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Uncertainty over Production Forecasts: An empirical analysis using monthly firm survey data

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Uncertainty over Production Forecasts: An empirical analysis using monthly firm survey data*

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Abstract

This study, using monthly micro data of firms' forecasted and realized production quantities, presents new findings on uncertainty over production forecasts. This is the first empirical study employing monthly-frequency quantitative forecast data at the firm level. According to the analysis, forecast errors are quite heterogeneous among individual manufacturers. For example, some firms underpredict their production, even when aggregate level production is overpredicted. In terms of firm characteristics, firms operating in the information and communications technology (ICT)-related industries, firms producing investment goods, and smaller firms exhibit higher forecast uncertainty. The forecast uncertainty is greater in contractionary phases of the business cycle. The uncertainty measures calculated from micro data have a predictive power over macroeconomic fluctuations, which cannot be detected from the measures derived from publicly available aggregated data, suggesting the value of firm-level micro data. Finally, 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

JEL Classifications: D84, E32, E66, L60

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1. Introduction

Uncertainty and its impact on economic activities, arising from repeated global financial crises, unexpected policy developments in major countries following changes of political power, and natural disasters, attract attention from policy practitioners and economic researchers. Uncertainty over the future course of the economy has a negative impact on firm behavior, particularly on long-term investments, including innovations and hiring of employees, through a "wait-and-see" mechanism (Carruth *et al*., 2000; Bloom, 2014, for surveys).

Since uncertainty is subjective in nature and is not directly observable from statistical data, various proxy variables have been proposed and constructed to capture the uncertainty that economic agents face. Representative uncertainty measures include: (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) the unexplained portion of macroeconomic variables derived from econometric models (Jurado *et al*., 2015), (4) ex post forecast errors of 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) the frequency of newspaper articles on policy uncertainty (Baker *et al*., 2016).[1]

The analysis of this study is based on the ex post errors of production forecasts among Japanese manufacturing firms as the measure of uncertainty. Although firms' forecast errors have been used in the literature, past empirical studies have depended on the qualitative outlook of business condition (e.g., increase, unchanged, or decrease) available from business surveys.[2] In contrast,

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

[2] Bachmann and Elstner (2015), using a quarterly survey data on manufacturing firms in Germany (IFO-BCS), estimate quantitative amounts of production errors and use them in the analysis. However, since the production quantities are not directly observed in the survey, they construct quantitative expectation errors for firms' production growth from the expectation about capacity utilization rates

this study uses quantitative data on ex ante production forecast and ex post realized production at the firm/product-level taken from a monthly official statistical survey, the "Survey of Production Forecast," conducted by the Ministry of Economy, Trade, and Industry (METI).

The "Survey of Production Forecast" is a unique statistical survey designed to capture cyclical movements of Japanese manufacturers' production on monthly frequency. The survey asks firms for quantitative data on their production forecasts for the next month and the realized production from the previous month. 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." Because there has been no analysis of the forecast errors (i.e. uncertainty) using monthly-frequency quantitative firm-level data, this study potentially contributes to the literature on uncertainty.

When data on qualitative forecasts and realizations are all that are available, unexpected improvements (or deteriorations) are treated equally, irrespective of the quantitative magnitude. However, in practice, the economic impacts of forecast errors of 5% and 50%, for example, are very different. We can accurately evaluate the uncertainty of firms by using quantitative information on both forecast production and realized production. Furthermore, firm/product-level micro data enable us to analyze not only the time-series property of uncertainty but also cross-sectional heterogeneity by industry or product category. It is natural to expect that production uncertainty is heterogeneous, depending on the characteristics of industries or products, but such an analysis has not yet been conducted, due to data limitations.

The major findings of this study are as follows. First, forecast errors are quite heterogeneous among individual firms. For example, even when the realized production at the aggregate level is corrected downward from the forecast (i.e., overpredicted), many firms' realized production data are corrected upward from their forecasted amounts (i.e., underpredicted). Second, while the realized productions tend to be slightly less than are the forecasted amounts, the average size of absolute forecast error is more than 10%. Third, by firm characteristics, firms operating in information and communications technology (ICT)–related industries, firms producing investment goods, and smaller firms exhibit greater production uncertainty. Fourth, the forecast

based on several assumptions, such as the production capacity being constant.

uncertainty heightens in contractionary phases of the business cycle. The production uncertainty heightened at the time of large exogenous shocks, such as the world financial crisis (2008) and the Great East Japan Earthquake (2011). Fifth, the uncertainty measures calculated from firm-level micro data have a predictive power over macroeconomic fluctuations, which cannot be detected from the measures constructed from publicly available aggregated data, indicating the value of firm-level forecast data. Sixth, the higher the volatility of actual production in the recent past, the greater the forecast uncertainty will be, suggesting that the volatility of production can be used as a proxy of uncertainty. Seventh, production uncertainty of Japanese manufacturing firms is associated with overseas policy uncertainty, in addition to Japan's own economic policy uncertainty.

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 the uncertainty measures, and the method of analysis. Section 3 reports results, including (1) descriptive observations on the time-series movements of forecast uncertainty; (2) differences in uncertainty by industry, product category, and firm size; (3) cyclical characteristics of the forecast uncertainty and their relationship with the production volatility; and (4) the relationship of the production uncertainty with the economic policy uncertainty (EPU) constructed from newspaper articles. Section 4 summarizes the conclusions, with policy implications, limitations of this study, and the issues to be addressed in future work.

2. Data and Method of Analysis

2.1. The Survey of Production Forecast

This study uses monthly firm/product-level micro data of the Survey of Production Forecast conducted by the METI from January 2006 to March 2015. The survey, a monthly survey of Japanese manufacturers, collects information about firms' forecasts of the next month's production quantity, the estimated production quantity for the current month, and the realized production quantity for the previous month. For example, the February survey asks for information on the production forecast for March, the estimated production for February, and the realized production for January. **Table 1** concisely illustrates the structure of the survey.

The survey is designed to provide background data to construct the Indices of Production Forecast. The Indices of Production Forecast, an index relative to the base year (currently, 2010), is published monthly at the same time as the release of the Indices of Industrial Production (IIP).[3] The Indices of Production Forecast is an important statistic used for judging business cycle phases. In particular, the "realization ratio"—the gap between the realized production of the current month's survey and the 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 the forecasted production of the previous month's survey—are regarded as important statistics to judge the turning points of business cycles. For example, unexpected negative (positive) figures of these ratios are the sign of approaching the peak (trough) of the business cycles.

In the Survey of Production Forecast, the number of manufacturing products surveyed is 195 and the number of firms surveyed is approximately 700. The sample firms are chosen on a product-by-product basis to cover approximately 80% of the total domestic production of each product, as determined from the annual Current Survey of Production (METI). As the forecasted and realized monthly productions of more than 90% of the surveyed products are expressed in quantity (not monetary value), such as the tonnage or the numbers of product, most of the production data are the real figures unaffected by the price changes. For example, the unit of quantities for iron and steel products and chemicals is expressed in tonnage and that of vehicles and household electronic appliances is expressed in the numbers of product.

The Survey of Production Forecast 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.

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

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[3] The IIP is similar to the Industrial Production and Capacity Utilization in the United States.

uncertainty at the time of the survey (February, in this case).

Of course, it is possible to calculate the aggregate level forecast error from the published series of the Indices of Production Forecast (**Figure 1**). This figure indicates the movements of the forecast errors for the whole manufacturing sector. We can observe that there are two huge negative surprises (forecasted production > realized production) at the times of the World Economic Crisis (2008) and the Great East Japan Earthquake (2011). At other times, negative surprises are frequent; however, sometimes, there are positive surprises (forecasted production < realized production). The absolute sizes of both positive and negative surprises proxies 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.[4] The aggregated forecast errors cancel out the heterogeneous movements of the individual firms. For example, when the overperformed production amount is exactly 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 higher when large positive and negative forecast errors co-exist than when both positive and negative errors are small.

In this respect, this study uses firm/product level micro data from the Survey of Production Forecast and presents new empirical evidence on the production forecast uncertainty of Japanese manufacturers. Although the currently available data period is limited to about ten years between January 2006 and March 2015, the total number of observations is more than 100,000.[5]

2.2. Method of Analysis

Using the data set explained above, we first calculate simple forecast errors at the firm/product-level. As the units of production differ by products, the production quantity of firm i at month t

[4] Past research using qualitative business survey data indicates that many positive and negative surprises co-exist at the firm-level, even when there is no forecast error at the aggregate level (Morikawa, 2016a). That is, there are large gross forecast errors behind the relatively small net forecast errors.

[5] As the Survey of Production Forecast contains highly confidential information about firms, more recent data are unavailable for researchers.

(q_{it}) is converted to the logarithmic form and the difference between the forecasted production ($\ln(E(q_{it}))$) and the realized production ($\ln(q_{it})$) is defined as the "forecast error" of production ($error_{it}$), which is a measure of production uncertainty at the firm/product level.

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

The positive $error_{it}$ indicates that the firm's production forecast was underpredicted (or a positive surprise), and the negative $error_{it}$ means overprediction (or a negative surprise). It should be mentioned that because the figures are expressed in logarithmic form, when either forecasted or realized production quantity is zero, the prediction error is treated as a missing value.[6] 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.[7]

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/product-level.

$$absfe_{it} = | error_{it} | \quad (2)$$

Based upon these micro level production uncertainty measures, we then construct time-series data of aggregate level production uncertainty. Specifically, following past studies using qualitative business survey data (Bachmann *et al*., 2013; Morikawa, 2016a), we define (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. These aggregated measures are the proxies of production uncertainty, although they are conceptually different from each other. For example, when all firms overpredicted their production in the next month (downward correction ex post) by the same magnitude, $MEANABSFE_t$ took positive values, but $FEDISP_t$ was zero by definition. However, according to studies using qualitative business

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[6] Zero production sometimes occurs in cases when a factory either goes into periodic maintenance or stops operation due to an accident.

[7] As the standard deviation of $error_{it}$ before removing outliers is 0.324, removing observations of $error_{it}$ exceeds unity is close to removing observations that are either three standard deviations larger or smaller than the sample mean.

survey data (Bachmann *et al*., 2013; Morikawa, 2016a), $MEANABSFE_t$ and $FEDISP_t$ generally exhibit similar time-series movements.

The published series of the Indices of Production Forecast are the weighted figures by the production amounts of producers and industry. However, as the purpose of this study is to analyze the production uncertainty that individual firms are facing, we do not apply a weighting procedure. We calculate these uncertainty measures ($MEANABSFE_t$ and $FEDISP_t$) by industry and by type of product, in addition to the whole manufacturing sector, to detect differences, either by industry or by type of product.

Using these firm and aggregate level measures of production uncertainty, we first simply document time-series properties of these measures and the differences by industry and types of product.

Then, we analyze the difference by producers' size by splitting the sample into large producers and small producers. Past studies using qualitative survey data indicate that forecast errors of large firms are less than are those of small firms (Bachmann and Elstner, 2015; Morikawa, 2016a). Unfortunately, however, the Survey of Production Forecast does not contain information about firm characteristics, such as the number of employees or the amount of capital. In this regard, we split the sample into large and small producers, based upon the mean production quantity of each product. Specifically, the production quantity of firm i ($\overline{\mathrm{qi}}$) averaged in the sample period is calculated, and the large (small) producer is defined as being a firm whose production quantity is larger (smaller) than the mean quantity ($\overline{\mathbf{q}}$) at the product level. We then test the statistical differences of $error_{it}$ and $absfe_{it}$ by size of producer.

Many past studies on uncertainty have indicated that the measures of uncertainty have a counter-cyclical 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 split the sample period into expansionary and contractionary phases and test the statistical differences of $error_{it}$ and $absfe_{it}$ by the cyclical phase.[8] In addition, we analyze the relationships between the aggregated uncertainty measures ($MEANABSFE_t$ and $FEDISP_t$) and the macroeconomic fluctuations, such as the leads–lags relationships. Although it is natural to use GDP statistics as a representative macroeconomic time-series, such data are available only quarterly. Therefore, we

[8] In Japan, the Reference Dates of Business Cycle are discussed in the Investigation Committee for Business Cycle Indicators and determined by the Economic and Social Research Institute (ESRI) of the Cabinet Office.

use the Indices of All Industry Activity (IAA, constructed by METI), which is available monthly, to analyze the relationships with the measures of production forecast uncertainty.

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

Finally, we analyze the relationship between the production uncertainty developed in this study and the Economic Policy Uncertainty (EPU) Index constructed from the frequency of newspaper articles (Baker *et al*., 2016). The global EPU index (EPU–Global) and the index for the United States (EPU–US), in addition to the EPU index for Japan (EPU-Japan), are available on a monthly basis.[9] We analyze the correlations and leads-lags relationships of our measure of forecast uncertainty with the EPU indices.

Overall, the purpose of this study is to present new descriptive findings from the data. The novelties of this study are (1) its use of firm-level high-frequency time-series data on production, (2) its construction of the measures of production uncertainty (ex post forecast error), by combining quantitative forecast and realized production, and (3) analyzing the differences in forecast uncertainty by disaggregated manufacturing industry and by types of product.

3. Results

3.1. Forecast Errors at the Firm-level: Overview

The summary statistics of the forecast errors ($error_{it}$) and the absolute forecast errors ($absfe_{it}$) throughout the sample period (2006–2015) are reported in **Table 2**. The means of $error_{it}$ and $absfe_{it}$ are -0.024 and 0.133, respectively. During the sample period, the realized production quantity falls short of the forecast by 2.4%, and the absolute forecast error is more than 10%, on

[9] The outline of the Global EPU index is explained in Davis (2016).

average. However, the medians are -0.007 and 0.074, respectively, which are smaller in absolute terms than are the mean figures. The distribution of the forecast errors ($error_{it}$) is depicted in **Figure 2**. Although the forecast errors calculated from published index of Production Forecast tend to show downward corrections (see **Figure 1** presented before), firm-level forecast errors are concentrated around zero and are distributed evenly on both positive and 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.

To visualize the time-series movements of the distribution of forecast errors, the composition of firms with positive error (underprediction), no error, and negative error (overprediction) are depicted in **Figure 3**. Although the percentages of negative errors are sometimes large, it is noteworthy that both positive and negative errors 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 error exceeded 70%; however, even in this period, more than 20% of firms experienced upward correction. It might be that these firms were either too cautious (underpredict) about their businesses or their performance improved unexpectedly, or both. The simple averages of positive, no, and negative errors are 42.6%, 4.3%, and 53.1%, respectively; however, in some months, the percentages of firms with a positive surprise exceed 50%.

Rather than the composition of firms, **Figure 4** depicts the separate sample means of positive errors and negative errors. For the purpose of comparison, forecast errors calculated from publicly available aggregated data (the same as those in Figure 1) is also drawn in this figure.[10] It is interesting to see that, at the time of the World Economic Crisis (2008) and the Great East Japan Earthquake (2011), not only the absolute sizes of the underperformers but also those of overperformers are larger than in normal times, indicating that many firms performed better than expected from their overly pessimistic forecasts. This observation suggests that the absolute forecast error, namely production uncertainty, heightens during huge exogenous macroeconomic shocks.

Another interesting observation from this figure is that, even in normal times, the means of both positive and negative errors (12.8% and -14.5%, respectively) exceed 10% in absolute terms. Positive and negative surprises are frequent and co-exist. The sizes of the forecast errors are, quantitatively, not small. Although these are simple observations, these are new findings that

[10] Publicly available aggregated statistics are the weighted figures of firms' and industries' sizes.

cannot be determined from qualitative surveys.

3.2. Production Uncertainty by Industry and Type of Product

Using data on the firm-level forecast error ($error_{it}$) and absolute forecast error ($absfe_{it}$), 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 $error_{it}$. Time-series movements of $MEANABSFE_t$ and $FEDISP_t$ are depicted in **Figure 5**. Although the two measures are conceptually different, the two series show a similar pattern. Both measures indicate heightened uncertainty at the times of the World Economic Crisis and the Great East Japan Earthquake.

We next calculate these uncertainty measures by industry and by type of product. The means during the sample period are summarized in **Table 3**. By industry, the information and communication electronics equipment industry shows the highest figures in both uncertainty measures; this is followed by 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 type of product, capital goods show the highest uncertainty in $MEANABSFE_t$ and $FEDISP_t$. As capital goods are, by definition, strongly related to equipment investments, the higher uncertainty of these products reflects large and unpredictable movements of investments at the macro level. The production forecast uncertainties are heterogeneous by both industry and product types.

3.3. Comparison of Forecast Error by Size of Producers

Past firm-level studies on uncertainty that use qualitative business survey data indicate that small firms exhibit either greater uncertainty or lower forecast accuracy than do large firms (e.g., Bachmann and Elstner, 2015; Morikawa, 2016a). **Table 4** indicates the differences of forecast errors ($error_{it}$) and absolute forecast errors ($absfe_{it}$) by size of producers. As explained in the previous section, as the Survey of Production Forecast does not have information about firm size, such as the number of employees or the amount of capital, we define small (large) producers as firms whose average production quantity during the period of analysis is smaller (larger) than the mean of firms belonging to the same industry 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.

However, the results are very different by industry or by type of product. While larger producers in three industries (general machinery, electrical machinery, and pulp and paper) exhibit smaller negative surprise, the opposite is true for the other three industries (non-ferrous metal, 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 types of product, larger producers exhibit smaller negative surprise 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 industries or product categories.

In 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. The differences are all 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 metal, and electronic parts and devices industries.

Rather than splitting the sample into large and small subsamples, we run a simple regression analysis, where producer size (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, alternatively (**Table 5**). In the regression, as both producer size and forecast errors are expressed in logarithm, the estimated coefficients for producer size can be interpreted as the elasticity of forecast errors with respect to firm 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 a continuous producer size variable. The difference by size is pronounced in the case of absolute forecast errors (column (2), **Table 5**), indicating that doubling the size of a producer reduces the absolute forecast error by 1.4%, 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 over production forecast than is the simple forecast error ($error_{it}$), which reflects optimism and pessimism, in addition to the pure (non-directional) uncertainty. In short, the production forecasts of large producers are either more accurate than are the small producers' forecasts or small producers face greater forecast uncertainty in relation to their production. This result is consistent with the findings from studies using quarterly business survey data (Bachmann and Elstner, 2015; Morikawa, 2016a). Our interpretation of the result is that the costs of gathering and processing information to make production forecasts have characteristics of fixed-costs, and that the large producers make efforts to forecast accurately by investing in such information activities.

3.4. Business Cycles and Production Uncertainty

Many past studies on macroeconomic uncertainty have indicated that uncertainty rises in recessions and falls in booms (Bloom, 2014). In this subsection, we first examine the differences of firm-level forecast errors by the phases of the business cycle. According to the Reference Dates of Business Cycle determined by the Cabinet Office of Japan, there are two contraction phases in the sample period of this study: from February 2008 to March 2009 and from March to November 2012. As the former contraction phase corresponds to the World Economic Crisis, which is very different from ordinary recessions, it is preferable to use longer time-series. However, as described in the previous section, the currently available time-series data of the Survey of Production Forecast start from January 2006.

The comparison results are summarized in **Table 6**. According to the result of the forecast errors ($error_{it}$) for the whole manufacturing sector, the means of negative surprise in expansionary and contractionary phases are -1.5% and -5.3%, respectively (panel A, **Table 6**). 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 out of eleven industries, with the exception of 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 difference by the cyclical phases are large in electronic parts and devices and chemicals.

By type of product, 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 the cyclical phases is prominent in firms/products belonging to producer goods for manufacturing: the means of negative surprise in expansionary and contractionary phases are -0.9% and -6.6%, respectively. As most of the products classified in electronic parts and devices and chemicals industries belong to producer goods, the results by industry and by product type are consistent with each other.

The comparisons of the absolute forecast errors ($absfe_{it}$) are reported in panel B of **Table 6**. For the whole manufacturing sector, the absolute forecast errors in expansionary and contractionary phases are 12.8% and 15.2%, respectively. While the difference is quantitatively not large, it is statistically significant at the 1% level. By industry, absolute forecast errors in contraction are larger than in expansion for every industry, with the exception of the transport equipment industry, and the differences are statistically significant in eight industries. By product type, the larger absolute forecast errors are found in capital goods, construction goods, and producer goods for manufacturing. Production forecasts of these 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 the overall economic activity is not taken into consideration. To incorporate the degree of macroeconomic conditions quantitatively, we compare the relationship between the measures of production uncertainty ($MEANABSFE_t$ and $FEDISP_t$) and the Indices of All Industry Activity (IAA). The scatter plots are presented as **Figure 6**. The horizontal axis of this figure is the seasonally adjusted indices of the IAA, and the vertical axis is the measures of production uncertainty for the whole manufacturing sector. As can be seen from this figure, the 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 $FEDISP_t$.

This figure plots the simultaneous relationships between the IAA and the production uncertainty measures, but there may be leads-lags relationships. In this respect, we estimate simple vector autoregressive (VAR) models to detect Granger causality running from the uncertainty measures to the IAA. According to this exercise, both uncertainty measures ($MEANABSFE_t$ and $FEDISP_t$) have significant Granger causality to the IAA at the 1% level (panel A, **Table 7**). [11]

However, the results may reflect a possible leads-lags relationship between the economic activity of the manufacturing sector and the whole economy (IAA). To check this possibility, we further conduct VAR models with three variables, including the Indices of Industrial Production (IIP) as an additional variable to test the Granger causality.[12] Even if we include the IIP in the model, both uncertainty measures still Granger cause to the IAA (panel B, **Table 8**). Conversely, we do not find significant causality running from the IIP to the IAA. The results of these exercises suggest that macroeconomic activity tends to decline with a lag when the production uncertainty calculated from the firm-level forecast errors heightens.

When we use the absolute forecast error of production (denoted as AGG_ABSFE_t) calculated from the publicly available aggregated Index of Production Forecast, we cannot detect Granger causality from this measure to the IAA (the lower parts of panel A and B, **Table 7**).[13] This result indicates that the uncertainty measures calculated from firm/product-level micro data contain valuable information to judge the development of business cycles, which is not obtainable from the publicly available series of the Index of Production Forecast.

3.5. Volatility of Production and Forecast Errors

The panel estimation results on the relationship between volatility of production and the forecast error at the firm-level are reported in **Table 8**. In these regressions, dependent variables are the forecast error ($error_{it}$) and absolute forecast error ($absfe_{it}$), alternatively. The explanatory variable is the volatility of production during the past twelve months, calculated as the coefficient of variation (standard deviation divided by the mean). We conduct four patterns of estimation where firm fixed-effects and/or time fixed-effects are either included or omitted. Time fixed-effects are used to control macroeconomic conditions common across firms.

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[11] On the other hand, the reverse causality from the IAA to the uncertainty measures is insignificant for both $MEANABSFE_t$, and $FEDISP_t$ (p-values are 0.825, 0.359).
[12] Seasonally adjusted series of the IIP are used.
[13] On the other hand, causality running from the IAA to AGG_ABSFE_t is significant at the 1% level.

The regression results when using simple forecast error ($error_{it}$) as the dependent variable are presented in columns (1) and (2) of the table. The coefficients for 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 coefficients turn to positive when firm fixed-effects are included (column (2)), meaning that, after accounting for the unobservable firm characteristics, greater volatility of 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 forecasts about their future production after experiencing large production fluctuation, resulting in underprediction of their production.

When the absolute forecast error ($absfe_{it}$) is used as the dependent variable, the coefficients for volatility are estimated to be positive and highly significant, irrespective of the inclusion of firm fixed-effects (columns (3) and (4), **Table 8**). The greater the production volatility in the recent past has been, the more uncertain the forecasts of future production will be. From the viewpoint of empirical research on uncertainty, the result suggests that volatility of production can be used as a practical proxy to uncertainty over production in the near future.

If we reverse the variables, using production volatility during the future twelve 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, and both are statistically significant at the 1% level (**Appendix Table A1**). The results hold, irrespective of including firm fixed-effects, indicating that greater production uncertainty is associated with volatile production in the future.

3.6. Production Forecast Uncertainty and the EPU Indices

In this subsection, we present evidence on the relationships between our measures of production forecast uncertainty (*MEANABSFE* and *FEDISP*) and economic policy uncertainty (the EPU indices). The newspaper based EPU indices, developed by Baker *et al*. (2016), have been used frequently in recent empirical studies on policy uncertainty.[14] Currently, the monthly

[14] Recent studies employing the EPU indices include Bernal *et al*. (2016), Gulen and Ion (2016),

EPU indices for the United States, the European Union, Japan, and some other countries are available for researchers. More recently, the Global EPU index (EPU–Global), which is the weighted average of the individual countries' EPU indices, has also been released,.

As we are interested in the effects of domestic and overseas policy uncertainties on Japanese manufacturing firms, this study uses the EPU index for Japan (EPU–Japan) as well as the EPU–Global or, alternatively, the index for the United States (EPU–US). [15] The reason for using the EPU–US as an alternative to the EPU–Global is because the EPU–Global, by construction, contains information about the EPU–Japan, which may not represent pure overseas policy uncertainty.

The correlation coefficients between our measures of production uncertainty and the EPU indices are presented in **Table 9**. *MEANABSFE* and *FEDISP* have positive correlations with both EPU–Japan and EPU–Global, indicating that production uncertainty is associated with uncertainty of policy developments. [16] Unexpectedly, the correlations with the EPU–US are slightly stronger than with the EPU–Japan, possibly because production forecast of Japanese manufacturing firms depends heavily on the policy developments in the United States. These observations are consistent with studies based on firm survey (Morikawa, 2016b, 2016c) that indicate that Japanese firms, particularly manufacturing firms, are concerned about policy uncertainty related to international trade.

The results from simple panel regression analysis, where absolute forecast error at the firm-level ($absfe_{it}$) is treated as a dependent variable and the EPU indices are used as explanatory variables, are reported in **Table 10**. In these estimations, firm fixed-effects are controlled. 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 not much different (columns (1)–(3)), suggesting that firms' production forecasts become inaccurate when domestic and overseas policy uncertainty heightens.

When the EPU–Japan and the EPU–Global are simultaneously used as explanatory variables,

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Caggiano *et al*. (2017), and Meinen and Roehe (2017), among others.

[15] The data on EPU–Japan used in this study is the latest series at the time of writing; provided by Dr. Arata Ito, a co-author of Arbatli *et al*. (2017). The other series were downloaded from the website of the Economic Policy Uncertainty.

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

both coefficients are positive and statistically significant, but the size of the coefficient for the EPU–Japan is about five times greater than that for the EPU–Global (column (4)). As the EPU–Global contains information about the EPU–Japan, we re-estimate replacing the EPU–Global by the EPU–US [column (5)]. Interestingly, in this specification, the coefficient for the EPU–US is slightly larger than that for the EPU–Japan, confirming that the accuracy of the Japanese manufacturing firms' production forecast is heavily affected by the economic policy uncertainty in the US.

Finally, the correlation coefficients with the EPU Indices by industry and type of product are reported in **Table 11**. Similar to the findings for the whole manufacturing sector, the production uncertainties of most industries correlate with, in descending order, the EPU–US, the EPU–Japan, and the EPU–Global. However, electronic parts and devices industry is an important exception. In this industry, both *MEANABSFE* and *FEDISP* of this industry have higher correlations with the EPU–Global and the EPU–US than with the EPU–Japan. Unexpectedly, the correlations of the production uncertainty of transport equipment industry with the EPU Indices are generally low, possibly reflecting the accuracy of production forecasts of this industry indicated before. By type of product, production uncertainty of construction goods has higher correlations with the EPU–Japan than the overseas EPU indices, as expected from the domestic nature of this industry. On the other hand, production uncertainty of capital goods and producer goods for manufacturing has the highest correlations with the 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 become affected by the development of overseas policy uncertainties.

4. Conclusion

This study, using monthly micro data of Japanese manufacturing firms' forecasted and realized production quantities taken from the Survey of Production Forecast, presents new findings on uncertainty over production forecasts. This is the first empirical study employing monthly-frequency quantitative production forecast data at the firm-level.

The major results and the implications are as follows. First, forecast errors at the firm-level are often very different from those derived from the publicly available aggregated data. Even when the 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, the realized productions tend 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, by firm characteristics, firms operating in ICT-related industries, firms producing investment goods, and smaller producers exhibit greater production uncertainty.

Fourth, the production uncertainty is greater in contractionary phases of the business cycle than in expansionary phases. This is in line with past empirical studies on uncertainty. The production uncertainty heightened at times of exogenous shocks, such as the World Economic Crisis (2008) and the Great East Japan Earthquake (2011).

Fifth, 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 the government agencies in charge of macroeconomic policy to pay attention not only to aggregate figures of the Indices of Production Forecast but also to the movements and dispersion of the firm-level production forecast errors.

Sixth, the higher the volatility of actual production in the recent past, the greater the future production uncertainty, suggesting that the production volatility frequently used in the literature is a good proxy of uncertainty.

Seventh, forecast uncertainty of Japanese manufacturing firms is associated with the movements of newspaper based indices of policy uncertainty (EPU). The relationships are found not only with Japan's own policy uncertainty (EPU–Japan) but also 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 developments.

Although this study is unique in its use of high-frequency firm-level data on production forecasts and realizations, there are obviously many limitations. The period of analysis is limited to about ten years due to data availability. The period includes extraordinary shocks, such as the World Economic Crisis and the Great East Japan Earthquake, which is, in some sense, desirable when analyzing production uncertainty; however, the results may be partly driven by these special events. Analysis using longer time-series is left for future research. In addition, the industry coverage of this study is limited to the manufacturing sector, but it is desirable to cover the non-manufacturing sector, such as wholesale and retail industries, under a trend toward the service economy. In this respect, it is expected for the governments' statistical agencies to develop and to conduct monthly firm survey on the production forecast of service firms.

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Table 1. Forecasted, Estimated, and Realized Production Quantities in the Survey of Production Forecast

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

	Nobs.	Mean	Std. Dev.	Median
$error_{it}$	102,051	-0.0235	0.2105	-0.0069
$absfe_{it}$	102,051	0.1332	0.1647	0.0742

Note: $error_{it}$ and $absfe_{it}$ denote forecast errors and absolute forecast errors calculated from the forecasted and realized productions at the firm-level.

Table 3. Production Forecast Uncertainty Aggregated by Industry and Type of Product

	(1) MEANABSFE	(2) FEDISP	(3) Nobs.
Manufacturing	0.1331	0.2104	102,281
1 Iron and steel	0.1178	0.1938	6,914
2 Non-ferrous metal	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 in any type, the sum of the observations by type of product (1 to 6 of the lower part of this table) falls short of the observations in whole manufacturing.

Table 4. Production Forecast Errors by Producer Size

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

	(1) Small	(2) Large	(3) (2)-(1)	
Manufacturing	-0.026	-0.021	0.005	***
1 Iron and steel	-0.020	-0.015	0.005	
2 Non-ferrous metal	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	

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

	(1) Small	(2) Large	(3) (2)-(1)	
Manufacturing	0.150	0.119	-0.030	***
1 Iron and steel	0.146	0.094	-0.053	***
2 Non-ferrous metal	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	***

Note: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. 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.

Table 5. Elasticities of Forecast Errors with Respect to Producer Size

	(1) $error_{it}$		(2) $absfe_{it}$	
SIZE	0.0047	***	-0.0209	***
	(0.0006)		(0.0005)	
Nobs.	102,281		102,281	
Adjusted R^2	0.0044		0.0572	

Notes: The size of a producer (SIZE) is the difference between a firm's production quantity and the mean quantity of the firms in the same product (both expressed in natural logarithms). *** indicates statistical significance at the 1% level.

Table 6. Production Forecast Errors by Business Cycle Phase

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

	(1) Expansion	(2) Contraction	(3) (2)-(1)	
Manufacturing	-0.015	-0.053	-0.038	***
1 Iron and steel	-0.006	-0.055	-0.049	***
2 Non-ferrous metal	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	**

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

	(1) Expansion	(2) Contraction	(3) (2)-(1)	
Manufacturing	0.128	0.152	0.024	***
1 Iron and steel	0.112	0.139	0.027	***
2 Non-ferrous metal	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: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7. Granger Causality Test from Production Forecast Uncertainty to the IAA

A. Two Variables VARs

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

B. Three variables 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 publicly available aggregated series of the Indices of Production Forecast. The IAA and IIP are seasonally adjusted series. *** and ** indicate statistical significance at the 1% and 5% levels, respectively.

Table 8. Volatility of Production and Forecast Errors (Panel Estimation Results)

	(1)	(2)	(3)	(4)
	$error_{it}$	$error_{it}$	$absfe_{it}$	$absfe_{it}$
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. *** indicates statistical significance at the 1% level. 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 twelve months.

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

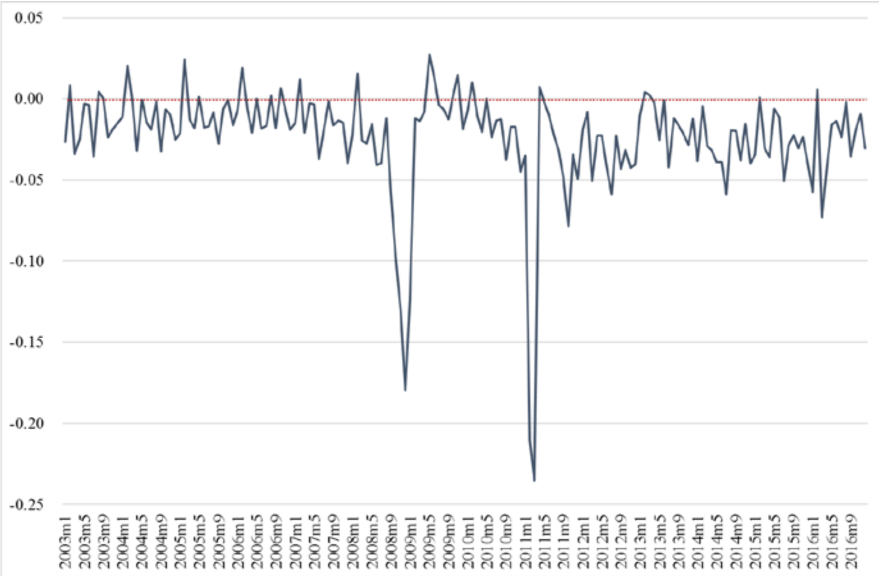
Notes: Fixed-effects estimation results with standard errors in parentheses. *** indicates statistical significance at the 1% level. The dependent variable is the firm-level absolute forecast errors ($absfe_{it}$). The EPU Indices are constructed by Baker *et al*. (2016).

Table 11. Correlation Coefficients between Production Uncertainty and the EPU Indices by Industry and Type of Product

	(1)	(2)	(3)	(4)	(5)	(6)
	MEANABSFE			FEDISP		
	EPU-Japan	EPU-Global	EPU-US	EPU-Japan	EPU-Global	EPU-US
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 metal	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

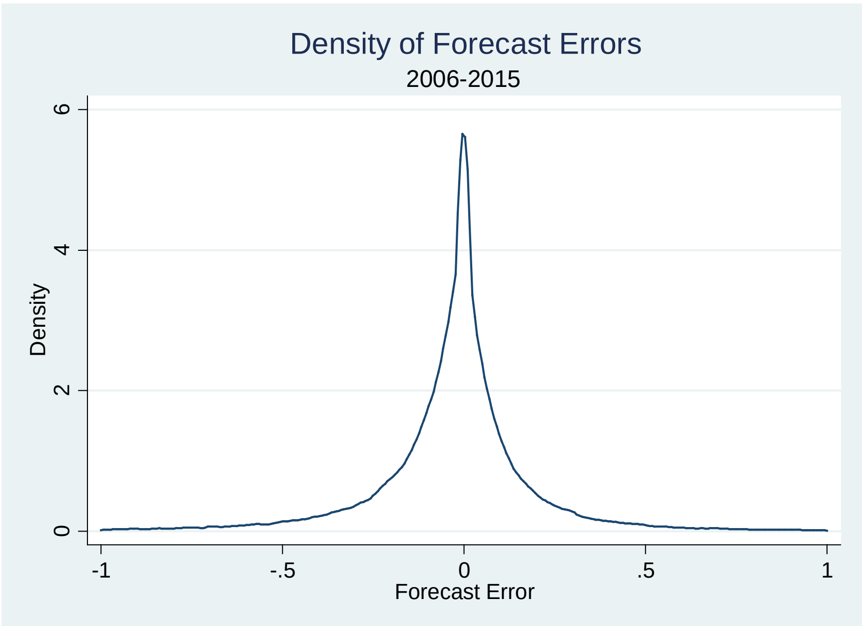
Note: The EPU Indices are constructed by Baker *et al*. (2016).

Figure 1. Production Forecast Errors at the Aggregate Level



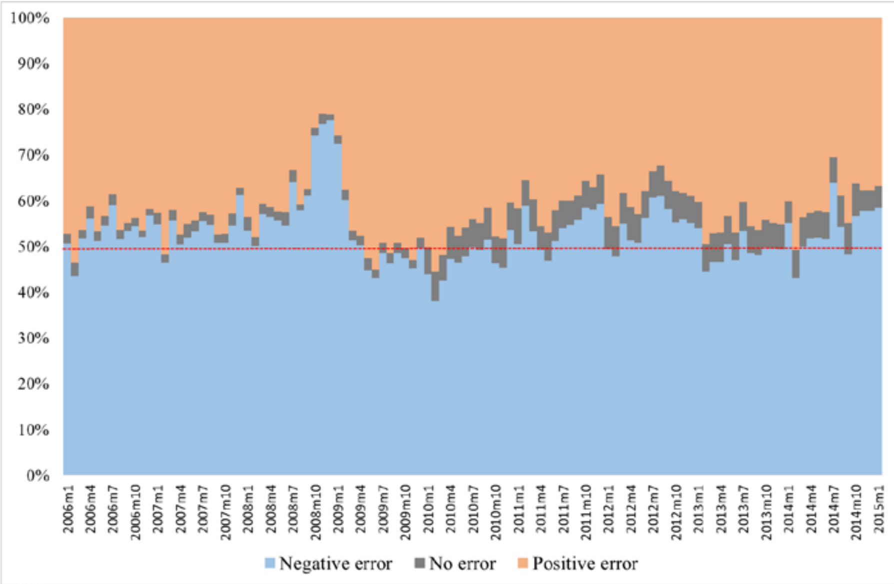
Note: The figure is constructed from publicly available aggregated series of the Indices of Production Forecast.

Figure 2. Distribution of the Forecast Errors ($error_{it}$)



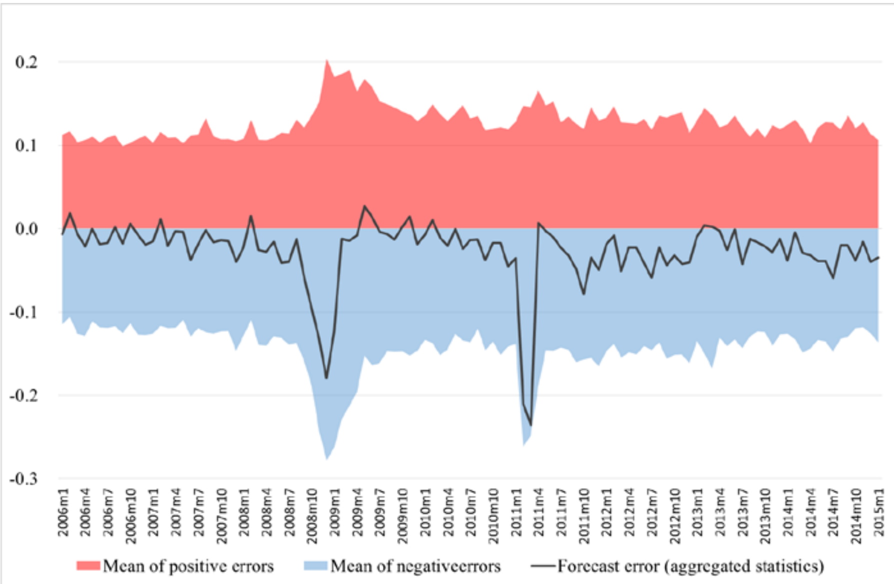
Notes: The figure is drawn from the micro data of the Survey of Production Forecast. Firm-level forecast errors ($error_{it}$) are calculated as $\ln(q_{it}) - \ln(E(q_{it}))$. The observations with the absolute value of $error_{it}$ exceeds unity are treated as outliers and removed from the sample.

Figure 3. Composition of Firms with Positive, No, and Negative Errors



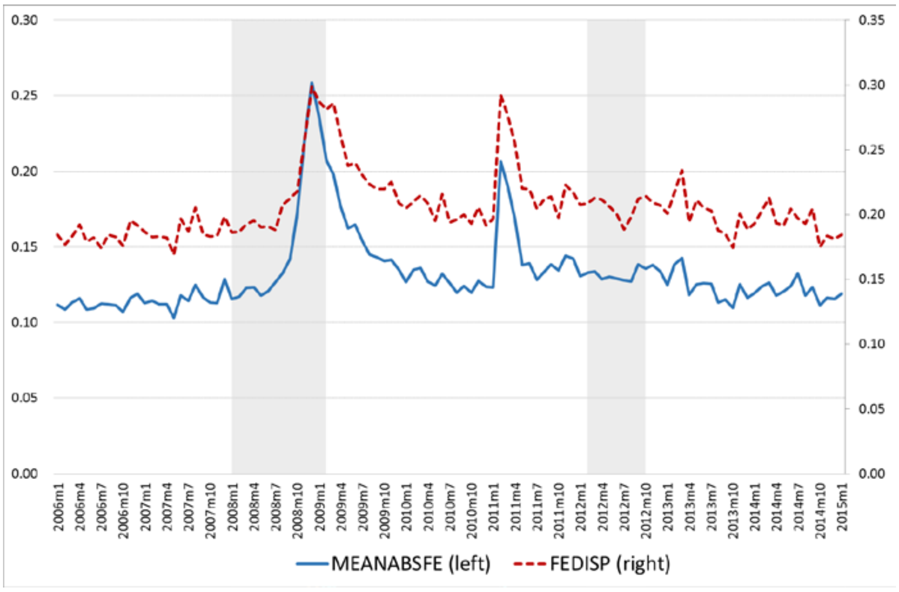
Note: Positive (negative) error means realized production quantity larger (smaller) than the forecast.

Figure 4. Mean Forecast Errors at the Micro and Macro Levels



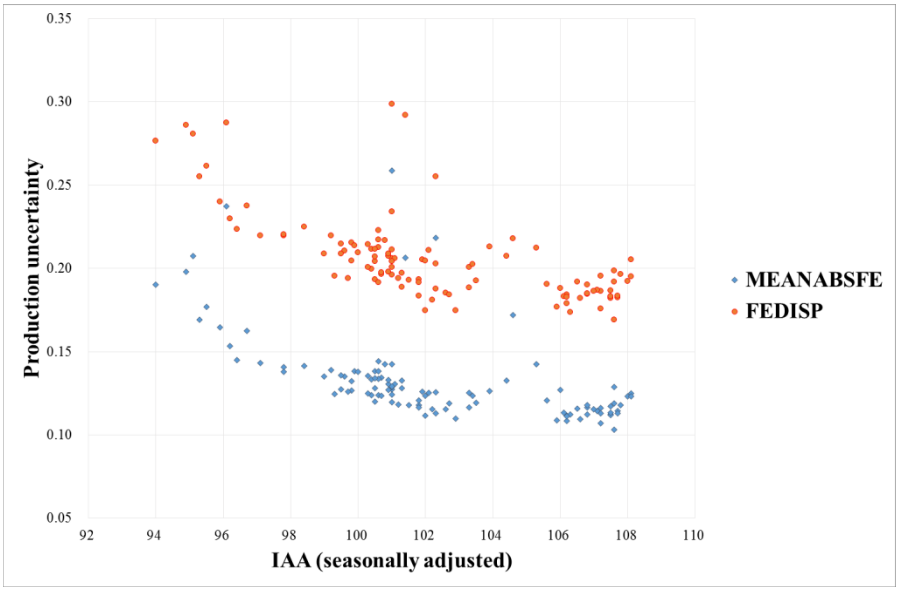
Note: The means of positive errors (in red) and negative errors (in blue) are calculated separately.

Figure 5. Movements of Production Uncertainty Measures for the Whole Manufacturing Sector



Note: Shaded areas indicate contractionary periods.

Figure 6. Indices of All Industry Activity (IAA) and Production Uncertainty



Note: The Indices of All Industry Activity (METI) 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. *** indicates statistical significance at the 1% level. Volatility, the dependent variable, is calculated as the coefficient of variation (standard error divided by the mean) of production quantity during the past twelve 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	**

Notes: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The EPU Indices are constructed by Baker *et al.* (2016).