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Monetary Policy Shocks and the Employment of Young, Middle-Aged, and Old Workers

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Abstract

We study how monetary policy affects the labor status of people of different ages and genders using Japanese data from the late 1990s to the late 2010s, with monetary policy shocks identified using high frequency market data. We first show that expansionary monetary policy shocks reduce the unemployment rate of all ages in both genders by almost the same amount. We then show that the impacts of these shocks are starkly different across ages in terms of changes in the labor force and number of employed. Expansionary monetary policy shocks cause the non-labor force of young and elderly people to join the labor force, leading to an increase in the number of employed of these age groups, leaving the middle-aged less affected. Our findings are consistent with the view that changes in the labor force participation rate play a role in determining the degree of labor market slack for specific ages.

Keywords: Monetary policy; Age structure; Labor market slack; Wage Phillips curve; High frequency identification

JEL classification: E24, E32, E52

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1 Introduction

The Japanese economy has experienced rapid changes in demographic structure over the course of history. Figure 1 shows the distribution of population in Japan by age in 1970 and 2019. In 1970, the distribution peaks around the 20s, and then declines with higher age. In 2019, the distribution has two peaks: one located around the 40s and the other located around the 70s. Indeed, Japan is not an exception; to some degree, other advanced economies such as the United States, the United Kingdom, and Germany have been experiencing similar changes in demographic structure.

The shifts in demographic structure have increased the labor supply of the elderly, altering the age composition of workers. This active participation of the elderly in the labor force may have suppressed wage growth during the recovery from the global financial crisis (e.g. see Bank of Japan (2018), and Mojon and Ragot (2019)). Thus, differences in the willingness to participate in the labor force, or the degree of labor market slack, across age groups are of great importance for elucidating the recent dynamics of wages and unemployment, which are the cornerstone for discussing related macroeconomic policies. Previous studies that investigated the relationship between policy and demographic change mostly focused on fiscal policy, since age structure is closely related to the social security policy and taxation system.[1] In light of the above argument of the relevance of labor market slack, wage dynamics and the age composition of workers, however, demographic change may be an important issue for the operation of monetary policy, as described in Yellen (2014). Indeed, the difference in sensitivity of monetary policy shocks across age groups potentially indicates that the efficacy of monetary policy can be strengthened or moderated depending on the demographic structure.

Therefore, in this paper we examine the effects of changes in demographic structure on the transmission of monetary policy. Central to this question is heterogeneous sensitivity to monetary policy innovations across age groups, which has been typically measured in terms of consumption or income level in preceding empirical studies.[2] We shed new light on this heterogeneity by looking in detail at how individuals in different age groups change their labor status in response to monetary policy shocks. Generally speaking, people face various choices during their life-cycles. For example, youths who are studying consider when to start working, whereas elderly people who are still working consider when to retire, depending on economic, social and institutional circumstances. If monetary policy shocks can quicken or delay their

[1] The relationship between fiscal policy and demographic shifts is studied in, for example, Ríos-Rull (2001), Abel (2003), and İmrohoroğlu and Kitao (2012).

[2] These studies include Coibion et al. (2017) and Inui et al. (2017), for example.

decisions by changing economic circumstances, the total amount of labor inputs in the economy and the aggregate output are altered in a straightforward manner.

To address the question regarding the heterogeneous sensitivity of labor status, we employ the disaggregated data of employed, unemployed, and labor force by age and gender collected in the "Labor Force Survey" in Japan, which has the highest proportion of elderly citizens in the world. We formulate a vector autoregression (VAR) to estimate how these disaggregated labor-related variables respond to a monetary policy shock. Our empirical specification closely follows the approach developed by Gertler and Karadi (2015) and identifies monetary policy shocks by instrumenting the two-year government bond yield with changes in Euroyen futures (Japanese short-term interest rate futures) as in Nakamura et al. (2021).

We find that the unemployment rate falls significantly in response to an expansionary monetary policy shock, and the magnitude of the decline is quantitatively the same across ages and genders. In terms of changes in the labor force and number of employed, however, the impacts of these shocks are starkly different across ages. First, the labor force increases by a larger amount for the youth and the elderly than the middle-aged. This observation implies that these shocks make labor market conditions favorable for workers of these ages, incentivizing them to join the labor force. Second, the number of employed increases significantly for the youth and the elderly while that of the middle-aged does not respond significantly to the shocks. This observation suggests that a rise in the demand for young and elderly workers may be met, if not fully, by a rise in participation in the labor force among these age groups.

Our findings are consistent with the view that changes in the labor force participation rate affect the labor market slack through changes in the amount of labor supply available in the economy. As already pointed out in existing studies, for example by Erceg and Levin (2014) and Elsby et al. (2015), such changes are considered to be important factors affecting the nominal wage dynamics. Indeed, Erceg and Levin (2014), stressing the role of the labor force participation rate, showed theoretically that the slope of the wage Phillips curve becomes less steep when the labor force participation rate has cyclical components. When the cyclicality of changes in the rate is age-specific, as demonstrated in the current paper, then the slope of the wage Phillips curve should differ across ages. To see if this prediction holds, we estimate the wage Phillips curve for different age groups. We find that the slope of the curve is steeper for the middle-aged compared with the youth and the elderly. This observation also implies that the aging of society has gone and will continue to go hand-in-hand with weak wage dynamics.[3]

This paper is organized as follows. Section 2 describes the related literature. Section 3 presents the econometric framework we use for the empirical analysis. Section 4 describes the data set. Section 5 documents the results. Section 6 discusses the implications of our results for the wage Phillips curve. Section 7 draws some conclusions.

2 Literature review

This paper is related to three strands of the literature. The first strand covers empirical work quantifying the heterogeneous effects of monetary policy shocks depending on the characteristics of each agent, including studies such as Coibion et al. (2017), Inui et al. (2017), Bahaj et al. (2019), Leahy and Thapar (2019), Cloyne et al. (2020), and Zens et al. (2020). Among these studies, Bahaj et al. (2019) and Zens et al. (2020) investigate the relationship between monetary policy and employment. Bahaj et al. (2019) focus on the collateral channel by exploiting the homes of firms' directors as a key source of collateral. The spatial separation of firms from their collateral enables them to separate the collateral channel from local demand effects. Zens et al. (2020) find that the effects of monetary policy shocks on unemployment rate differ depending on the occupational group. Compared to these papers which use the characteristics of companies, this paper focuses on the heterogeneous effects of monetary policy shocks depending on workers characteristics. Moreover, Coibion et al. (2017) and Inui et al. (2017) investigate the relationship between consumption inequality and the transmission of monetary policy in the U.S. and in Japan, respectively. Inui et al. (2017) find that monetary policy shocks do not have statistically significant impacts across Japanese households in a stable manner in terms of income and consumption inequality. On the other hand, the present paper discusses the relationship between monetary policy and labor status, and finds that impacts are starkly different across ages.[4]

The second strand of the literature covers empirical work quantifying the relationship between population aging and the business cycle including the implications for monetary policy such as Jaimovich and Siu (2009), Imam (2015), and Wong

[3]Indeed, the flattening of the wage Phillips curve has been seen in several advanced countries including Japan. See, for example, an empirical study conducted by Iwasaki et al. (2021).

[4]Regarding the relationship between monetary policy and inequality, Bernanke (2015) points out the possibility that quantitative easing can reduce inequality through promoting job creation since a stronger labor market benefits the middle class. This paper provides evidence supporting this argument by showing that expansionary monetary policy shocks increase the employment of young and old workers whose wages are relatively low.

(2019). Among these studies, Jaimovich and Siu (2009) find the relatively large variation of employment among the youth and the elderly, and also find that the change in the age composition of the labor force accounts for a significant fraction of the cyclical fluctuation of business cycles in the U.S. On the other hand, we show that a similar pattern can be seen in respect to monetary policy analysis in Japan as well as in the U.S.: a larger response of the number of employed among the young and the old. Moreover, Imam (2015) investigates the relationship between population aging and monetary policy in terms of inflation and unemployment by Bayesian estimation techniques, while this paper directly assesses the effect of monetary policy shocks on different age groups.

The third strand of the literature consists of studies investigating the labor market slack and wage settings including studies such as Erceg and Levin (2014), Elsby et al. (2015), Blanchflower and Levin (2015), and Christiano et al. (2021). Erceg and Levin (2014) argue theoretically that monetary policy affects the labor force participation rate. Christiano et al. (2021) construct a monetary model incorporating the labor force participation rate varying with the business cycle. Elsby et al. (2015) and Blanchflower and Levin (2015) empirically point out the importance of labor force participation margin. Since some workers who are not actively searching for a job can rejoin the workforce if the job market gets stronger, labor market slack exerts significant downward pressure on nominal wages. Compared to these studies, we argue that the slack is larger for the young and the old, which, together with the shift in age composition, accounts for the downward pressure on the aggregate-level nominal wage in Japan.

3 Econometric framework

Our estimation procedure consists of two steps. First, we formulate a VAR that consists of macroeconomic variables of the sample period running from 1999 to 2018 and estimate the response of the variables to monetary policy shocks. We identify monetary policy shocks by using high frequency data as external instruments following Gertler and Karadi (2015). Almost all of our sample period coincides with the period when the short-term interest rate was set close to zero and the Bank of Japan had launched several policy initiatives trying to reduce not only the current short-term nominal interest rate but also the expected short-term nominal interest rate and the term premium.[5] We therefore incorporate financial variables

[5]Our data set includes the period in which the Zero Interest Rate (ZIR), Quantitative Easing (QE), Comprehensive Monetary Easing (CME), and Quantitative and Qualitative Monetary Easing (QQE) policies were in place. Note also that QQE includes QQE with a Negative Interest Rate

including the government bond rate instead of the short-term nominal interest rate in our VAR and isolate variations in the government bond rate that stem from the exogenous policy shocks thanks to high frequency identification.[6] Second, we regress a disaggregated labor-related variable, such as the unemployment rate of males in their 30s, on macroeconomic variables and estimate the response of the variable of interest to monetary policy shocks. We assume a block recursive framework (see Lee and Ni (2002)) so that a shock to disaggregated variables does not affect the dynamics of macrovariables in the VAR estimated in the first step.

3.1 Macro-variable block

Our VAR contains N_x number of monthly series of macroeconomic variables and is expressed in the following structural form:

$$A_x X_t = A_x c_x + \sum_{j=1}^{p} A_x B_{xx,j} X_{t-j} + \varepsilon_{x,t}, \tag{1}$$

where X_t is the N_x dimensional vector of macroeconomic variables, $B_{xx,j}$ is the matrix of polynomials that represent the structural relationships among macroeconomic variables, A_x and c_x are coefficient matrices, and $\varepsilon_{x,t}$ is a vector of structural white noise shocks.[7] Multiplying each side of the equation by A_x^{-1} yields the reduced form VAR model given by

$$X_t = c_x + \sum_{j=1}^{p} B_{xx,j} X_{t-j} + u_{x,t}, \tag{2}$$

where $u_{x,t}$ is the reduced form shocks. The relationship between the reduced form shock, $u_{x,t}$, and the structural shock, $\varepsilon_{x,t}$, is given by

$$u_{x,t} = S\varepsilon_{x,t}, \tag{3}$$

with $S = A_x^{-1}$. The variance-covariance matrix of the reduced form model Σ can be written as

$$E\left[u_{x,t}u'_{x,t}\right] = E\left[SS'\right] = \Sigma. \tag{4}$$

and QQE with Yield Curve Control. ZIR runs from 1999M2 to 2000M8, QE runs from 2001M3 to 2006M3, CME runs from 2010M10 to 2013M4, and QQE runs from 2013M4 to the present.

[6]External instruments are employed in a growing body of studies including Stock and Watson (2012) and Mertens and Ravn (2013). High frequency identification for Japan used in the current paper are the same as those constructed in Nakamura et al. (2021).

[7]We use 12 lags, $p = 12$, in our baseline estimation. The results are little changed when other number of lags, $p = 6$ or 18, are used for the estimation.

Now, let r be the interest rate included as one of the macroeconomic variables in this VAR block, and $X_{q,t}$ be macroeconomic variables other than r. We denote reduced form residuals $u_{x,t}$ of r as $u_{r,t}$ and of $X_{q,t}$ as $u_{q,t}$. We define $\varepsilon_{r,t}$ and $\varepsilon_{q,t}$ similarly to $u_{r,t}$ and $u_{q,t}$. Regarding the component of the matrix S, s is defined as the column in matrix S corresponding to $\varepsilon_{r,t}$. To obtain the impulse response to the monetary policy shocks, we do not have to identify all of the coefficients in S. Specifically, we need to estimate the following equation:

$$X_t = c_x + \sum_{j=1}^{p} B_{xx,j} X_{t-j} + s\varepsilon_{r,t}. \tag{5}$$

In order to obtain the coefficient of the matrix $B_{xx,j}$, we can simply use the least squares estimation in equation (2). Since we focus on the case of Japan where the policy target rate is constrained by the effective lower bound, it is important for a policy indicator to include shocks to unconventional monetary policy such as forward guidance. Thus, we choose one-year and two-year rates as candidates for the policy indicator. To isolate movements of the policy indicator made by exogenous monetary policy shocks, we use instrument variable Z_t. The conditions of the instrument variables Z_t are:

$$E\left[Z_t \varepsilon_{r,t}\right] = \rho, \tag{6}$$

$$E\left[Z_t \varepsilon_{q,t}\right] = 0. \tag{7}$$

These equations state that instruments Z_t are only correlated with monetary policy shocks $\varepsilon_{r,t}$, but they are orthogonal to other macroeconomic variables shocks $\varepsilon_{q,t}$. If we are able to obtain these instrument variables, s can be estimated as follows.

1. From the instrument variables Z_t, and the residual u_t obtained from the VAR regression, estimate the following equation

$$u_{r,t} = \alpha_1 + \beta_1 Z_t + \xi_{1,t}, \tag{8}$$

where α_1 and β_1 are coefficients and $\xi_{1,t}$ is the residual. From the equation, we can calculate the fitted value $\widehat{u}_{r,t}$.

2. Using the fitted value $\widehat{u}_{r,t}$, estimate the following equation using the ordinary least squares:

$$u_{q,t} = \alpha_2 + \beta_2 \widehat{u}_{r,t} + \xi_{2,t}. \tag{9}$$

The estimated coefficient β_2 corresponds to the ratio s_q/s_r where s_r and s_q are elements of s and they correspond to the response of $u_{r,t}$ and $u_{q,t}$ to a unit increase in the policy shocks $\varepsilon_{r,t}$. Finally, s_r can be obtained from the reduced form variance-covariance matrix.[8]

Given these coefficients of s and $B_{xx,j}$, the impulse response to the monetary policy shocks can be estimated from the macro-variable block.

3.2 Segment-variable block

We denote the N_y dimensional vector of segment-variables at time t by Y_t. In this segment-variable block, the dynamics of macroeconomic variables do not depend on segment-level variables, while those of the segment-variables depend on the macroeconomic variable block. Specifically, the reduced form VAR can be described as follows:

$$Y_t = c_y + \sum_{j=0}^{q_1} B_{yx,j} X_{t-j} + \sum_{j=1}^{q_2} B_{yy,j} Y_{t-j} + u_{y,t}, \tag{10}$$

where $u_{y,t}$ is the reduced form shocks of segment-variables.[9] Here, we assume that the macroeconomic variables have contemporaneous effects on the segment-variables. We can estimate the impulse response functions of the segment variable block using the above relationship. Specifically, for the second term which corresponds to the behavior of the macroeconomic variables, we substitute an estimated impulse response function in the macroeconomic-variable block using the external instruments to obtain the impulse response functions.

The standard errors are calculated by the wild bootstrap following Mertens and Ravn (2013). The wild bootstrap generates valid confidence intervals under heteroskedasticity. We consider not only estimation errors related to macroeconomic and segment-level variables, but also those related to instrument variables, by including all the steps of estimation for the bootstrap procedure.

3.3 Assumptions of VAR model

Our specification of the VAR model is based on several assumptions. First, we assume that the instrument variables using high frequency data can extract the exogenous component of monetary policy shocks. In other words, the price changes within the narrow window between monetary policy announcements are only due to the monetary policy, and do not contain other economic or financial news. The

[8]Details of the estimation of s_r are described in Gertler and Karadi (2015).

[9]In the baseline estimation, we use $q_1 = q_2 = 4$ on a quarterly basis since some of the segment-level variables are only available in quarters. Even if we change the number of lags to shorter (1 and 2) or longer (6) values, we obtain similar results.

data we use is described in the next section, and the validity of the assumption is checked in Nakamura et al. (2021).

Second, we assume that macroeconomic variables are isolated from the segment-variable block, and that the dynamics of macroeconomic variables do not depend on the segment variables. In order to check the validity of this block recursive restriction on the lag coefficients as we do here, we use the single-equation F-test, following Lee and Ni (2002). The results show that segment variables are not significant in the macroeconomic variable equations, which justifies our assumption.

4 Data

Our data sample consists of three groups of variables: aggregate data, disaggregated labor-related variables by age and gender, and high frequency data used for the identification of monetary policy shocks. We first estimate the responses using Japanese data and then compare with those estimated from U.S. data.

4.1 Macroeconomic variables and disaggregated labor-related variables

The set of macroeconomic variables used for estimating the VAR in equation (2) includes the two-year government bond yield, Nikkei 225 stock price, consumer price index (CPI), capacity utilization, unemployment rate, and number of employed. They are all used in the VAR in the log level, except for the two-year government bond yield and the unemployment rate. Financial data such as the two-year rate and Nikkei 225 stock price come from Bloomberg. CPI, unemployment rate, and number of employed are taken from statistics released by the Ministry of Internal Affairs and Communications, and the capacity utilization rate is taken from the Indices of Industrial Production released by the Ministry of Economy, Trade and Industry. The disaggregated labor-related variables including the employment status by age and gender are taken from the labor force survey released by the Ministry of Internal Affairs and Communications. The sample period is from 1999Q1 to 2018Q4.[10] The data series used for the estimation are shown in Figure 2, 3, and 4.

[10]Some disaggregated labor-related variables are only available from 2002Q1 onwards. When estimating the response of these variables, we use the sample period that runs from 2002Q1 to 2018Q4.

4.2 High frequency data

High frequency data used as instrument variables are the key to our econometric framework.[11] We use tick-by-tick price data of interest rate futures.[12] The data we use are the three-month Euroyen interest rate futures (YE) with a variety of contract dates: 1 day to 3 months ahead (YE1), 3 to 6 months (YE2), 6 to 9 months (YE3), and 9 to 12 months (YE4). For the baseline estimation, following Nakamura et al. (2021), we use the primary factor extracted from changes in YE1 to YE4 (denoted "YEF" hereafter) over a 30-minute window around the announcement of the monetary policy meetings as the external instrument. These high frequency data come from the Tokyo Financial Exchange Inc.[13]

To check the validity of the extracted monetary policy shocks, we estimate the response of the financial variables. Specifically, we use the following equation:

$$\Delta R_t = \alpha + \beta \Delta i_t + \varepsilon_t, \tag{11}$$

where ΔR_t and Δi_t correspond to the change in asset return and the change in interest rate on the day that a policy announcement is made. We estimate this equation using the two-stage least squares by instrumenting YEF for a daily change in a policy indicator, Δi_t. Our identifying assumption is that the instrument variables (YEF changes) are orthogonal to the error term, and the instrument affects ΔR_t only through the policy indicator Δi_t. We estimate the regressions over the available 2003M4-2017M10 samples.

Table 1 shows the results of the two-stage regression. Each row represents a particular policy indicator. The coefficient represents the impact of a 1 percent point increase in a given policy indicator due to an exogenous monetary policy shock on a corresponding asset return. From the table, we can find that monetary policy easing shocks (in Japan) decrease two- to ten-year government bond rates, and depreciate the value of the Japanese yen, as expected. All of the results except for the ten-year bond rate and the exchange rate with one-year government bonds as policy indicators are statistically significant at the 1 percent level, and these results are also statistically significant at the 5 percent level.

[11]The identification of monetary policy shocks using high frequency financial data is developed in the U.S. by studies such as Gürkaynak, Sack, and Swanson (2005), Gertler and Karadi (2015), and Nakamrua and Steinsson (2018).

[12]Other methods for the popular identification of monetary policy shocks follow Romer and Romer (2004). Studies such as Coibion et al. (2017) and Nakamura (2019) use such methods for the identification for the empirical analysis in the U.S. using the sample period before the global financial crisis. However, it is not applicable to the sample period including the effective lower bound period, and is not suitable for the estimation in Japan.

[13]We follow Munakata et al. (2019) for the data cleaning regarding the high frequency data.

As shown in Table 1, high frequency data of monetary policy shocks indeed has a statistically significant impact on financial variables. This result indicates that YEF can be used as instruments when estimating the effects of monetary policy shocks. Then, the next issue is the choice of a policy indicator in the VAR specification: a financial variable whose shock corresponds to monetary policy innovation. As discussed in Gertler and Karadi (2015), traditional VARs use the same policy instruments and policy indicator, namely the overnight interest rate. This is because a structural shock to a policy indicator can be regarded as an exogenous monetary policy shock. On the other hand, we use the longer maturity rate of government bonds to capture shifts in unconventional monetary policy such as forward guidance. The longer term government bond might incorporate various information other than monetary policy such as news on the economy reflecting the economic fundamentals. However, the high-frequency identification successfully eliminate the component of innovations in longer term government bonds that is unrelated to monetary policy shocks.

When choosing the policy indicator, we need to avoid the weak instrument problem. Stock et al. (2002) recommended that the F-statistic from the first-stage regression in the two-stage least squares should be above 10 in order to state that weak instrument problems are not present. Thus, we estimate the effects of high frequency instruments on the first stage residuals described in equation (2). Table 2 shows the results. The left column shows the result when the one-year rate is the policy indicator, and the right column shows the case when the two-year rate is the policy indicator. The first row shows the estimates for the coefficient and the second row shows the R^2. The third row shows the robust F-statistic for each regression. From the table, we can see that monetary policy shocks denoted as YEF explain nearly ten percent of the monthly innovation of the two-year rate, and the associated robust F-statistic is around 11, which is above the threshold value, 10. On the other hand, the robust F-statistic for the one-year rate is less than 10. Thus, we use the two-year rate as a policy indicator in our baseline estimation.[14]

5 Empirical results

5.1 Macroeconomic variable responses

Figure 5 shows the impulse response function of the macroeconomic variables to an expansionary monetary policy shock estimated using the VAR in equation (2). The

[14]Even if we use the one-year rate as a policy indicator, we obtain almost the same results.

size of the monetary policy shock is normalized so that the two-year rate declines by one basis point at the time of the impact, and the shock is identified by high frequency data of YEF (factor of the Euroyen interest rate futures). The dashed lines show 90% confidence intervals. Consistent with the conventional view about the effects of an expansionary monetary policy shock, the CPI, capacity utilization, Nikkei 225 stock price, and number of employed all increase and the unemployment rate falls following the expansionary shock.[15]

5.2 Segment variables responses

5.2.1 Unemployment rate

Figure 6 shows the unemployment rate responses to an expansionary monetary policy shock by age. For each panel titled "x" at the top, except that titled "65-,"the impulse response is that of the unemployment rate of age plus and minus ten years around age x. For example, the top-left panel titled "25" shows the response of the unemployment rate aged from 15 to 35 to a monetary policy shock. The panel titled "65-" shows the response of the unemployment rate above 65. For all of the groups except for aged above 65,[16] the unemployment rate does not respond in the first few quarters and starts to decline in around two years after the shock occurs.[17] The point estimates indicate that there is not much difference in terms of the timing and size of the decline across groups.[18]

5.2.2 Number of employed

Figure 7 shows the number of employed in response to an expansionary monetary policy shock. From the figure, we find that the increase in response to an expansionary monetary policy shock is large in younger age and older age groups.[19] More

[15]As for the variables used in the VAR analysis, we use the logarithmic scale in the CPI, capacity utilization, Nikkei225 stock price, and number of employed for the estimation.

[16]One potential reason why the response of the unemployment rate above 65 differs from that of the unemployment rate for other ages is the mandatory retirement age, which is now typically 60 in Japan. The Act on Stabilization of Employment of Elderly Persons revised in 2000 required firms to make efforts to employ workers until the age of 65. The law was then revised in 2013, requiring firms to guarantee the employment of all personnel seeking to remain employed until the age of 65 by 2025.

[17]We also check the impulse responses of the number of unemployed by age to an expansionary monetary policy shock, instead of unemployment rate, and find that the results are similar to the responses of the unemployment rate by age.

[18]By decomposing the unemployment into voluntary unemployment and involuntary unemployment, we find that the decline of the unemployment rate in response to an expansionary monetary policy shock is mainly due to the decrease in involuntary unemployment.

[19]The active labor participation of the youth may contribute to alleviate the scarring effect presented in, for example, Arulampalm et al. (2000) and Arulampalm (2001) who argue that an individual's previous unemployment experience increases the probability of current unemploy-

specifically, the number of employed of age around 25,[20] and that of age older than 50, increase. On the other hand, the response between age 30 to 45 is close to zero in the entire period.

5.2.3 Labor Force

Generally, an increase in the number of employed is mainly attributed to two driving forces: a decrease in the number of unemployed, or an increase in the labor force. In our case, the former is unlikely to be the driving force, since the homogeneous impulse responses of the unemployment rate cannot account for the heterogeneous impulse responses of the number of employed. By contrast, we find evidence that the latter is the case: the shape of the response of labor force and that of the number of employed to a monetary policy shock are indeed similar. The impulse responses of the number of labor force are shown in Figure 8. The size of the expansionary monetary policy shock is the same as in the previous figures. The figure reveals that age 25 and age older than 50 show larger responses. On the other hand, the response between age 30 and 45 does not increase after an expansionary monetary policy shock in the point estimate.

An increase in the number of labor force means that the number of non-labor force decreases. To explore the reason for this decrease, we decompose the non-labor force into students, homemakers, and others, following the definition in the labor force survey. Figure 9 shows the impulse response of each component to monetary policy shocks. Although all the responses are not statistically significant at the 90% confidence interval, the point estimates indicate that the size of the decrease is the largest in students, and larger in others compared to homemakers. Figure 10 shows the breakdown of the number of non-labor force by age. It shows that students are dominant in the non-labor force between age 15 and 24. For age between 30 to 54, most of the non-labor force consists of homemakers, and for the old, especially older than 65, the percentage of others is large.

Figure 9 and 10 give the reason why we obtain a heterogeneous labor force response to monetary policy shocks. Specifically, for the young, students are dominant in the non-labor force, and under the system of simultaneous recruiting of new graduates in Japan, students might cautiously choose when to enter the job market, because the first job is a key determinant of lifetime earnings, as pointed out by

ment and contributes to wage inequality or poverty. Thus, our results imply that the increasing employment of the youth potentially reduces the risk for their future unemployment.

[20]By investigating which type of workers contributes to the increase in the number of employed, we find that, for the younger worker around age 25, the main driving force of the increase is regular employment. On the other hand, non-regular employment including part-time job is the main contributor to the increase in the number of employed for the elderly (age above 65).

Kondo (2007). For the old, the ratio of others increases, and retired persons account for a large portion of the non-labor force. Thus, the old workers might choose to work after the economy improves in response to an expansionary monetary policy shock. On the other hand, in middle age between 30 to 50, most of the non-labor force is explained by homemakers, and some of them are not able to work even if the economy improves due to the need to take care of their children. The weak response of the middle-aged workers might also arise from the low liquidity of the labor market in Japan. This issue is discussed in the following section, in which the results in the U.S. are explained.

5.2.4 Gender differences

We also estimate the impulse response for each gender to check if the effects of monetary policy differ across gender. Figure 11 shows the responses for men (blue circles) and women (red squares) to an expansionary monetary policy shock. Again, the shock is normalized so that the two-year rate decreases by one bp. Each point in the number of employed and labor force shows the impulse response at 20 quarters after the monetary policy innovation, and that in the unemployment rate shows that at 15 quarters after the shock.[21] The horizontal axis shows the age. Error bars show 90% confidence intervals.

The figure shows that for the responses of the number of employed and labor force, the magnitude of the response decreases as age increases from 25, but around age 50, the magnitude of the response starts increasing. Regarding the unemployment rate, the responses are homogeneous across ages. Moreover, when focusing on the difference between men and women in each age, the response of men is almost the same as that of women.[22] From these results, we can conclude that the responses of employment, unemployment and labor force are similar between men and women.[23]

[21]These periods (20Q for employed and labor force, and 15Q for unemployment rate) are chosen so that the indicated plots coincide overall with the peak of each impulse response. Coibion et al. (2017) and Gertler and Karadi (2015) also obtain impulses that peak around three to four years after monetary policy shocks.

[22]We also check the response of the number of unemployed instead of unemployment rate, but the results are almost the same: the size of the reduction of the number of unemployed is almost the same between genders.

[23]Note that while the Bank of Japan (2018) indicates that the labor supply of women is more elastic than that of men, this paper finds that the response of the labor force to our identified monetary policy shocks is quite similar between the two genders. The Bank studies differences in the elasticity of labor supply reflecting various changes in the economic environment, including the Japanese government's policies that encourage the participation and advancement of women in the labor force, whereas our paper investigates changes in the number of employed and labor force in response to monetary policy shocks identified using high-frequency market data.

5.3 Impulse response using U.S. data

In the previous section, we show that the responses of the number of employed to an expansionary monetary policy shock are heterogeneous across ages in Japan: young and old workers' responses are larger compared to those of middle-aged workers. Meanwhile, the unemployment rate responses are homogeneous across all ages. In this section, we empirically show that similar patterns can be observed in the U.S.

For the estimation using U.S. data, we use the same econometric specification described in section 3. Regarding the high frequency data, which is used as the external instruments, we use the shocks in the three-month ahead futures rate from Gertler and Karadi (2015). The one-year U.S. government bond rate is used as the policy indicator for the baseline analysis, but using the two-year bond rate gives very similar results. For the macroeconomic variables, we use the CPI, industrial production (IP), Standard and Poor's 500 index (SP500), real gross domestic product (RGDP), and excess bond premium (EBP), which is defined in Gilchrist and Zakrajšek (2012).[24] Regarding the segment variable of employment, we use the Current Population Survey (CPS) for the specific age groups of individuals over 15 years of age and older. The sample period is from 1979:M7 to 2016:M12.[25] The starting point coincides with the beginning of Paul Volker's tenure as chairman of the Federal Reserve.

Figure 12 shows the macroeconomic variable responses to an expansionary monetary policy shock in the U.S. The shock is normalized so that the one-year bond rate decreases by one bp. We can see that in response to an expansionary monetary policy shock, the CPI, IP and RGDP improve and SP500 rises, while the EBP, which is an indicator of credit spreads, falls. The response is consistent with the high frequency identification VAR analysis using U.S. macroeconomic data such as Gertler and Karadi (2015) and Jarociński and Karadi (2020).

Figure 13 shows the responses of the unemployment rate to an expansionary monetary policy shock by age (given at the top of each graph). Each graph at age

[24]We use macroeconomic variables data from Jarociński and Karadi (2020). In this dataset, GDP is interpolated monthly following Stock and Watson (2010). Basically, it uses a kalman filter to distribute the quarterly GDP across months using a dataset of monthly variables that are closely related to economic activity. The robust-F statistics when estimating the effects of high frequency instruments on the first-stage residuals is 12.7, which is above 10. This indicates that the weak instrument problem is not present.

[25]We use the 1979:M7 to 2016:M12 samples for the estimation of VAR coefficients. For the instruments variable, which is used to identify the monetary policy shocks, we use the available 1991:M1-2012:M6 sample for the baseline two step regression. We estimate the results excluding 2008:M7-2009:M6, which corresponds to the period of financial turbulence, but the results are very similar to the ones including the financial turbulence period.

x is estimated using the sample between age $x - 5$ and $x + 5$. Dashed lines show 90% confidence intervals. Importantly, the responses of the unemployment rate are homogeneous across ages. On the other hand, Figure 14 shows the results for the number of employed. The figure shows that the response of the number of employed in the U.S. is large at age 20 and age 50. Compared to these ages, each of the responses at age 30 and age 40 is weaker. Figure 15 shows the results of labor force response. We can see that each of the responses at age 20 and age 50 is also larger compared to that of the middle-aged, which is similar to the number of employed case.[26]

Compared to the results of the estimation in Japan, we find a similar pattern in the results for the U.S. in two respects. First, the responses of the unemployment rate to a monetary policy shock are homogeneous across the age groups. Second, the number of employed and labor force shows heterogeneous responses across the ages, and especially, younger and older workers respond more than middle-aged workers. The difference between Japan and the U.S. is the response of the number of employed for middle-aged workers: a larger response can be observed in the U.S. results. This might arise from the difference in labor market structure between Japan and the U.S. As Owan (2004) points out, labor mobility is lower in Japan than the U.S. Figure 16 supports this argument. It shows the years of tenure with the current employer in Japan and the U.S. by age group. Older workers tend to have worked longer in their current job, but the key point is that workers in Japan show longer years of tenure with their current employer. For example, between ages 35 and 44, the job tenure in Japan is about 10 years, while it is 5 years in the U.S. For all age groups, job tenure in Japan is double that in the U.S.[27] Figure 17 shows the number of job transfers and the job transfer rate by age group in Japan. More specifically, it shows the number of employed persons who changed jobs in the past one year (left axis, ten thousand), and the rate of employed persons who changed jobs in the past one year (right axis, percent). We can see that the youngest age group (between 15 and 24) shows a job transfer rate as high as 12%, while for older ages, it is low,

[26]Compared to the empirical results in Japan, in which the response of the number of employed and that of labor force show similar results, the response of labor force in the U.S. is smaller overall than that of employed. This might be because the size of the response of employed is smaller than that in Japan, which means that decrease in the number of unemployed contributes to an increase in the number of employed. Supporting this view, the response of the labor force is smaller than that of employed between 10 to 20 months after the shock, which corresponds to the period when the response of the unemployment rate is the smallest.

[27]We need to note that the definition of tenure is slightly different between Japan and the U.S. Specifically, in Japan, employee tenure is a measure of how long workers have been with their current employer, while in the U.S. it is a measure of how long wage and salary workers have been with their current employer at the time of the survey. Thus, employee tenure may be shorter in the U.S. However, promotion within the company is not so common in the U.S. compared to Japan, and thus this difference of definition might not significantly change the results.

and above age 35, it is less than 5%. In sum, the job market is more liquid in the U.S. than those in Japan, and the small response of the number of employed for the middle-aged workers to an expansionary monetary policy shock might be attributed to the low labor mobility in Japan, since middle-aged workers have relatively fewer job vacancy opportunities even if business conditions improve.

6 Implications for the wage Phillips curve

In the previous section, we show that the responses of the number of employed and labor force to expansionary monetary policy shocks are larger among the young and old generations. This section derives an important implication of these heterogeneous responses for nominal wage dynamics, using the concept of the wage Phillips curve in Japan.[28] Theoretically speaking, as Galí (2011) points out, the wage Phillips curve is flatter when the labor supply is elastic. Therefore, if the young and the old more sensitively adjust their labor force inflow in response to a shock (as empirically shown in the previous section), the wage Phillips curve for the young and the old, *ceteris paribus*, should be flatter than that for the middle-aged.[29]

In order to assess this argument quantitatively, we estimate the wage Phillips curve for each age group of workers. For this estimation, we need the unemployment rate and wage inflation rate of each age group. The data of unemployment rate come from the labor force survey published by the Ministry of Internal Affairs and Communications. We use the deviation from the average unemployment rate in each group to estimate the slope of the wage Phillips curve.[30] The wage data come from the Basic Survey on Wage Structure published by the Ministry of Health, Labour and Welfare. Wage inflation rate is calculated from the baseline wage of the Basic Survey on Wage Structure; scheduled salary in June excluding overwork salary.[31] The sample period is from 1996 to 2019.

[28]The derivation of the wage Phillips curve is explained in, for example, Erceg et al. (2000) and Galí (2011). The wage Phillips curve in Japan is empirically estimated, for instance, by Iwasaki et al. (2021) and Muto and Shintani (2020).

[29]Muto and Shintani (2020) point out that the slope of the wage Phillips curve is determined also by wage stickiness. Nonetheless, since wages for workers in Japan, regardless of age, are likely to be simultaneously revised in April by Shunto, it is reasonable to assume that wage stickiness is more or less the same across the ages.

[30]We also correct the linear component of unemployment rate in each age. However, the method of calculating the deviation does not significantly change the results.

[31]Another definition of wage inflation rate used in estimating the wage Phillips curve is monthly total wage divided by monthly total working hours. We also estimate the results based on this definition, but obtain similar results. Moreover, the hourly wage of short-time workers also gives similar results: the slope of the middle-aged worker is the steepest.

Figure 18 shows the wage Phillips curve for each indicated age. Each circle corresponds to each data point, and the line shows the fitted curve obtained from the OLS. To estimate the slope of the wage Phillips curve at age x, we use the data from $x-5$ to $x+4$. Also, we use the data of males and females separately to increase the number of data.[32] The horizontal axis corresponds to the deviation of the unemployment rate from the average. The vertical axis corresponds to the wage inflation rate. From the figure, we can see that all of the slopes are negative; a decrease in unemployment leads to higher wage inflation. Furthermore, most importantly, the slope of the wage Phillips curve of middle-aged workers is the steepest.

In order to check the statistical significance, we use two regression equations. The first one is the simple regression,[33]

$$\pi_{w,t} = \alpha_0 + \alpha_1 unemp_t + \xi_t, \tag{12}$$

where $\pi_{w,t}$ is the wage inflation rate and $unemp_t$ is the unemployment rate. The α terms represent the regression coefficient, and ξ_t is the regression error term. This equation corresponds to the most basic wage Phillips curve estimation, and we estimate one for each age group. Table 3 shows the regression results of wage Phillips curve for the age groups 25, 35 and 50. The table also shows the robust t-statistics and 90% confidence interval. These regression results are used to describe the fitted line in Figure 18. The results indicate that the slope of the coefficient is statistically significant at the 1% level for age 25 and age 35, and the slope of age 35 is the steepest. Moreover, the point estimate of age 35 is out of the 90% confidence interval of age 25 and age 50.

The second estimation is the pooled regression with age dummy variable written as,

$$\pi_{w,t} = \alpha_0 + \alpha_1 unemp_t + \alpha_{2,x} dummy_{x,t} unemp_t + \xi_t. \tag{13}$$

[32]Since we use the Basic Survey on Wage Structure, only the wage change on a yearly basis is available. Thus, we use male and female data separately to increase the number of data. To ensure robustness, we also check that even if we use the consolidated data, we obtain similar results to the baseline ones.

[33]By assuming a simple autoregressive model for the determination of the unemployment rate, we can obtain the closed-form representation of the wage Phillips curve similar to equation (12) rather than the standard forward-looking form of the New Keynesian wage Phillips curve, as described in Galí (2011). One may think that this simple specification cannot avoid the endogeneity problem. Indeed, several preceding studies such as Galí (2011) and Muto and Shintani (2020) control for inflation in estimating the wage Phillips curve. We also control this inflation rate as a robustness check, and obtain similar results; the wage Phillips curve for the young and the old is flatter.

Here, $dummy_{x,t}$ corresponds to the dummy variable, which takes 1 at age x.[34] For this regression, we use the sample between ages 20 and 59. Table 4 shows the results. It reveals that all the coefficients for unemployment are statistically significant at the 1% level. Moreover, the point estimate of unemployment rate times dummy 35 is negative, while that with dummy 25 and dummy 50 is positive. More importantly, in case 3, α_2 is statistically significant at the 1% level when dummy 35 is used; together with that in case 5, α_2 is significantly different from zero when dummy 25 and dummy 50 are used simultaneously. These results confirm that the slope of the wage Phillips curve is the steepest for middle-aged workers (age 35), which is consistent with the VAR analysis obtained in the previous section.

In addition, the Appendix shows the results of estimating the wage Phillips curve in the U.S. We find that the slopes of the wage Phillips curve are similar across ages. This is consistent with the impulse response of the U.S. in the sense that the inflow of labor force does not differ between ages.

7 Conclusion

In this paper, we address the question of which age group of workers' employment is the most responsive to monetary policy shocks. Using the block recursive structure of the VAR model as well as monetary policy shocks identified by high frequency data in Japan, the paper empirically shows that the responses of the number of employed are large among young and old workers compared to the middle-aged. This is mainly caused by the increase in the number of labor force. On the other hand, the unemployment rate shows homogeneous impulse responses across all the age groups. Similar patterns can be observed in the U.S. labor market as well. These results indicate that there exists a higher degree of under-utilization of young and old workers, which leads to the weak responses of wage inflation. Supporting this view, we find that the wage Phillips curve of middle-aged workers is steeper than those of young and old workers.

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Appendix: Estimation of the wage Phillips curve in the U.S.

We estimate the wage Phillips curve for each age group of workers in the U.S. The unemployment data come from the Current Population Survey (CPS). The wage data come from the median usual weekly earnings full-time wage.[35] The sample period is from 1996 to 2019.[36]

In order to check the statistical significance, we use two regression equations, the same as the regression in the main text. The first one is the simple regression,

$$\pi_{w,t} = \alpha_0 + \alpha_1 unemp_t + \xi_t, \tag{14}$$

where $\pi_{w,t}$ is the wage inflation rate and $unemp_t$ is the unemployment rate. The α terms represent the regression coefficient, and ξ_t is the regression error term. Table 5 shows the regression results for the wage Phillips curve of each age group. The results indicate that the slope is similar across the ages.

The second estimation is the pooled regression with the age dummy variables,

$$\pi_{w,t} = \alpha_0 + \alpha_1 unemp_t + \alpha_{2,x} dummy_{x,t} unemp_t + \xi_t. \tag{15}$$

where $dummy_{x,t}$ takes 1 at age x. For this regression, we use the sample between ages 16 and 54. Table 6 shows the results. These show that none of the coefficients of the dummy variables is statistically significant. The results are consistent with the impulse response described in the main text. Namely, the impulse responses of the labor force in the U.S. are heterogeneous, but the differences between ages are not so distinctive compared to the results in Japan. Thus, the slope of the wage Phillips curve does not change with age in the U.S. regression.

[35] Galí (2011) uses the average hourly earnings from the Establishment Survey, which is from the company data. On the other hand, we need the age information and use the data from the household side.

[36] To estimate the slope of the wage Phillips curve at age x, we use the age from $x-5$ to $x+4$.

Table 1: Effects of monetary policy shocks on financial markets

Policy indicator	2 year	5 year	10 year	USD/JPY
1 year	1.211***	1.457***	1.457**	-43.118**
	(4.235)	(5.377)	(2.591)	(-2.069)
2 year		1.203***	1.203**	-35.592***
		(5.147)	(2.512)	(-2.762)

Note: Robust t-statistics in parentheses.
***: Significant at the 1 percent level.
**: Significant at the 5 percent level.
*: Significant at the 10 percent level.

Table 2: Effects of instruments on the first stage residuals

Policy indicator	1 year	2 year
Coefficient	2.03***	2.06***
R^2	0.12	0.10
Robust F-statistic	9.75	11.19

Note: ***: Significant at the 1 percent level.

Table 3: Wage Phillips curve depending on age

Age	Unemployment rate	Intercept
25	-0.34***	0.38***
(Robust-t)	(-4.86)	(4.67)
(90% CI)	[-0.46 -0.22]	[0.25 0.52]
35	-0.75***	0.17*
(Robust-t)	(-6.03)	(1.75)
(90% CI)	[-0.95 -0.54]	[0.01 0.34]
50	-0.23	0.39***
(Robust-t)	(-1.12)	(3.03)
(90% CI)	[-0.57 0.11]	[0.18 0.61]

Note: ***: Significant at the 1 percent level.
**: Significant at the 5 percent level.
*: Significant at the 10 percent level.
Robust-t denotes robust t-statistics.
90% CI denotes 90 percent confidence interval.

Table 4: Estimation of the wage Phillips curve with dummy variables

Age	u	u*dmy25	u*dmy35	u*dmy50	Intercept
Case 1	-0.45***				0.35***
	(-7.27)				(6.07)
Case 2	-0.55***	0.22			0.35***
	(-5.87)	(1.85)			(6.08)
Case 3	-0.36***		-0.38*		0.35***
	(-5.53)		(-2.64)		(6.10)
Case 4	-0.48***			0.25	0.35***
	(-7.34)			(1.17)	(6.07)
Case 5	-0.66***	0.33***		0.44*	0.35***
	(-6.33)	(2.60)		(1.92)	(6.10)

Note: ***: Significant at the 1 percent level.
**: Significant at the 5 percent level.
*: Significant at the 10 percent level.
Robust t-statistics in parentheses.

Table 5: Wage Phillips curve in the U.S.

Age	Unemployment rate	Intercept
20	-0.11*	0.75***
(Robust-t)	(-1.71)	(3.81)
30	-0.16***	0.69***
(Robust-t)	(-4.54)	(10.59)
40	-0.11***	0.68***
(Robust-t)	(-3.82)	(14.36)
50	-0.10**	0.62***
(Robust-t)	(-2.62)	(10.84)

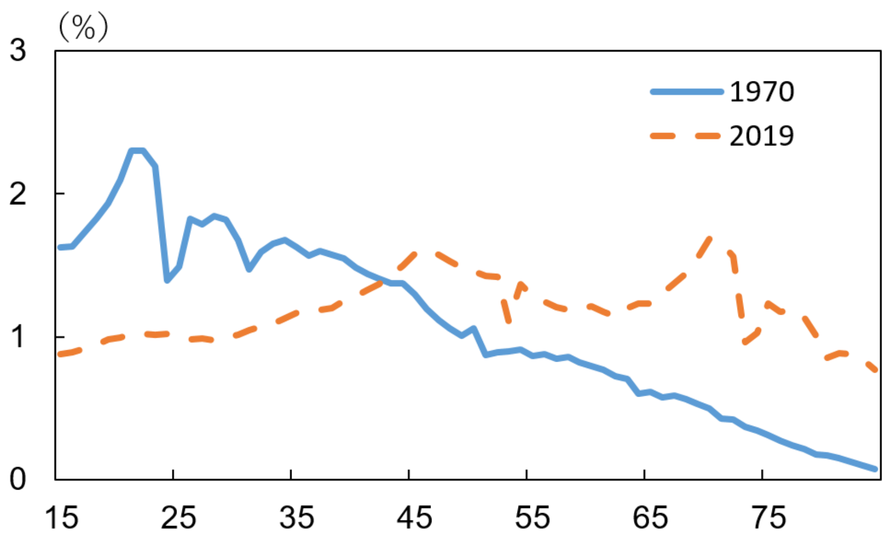
Note: ***: Significant at the 1 percent level.
**: Significant at the 5 percent level.
*: Significant at the 10 percent level.
Robust-t denotes robust t-statistics.

Table 6: Estimation of the wage Phillips curve with dummy variables in the U.S.

Age	u	u*dmy20	u*dmy30	u*dmy40	u*dmy50	Intercept
Case 1	-0.12**	0.01				0.71***
	(-2.42)	(0.10)				(8.61)
Case 2	-0.11**		-0.05			0.71***
	(-2.08)		(-0.48)			(8.61)
Case 3	-0.11***			0.00		0.71***
	(-3.29)			(0.00)		(8.61)
Case 4	-0.11***				0.01	0.71***
	(-2.26)				(0.12)	(8.61)

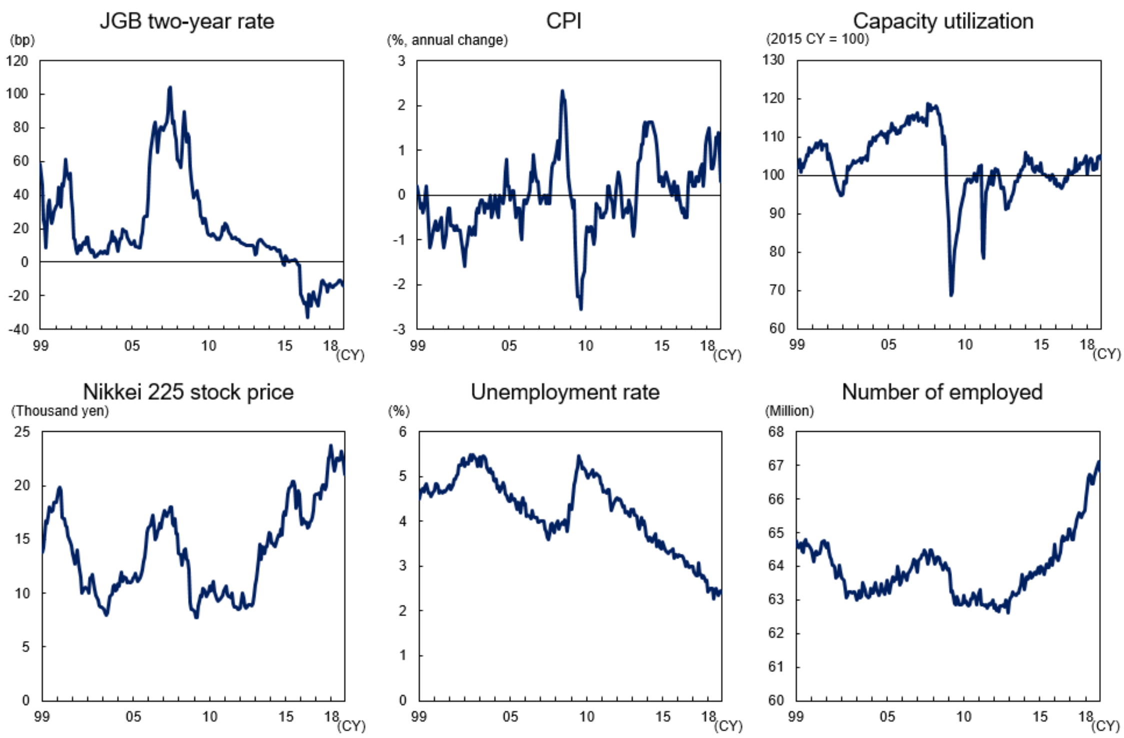
Note: ***: Significant at the 1 percent level.
**: Significant at the 5 percent level.
*: Significant at the 10 percent level.
Robust t-statistics in parentheses.

Figure 1: Distribution of population by age in Japan



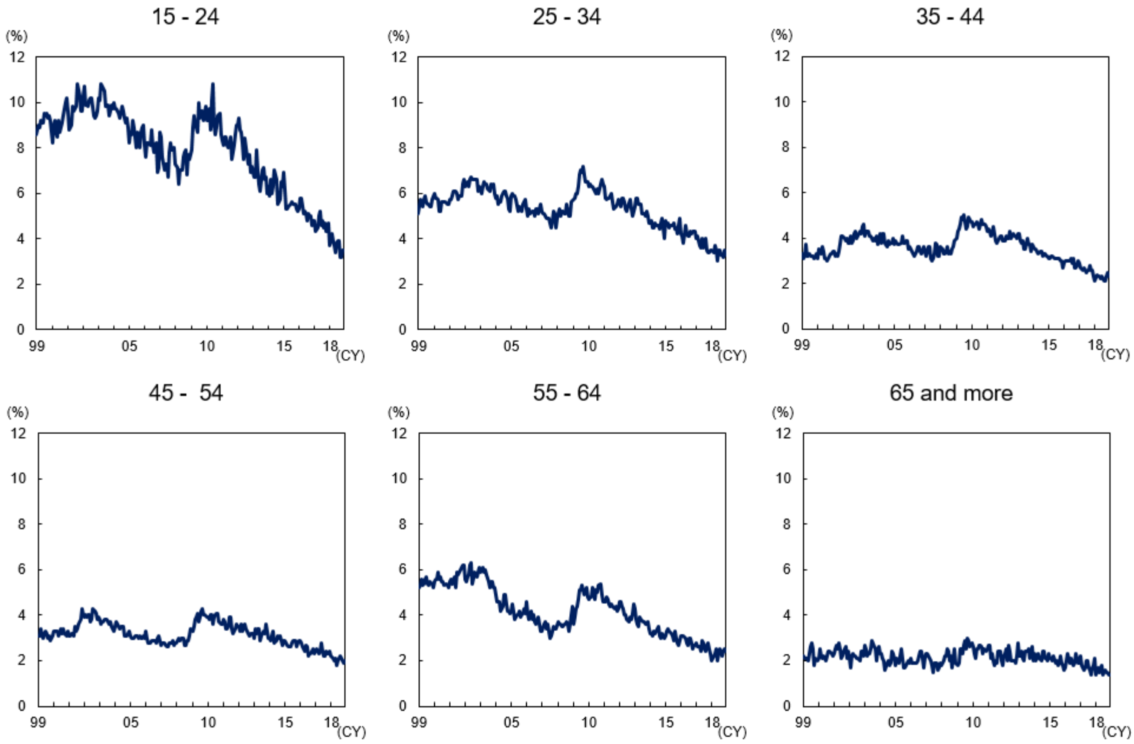
Note: This figure shows the distribution of population by age in Japan. The solid line and the dashed line show the distribution in 1970 and 2019, respectively. The data come from the Ministry of Internal Affairs and Communications.

Figure 2: Data used for the estimation: Macroeconomic variables



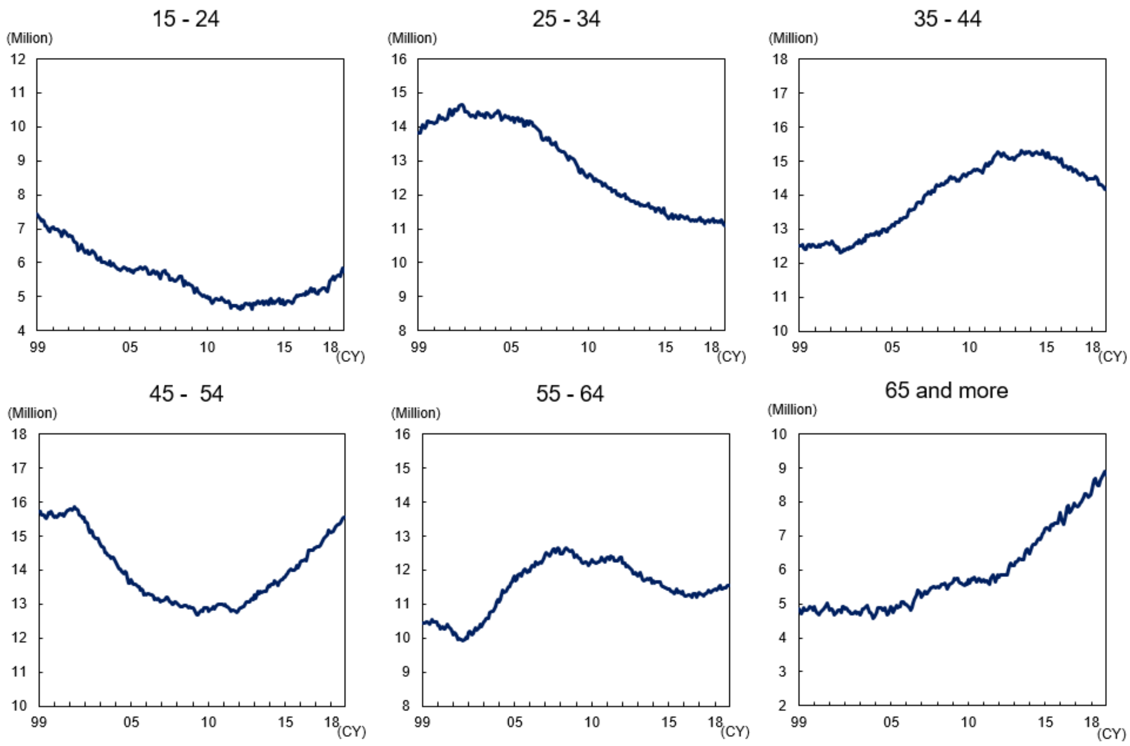
Note: Financial data such as the two-year rate and Nikkei 225 stock price come from Bloomberg. CPI, unemployment rate, and number of employed are taken from statistics released by the Ministry of Internal Affairs and Communications, and the capacity utilization rate is taken from the Indices of Industrial Production released by the Ministry of Economy, Trade and Industry.

Figure 3: Data used for the estimation: unemployment rate by age



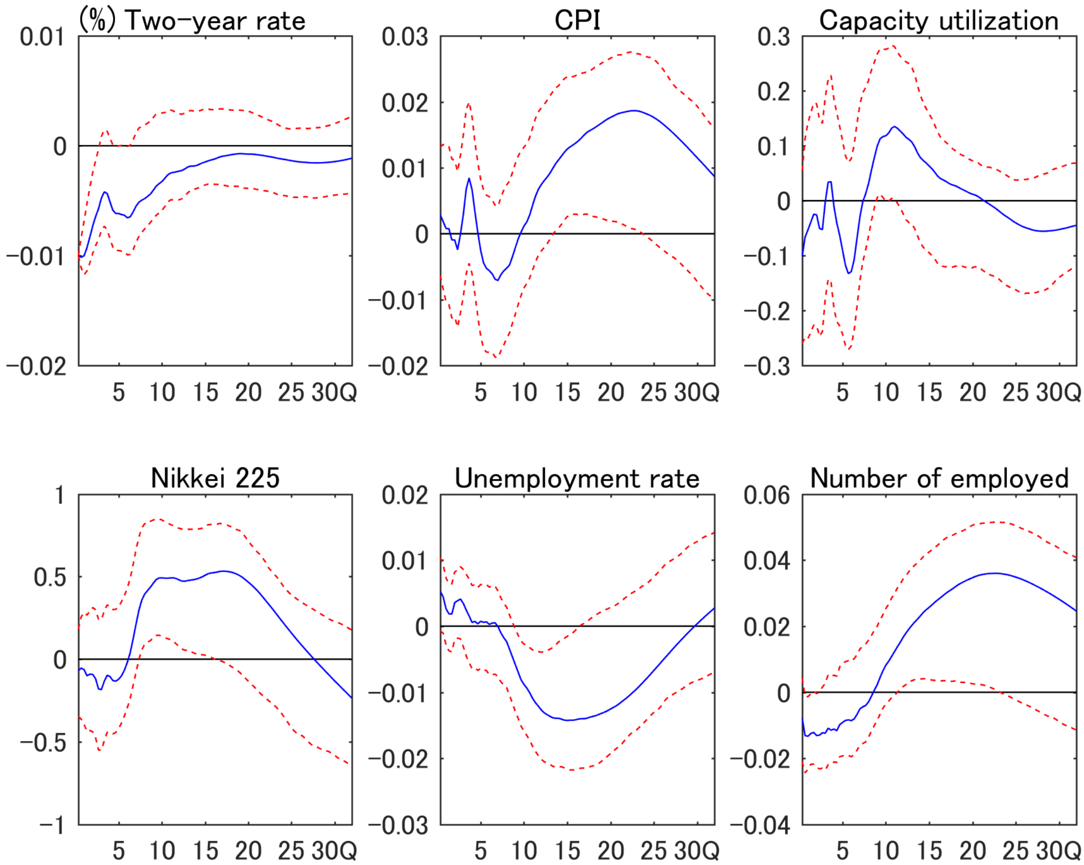
Note: The data come from the labor force survey.

Figure 4: Data used for the estimation: number of employed by age



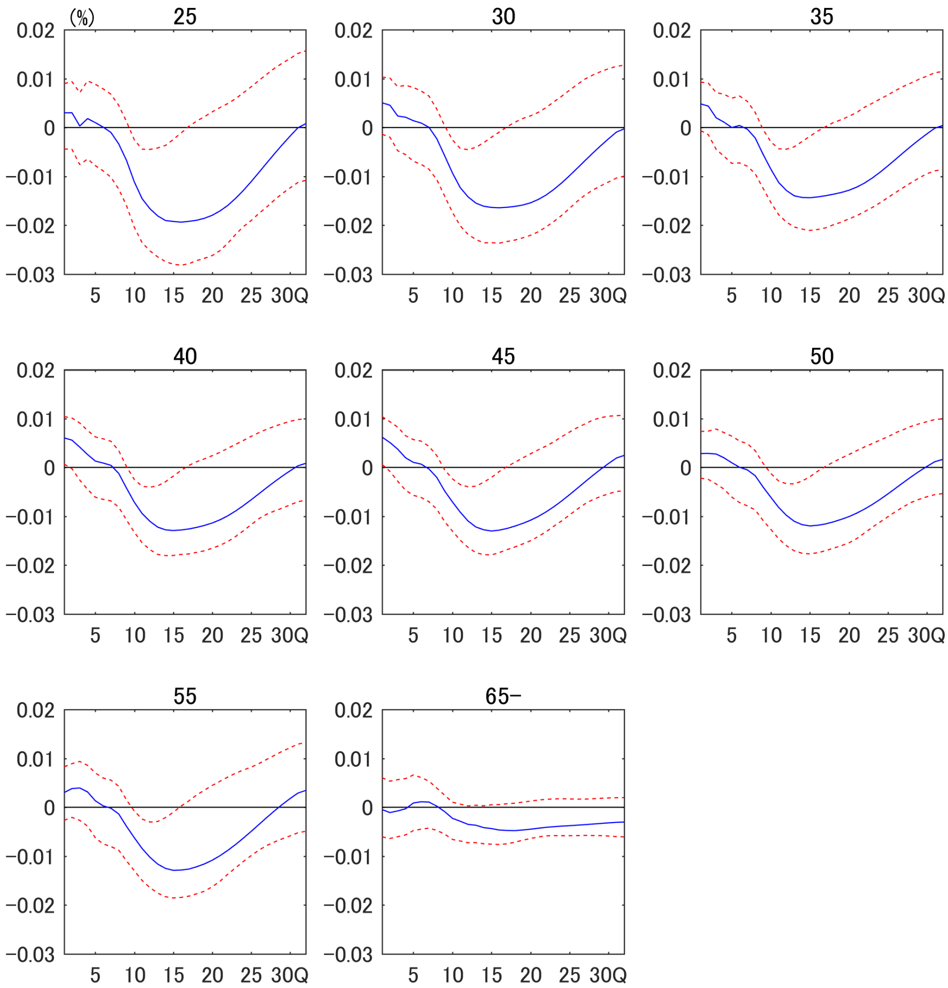
Note: The data come from the labor force survey.

Figure 5: Macroeconomic responses to a monetary policy innovation



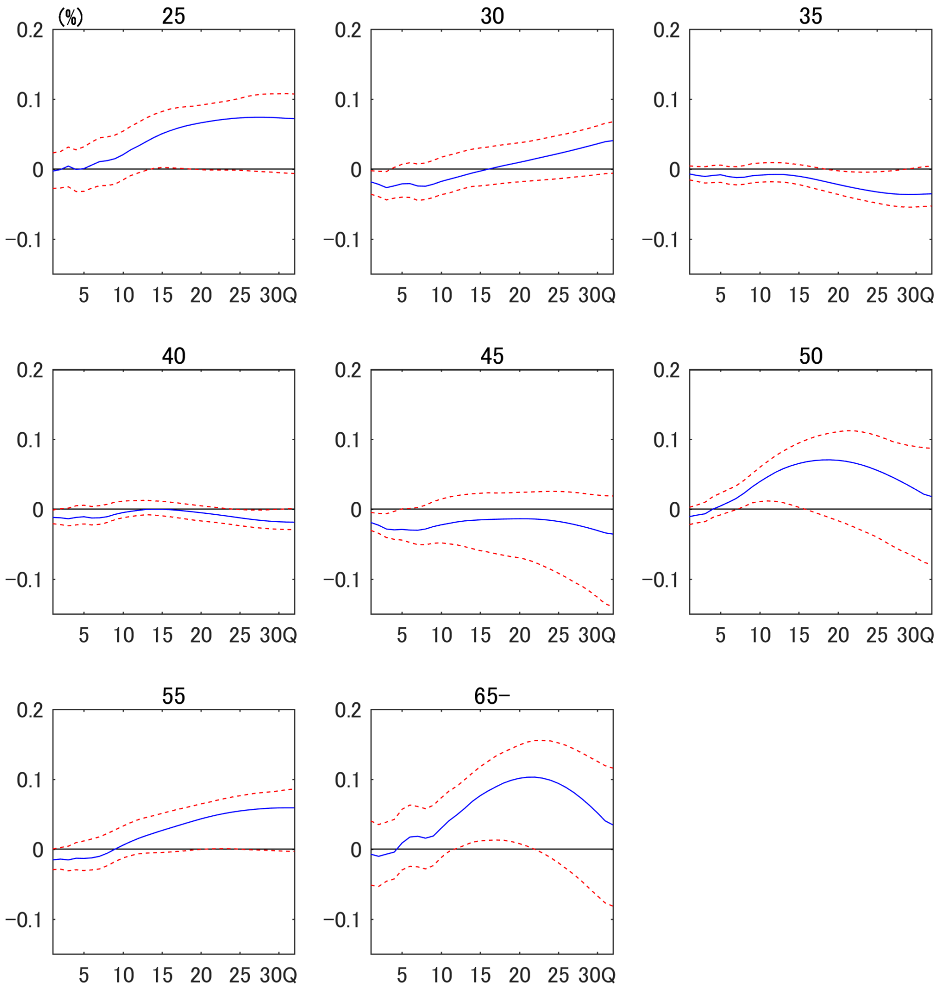
Note: This figure shows the responses of macroeconomic variables to an expansionary monetary policy shock. The shock is identified by high frequency data of YEF and normalized so that the two-year rate decreases by one bp. Dashed lines show 90% confidence intervals.

Figure 6: Unemployment rate responses



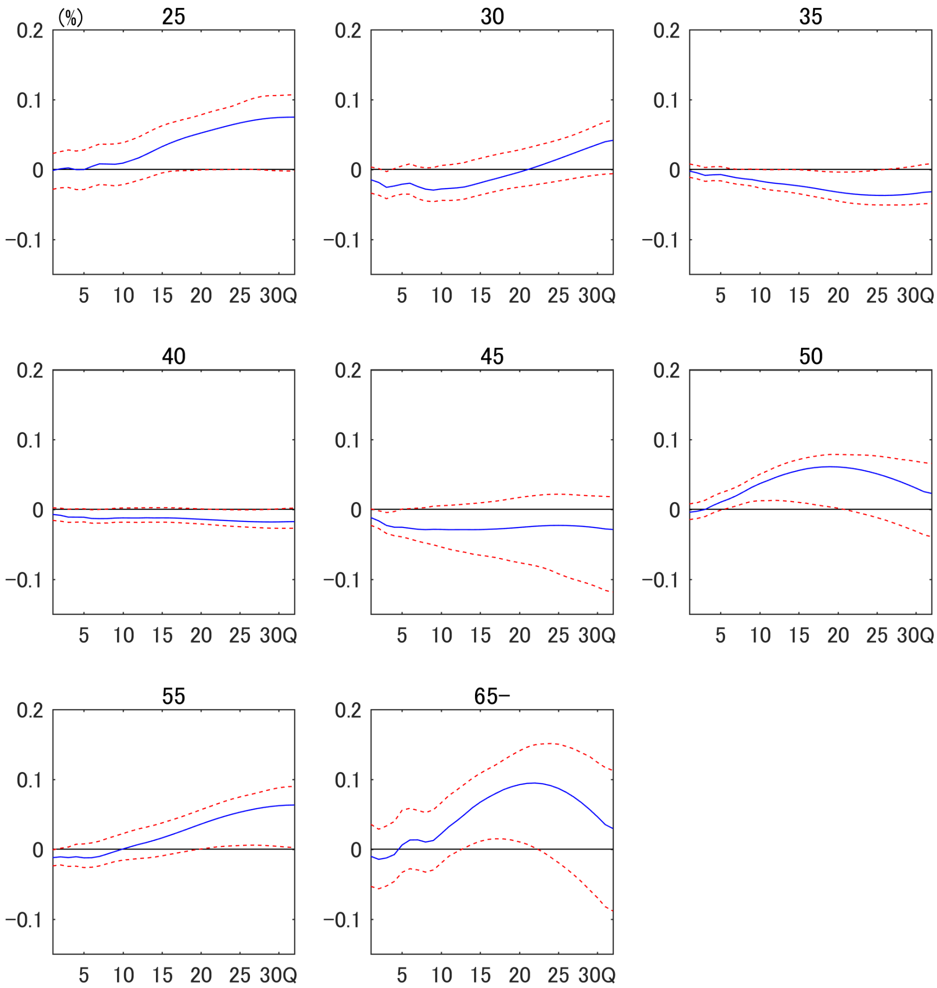
Note: This figure shows the responses of the unemployment rate to an expansionary monetary policy shock depending on the age given at the top of each graph. The shock is identified by high frequency data of YEF and normalized so that the two-year rate decreases by one bp. Dashed lines show 90% confidence intervals. Each graph is estimated using the sample between 10 years younger and 10 years older. "65-" denotes the estimated impulse response functions using samples older than 65 years old.

Figure 7: Number of employed responses



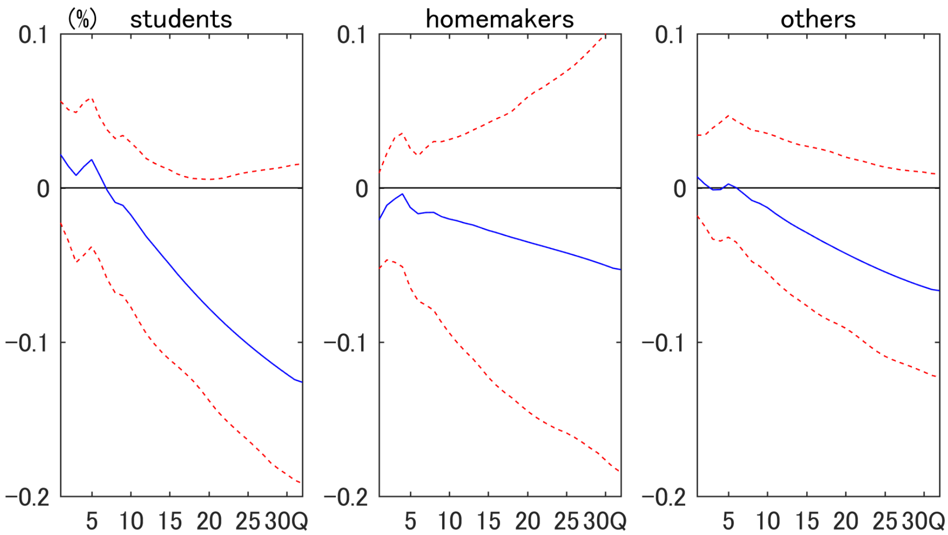
Note: This figure shows the responses of the number of employed to an expansionary monetary policy shock depending on the age given at the top of each graph. "65-" denotes the estimated impulse response functions using samples older than 65 years old. The shock is identified by high frequency data of YEF and normalized so that the two-year rate decreases by one bp. Dashed lines show 90% confidence intervals.

Figure 8: Labor force responses



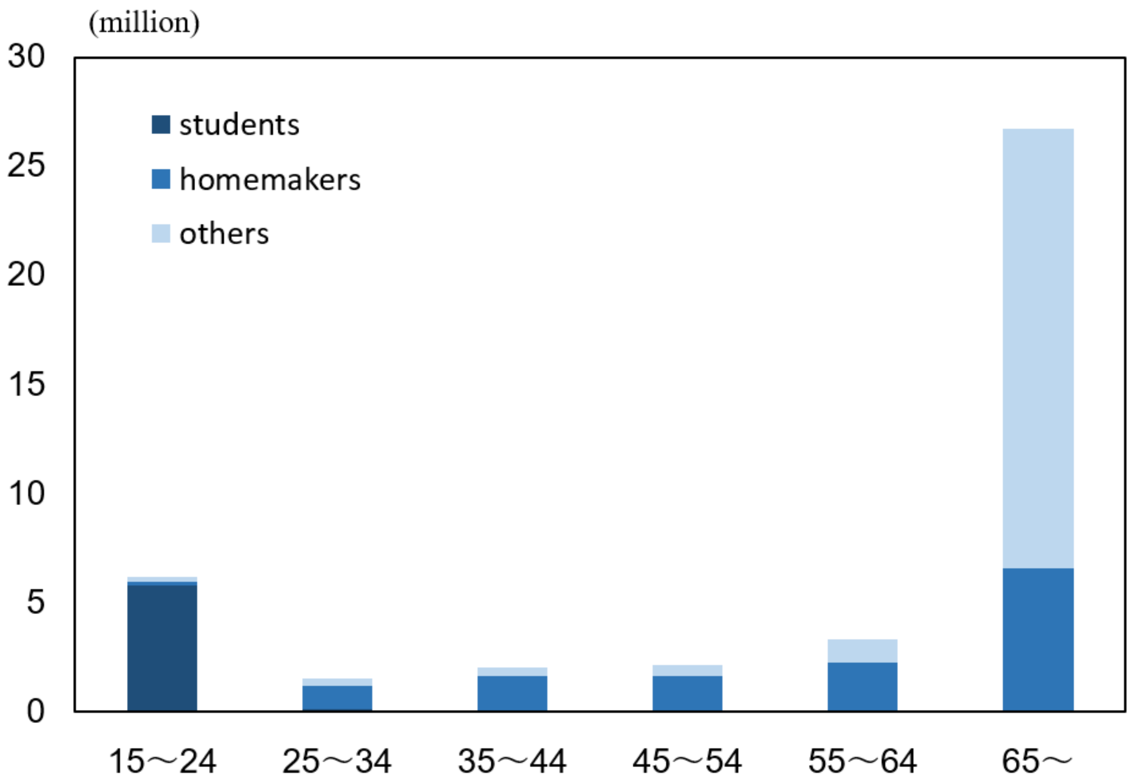
Note: This figure shows the responses of the labor force to an expansionary monetary policy shock depending on the age given at the top of each graph. The shock is identified by high frequency data of YEF and normalized so that the two-year rate decreases by one bp. Dashed lines show 90% confidence intervals. Each graph is estimated using the sample between 10 years younger and 10 years older. “65-” denotes the estimated impulse response functions using samples older than 65 years old.

Figure 9: Non-labor force responses



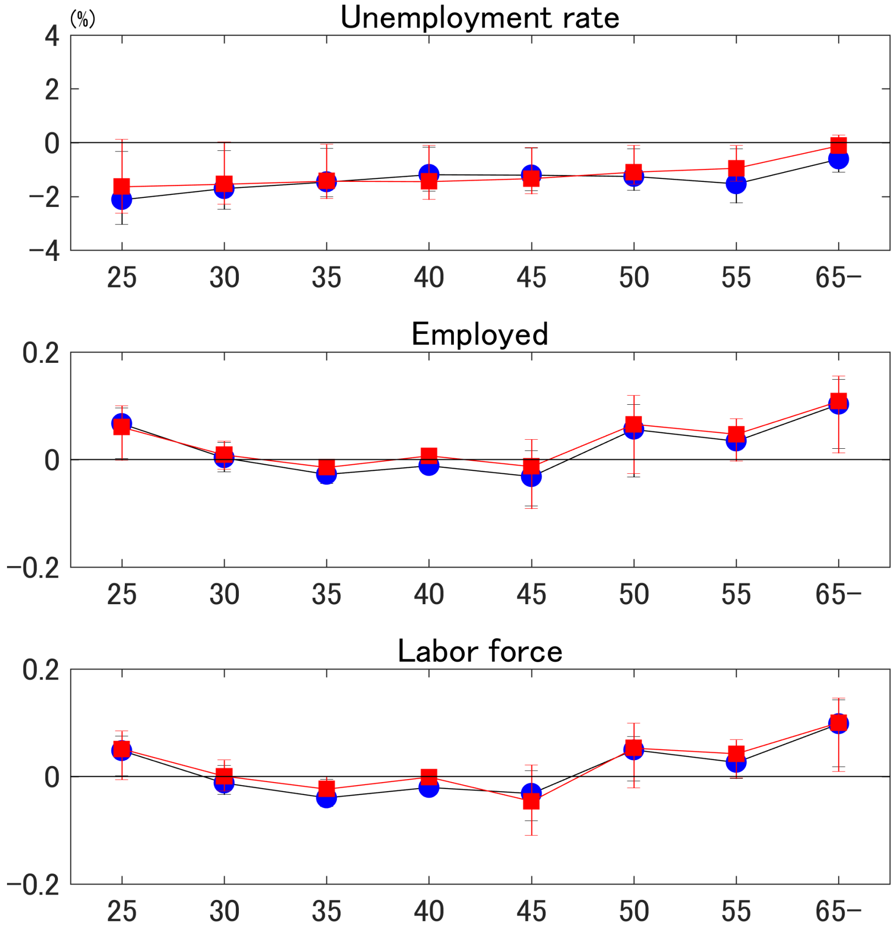
Note: This figure shows the responses of the non-labor force to an expansionary monetary policy shock. The shock is identified by high frequency data of YEF and normalized so that the two-year rate decreases by 1 bp. Dashed lines show 90% confidence intervals.

Figure 10: Breakdown of non-labor force



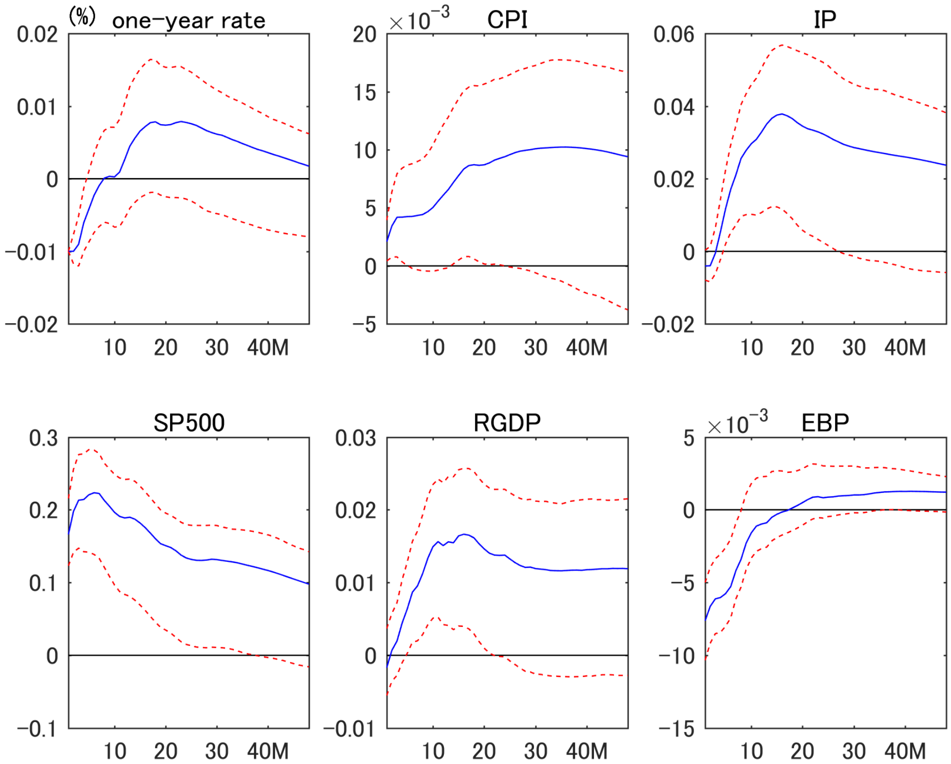
Note: This figure shows the breakdown of the non-labor force by age. The data come from the labor force survey.

Figure 11: Responses by gender



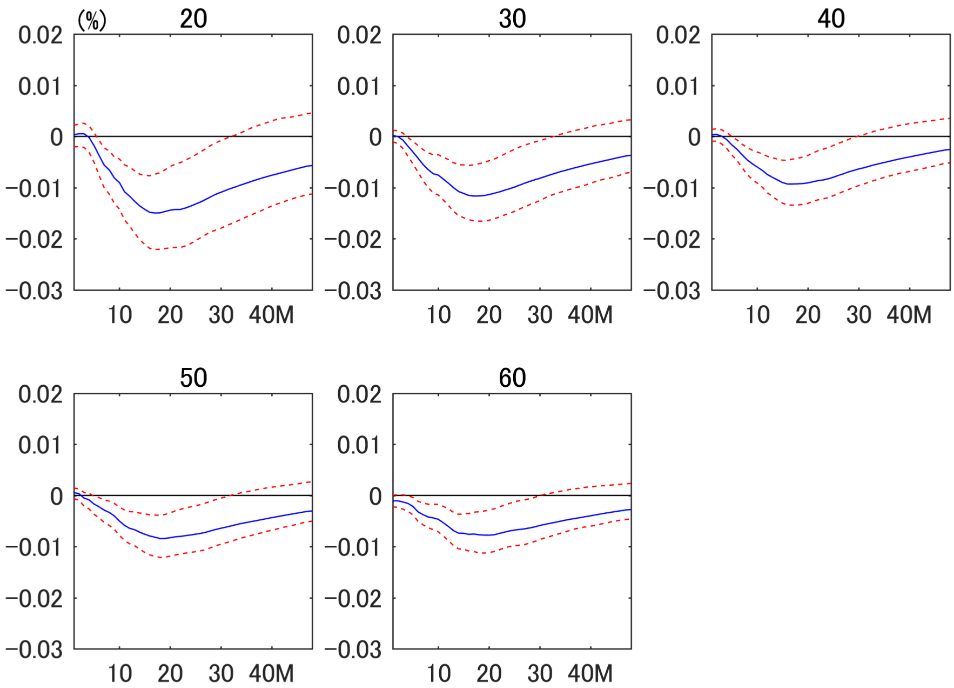
Note: This figure shows the responses of men (blue circles) and women (red squares) to an expansionary monetary policy shock. The shock is identified by high frequency data of YEF and normalized so that the two-year rate decreases by one bp. Number of employed and labor force show the impulse response at 20 quarters after the monetary policy shock, and unemployed shows that at 15 quarters after the shock. The horizontal axis shows the age. The error bars show 90% confidence intervals.

Figure 12: Macroeconomic variable responses in the U.S.



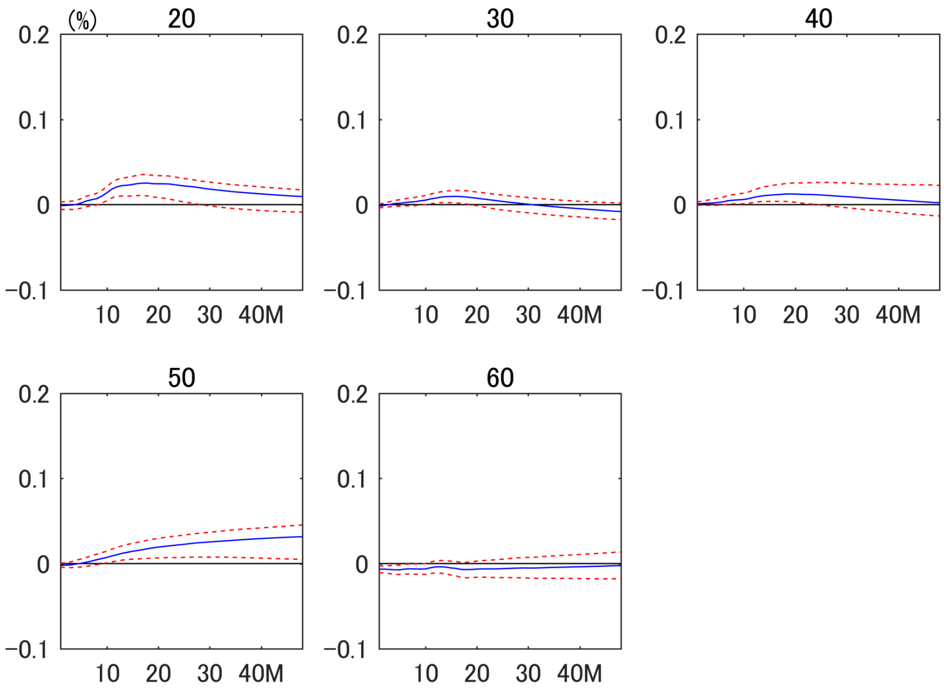
Note: This figure shows the responses of macroeconomic variables to an expansionary monetary policy shock in the U.S. The shock is normalized so that the one-year rate decreases by one bp. Dashed lines show 90% confidence intervals.

Figure 13: Unemployment rate responses in the U.S.



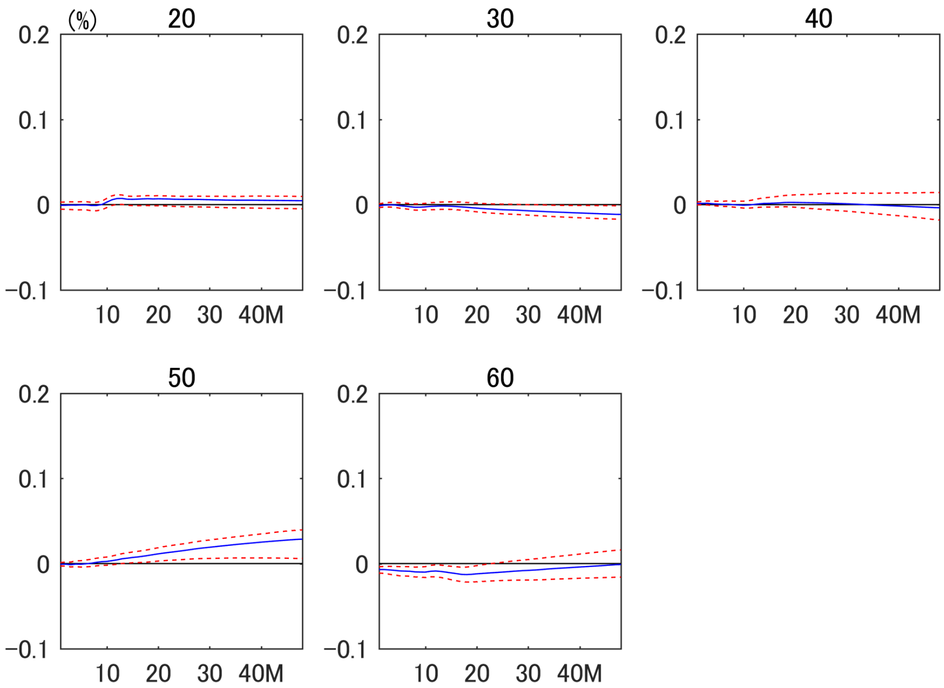
Note: This figure shows the responses of the unemployment rate to an expansionary monetary policy shock at the age given at the top of each graph. The shock is normalized so that the one-year rate decreases by one bp. Dashed lines show 90% confidence intervals.

Figure 14: Number of employed responses in the U.S.



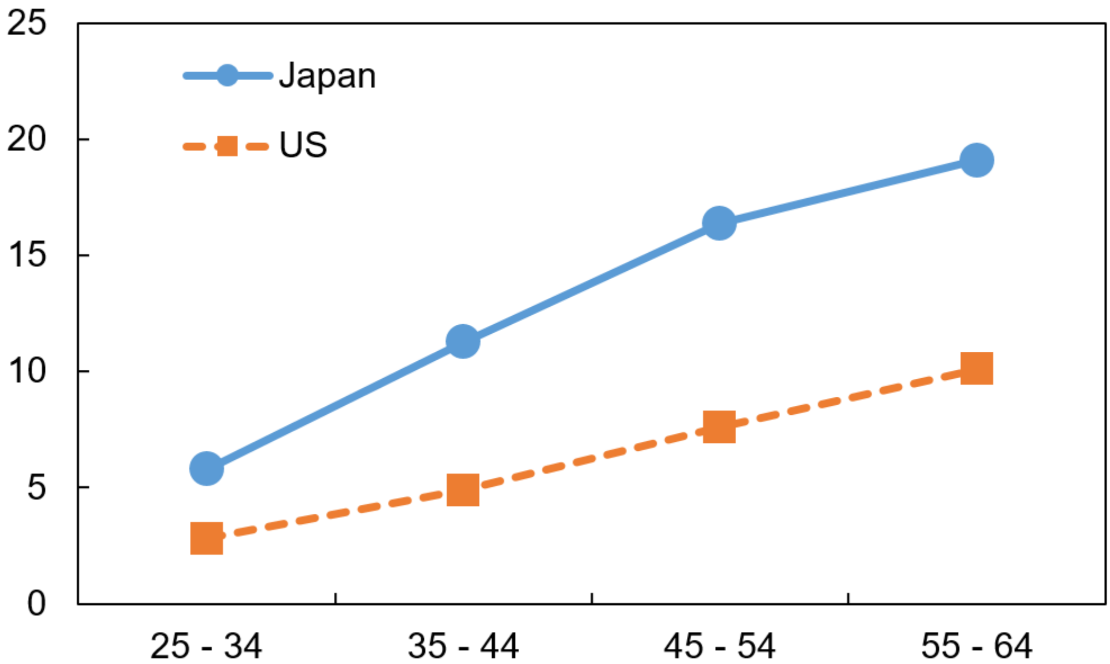
Note: This figure shows the responses of the number of employed to an expansionary monetary policy shock at the age given at the top of each graph. The shock is normalized so that the one-year rate decreases by one bp. Dashed lines show 90% confidence intervals.

Figure 15: Labor force responses in the U.S



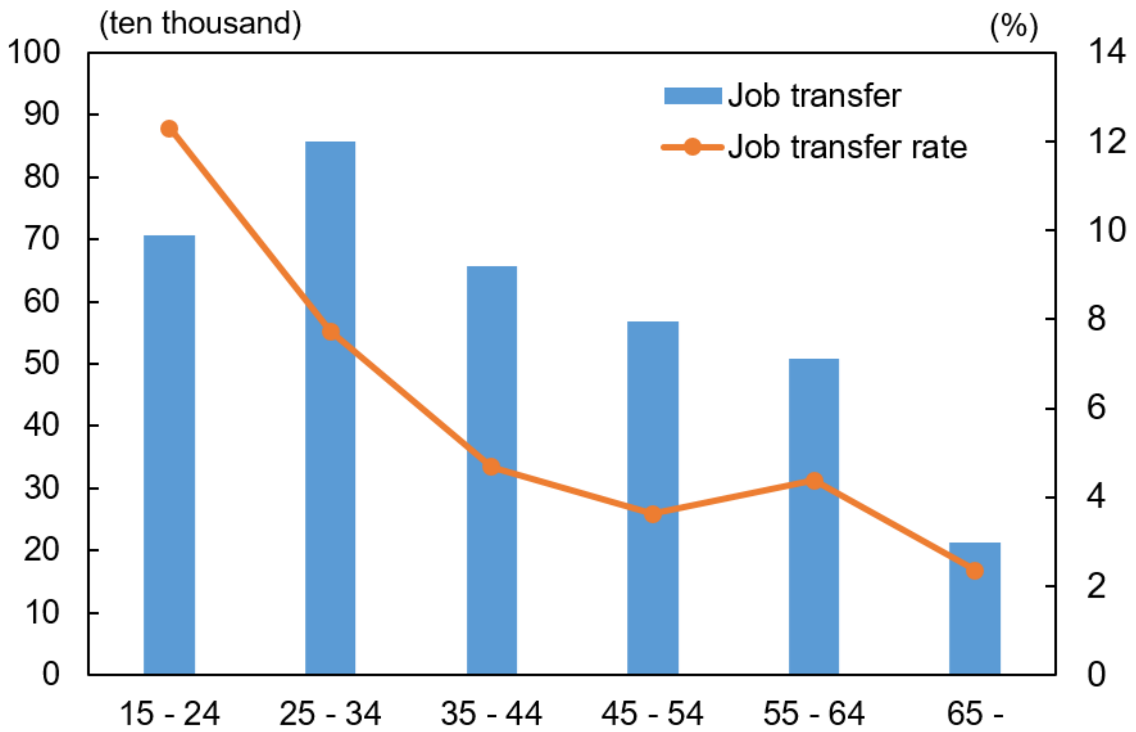
Note: This figure shows the responses of the labor force to an expansionary monetary policy shock at the age given at the top of each graph. The shock is normalized so that the one-year rate decreases by one bp. Dashed lines show 90% confidence intervals.

Figure 16: Years of tenure with current employer



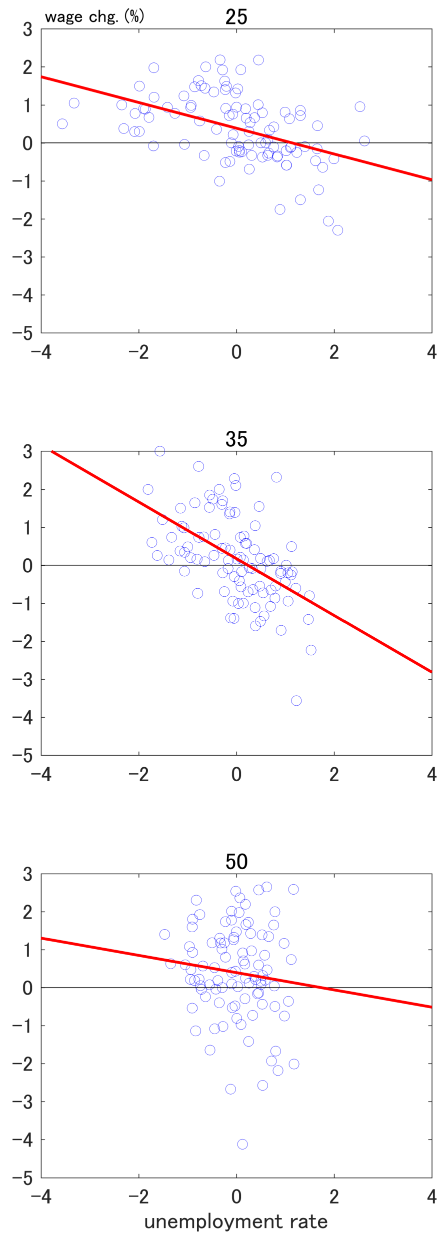
Note: This figure shows the years of tenure with the current employer in Japan and the U.S. for each age group in 2018. Japanese data come from the Ministry of Health, Labour and Welfare. The U.S. data come from the Bureau of Labor Statistics.

Figure 17: Job transfer rate in Japan



Note: This figure shows the employed persons who changed jobs in the past 1 year (left axis, ten thousand), and the rate of employed persons who changed jobs in the past 1 year (right axis, percent). The data come from the labor force survey.

Figure 18: The wage Phillips curve of each age group



Note: This figure shows the wage Phillips curve of each age given at the top of each graph. The horizontal axis corresponds to the unemployment rate deviations from the average unemployment rate. The vertical axis corresponds to the wage inflation rate. Each circle corresponds to each data point, and the red lines show the fitted line from the OLS. The unemployment data come from the Ministry of Internal Affairs and Communications, and wage data come from the Ministry of Health, Labour and Welfare. The sample period is from 1996 to 2019.