. GRANGER CAUSALITY TEST FROM THE EPU INDICES TO PRODUCTION UNCERTAINTY

(1) EPU → Production uncertainty		p-value	(2) Production uncertainty → EPU		p-value
EPU-Japan	*MEANABSFE*	0.038 **	*MEANABSFE*	EPU-Japan	0.285
	FEDISP	0.085 *	*FEDISP*		0.150
EPU-Global	*MEANABSFE*	0.086 *	*MEANABSFE*	EPU-Global	0.274
	FEDISP	0.027 **	*FEDISP*		0.078 *
EPU-US	*MEANABSFE*	0.053 *	*MEANABSFE*	EPU-US	0.160
	FEDISP	0.007 ***	*FEDISP*		0.031 **

Note: The EPU Indices are constructed by Baker *et al.* (2016). The lag lengths in the VAR models are one and two months. * p < 0.10, ** p < 0.05, *** p < 0.01.

APPENDIX TABLE A3. CORRELATION COEFFICIENTS BETWEEN PRODUCTION UNCERTAINTY AND THE EPU INDICES BY INDUSTRY AND PRODUCT TYPE

	(1)	(2)	(3)	(4)	(5)	(6)
		MEANABSFE			*FEDISP*	
	EPU-Japan	EPU-Global	EPU-US	EPU-Japan	EPU-Global	EPU-US
All manufacturing	0.436	0.349	0.458	0.427	0.317	0.465
1 Iron and steel	0.414	0.317	0.451	0.418	0.304	0.461
2 Non-ferrous metals	0.402	0.332	0.417	0.319	0.242	0.352
3 Fabricated metals	0.242	0.154	0.318	0.152	0.108	0.252
4 General machinery	0.417	0.221	0.424	0.360	0.175	0.415
5 Electronic parts and devices	0.395	0.486	0.460	0.359	0.473	0.459
6 Electrical machinery	-0.010	-0.114	0.024	-0.084	-0.163	-0.066
7 Information and communication electronics	0.288	0.234	0.258	0.264	0.240	0.225
8 Transport equipment	0.080	0.028	0.193	0.112	0.100	0.200
9 Chemicals	0.455	0.421	0.431	0.406	0.331	0.380
10 Pulp, paper, and paper products	0.358	0.351	0.391	0.261	0.238	0.285
11 Other manufacturing	0.274	0.148	0.201	0.206	0.074	0.096
1 Capital goods	0.405	0.248	0.418	0.348	0.212	0.390
2 Construction goods	0.320	0.200	0.263	0.245	0.147	0.157
3 Durable consumer goods	-0.030	-0.158	0.030	-0.043	-0.168	-0.028
4 Non-durable consumer goods	0.032	-0.057	-0.132	0.065	-0.020	-0.105
5 Producer goods for manufacturing	0.439	0.393	0.467	0.429	0.364	0.494
6 Producer goods for non-manufacturing	0.099	0.111	0.157	0.090	0.021	0.085

Note: The EPU indices are constructed by Baker *et al*. (2016).