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Extracting Firms' Short-Term Inflation Expectations from the Economy Watchers Survey Using Text Analysis*

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Abstract

This paper discusses the Price Sentiment Index (PSI), a quantitative indicator of firms' outlook for general prices proposed by Otaka and Kan (2018). The PSI is developed from the textual data of the Economy Watchers Survey conducted by the Cabinet Office; it is computed by extracting firms' views from survey comments, using text analysis. In this paper, we revisit the PSI and quantitatively analyze the determinants of changes in the PSI and the relationship between the PSI and macroeconomic variables. We also address a shortcoming in the text analysis used for computing the PSI that we discover when examining the performance of the PSI since the COVID-19 outbreak. The results of our analyses show that the PSI tends to precede consumer prices by several months and that it reflects various factors affecting price developments, including demand factors associated with the business cycle and cost factors such as changes in raw materials prices and exchange rates. Our analysis suggests that the PSI is a useful monthly indicator of inflation expectations, in that it captures the price-setting stance of firms responding to the Economy Watchers Survey. While the PSI is subject to large short-term fluctuations, it can be used to complement other indicators used for the analysis of price developments such as the output gap, existing indicators of inflation expectations, and anecdotal information from various sources.

JEL classification: C53, C55, E31, E37.
Keywords: Inflation Expectations, Machine Learning, Text Analysis, Big Data.

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1. Introduction

Inflation expectations are a key variable affecting macroeconomic outcomes and in recent years have attracted attention in both theoretical and empirical research. Significant progress has been made in the study of households' and market participants' inflation expectations, reflecting the accumulation of related data. On the other hand, there has been relatively little progress in the study of firms' inflation expectations, partly reflecting the paucity of relevant data. Firms are price setters and their inflation expectations are conventionally regarded as a critical variable that affects price developments by shifting the Phillips curve. Some recent studies suggest that firms form their inflation expectations through a different mechanism than households and investors.[1] Meanwhile, some central banks have been conducting surveys to capture firms' inflation expectations and/or have econometrically estimated the contribution of inflation expectations to macroeconomic fluctuations.[2]

In Japan, developments in firms' inflation expectations have primarily been tracked by the forecast diffusion index (DI) for changes in output prices and the inflation outlook of enterprises (one, three, and five years ahead) in the Bank of Japan's *Tankan* (Short-Term Economic Survey of Enterprises in Japan). Of these, the forecast DI for changes in output prices has been compiled for decades, thus providing long-term times series data that have long been used to monitor firms' inflation expectations. Another indicator of firms' inflation expectations is the Price Sentiment Index (PSI) proposed by Otaka and Kan (2018) in the *Bank of Japan Working Paper Series*. The PSI is a quantitative indicator of firms' views regarding the outlook for prices extracted from respondents' comments in the *Economy Watchers Survey* (EWS, hereafter) conducted by the Cabinet Office, using text analysis.

The PSI has the following advantages. First, it is timely, since the EWS is a monthly survey and its results are released early in the following month. Second, the PSI can be computed back to January 2000, meaning that it provides sufficiently long time series data to allow for quantitative analyses. Third, the PSI reflects the views of EWS respondents, who hold jobs that enable them to closely watch developments in economic activity, in particular, of households. Fourth, the PSI tends to lead consumer prices by several months.

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[1] See, for example, Kumar et al. (2015), Coibion, Gorodnichenko, and Kamdar (2018), and Coibion, Gorodnichenko, and Kumar (2018). Studies examining Japanese firms' inflation expectations include Uno et al. (2018a,b), Inatsugu et al. (2019), and Kitamura and Tanaka (2019).

[2] In the United States, the Federal Reserve Bank of Atlanta began conducting the *Business Inflation Expectations* survey in 2011, which surveys businesses managers. Examples of long-standing surveys asking firms for their expectations of the economy are the *Survey of Expectations* conducted by the Reserve Bank of New Zealand since 1987 and the *Business Outlook Survey* conducted by the Bank of Canada since 1997.

On the other hand, much remains to be examined regarding the PSI, including the determinants of fluctuations in the PSI, the link with macroeconomic variables, and its usefulness in forecasting consumer prices. Moreover, since the start of 2020, new terms such as "COVID-19" and "'Go To' campaign" have emerged and increased significantly in EWS respondents' comments amid the spread of COVID-19.[3] This raises the possibility that the PSI since then does not sufficiently capture future developments in prices. Based on these considerations, this paper highlights a shortcoming in the PSI computed based on the current method and addresses this shortcoming by revising the computation method. Further, it quantitatively examines the determinants of fluctuations in the PSI and the link between the PSI and macroeconomic variables.

The remainder of the paper is organized as follows. Section 2 explains how the PSI is computed using text analysis, examines developments in the PSI, and details the aforementioned shortcoming in the PSI computed based on the current method. Section 3 seeks to address the shortcoming by revising the way the PSI is computed. Section 4 analyzes the causes of changes in the PSI and the relationship between the PSI and macroeconomic variables. Section 5 concludes.

2. Methodology to compute the PSI using text analysis

2.1. The Economy Watchers Survey (EWS)

The EWS has been conducted monthly by the Cabinet Office since January 2000. The survey aims to grasp developments in Japan's economy in a timely manner. Each month, 2,050 people across Japan receive the survey and about 1,800 of them provide valid responses.[4] Survey respondents consist of "economy watchers," that is, individuals holding jobs that enable them to closely watch developments in economic activity: for example, business managers and grocery clerks. Figure 1 shows the composition of EWS respondents by industry and region. Figure 1(a) indicates that those engaged in household activity-related sectors account for about two thirds of respondents, while those working in corporate activity-related and employment-related sectors account for around 20 percent and 10 percent, respectively. This means that many of the survey respondents are engaged in industries that have a relatively close link with consumers. Meanwhile, Figure 1(b) shows that the regional distribution of survey respondents is well balanced, with respondents

[3] Note that the terms we use to refer to comments in the EWS are our translations of the comments in the Japanese original.

[4] In this paper, we use the PSI from 2001 onward for econometric analyses as the number of responses in 2000, the year the survey was started, is considerably smaller than from 2001 onward.

representing all the major regions across Japan, from Hokkaido to Okinawa.

The headline results from the EWS are the DIs for current and future economic conditions, presented in Figure 2. They are calculated using each respondent's assessment of current or future economic conditions on a scale comprising five categories ranging from, e.g., "better" to "worse." The DI for current economic conditions has been regarded as a timely and useful indicator for assessing economic activity, as it shows some correlation with other macroeconomic indicators that capture economic developments.

The EWS is unique in that it collects not only respondents' assessment of economic conditions on a scale as just described but also their comments giving reasons for their assessment. Examples of such comments are provided in Table 1. On average, approximately 1,100 of the about 1,800 respondents in each survey provide comments on their economic assessments. These comments are organized and released as textual data on the Cabinet Office's website.[5] Such data in the release for each survey consist of about 100,000 words in total and around 3,000 unique words, and can therefore be regarded as big data. The PSI is derived from this big textual data and is computed by extracting and quantifying information regarding price developments from the data, using text analysis.[6] The specific methods for computing the PSI are presented in the next subsection.

2.2. Computing method for the PSI

When respondents provide comments giving the reasons for their economic assessments in the EWS, they sometimes also refer to consumers' spending stance and to developments in prices such as commodity prices. The PSI is designed to capture developments in the difference between the share of comments implying inflation and the share of comments implying deflation by classifying comments.

Specifically, survey comments are classified into the following four types:

A. Comments implying inflation

B. Comments implying deflation

C. Comments implying zero inflation (neither inflation nor deflation)

D. Comments not referring to price developments

Manually screening the over 1,000 comments received in each survey to classify them into these four types would require considerable time and effort. Moreover, such manual

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5 Note that the textual data we mention here is in Japanese.

6 An example of a study analyzing the textual data of the EWS is that by Goshima et al. (2021).

classification could result in incorporating the analysts' subjective views into the PSI. Therefore, for computing the PSI, comments are automatically classified into the four types based on the terms contained in each comment. This is done using machine learning.

Specifically, before the automatic classification, selected terms are assigned scores indicating to which type a comment containing the term is likely to belong. The procedure starts by randomly extracting 1,500 sample comments from the EWS during the period 2001–2017. Each of these comments is then manually examined and classified into one of the four types (A to D). This process is essential for the text analysis to compute the PSI, although it leaves some room for analysts' subjective views to be incorporated into the index. To minimize such potential bias to the greatest extent possible, in this process, comments in which respondents' views on price developments appear to be ambiguous are classified as type D.

The sample comments and their classification results are then used as supervised training data to train the machine learning algorithm. This is shown as Step 1 in Figure 3, which provides an illustration of the procedure used for computing the PSI. In this step, the training data and the Naïve Bayes classifier are used to estimate scores for the terms in the sample comments. Specifically, each sample comment is inputted into the classifier so as to obtain the optimal term scores yielding the "correct" output, that is, the same classification result as that obtained from the manual classification. A key variable in the estimation is the relative frequency with which a term appears in each type of comment A to D. For example, if the term "pass on" appears more frequently in comments implying inflation (type A) than in comments implying deflation (type B), this means that the score of "pass on" for type A is larger than that for type B. Given this, term scores can be interpreted as measures gauging the marginal increase in the likelihood of a comment being classified as a certain type if the comment contains the term.[7]

Using the estimated term scores, comments from each survey are classified into types A to D. In Figure 3, this is shown as Step 2, where comments are classified into the type that received the highest score based on the terms contained in the comment. Finally, for each survey, the PSI is calculated as the share of comments implying inflation (type A) minus the share of comments implying deflation (type B). Specifically, the PSI is defined as follows:

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[7] It should be noted that the score also depends on the number of comments classified into each type in the manual classification. For a detailed description of the Naïve Bayes classifier, see, for example, Murphy (2012).

$$\mathrm{PSI} = \frac{\text{Number of type A comments} - \text{Number of type B comments}}{\text{Total number of type A, B, and C comments}}$$

In the remainder of this paper, we use the PSI data normalized by the mean and standard deviation for the period 2000–2019. While the PSI is computed separately for comments on current economic conditions and on future economic conditions, the following analyses use the PSI based on comments on current economic conditions. We also conducted the analyses using the PSI based on comments on future economic conditions and found that results do not change significantly.

2.3. Developments in the PSI

In this subsection, we examine developments in the PSI computed using the method described in the previous subsection (we will refer to this as the broad-based PSI hereafter). As shown in Figure 4(a), developments in the broad-based PSI clearly differ from those in the current economic conditions DI. For example, around 2007–2008, when commodity prices were surging, the current economic conditions DI declined due to concerns over a decrease in profits, whereas the broad-based PSI rose, clearly reflecting the rise in raw materials prices. Around 2008–2009, on the other hand, the broad-based PSI fell substantially in tandem with the current economic conditions DI amid the significant decline in demand both at home and abroad due to the impact of the global financial crisis. These findings suggest that developments in the PSI are significantly affected by changes in demand due to the business cycle and also by cost factors such as commodity price changes.

Figure 4(b) presents developments in the PSI and the year-on-year rate of change in the consumer price index (CPI, all items less fresh food and energy). As can be seen in the figure, developments in the PSI appear to somewhat precede those in the CPI inflation rate. This visual impression is confirmed when we estimate simple lead-lag correlation coefficients between the two indexes for the period through the end of 2019.We find that the correlation coefficient between the PSI and the seasonally adjusted quarter-on-quarter rate of change in the CPI is largest – taking a value of 0.54 – when the PSI leads the CPI inflation rate by one month. We further find that the correlation coefficient between the PSI and the year-on-year rate of change in the CPI is largest – taking a value of 0.76 – when the PSI leads the CPI inflation rate by seven months.

However, from the start of 2020, this relationship between the broad-based PSI and the CPI appears to break down. Unlike the CPI inflation rate, the PSI registered a relatively substantial rise during the COVID-19 pandemic. This seems to be largely due to the fact that since the PSI was originally developed in 2018, new terms such as "COVID-19" and "'Go

To' campaign" have emerged and increased in number in the EWS comments. Although terms such as "virus" and "campaign" appeared in survey comments collected before the COVID-19 outbreak, the sense in which they were used partly differs from that since the COVID-19 pandemic.

This matters because of the scores assigned to the terms for computing the broad-based PSI. For instance, "virus" was assigned a relatively high score for type A price changes (pointing to inflation). This means that the rise in the PSI during the pandemic partly reflects the increase in the number of comments referring to the "coronavirus." The term "campaign" was also assigned a high score for type A price changes, meaning that mentions of the "'Go To' campaign" push up the PSI. Given that the term scores are based on data prior to the outbreak of COVID-19, they may not sufficiently reflect price conditions today under the pandemic. For example, while a discount on hotel charges through the "Go To Travel" campaign directly pushes down consumer prices in the short run, mentions of the term "campaign" push up the broad-based PSI, pointing to inflation, due to the scores assigned to the term based on pre-pandemic textual data.

Examining developments in the broad-based PSI, we find that the PSI may not sufficiently capture future price developments when the use of new terms increases significantly. Therefore, the pandemic has revealed a shortcoming in the text analysis used for computing the PSI. To address this shortcoming, we revise the computation method for the PSI.[8]

3. Revision of the computation method for the PSI

3.1. Methodology

The broad-based PSI is based on around 3,000 terms that are assigned scores. We find that the relationship of some of these terms with the direction of prices is unclear, and that others appear in the comments only for a certain period. When the PSI is significantly affected by such terms, the change in the index can be difficult to interpret and the relationship between the PSI and the underlying trend in prices may break down.

To improve the PSI, we narrow down the list of 3,000 terms to those satisfying the following criteria: terms (1) that on average appear at least five times a month during the

[8] As one potential approach to revising the computation method for the PSI, we considered simply extending the period used for extracting sample comments to incorporate data up to the most recent month for which data are available. However, we found that currently the number of observations is too small to link new terms such as "COVID-19" with a particular direction of prices, so that we need to wait for more data to become available.

period 2001–2019, (2) that can be regarded as indicating a clear direction in prices and economic activity, and (3) whose number of appearance is correlated with the actual inflation rate in that the sign of that correlation matches the direction of prices and economic activity with which one would associate the term. For example, the term "sale" meets criterion (1), but the term "campaign" does not because it only appears in the comments for a certain period. While criterion (2) involves some judgement in the selection of terms, we find that there are terms that clearly imply the direction of prices, such as "raising prices," and terms that do not necessarily suggest such direction, such as "unit price." Finally, an illustration of criterion (3) is that, a priori, one would expect the correlation between the CPI inflation rate and the number of times the term "rise" appears to be positive.

Among the terms satisfying the above criteria, we search the combination of terms that yields the highest correlation coefficient with the year-on-year rate of change in the CPI (all items less fresh food and energy). Using this optimization process, we obtain 20 terms to compute a new PSI.[9] Having referred to the PSI developed based on the original method as the broad-based PSI, we call the PSI built using these 20 terms the narrow-based PSI.

3.2. Developments in the narrow-based PSI

Next, we compare developments in the narrow-based PSI with those in the broad-based PSI. As shown in Figure 4(b), developments in the narrow-based PSI are generally similar to those in the broad-based PSI for the period through the end of 2019. However, unlike the broad-based PSI, which rose in early 2020, the narrow-based PSI declined in the March–May period and since then, despite some fluctuations, has been around the same level as in 2019. To investigate the link between the broad- and the narrow-based PSI on the one hand and the CPI inflation rate on the other, we calculate the lead-lag coefficients for the period from January 2010 through December 2020. In terms of the correlation with the year-on-year rate of change in the CPI for all items less fresh food and energy, the largest coefficient we obtain for the broad-based PSI is 0.75 (when it leads the CPI by 8 months), while the largest coefficient for the narrow-based PSI is 0.80 (when it leads the CPI by 10 months). In terms of the correlation with the year-on-year rate of change in the CPI for all items less fresh food (i.e., including energy), the largest coefficient for the broad-based PSI is 0.61 (when it leads the CPI by 3 months), while the largest coefficient for the narrow-based PSI

[9] The selected terms are as follows: rise; good; high; exceed; price increase; raising prices; surge; stable; decline; bad; cheap; low; price cut; fall; sluggish; deteriorate; decrease; severe; competition; and sale. We note that we end up with the same set of terms when we search the combination of terms that yields the largest correlation coefficient vis-à-vis the year-on-year rate of change in the CPI for all items less fresh food (i.e., including energy).

is 0.71 (when it leads the CPI by 3 months). Therefore, in both cases, the largest coefficient for the narrow-based PSI is larger than the largest coefficient for the broad-based PSI.

These findings suggest that the narrow-based PSI provides a better indicator which robustly tends to lead the CPI than the broad-based PSI when the economy and prices enter a new phase and the use of new terms increases in the EWS comments. That said, since the number of terms on which the narrow-based PSI is based is limited to 20, it potentially fails to incorporate the implications of a number of comments that are covered by the broad-based PSI. In sum, both the broad-based and narrow-based PSIs have advantages and disadvantages depending on the circumstances. Therefore, from a practical perspective, monitoring developments in both PSIs is desirable.

In what follows, we quantitatively analyze the empirical properties of the narrow-based PSI. We note that conducting the same analysis for the broad-based PSI yields qualitatively similar results.

4. The PSI as a proxy for short-term inflation expectations

4.1. The link between the PSI and economic indicators

Figure 5 presents developments in the PSI and in the Tankan DIs for all industries and enterprises. We find that the PSI has a high correlation with the DIs for output prices, for input prices, and for domestic supply and demand conditions. This suggests that the PSI reflects not only firms' price-setting behavior but also firms' perceptions of their demand conditions and input costs. Table 2(a) shows that the correlation coefficients between the PSI and these Tankan DIs, at over 0.8, are high, and that the coefficients are all – albeit slightly – higher for the forecast DI (one quarter ahead) than for the actual DI. This suggests that the PSI provides a useful proxy for short-term inflation expectations that captures firms' price-setting stance for the period ahead rather than their present price-setting stance. This is also consistent with the earlier finding that the PSI somewhat leads the inflation rate. Figure 6 and Table 2(b) provide further support: they suggest that the PSI shows some correlation with firms' one-year-ahead outlook for both general prices and output prices reported in the Tankan. These findings suggest that the PSI is closely linked with macroeconomic variables that affect price developments.

4.2. The link between the PSI and consumer prices

In this subsection, we examine whether the PSI provides unique information such that it complements information on the output gap and other conventional macroeconomic variables for the forecasting of inflation. Specifically, we conduct regression analyses using the one-quarter-ahead inflation rate as the dependent variable. In this analysis, we first estimate a regression equation using the exchange rate and the output gap as independent variables. We then add the PSI as an independent variable to the equation and examine how the regression results change as a result. The inflation rate is measured in terms of the year-on-year rate of change in the CPI (all items less fresh food and energy, excluding the effects of the consumption tax hikes), while for the exchange rate the year-on-year rate of change in the nominal effective exchange rate is used. The output gap is estimated by the Bank of Japan's Research and Statistics Department. The estimation period for the regression is from the January–March quarter of 2001 to the October–December quarter of 2019.

The regression results are shown in Table 3. In the specification without the PSI, the coefficients on the exchange rate and the output gap are statistically significant. When the PSI is added, these coefficients remain statistically significant and the coefficient on the PSI is also significant. We further find that the explanatory power in terms of the adjusted R-squared is higher when the PSI is included. These results suggest that the PSI appears to capture additional information relevant for changes in the inflation rate not captured by the output gap and the exchange rate. It should be noted that we obtain similar results when adding crude oil prices as an independent variable or replacing the exchange rate with import prices.

Next, we employ a vector autoregression (VAR) model to examine the relationship between the PSI and macroeconomic variables including the inflation rate. In this estimation, we use four variables: the nominal effective exchange rate (quarter-on-quarter change); the output gap; the PSI; and the CPI (all items less fresh food and energy; seasonally adjusted quarter-on-quarter change). We identify shocks using Cholesky decomposition, with the variables ordered as above.[10] The estimation period is from the January–March quarter of 2001 to the October–December quarter of 2019. Based on the Akaike information criterion (AIC), the lag length is set to two quarters.

Figure 7 shows the impulse responses of the VAR model. Figure 7(a) indicates that the responses of the PSI to an exchange rate shock and an output gap shock are statistically

[10] The variables are ordered from the most exogenous to the least exogenous one. This reflects our assumptions regarding the nature of the quarterly shock to each variable. Specifically, we assume that, during the same quarter, (1) an exchange rate shock may affect all the other variables, (2) an output gap shock may influence firms' inflation expectations (the PSI) and the actual inflation rate (the CPI), and (3) a PSI shock may have an impact on the CPI. A shock to the CPI here is assumed to have no impact on the PSI during the same quarter. It should be noted that even if we change the order of the PSI and the CPI by assuming that a CPI shock in this ordering may affect the PSI during the same quarter, we obtain qualitatively the same impulse responses of the variables as presented below.

significant. The PSI reacts to an exchange rate shock almost contemporaneously and to an output gap shock with a lag of about 3–4 quarters. This implies that the PSI is closely related to the macroeconomic variables which affect the inflation rate.

Turning to Figure 7(b), we further find that the response of the inflation rate to a PSI-specific shock is statistically significant. It is noteworthy that the inflation rate reacts to a PSI-specific shock with a lag of about 1–2 quarters, indicating that the PSI tends to lead the inflation rate. These results suggest that the PSI contains unique information regarding future changes in the inflation rate not captured by the exchange rate and the output gap.

Using the regression model, we now test the predictive power of the PSI for the inflation rate (i.e., the year-on-year rate of change in the CPI for all items less fresh food and energy). Specifically, we conduct one-quarter-ahead forecasting of the inflation rate for each quarter from the January–March quarter of 2012 to the October–December quarter of 2019. We start the test by estimating the regression equation using the data for the period through the October–December quarter of 2011 and then predict the inflation rate for the January–March quarter of 2012. Next, we estimate the regression equation again using the data for the period through the January–March quarter of 2012 and then forecast the inflation rate for the April–June quarter of 2012. By repeating this out-of-sample forecasting for each quarter, we obtain the predicted inflation rates for the period through the October–December quarter of 2019. Finally, we measure the accuracy of these out-of-sample forecasts by calculating the root-mean-squared error (RMSE) between the forecasts and the actual inflation rates. The bottom row of Table 3 shows the results of this forecasting exercise, which indicate that the RMSE of the specification including the PSI is about 10 percent smaller than that of the specification without the PSI.

In sum, the analyses reveal that the PSI provides additional information on changes in consumer prices over the next several months not captured by such macroeconomic variables as exchange rates and the output gap. Computed from comments by respondents to the EWS, i.e., individuals holding jobs that enable them to closely watch developments in economic activity, the PSI thus appears to be a useful proxy for firms' short-term inflation expectations.[11]

[11] Among studies using text analysis to examine inflation expectations, Guzman (2011) develops an indicator of U.S. inflation expectations using the number of Google search queries, while Angelico et al. (2021) construct an indicator of Italian inflation expectations using textual data from Twitter. Studies predicting the CPI inflation rate using text analysis include Seabold and Coppola (2015), Wei et al. (2017), and Goshima et al. (2021).

5. Concluding remarks

This paper focused on the Price Sentiment Index (PSI), a quantitative indicator of firms' outlook for general prices computed from comments provided by respondents to the Economy Watchers Survey, using text analysis. We provide empirical evidence that the PSI is a useful indicator of firms' short-term inflation expectations. Our analyses suggest that the PSI reflects demand factors associated with the business cycle and cost factors such as changes in raw materials prices and in exchange rates. While the PSI is subject to large short-term fluctuations, it does appear to be useful in capturing, on a monthly basis, the price-setting stance of firms responding to the Economy Watchers Survey. Overall, the analysis suggests that the PSI is a useful indicator to supplement existing measures for monitoring developments in inflation expectations such as the output gap, existing indicators of inflation expectations, and anecdotal information.

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Table 1. Comments by Economy Watchers Survey respondents on their assessment of economic conditions

Assessment of economic conditions	Sector (Occupation)	Comment
Slightly better	Supermarket (Store manager)	While average sales per customer remain below last year's levels, the number of customers has been picking up.
Unchanged	Job placement office (Staff)	Despite a downward trend in job openings compared with the previous year, business managers seem to struggle to fill vacancies and that there remains a sense of labor shortage in the nursing-care and construction sectors.

Note: Comments are authors' translations of the Japanese original.

Table 2. Correlation between the PSI and selected economic indicators

(a) PSI and Tankan DI

	Actual result	Forecast
DI for output prices	0.896	0.927
DI for input prices	0.860	0.903
DI for supply and demand conditions	0.832	0.841

(b) PSI and inflation outlook of enterprises (Tankan)

	1 year ahead	3 years ahead	5 years ahead
Outlook for general prices	0.644	0.612	0.571
Outlook for output prices	0.754	0.741	0.662

Note: The narrow-based PSI is used. The Tankan series are for all industries and enterprises. The estimation period in panel (a) is from the January–March quarter of 2001 to the October–December quarter of 2019, while that in panel (b) is from the January–March quarter of 2014 to the October–December quarter of 2019.

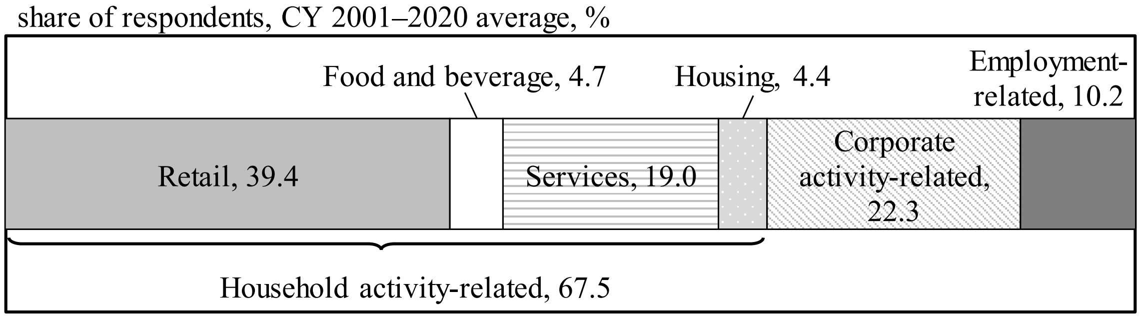
Table 3. Regression results

	Dependent variable: CPI (1 quarter ahead)	
Independent variables	Not including PSI	Including PSI
Constant	0.046 **	0.016
	(0.022)	(0.026)
CPI (current quarter)	0.868 ***	0.814 ***
	(0.037)	(0.047)
Output gap	0.066 ***	0.035 *
	(0.024)	(0.020)
Exchange rate	-0.009 ***	-0.007 **
	(0.003)	(0.003)
PSI		0.099 *
		(0.057)
Standard errors	0.201	0.194
Adjusted R-squared	0.914	0.920
RMSE	0.177	0.162

Note: The narrow-based PSI is used. "CPI (current quarter)" refers to the year-on-year rate of change in the CPI (all items less fresh food and energy, excluding the effects of the consumption tax hikes and policies concerning the provision of free education). "Exchange rate" refers to the year-on-year rate of change in the nominal effective exchange rate. The estimation period is from the January–March quarter of 2001 to the October–December quarter of 2019. Figures in parentheses are heteroskedasticity- and autocorrelation-consistent (HAC) standard errors. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively. The RMSE is computed to assess the predictive performance of the out-of-sample forecasts from the January–March quarter of 2012 to the October–December quarter of 2019.

Figure 1. Economy Watchers Survey: Composition of survey respondents

(a) By industry



(b) By region

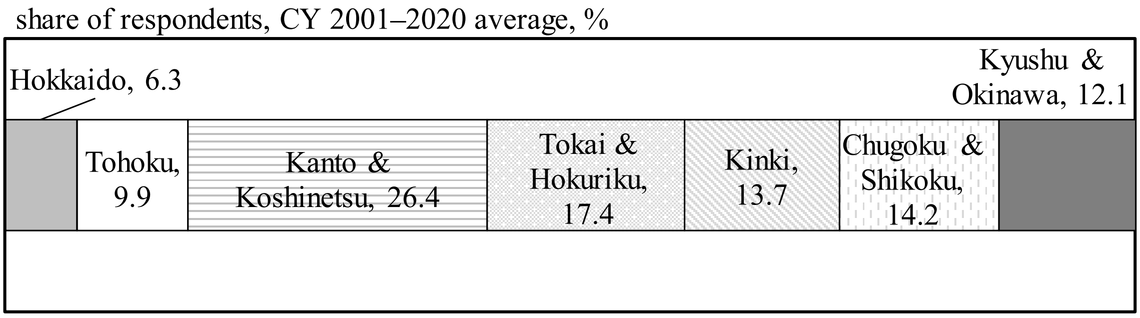


Figure 2. Economy Watchers Survey: DIs for current and future economic conditions

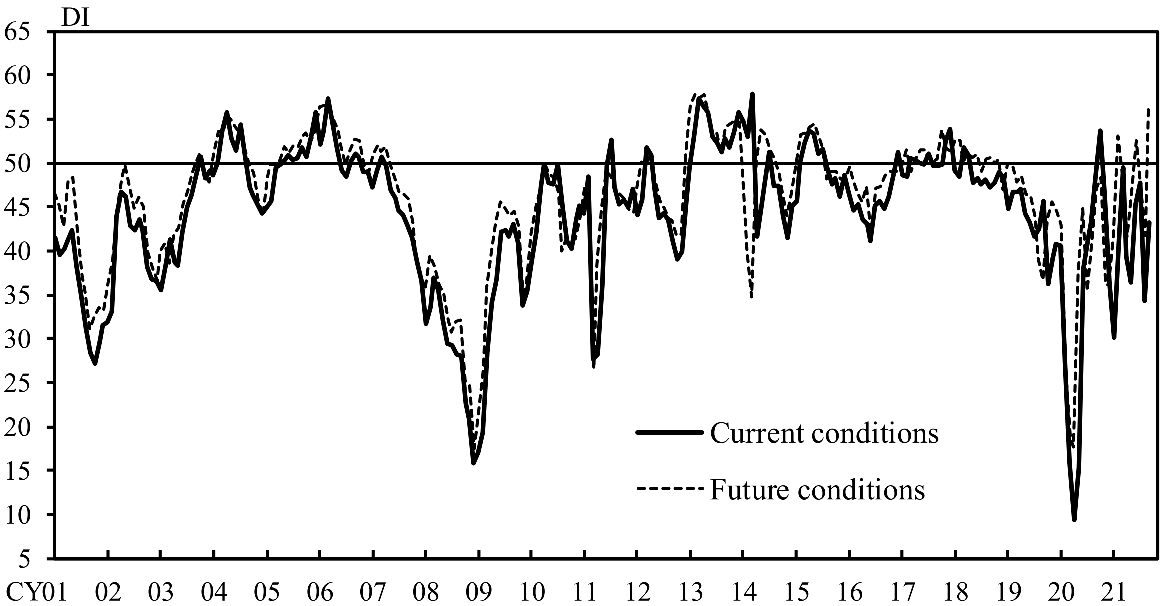


Figure 3. Computation method for the PSI using text analysis

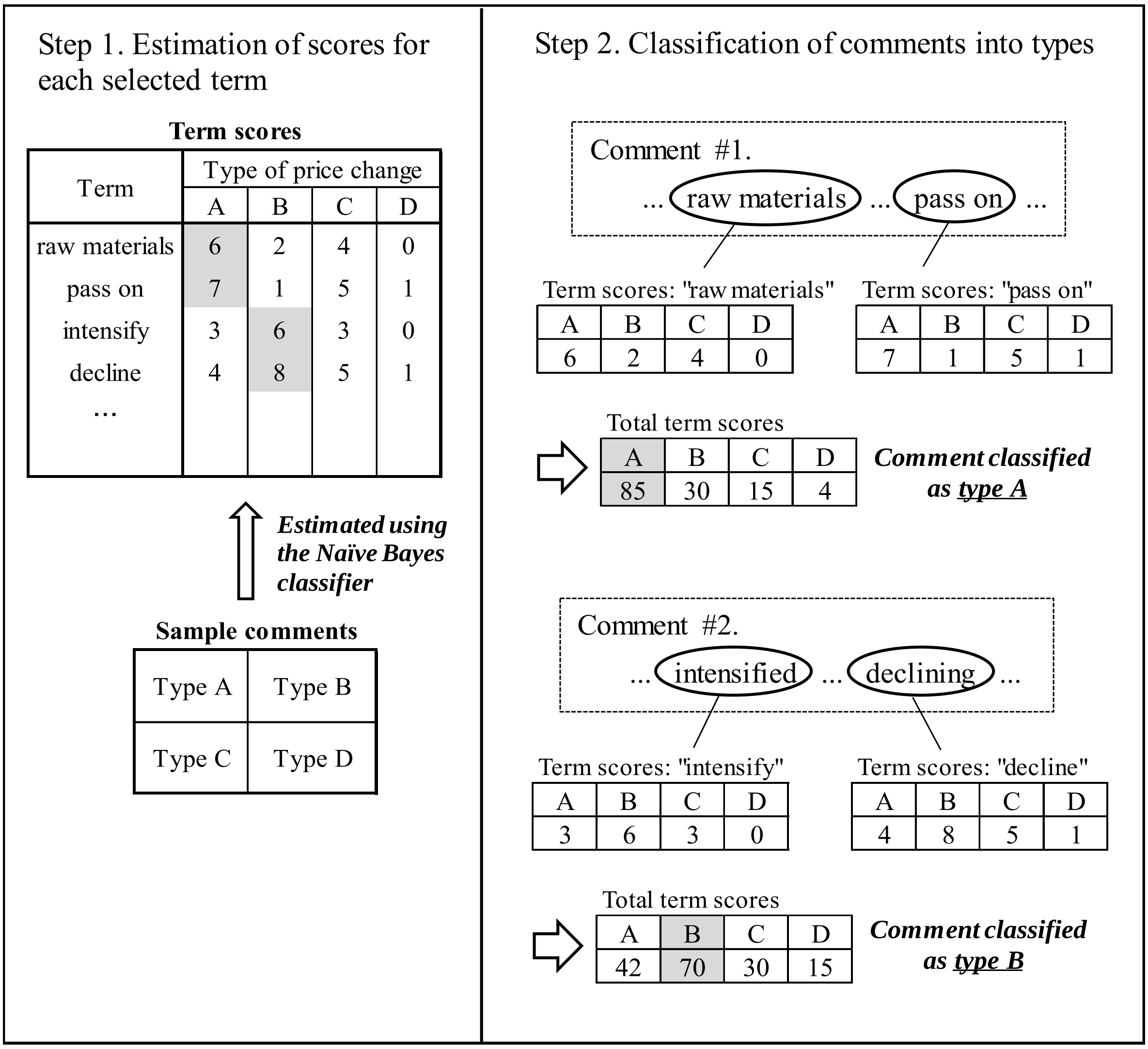
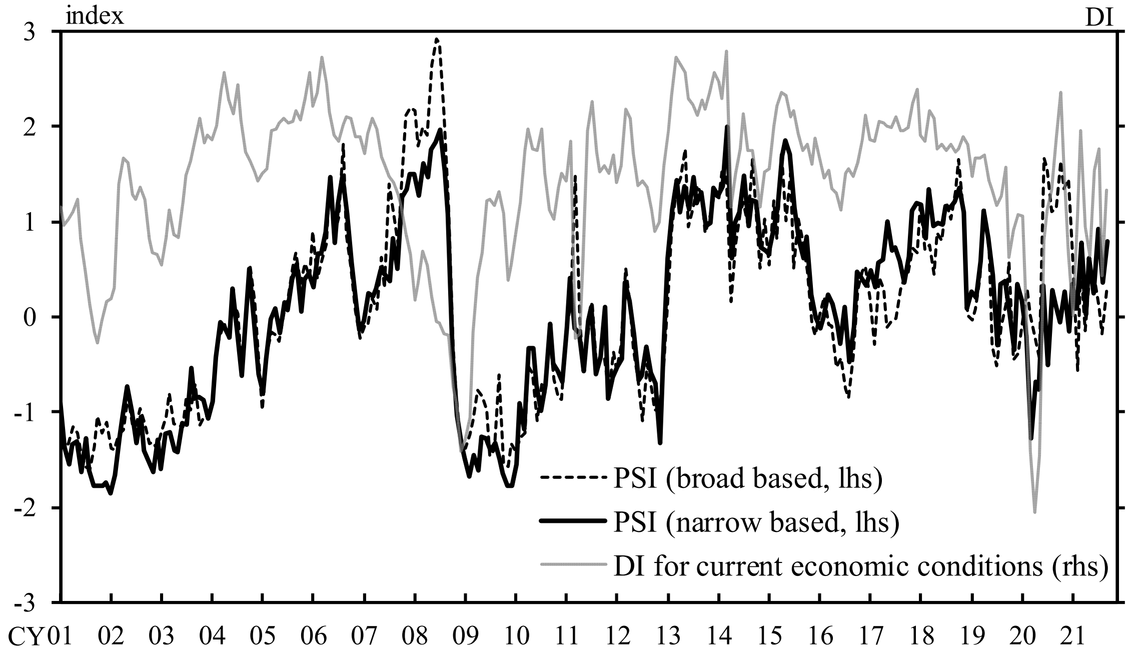
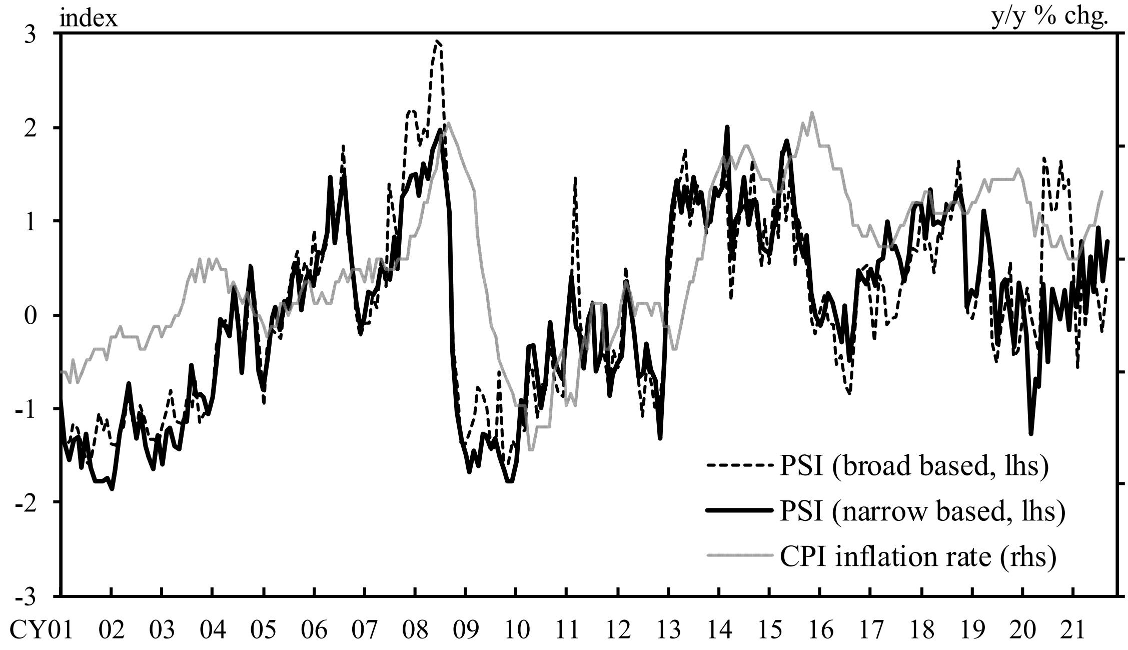


Figure 4. PSI and selected economic indicators

(a) PSI and DI for current economic conditions



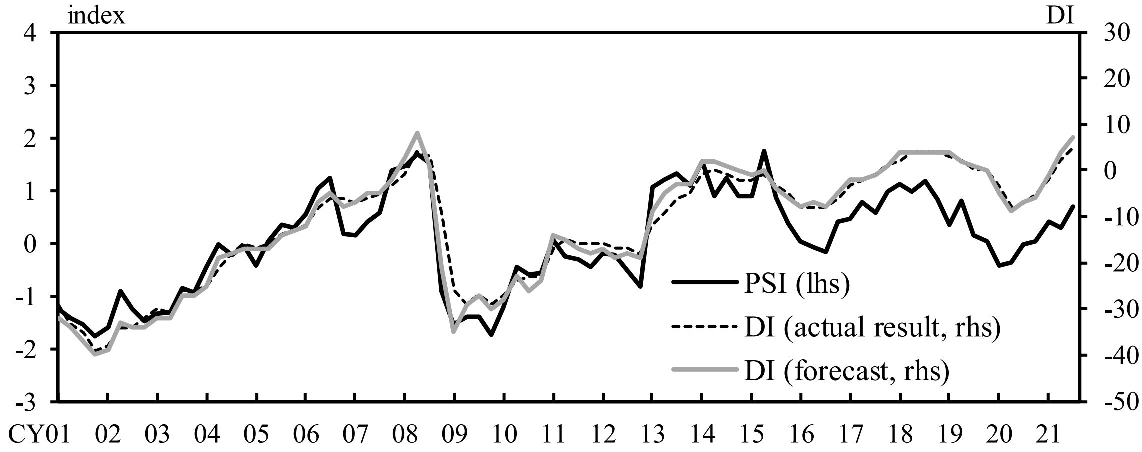
(b) PSI and CPI inflation rate



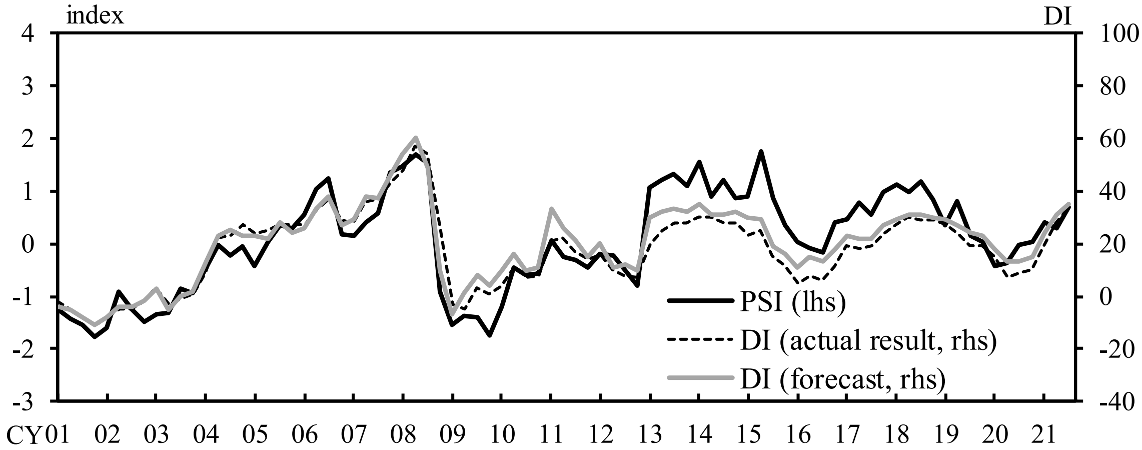
Note: The broad-based PSI is computed using Otaka and Kan's (2018) method, in which about 3,000 terms are assigned scores, while the narrow-based PSI is calculated based on 20 terms. The CPI inflation rate is for all items less fresh food and energy, excluding mobile phone charges and the effects of the consumption tax hikes, policies concerning the provision of free education, and the "Go To Travel" campaign (Bank of Japan's staff estimates).

Figure 5. PSI and Tankan DIs

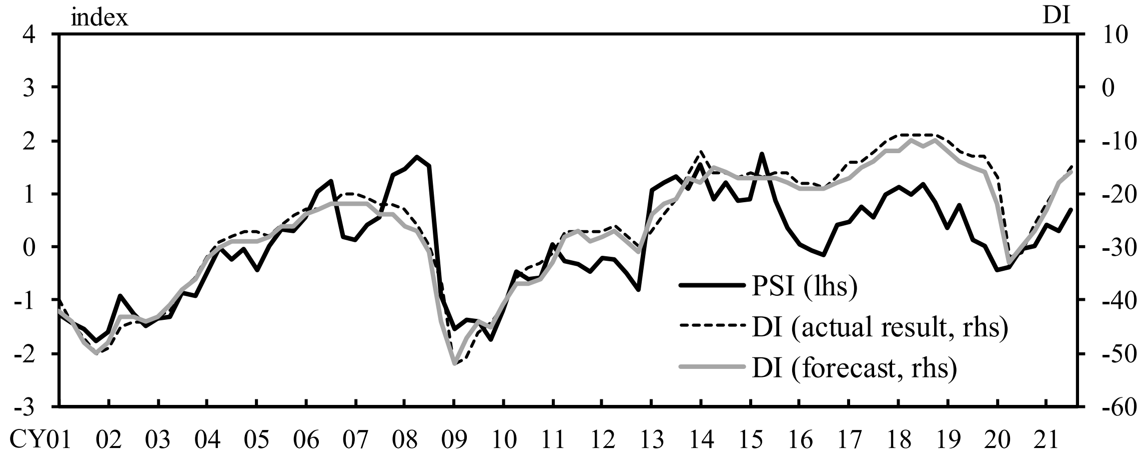
(a) PSI and DI for output prices



(b) PSI and DI for input prices

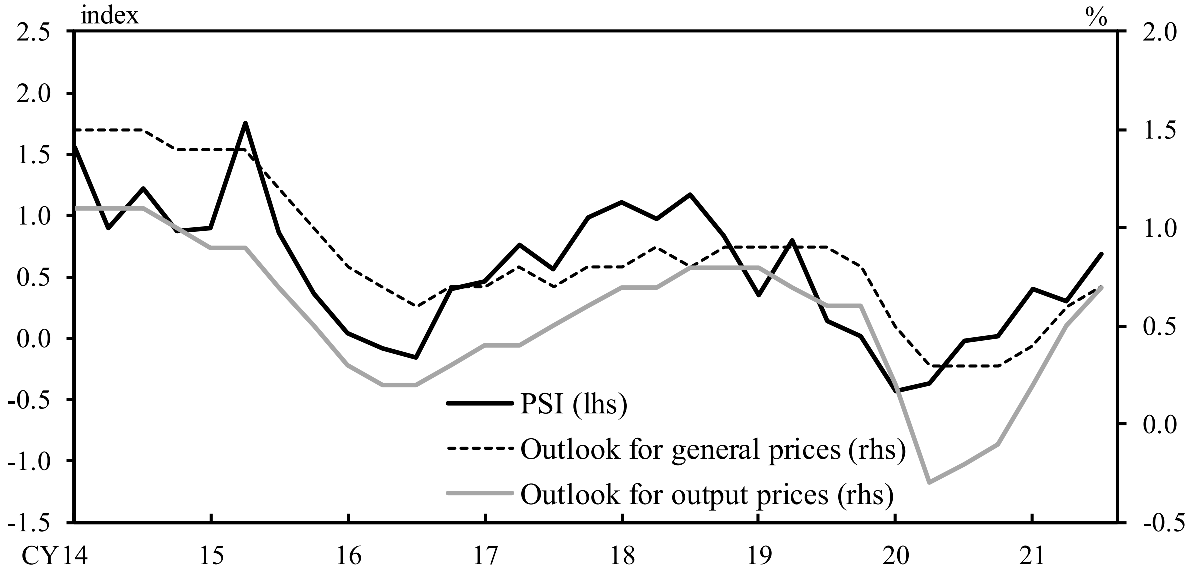


(c) PSI and DI for supply and demand conditions



Note: The narrow-based PSI is used. The Tankan DIs are for all industries and enterprises.

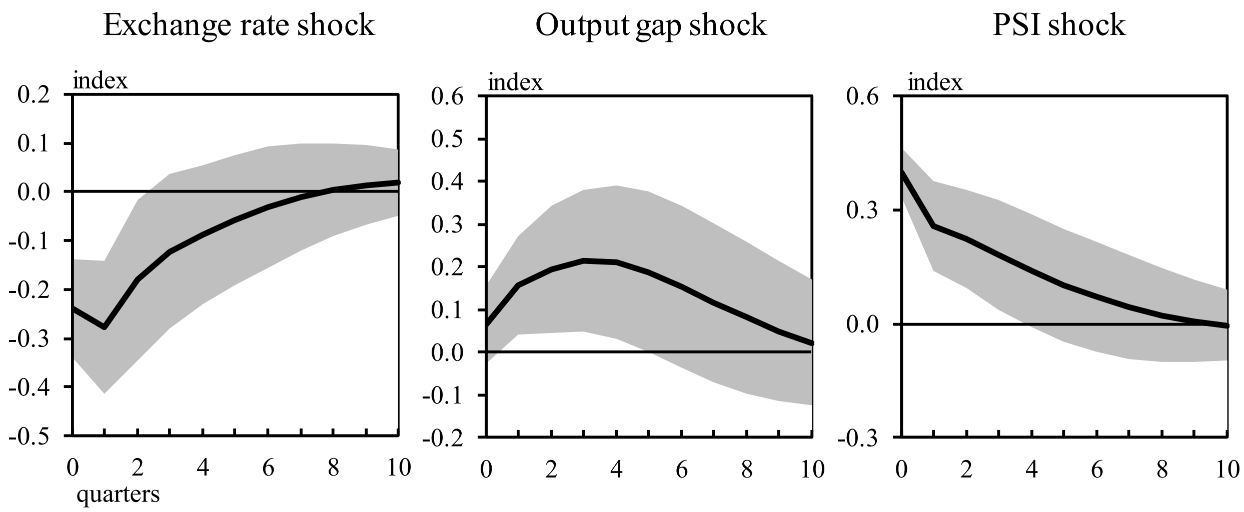
Figure 6. PSI and 1-year-ahead inflation outlook of enterprises (Tankan)



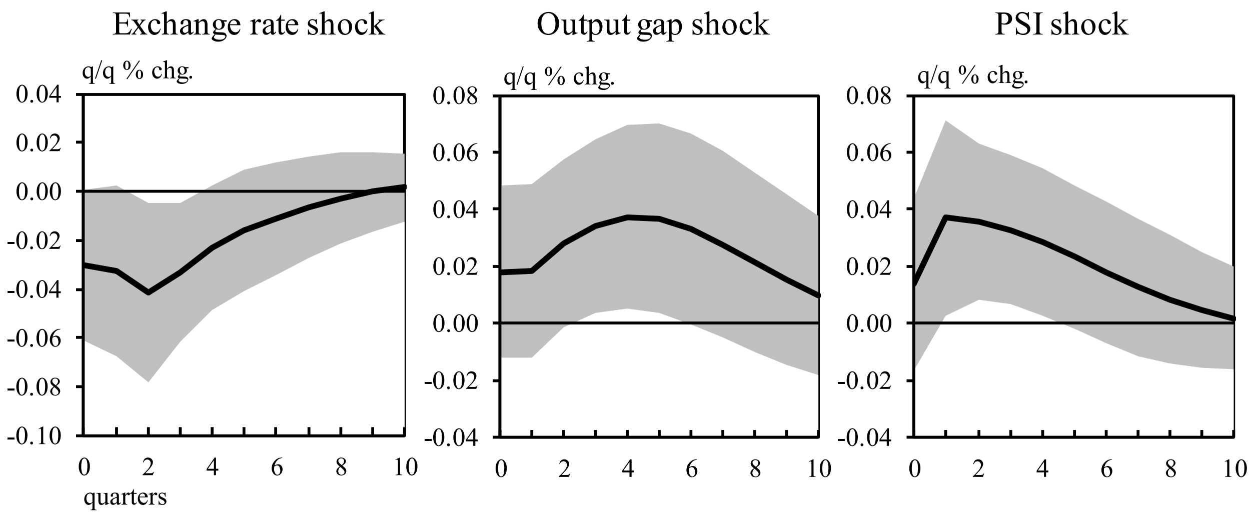
Note: The narrow-based PSI is used. The Tankan series for the inflation outlook of enterprises are for all industries and enterprises.

Figure 7. Impulse responses from VAR model

(a) Impulse responses of the PSI



(b) Impulse responses of the inflation rate



Note: The narrow-based PSI is used. The size of the shock is one standard deviation. The shaded areas indicate the 95 percent confidence intervals. The estimation period is from the January–March quarter of 2001 to the October–December quarter of 2019.