



Bank of Japan Working Paper Series

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No.20-E-4
July 2020

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Flattening of the Wage Phillips Curve and Downward Nominal Wage Rigidity: The Japanese Experience in the 2010s*

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July 2020

Abstract

In this paper, we examine from both a theoretical and an empirical perspective the validity of the hypothesis that downward nominal wage rigidity (DNWR) induced upward rigidity in wage setting, thereby contributing to the flattening of the wage Phillips curve. We focus in particular on Japanese regular workers, those workers who are characteristically employed on long-term contracts. Our theoretical study, which incorporates long-term employment contracts, indicates that DNWR induces upward wage rigidity through the following two channels: first, due to the lack of sufficient downward wage adjustments during economic downturns, firms may become reluctant to increase wages in economic recovery phases; second, firms contain wage increases even in economic expansion phases as they take into account the risk of pay cuts in the future. The strength of the latter channel largely depends on expected economic growth and its uncertainty. As a result, the wage Phillips curve becomes flatter than would be the case without DNWR. In line with the theoretical result, our empirical study using the panel data of Japanese regular workers reveals that the slower growth of monthly earnings, which excludes bonuses but includes overtime pay, for workers who display a strong degree of DNWR pushed down the growth of monthly earnings at the aggregate level by 0.4 percentage points per year (a range of 0.2 to 0.6 percentage points, given uncertainty regarding the identification of DNWR) between 2010-17. In particular, the channel arising from future pay cut risks became relatively stronger in the late 2010s, when labor market conditions became markedly tighter.

JEL Classification: E24; E31; J30

Keywords: Wage Phillips curve; Downward nominal wage rigidity; Long-term employment contracts

* The data used for this analysis, Japan Household Panel Survey (JHPS/KHPS), was provided by the Panel Data Research Center at Keio University. The authors are grateful to Kazuhiro Hiraki, Tomiyuki Kitamura, Ichiro Muto, Kenji Nishizaki, and Masaki Tanaka for their helpful comments and discussions. Any remaining errors are the sole responsibility of the authors. The views expressed in this paper are those of the authors and do not necessarily reflect the official views of the Bank of Japan.

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1 Introduction

Nominal wage growth in advanced economies remained moderate throughout the 2010s, relative to improvements in labor market conditions. The growth of scheduled cash earnings for regular workers in Japan, who correspond to full-time employees in Panel (A) of Figure 1, was modest during the long-lasting improvement of labor market conditions in the 2010s, and the wage Phillips curve during the period appears to have flattened compared with previous periods, as Bank of Japan (2017) indicates (Panel (B) of Figure 1).

There has been active debate on the causes of the flattening of the wage Phillips curve in recent years, with various hypotheses proposed.¹ Among others, central bankers have pointed to the importance of downward nominal wage rigidity (DNWR). For example, former Chair of the Board of Governors of the Federal Reserve System Janet Yellen pointed to the “pent-up wage deflation” mechanism: firms could not cut wages due to the presence of DNWR during the global financial crisis (GFC) in the late 2000s, and they became reluctant to increase wages in the subsequent economic recovery phase (Yellen 2014). Moreover, as Kuroda (2019) argued, firms may prioritize the stability of long-term employment over immediate wage increases so as to avoid the risk of pay cuts in the future. Japanese regular workers, who are characteristically subject to long-term employment practices, seem to be particularly affected by these factors.

In this paper, we examine from both a theoretical and an empirical perspective

¹For example, in the U.S., Elsby et al. (2015) pointed out the possibility that a broad measure of labor market slack, e.g., the number of discouraged workers, has remained persistent since the global financial crisis, while Krueger et al. (2014) mentioned that long-term unemployment, which increased during the same period, could have rendered wage growth sluggish. In addition, Acemoglu and Restrepo (2018) argued that recent advances in automation technologies have substituted in part for human labor, which may put downward pressure on wages. Regarding the Japanese economy, while some types of wages, such as the hourly scheduled cash earnings for part-time employees, as shown in Figure 1, and bonuses for regular workers, rose more clearly than the scheduled cash earnings for regular workers, it is argued that their growth was still contained compared with the tightening of labor market conditions and the improvement in corporate profits. In this respect, Genda (2017) investigated the causes of the slow wage growth in the 2010s from various perspectives, including expansion of the non-regular labor market and sector-specific wage systems. In addition, Bank of Japan (2018) and Ozaki and Genda (2019) investigated other factors such as the wage-elastic labor supply of the peripheral labor force in the non-regular labor market and the asymmetric adjustment of bonuses.

the validity of the hypothesis that DNWR induced upward rigidity and contributed to the flattening of the wage Phillips curve, paying particular attention to Japanese regular workers. We focus on the following two channels through which DNWR leads to upward rigidity. First, due to the lack of sufficient downward wage adjustments during economic downturns, firms may become reluctant to increase wages in economic recovery phases (the backward-looking channel of DNWR). Second, with a tendency to place priority on the stability of long-term employment over wage increases, firms may contain wage increases in economic expansion phases as they take into account the risk of pay cuts in the future (the forward-looking channel of DNWR).

This paper's analyses and findings are summarized as follows. In our theoretical analysis, we explore how DNWR affects the wage Phillips curve under long-term employment. We indeed find that, in the presence of DNWR, the wage Phillips curve becomes flatter than would be the case without DNWR through the backward- and forward-looking channels mentioned above. Moreover, as labor market conditions improve, the forward-looking channel comes to be more significant than the backward-looking channel, and the degree of economic significance of the forward-looking channel depends considerably on factors such as expected growth and its uncertainty.

Our empirical analysis investigates whether each channel of DNWR implied by our theoretical analysis affected Japanese regular workers, using Japanese individual workers' panel data in the Japan Household Panel Survey (JHPS/KHPS) compiled by the Panel Data Research Center at Keio University. We find that the growth rate of monthly earnings² for workers who displayed a strong degree of DNWR was significantly lower than that for workers who displayed a low degree of DNWR amid the improvement in labor market conditions during 2010 to 2017. The estimate implies that the slower growth of monthly earnings for workers who displayed a strong degree of DNWR pushed down the growth of monthly earnings for regular workers at the aggregate level by 0.4 percentage points per year (a range of 0.2 to

²Monthly earnings in this paper exclude bonuses but include overtime pay.

0.6 percentage points, given uncertainty regarding the identification of DNWR) on average. We also find that, consistent with the predictions of our theoretical model, both the backward- and forward-looking channels of DNWR contributed to these results. Moreover, the latter channel became relatively stronger in the late 2010s, when a tightening of labor market conditions became notable.

Previous studies on the relationship between DNWR and the wage Phillips curve have been conducted mainly from a theoretical perspective. Building upon studies that focused on the role of DNWR in economic downturns, such as Akerlof et al. (1996) and Benigno and Ricci (2011), more recent studies have investigated the consequences of DNWR in economic recovery and expansion phases. For instance, Daly and Hobijn (2014) and Iwasaki et al. (2018) demonstrated that DNWR bends the wage Phillips curve: nominal wage growth remains slow in the early stage of economic recovery. Our theoretical analysis elaborates on these previous studies by decomposing the causes due to which DNWR leads to upward rigidity, and thereby flattens the wage Phillips curve, into the backward- and forward-looking channels of DNWR. This enables us to investigate the determinants of these channels and to uncover their relative importance in each stage of a business cycle. Our analysis indicates that the slope of the wage Phillips curve is endogenously determined by various factors that affect each channel of DNWR.

On the other hand, there are few studies that have assessed empirically the hypothesis that DNWR contributes to the flattening of the wage Phillips curve by inducing upward rigidity.³ One exception is Yamamoto and Kuroda (2016), who analyzed a Japanese firm survey. They reported that the firms that had not cut the scheduled earnings in the past were more reluctant to increase the scheduled earnings and bonuses during the economic expansion of 2014 to 2015. In our empirical analysis, we employ a longer series of individual workers' panel data (until 2017) to investigate the validity of both the backward- and forward-looking channels as a cause of the modest wage growth in spite of the long-lasting improvement in labor

³In recent years, several studies, such as Pischke (2018) and Born et al. (2019), empirically investigated the effects of DNWR on the dynamics of other variables than wages. To our knowledge, this paper is the first attempt to explicitly study its impacts on the wage Phillips curve.

market conditions in the 2010s.

There is a wealth of studies on the existence and degree of DNWR, from a number of perspectives. For example, Kim and Ruge-Murcia (2009) and Iwasaki et al. (2018) assessed the degree of DNWR, while it is consistent with developments in other macroeconomic variables, by estimating a general equilibrium model according to the aggregate data. In addition, a number of studies, mainly in Europe and the U.S., have been conducted using micro data on individual workers' wage adjustments since around the 1990s. Dickens et al. (2007) conducted a comprehensive analysis of 16 countries in Europe and the U.S., and reported the existence of DNWR, though its degree differs substantially across countries. Recent studies in particular, such as Fallick et al. (2020) for the U.S. and Branten et al. (2018) for Europe, have shown that DNWR remained to a considerable degree even in the severe economic downturn after the GFC. In the case of Japan, with the enhancement of micro data since the 2000s, there has been a growing empirical literature on this topic, which has analyzed the data mainly until the early 2000s. For example, Kuroda and Yamamoto (2003, 2005), Yamamoto (2007), and Kambayashi (2011) studied the degree of DNWR by assessing the shape of wage-growth distribution. Some studies have argued that DNWR, measured by the total annual earnings of full-time employees (mainly represented by regular workers) in the Japanese labor market, was observed from 1992 to 1997, but disappeared after the Japanese financial crisis of 1998 (Kuroda and Yamamoto 2005). However, looking at each employment status and salary item, other studies have reported that the scheduled monthly earnings of regular workers display strong DNWR even from an international perspective (Yamamoto 2007). Given these previous studies and the observed fact that the growth of scheduled cash earnings remained modest mainly for regular workers in the 2010s, our analysis focuses on the earnings of regular workers that are assumed to be subject to strong DNWR.

The remainder of this paper is organized as follows. Section 2 develops a theoretical model that embeds long-term employment contracts and DNWR, and investigates the implications of DNWR for the wage Phillips curve, with particular focus

on the upward rigidity induced by DNWR. Section 3 then examines empirically the effects of DNWR with respect to Japanese regular workers using Japanese household panel data. Section 4 concludes.

2 Theoretical study

In this section, we build a model for wage setting that incorporates long-term employment contracts and DNWR. Our model extends that of Elsby (2009) in the following two aspects. First, while Elsby (2009) treated hours worked as fixed, we allow for time-variations in hours worked, thereby enabling consideration of a situation in which both wages and hours worked are endogenously determined. Second, we take into account the dynamics of aggregate wages and hours worked by introducing an aggregate exogenous shock, while Elsby (2009) focused on a stationary environment in which all aggregate variables are constant. These extensions enable us to investigate the effects of DNWR on the wage Phillips curve. Then, we derive the model's predictions that will be examined in the empirical study in Section 3.

2.1 A stylized model with DNWR

Wage setting of individual workers

To describe the typical employment practice for Japanese regular workers, we assume that a representative firm makes a long-term employment contract with each of the individual workers. As we will describe shortly, the firm sets individual workers' wages taking into account the fact that workers' labor intensity depends on the wages paid to them. Note that labor intensity captures workers' morale and labor productivity is positively associated with labor intensity. We follow Elsby (2009) in assuming labor intensity $z(\cdot)$ is given by

$$z\left(\frac{W_{it}}{P_t}, \frac{W_{it}}{W_{it-1}}\right) = \ln(b) + \ln\left(\frac{W_{it}}{P_t}\right) + c \ln\left(\frac{W_{it}}{W_{it-1}}\right) 1_{\{W_{it}/W_{it-1} < 1\}}, \quad (1)$$

where W_{it} is the nominal wage for worker $i \in [0, 1]$ and P_t is the price level.

$1_{\{W_{it}/W_{it-1}<1\}}$ is an indicator function that takes one if nominal wage decreases from the previous period ($W_{it} < W_{it-1}$) and zero otherwise. $b > 0$ in the first term of the right-hand side of (1) captures the baseline level of labor intensity. In the second term, we assume that a higher real wage leads to higher labor intensity, as in the efficiency wage theory (see, for example, Solow 1979). In the third term, moreover, we assume that a decline in nominal wages lowers labor intensity. The assumption reflects the empirical fact that nominal wage reductions have a negative impact on workers' morale (see, for example, Kahneman et al. 1986 and Bewley 1999, and Kawaguchi and Ohtake 2007 for the Japanese economy). $c > 0$ governs the impact of nominal wage decreases on labor intensity. Note that the third term depends on the size of nominal wage decrease rates $\ln(W_{it}/W_{it-1})$, implying the negative effect on labor intensity is larger for a larger declining rate in nominal wage. The asymmetric cost induced by nominal wage decreases is the source of DNWR in our model.

The firm maximizes the expected present discounted value of future profits generated by the long-term contract. The value function for each worker-firm pair is given by

$$V(W_{it-1}, A_{it}) = \max_{W_{it}, H_{it}} A_{it} \left(z \left(\frac{W_{it}}{P_t}, \frac{W_{it}}{W_{it-1}} \right) H_{it} \right)^\alpha - \frac{W_{it}}{P_t} H_{it} - \delta \frac{W_{it}}{P_t} \max \{ H_{it} - \tilde{H}, 0 \} + \beta \mathbb{E}_t [V(W_{it}, A_{it+1})], \quad (2)$$

$$\text{s.t. } \underline{H} \leq H_{it} \leq \overline{H}, \quad (3)$$

where H_{it} is hours worked and A_{it} is exogenous productivity of worker i . Labor intensity $z(\cdot)$ is given by (1). Notice that the value function depends on the previous period's nominal wage, as nominal wage decreases reduce output by lowering labor intensity. The first term in the right-hand side of (2) represents the output produced by labor input in the current period, and $0 < \alpha < 1$ is the degree of decreasing returns to scale for labor input, while the second term is the worker's base pay, and the third term is overtime pay. The last term is the expected present discounted

value of future profits. $0 < \beta < 1$ is the discount factor for future profits, which captures time preference and the probability of the contract being extended. For example, β is equal to zero for a spot contract, whereas β gets close to one for a long-term employment contract.

One difference between our model and that of Elsby (2009) is that we endogenize hours worked, and therefore the firm chooses both nominal wages and labor input to maximize the present discounted value. In line with Japanese legislation and employment practice, we incorporate the overtime premium $\delta > 0$ and lower and upper bounds of hours worked, denoted by \underline{H} and \bar{H} , respectively.

Another difference from Elsby (2009) is the presence of an aggregate shock. We assume that exogenous productivity A_{it} consists of the aggregate component A_t^{agg} and idiosyncratic component A_{it}^{id} , each of which follows

$$\ln A_{it} = \ln A_t^{agg} + \ln A_{it}^{id}, \quad (4)$$

$$\ln A_t^{agg} = (1 - \rho^{agg})g + \rho^{agg} \ln A_{t-1}^{agg} + \epsilon_t^{agg}, \quad \epsilon_t^{agg} \sim N(0, (\sigma^{agg})^2), \quad (5)$$

$$\ln A_{it}^{id} = \begin{cases} \rho^{id} \ln A_{it-1}^{id} + \epsilon_{it}^{id}, & \epsilon_{it}^{id} \sim N(0, (\sigma^{id})^2) & \text{with probability } 1 - \gamma \\ \ln A_{it-1}^{id} & & \text{with probability } \gamma \end{cases}, \quad (6)$$

where ρ^{agg} and σ^{agg} are the AR(1) coefficient and the standard deviation of innovations for the aggregate component, and ρ^{id} and σ^{id} are those for the idiosyncratic component. We assume that the aggregate component follows an AR(1) process with deterministic trend g . While Elsby (2009) considered a stationary environment, we allow for time-variations of aggregate productivity, so aggregate wages and hours worked fluctuate accordingly. The idiosyncratic component follows an AR(1) process with a new innovation with probability $1 - \gamma$, otherwise remaining at the previous period's level. The infrequent productivity shocks capture kurtosis of the wage-growth distribution observed in the data—a large spike at zero wage-growth while fat-tailed distribution—. Similar specifications are often used in the literature to describe the dynamics of individual productivity of workers and firms

(e.g., Kaplan et al. 2018, Vavra 2014). For descriptive purposes, we refer to A_{it} as a labor demand shock in the sense that a rise (decline) in A_{it} increases (decreases) marginal products of labor input leading to higher (lower) labor demand.

Aggregate dynamics in the labor market

The aggregate nominal wages W_t and hours worked H_t are defined below.⁴

$$W_t = \int_0^1 W_{it} di, \quad (7)$$

$$H_t = \int_0^1 H_{it} di. \quad (8)$$

It should be noted that although we do not explicitly describe households' behavior, the model setting can be interpreted as assuming that households supply labor and earn wages based on the wages and hours worked determined by the firm, and that they consume so that the goods market clears. The aggregate nominal wage growth rate is given by $\pi_t^w = \ln(W_t/W_{t-1})$. We assume the inflation rate π_t is constant over time (π):

$$\pi_t \equiv \ln\left(\frac{P_t}{P_{t-1}}\right) = \pi. \quad (9)$$

In this regard, our model describes a partial equilibrium in which labor market outcomes, such as individual workers' wages, are determined given an inflation rate. However, compared with a fully specified non-linear dynamic general equilibrium model, it provides a parsimonious framework to study labor market dynamics in the presence of aggregate shocks. In addition, the setting of our model is consistent with our empirical study in the next section, in which we assess individual wage determination given macroeconomic conditions.⁵

⁴Consistent with our empirical study in the next section, we define aggregate nominal wages as the average of individual workers' wages. We confirm that our result does not change much when we consider an alternative definition under which the aggregate wages are calculated by dividing the aggregate labor income ($\int_0^1 W_{it} H_{it} di$) by the aggregate hours worked ($\int_0^1 H_{it} di$).

⁵A potential extension is to accommodate the interaction between wages and prices by introducing nominal price rigidity. However, the implications of DNWR—the focus of this paper—would remain unchanged under variable inflation rates, at least qualitatively. As reference, Kim and

2.2 Numerical analysis

Numerical method and calibration

The wage setting of individual workers described in the previous subsection includes nonlinearity arising from DNWR. Hence, an approximation of wage setting using, for example, the perturbation method is not applicable. We solve for the individual wage function f by using the value function iteration method.

$$W_{it} = f(A_{it}, W_{it-1}). \quad (10)$$

In this baseline case, $f(\cdot)$ depends on the previous period's wage level W_{it-1} due to DNWR in addition to exogenous productivity A_{it} .

To decompose two channels through which DNWR induces upward rigidity, we consider the wages, W_{it}^* , that exclude the effects of the past wages as below.

$$W_{it}^* = f(A_{it}, \underline{W}), \quad (11)$$

where $f(\cdot)$ is identical to that in (10) while \underline{W} takes a sufficiently low value. In this alternative case, while DNWR does not bind in the current period since the previous period's wage is assumed to be sufficiently low, DNWR is still relevant because it may bind in the future, depending on the wage chosen in the current period.

Moreover, for comparison purposes, we also define the wages, W_{it}^{**} , that realize when nominal wages are flexible :

$$W_{it}^{**} = g(A_{it}), \quad (12)$$

where $g(\cdot)$ is obtained by setting $c = 0$ in (2). In this case, the current wages do not depend on the previous period's wage W_{it-1} as DNWR does not exist.

Using these wage functions, we conduct a stochastic simulation of the calibrated model to generate the series of wages and hours worked for individual workers.

Ruge-Murcia (2009) and Iwasaki et al. (2018) investigated the interaction between wages and prices using a general equilibrium model with DNWR and nominal price rigidity.

Aggregate variables are obtained by integrating them across workers. Given that the main focus of this analysis is on deriving qualitative predictions that will be tested in the light of the data in Section 3, we calibrate the model by assigning plausible parameter values that are broadly consistent with salient features of the Japanese labor market up until the 2010s.

The calibrated parameter values are listed in Table 1. The model's frequency is annual. The discount factor β is set to 0.95 (5% annual rate). The value reflects the subjective discount factor, which is calibrated to an annual rate of around 2% in previous studies, and the separation rate for regular workers, which is around 3% per year according to the JHPS/KHPS (described shortly). Regarding the parameters for labor intensity, the baseline level of labor intensity b is normalized to $b = \exp(1)$ so that the real wage in the steady state is equal to one. The degree of DNWR c is set to $c = 1.00$ so that the relationship between the hours worked and the wage growth when DNWR is present in the model is broadly consistent with the data. The degree of decreasing returns to scale α is set to 0.66 in line with the conventional value in the macroeconomic literature. The parameters for hours worked are calibrated according to the related legal system and employment practice.⁶ Specifically, the upper bound of hours worked is set to $\bar{H}/H^{ss} = 1.30$ according to the difference between the limit of overtime work determined in the Japanese Labor Standards Act and the average hours worked in the data, which corresponds to H^{ss} in the model. The lower bound of hours worked is set to $\underline{H}/H^{ss} = 0.85$ based on the standard scheduled hours worked in practice. The presence of the lower bound of hours worked implies that, under long-term employment practices, layoffs are not readily implemented for regular workers even in economic downturns. The overtime premium δ is set to 0.25 as the Japanese Labor Standards Act requires a premium of more than 25% for overtime work. We assume that statutory working hours \tilde{H} are equal to the average hours worked in the data, i.e., $\tilde{H}/H^{ss} = 1.00$. The inflation rate π is set to an annual rate of 2%. The trend productivity growth rate in the

⁶Note, however, that the calibration for hours worked is subject to a considerable margin of error as, within the law, they may differ across firms.

baseline calibration is set to 0%, while we examine the cases in which the value changes in the later part of this subsection. As for exogenous productivity, we set $\rho^{agg} = 0.70$, $\sigma^{agg} = 0.015$, $\rho^{id} = 0.70$, $\sigma^{id} = 0.15$, and $\gamma = 0.5$ according to the moments of nominal wage growth, such as standard deviation, in the aggregate and individual data.

Implications for individual wage setting

Panel (A) of Figure 2 shows the wage functions for individual workers in the calibrated model. The figure indicates two channels through which DNWR induces upward rigidity in wage setting. The first is the mechanism arising from insufficient wage adjustment in the past (the backward-looking channel of DNWR). In the blue region in the figure ($W_{it} > W_{it}^*$), the previous period's wage remains at a high level—workers receive higher wages than implied by their labor productivity—. In that case, the firm does not increase wages even if labor demand rises, as long as the insufficient downward wage adjustment in the past remains. The other is the mechanism arising from pay cut risks in the future (the forward-looking channel of DNWR). In the red region in the figure ($W_{it} < W_{it}^{**}$), the firm internalizes the fact that DNWR will be more likely to bind in the future once they increase wages, resulting in lower wage growth than under flexible wages. This is the case even when strong labor demand offsets the insufficient wage adjustments in the past.

Panel (B) of Figure 2 compares the cross-sectional wage-growth distribution obtained in the stochastic simulation with and without DNWR. When DNWR is present, the share of workers who receive positive wage growth decreases, as does the share of those who receive negative wage growth, because DNWR induces upward rigidity. Consequently, the share of workers who receive wage freezes increases, rendering the distribution less dispersed than under flexible wages.

Implications for wage Phillips curve

One notable feature of our model is that, unlike Elsby (2009)'s framework, we can derive the wage Phillips curve as aggregate wages and hours worked fluctuate upon

aggregate shocks. Panel (A) of Figure 3 displays the wage Phillips curve, obtained as the quadratic fitted curve of the relationship between aggregate nominal wage growth and hours worked in the stochastic simulation. The wage Phillips curve suggests a positive association between hours worked and nominal wage growth at the aggregate level. More importantly, the cases with and without DNWR shown in the figure indicate that the wage Phillips curve becomes flatter in the presence of DNWR.

It is worth mentioning that the wage Phillips curve becomes flatter for all regions of hours worked when DNWR is present. This is because DNWR endogenously induces upward rigidity when labor demand increases, in addition to preventing wage declines when labor demand decreases. The endogenous upward rigidity arises from the two channels described above: the backward- and forward-looking channels of DNWR. To see the effect of each channel in more detail, Panel (B) of Figure 3 decomposes the causes of the flattening of the wage Phillips curve into the two channels. The figure indicates that both channels contribute to the flattening at each level of labor demand. It is also worth mentioning that the forward-looking channel becomes more significant than the backward-looking channel as hours worked increases. Intuitively, as labor demand increases, the insufficient wage adjustment in the past gradually diminishes.⁷ On the other hand, the firm still contains wage increases because they become more cautious about the risk that labor demand will begin to decrease at some point in the future and they will thereby be constrained by DNWR.

Determinants of the forward-looking channel of DNWR

The forward-looking channel of DNWR arises because of the firm's desire to avoid the risk of being unable to cut nominal wages in the future, which leads to lower labor intensity. Thus, the channel becomes particularly significant when such risk grows. This would be the case, for example, when expected growth decreases

⁷The backward-looking channel diminishes but does not disappear, even at high levels of labor demand. This is because some workers remain subject to insufficient wage adjustments due to idiosyncratic labor demand shocks at the individual level.

or uncertainty regarding economic growth increases.

To examine this point, we extend the model so that the trend productivity growth rate g and the standard deviation of labor demand shock σ approximately follow AR(1) processes, and we then compute the generalized impulse responses (GIR) to these shocks.⁸ Note that g acts as the expected growth rate of the economy while σ represents uncertainty in our model. Figure 4 shows the GIR of aggregate variables upon each shock. The figure displays three cases: the baseline case with DNWR; the case with only the forward-looking channel of DNWR (corresponding to wage function (11)); and the case without DNWR (flexible wages). As for the responses to a decline in expected growth, the case with only the forward-looking channel of DNWR exhibits a deeper decline in nominal wage growth than under flexible wages.⁹ When it comes to the responses to a rise in uncertainty, nominal wage growth sharply decreases on impact in the case with only the forward-looking channel of DNWR.¹⁰

The results in this section imply that, even when labor demand increases in economic expansion phases, if economic growth stays at a low level or uncertainty regarding future economic growth increases, nominal wage growth may remain modest as DNWR flattens the wage Phillips curve.

⁸For simplicity, we assume that the trend productivity growth rate may take two values: $g_t = \{g_h, g_l\}$ with $g_h > g_l$. The transition probabilities between the two values are given by p_{hl} and p_{lh} . Likewise, the standard deviation of labor demand shock is discretized as $\sigma_t^s = \{\sigma_h^s, \sigma_l^s\}$ with $\sigma_h^s > \sigma_l^s$ for $s \in \{agg, id\}$. We assume that the standard deviation for the aggregate and idiosyncratic components of productivity stays in the same regime. We set $p_{hl} = p_{lh} = 0.2$. In Figure 4, we compute the GIR to a decline in expected growth by 1 percentage point, i.e., $g_h = 0.01, g_l = 0.00$, and that to a rise in uncertainty by 1 percentage point for aggregate component and 10 percentage points for idiosyncratic one, i.e., $\sigma_h^{agg} = 0.02, \sigma_l^{agg} = 0.01, \sigma_h^{id} = 0.20$, and $\sigma_l^{id} = 0.10$. Notice that though each variable is discretized with two values the GIR takes a smooth path because it is the conditional expectation upon an initial shock.

⁹In the case with full DNWR, the decline in nominal wage growth is smaller than under flexible wages, as DNWR prevents wage decreases upon the shock for a considerable share of workers.

¹⁰Note that under flexible wages the aggregate wage growth remains unaffected by changes in uncertainty because wages can be adjusted both upwardly and downwardly by necessary amounts when productivity shocks occur.

3 Empirical study

The theoretical study in Section 2 indicates that DNWR induces upward rigidity, leading to lower nominal wage growth during economic recovery and expansion phases compared with that under flexible wages. In this section, we examine empirically the theoretical predictions using Japanese household panel data.

3.1 Data

JHPS/KHPS

In our empirical study, we use individual data from the Japan Household Panel Survey (JHPS/KHPS) compiled by the Panel Data Research Center at Keio University. The JHPS/KHPS tracks the employment status and consumption expenditure, etc., of the same individuals over time. The subjects surveyed are chosen in order to reflect the population composition of the Japanese economy. The spouse of each subject also receives the questionnaire, answering separately regarding their own employment status.

We restrict our sample to workers who are below 59 years old and who have worked for the same company for two consecutive years. The sample excludes individuals not under employment contract with a company, such as the self-employed, freelancers, workers at a family business, and consigned workers. In addition, we exclude worker-year pairs in which the workers have changed jobs, and we limit our sample to full-time/regular workers whose pay-period is monthly, because we are interested in regular workers under long-term employment contracts. We also confine our sample to workers who worked every month in each survey year so as to exclude the potential effects on wage dynamics of absence from work or unemployment. As a result, our final sample, including spouses, contains approximately 3,300 workers as of the 2018 survey. Our measures of wage are monthly earnings and bonuses. Monthly earning excludes bonuses but includes overtime pay. The sample covers the years from 2003 to 2017 (from the 2004 to 2018 surveys).

Descriptive statistics

Table 2 reports the descriptive statistics of key variables in our sample.¹¹ To begin with, Table 2-1 compares characteristics of our sample with the Employment Status Survey (ESS), a representative survey for employment status in Japan. The table shows that our sample characteristics are consistent with those of the regular employees in the ESS in terms of gender, educational background, and employment status, including industry and firm size. Table 2-2 compares the descriptive statistics of wages in our sample with the Basic Survey on Wage Structure (BSWS), a representative wage survey in Japan. This table shows that the average monthly earnings, bonuses, and hours of paid work per week in our sample are close to those of full-time workers in the BSWS.¹² Moreover, Panel (A) of Figure 5 shows that the average wage of our sample fluctuates in line with the aggregate statistics derived from the BSWS and the Monthly Labour Survey. These facts confirm that our empirical study using the JHPS/KHPS provides an accurate representation of Japanese regular workers.

3.2 Empirical strategy

Differences-in-Differences

Our empirical study first assesses whether individual wages for regular workers in the JHPS/KHPS displayed DNWR during the GFC that occurred in the late 2000s. We then use the Differences-in-Differences (DID) to examine if the wage growth of the workers who displayed a strong degree of DNWR was lower during the recovery and tightening phases in the 2010s than that of workers whose wages can be flexibly adjusted. We also test the validity of the backward- and forward-looking channels of DNWR, which are implied by our theoretical model, by exploiting relevant information on each worker, as described shortly. Our baseline regression equation is

¹¹See Higuchi (2005) for a descriptions of the entire sample of the JHPS/KHPS.

¹²Strictly speaking, the average level of bonuses is somewhat lower in our sample. This may reflect the fact that the special cash earnings in the BSWS include temporary earnings paid to workers other than bonuses. In addition, the average age and tenure in our sample are slightly higher, partly because the JHPS/KHPS covers only workers aged 20 years or above.

given by

$$\Delta W_{it} = c + \beta X_{it} Y_{it} + \gamma' \mathbf{Z}_{it} + \mu_i + \lambda_t + \epsilon_{it}, \quad (13)$$

where ΔW_{it} on the left-hand side of (13) denotes the year-on-year rate of wage growth of worker i in year t . On the right-hand side, X_{it} is a measure of the degree of DNWR for each worker, which we will describe shortly. Y_{it} is a measure of labor market conditions. c is a constant, and ϵ_{it} is an error term. As an example of identification, suppose that X_{it} is a dummy variable that takes one for workers who display a strong degree of DNWR, and zero otherwise. Also, let Y_{it} be a measure of the aggregate labor market conditions under the assumption that each worker faces the same labor demand. In this case, the coefficient β represents the difference between the two groups of workers ($X_{it} = 0$ or 1) in the sensitivity of wage growth with respect to changes in aggregate labor market conditions—the restraining effect of DNWR on wage growth under improving labor market conditions—. Note that individual factors and factors common across workers are captured by μ_i and λ_t , and observable characteristics are contained in the vector of controls \mathbf{Z}_{it} . The advantage of the DID is that we can estimate the effect of interest controlling these various factors.¹³

Classification of workers

To implement the above empirical strategy, we need to distinguish the degree of DNWR for each worker. Many existing studies claimed the existence of DNWR based on the observation that there is a spike at zero in the cross-sectional wage-growth distribution and that the distribution exhibits much fewer incidences of wage decrease than increase. However, as Kuroda and Yamamoto (2003, 2005) and Barattieri et al. (2014) pointed out, it may not be appropriate to judge the degree of DNWR only from the unconditional wage-growth distribution, given that

¹³In the DID specification here, determinants of wage growth other than DNWR are captured by these controls and others. That is, our empirical study does not exclude other hypotheses regarding the slower wage growth in the 2010s.

wage settings are state-dependent: there would be little incentive to cut wages even without DNWR when the inflation rate is high on average or the economy is booming.

To overcome this challenge in measuring the degree of DNWR from the data, we define workers who displayed a strong degree of DNWR as those who did not receive any wage decreases during the GFC (2008 and 2009), when most firms experienced a sharp drop in sales—the source of wage disbursements—amid the severe economic downturn. The premise of this classification method is that the GFC that occurred when inflation in Japan was low can be thought of as a large negative labor demand shock that imposed downward pressure on wages for a wide range of workers, therefore the lack of wage decreases during the period implies some sort of friction in wage adjustments. Note, Branten et al. (2018) and Fallick et al. (2020) also used information on wage changes during the GFC to evaluate the degree of DNWR. A similar method is used by Yamamoto and Kuroda (2016) for the Japanese economy.

Based on this method, the share of workers who displayed a strong degree of DNWR is around one third of the sample during the GFC.¹⁴ While the fraction is lower than the average share of workers without wage decreases for a given year during our sample period (around 70%), it implies the presence of some sort of friction in downward wage adjustments for Japanese regular workers. However, there is uncertainty around the identification of DNWR. In the second half of Section 3.3, we conduct a robustness check with respect to the classification of workers who have a strong degree of DNWR.

In addition, when examining the backward- and forward-looking channels of DNWR in Section 3.4, it is necessary to identify the workers who are prone to be affected by each channel. We do so by comparing actual wages and potential wages for workers who displayed a strong degree of DNWR, where the latter is estimated

¹⁴Studies based on this method would be conservative in their estimate of the effects of DNWR for the following two reasons. First, the monthly earnings in the JHPS/KHPS include overtime pay as well as base pay. Given that a decline in hours worked in economic downturns leads to a decrease in monthly earnings even when the base pay remains unchanged, our classification may understate the degree of DNWR embedded in the base pay. Second, there may be measurement errors in the classification. In the regression analysis, the presence of measurement errors generates attenuation bias.

from various factors, such as tenure and educational background.¹⁵ For example, suppose that a worker’s actual wage is above their potential wage. We then consider that this worker has inherited the insufficient wage adjustment from the past, hence classifying the worker as one who is prone to be affected by the backward-looking channel of DNWR. On the other hand, if the worker’s actual wage is lower than their potential wage, we consider that the worker exhibits no wage adjustment pressure inherited from the past. Then, we classify the worker as one who is prone to be affected by the forward-looking channel of DNWR.¹⁶

3.3 Overall effects of DNWR on wage growth rate

This section examines the overall effect of DNWR on wage growth of regular workers after the GFC, regardless of its channels. To examine the effect, we first divide the sample period during and after the GFC into three phases based on labor market conditions: the deterioration phase during 2008–2009, the recovery phase in 2010–2012, and the tightening phase during 2013–2017 (Panel (B) of Figure 5). We then examine how much the wage growth of the workers who displayed a strong degree of DNWR was lower (or higher) than that of the workers who displayed a low degree of DNWR in each phase. The estimation equation is given by

$$\Delta W_{it} = c + \beta_1 X_i D_{08-09} + \beta_2 X_i D_{10-12} + \beta_3 X_i D_{13-17} + \gamma' \mathbf{Z}_{it} + \mu_i + \lambda_t + \epsilon_{it}, \quad (14)$$

where X_i is a DNWR dummy equal to one if the worker did not receive any wage decreases during the GFC (2008 and 2009), and zero otherwise. D_{08-09} , D_{10-12} and

¹⁵More specifically, we extend the Mincer wage equation (Mincer 1974) to include aggregate labor market conditions as well as individual workers’ characteristics such as tenure and educational background. The estimated potential wages can be interpreted as the average wage level determined by worker characteristics as the wage adjustment proceeds in the medium- and long-run. In that sense, they correspond approximately to the flexible wages in our theoretical model. The details are presented in Appendix A.

¹⁶This classification is conducted in each year by comparing the level of actual wages and potential wages in the previous year. Consequently, a worker who was subject to the backward-looking channel at some point in time may later switch to one who is subject to the forward-looking channel.

D_{13-17} are time dummies equal to one if the period is 2008–2009, 2010–2012 and 2013–2017 respectively, and zero otherwise. \mathbf{Z}_{it} is a vector of control variables displaying each worker’s characteristics such as tenure and educational background.¹⁷ μ_i is a random effect for each worker.¹⁸ λ_t is a time fixed effect. We estimate (14) for the period 2004–2017.

Empirical result

Table 3 reports the estimation result. Looking at the result of the monthly earnings, both β_2 and β_3 are negative and they are statistically significant. This result, consistent with the predictions of our theoretical model, shows that the wage growth of workers with a strong degree of DNWR was significantly lower than that of workers with a low degree of DNWR during the recovery and tightening phases after the GFC.

β_1 is positive, but this is by the definition of DNWR dummy: we define the workers who displayed a strong degree of DNWR as those who did not receive any wage decreases during the GFC. Regarding bonuses, β_2 and β_3 are negative, but not statistically significant. These results show that while DNWR induced upward rigidity for monthly earnings including base pay, DNWR did not induce upward rigidity for bonuses. This result may be partly due to the limited number of workers without any bonus decrease during the GFC, which would make it difficult to infer

¹⁷Control variables include interaction term of industry dummy and year dummy (industry consists of manufacturing, wholesale and retail, construction, medical services and welfare, and other non-manufacturing), tenure, age category dummy (24 years old or less, 25–29 years old, 30–34 years old, 35–39 years old, 40–44 years old, 45–49 years old, 50–54 years old, and 55–59 years old), title dummy, labor union dummy, firm size dummy (1–29 workers, 30–99 workers, 100–499 workers, 500 workers or more, and government), gender dummy, dummy for type of school last attended (junior high school, high school, junior college or technical school, university, and graduate school), region dummy (Hokkaido, Tohoku, Kanto, Chubu, Kinki, Chugoku, Shikoku, and Kyusyu), occupation dummy (service worker, manager, specialized or technical worker, clerical worker, salesperson, agriculture, forestry, fishery and mine worker, and others), CPI by region, hours of paid work per week in the previous year (only in the estimate regarding monthly earnings).

¹⁸The JHPS/KHPS includes workers added to the sample after 2008. If we used an individual fixed effect instead of a random effect, both the fixed effect and the DNWR dummy would be constant over time for these samples of workers, hampering the identification of each effect. This leads us to employ the random effect model. Note instead that we control for the characteristics of each worker that are constant over time by \mathbf{Z}_{it} , the vector of control variables.

the precise effect of DNWR on bonuses. Based on these results, we hereafter focus on the monthly earnings for which DNWR is considered to induce a large degree of upward rigidity.

Calculation of the effect on wage growth at the aggregate level

Next, we calculate the effect of DNWR on the wage growth of regular workers at the aggregate level. For the calculation, it is necessary to take into account the share of workers who displayed a strong degree of DNWR in our sample, in addition to the effect of DNWR on the wage growth of each worker, shown in Table 3. In this respect, as noted in Section 3.2, the share of workers who displayed a strong degree of DNWR is around one third of the sample during the GFC.¹⁹ Based on this information, we calculate the effect of DNWR on the wage growth of regular workers at the aggregate level during the recovery and tightening phases of labor market conditions after 2010, as shown in Panel (A) of Figure 6. This figure shows that the slower wage growth of the workers who displayed a strong degree of DNWR pushed down the growth rate of monthly earnings at the aggregate level by 0.4 percentage points per annum during both 2010–2012 and 2013–2017. During the recovery and tightening phases, DNWR of regular workers induced upward rigidity, which can be considered a non-negligible cause of the flattening of the wage Phillips curve in the 2010s. In Section 3.4, we will look at the channel behind this.

Robustness check

The above results may be driven by our assumptions regarding the identification of workers who displayed a strong degree of DNWR. To assess the robustness of the results, we employ two alternative criteria for identifying DNWR for each worker. First, workers who displayed a strong degree of DNWR are defined as workers without any wage decreases in the last three years. This can be regarded as a looser criterion than our baseline, because we consider the economic recovery

¹⁹We confirm that, among the workers whose wage growth can be observed both during and after the GFC, the workers who displayed a strong degree of DNWR constantly accounts for around one third after 2010.

and expansion phases in addition to the downturn when identifying DNWR. Second, as a stricter criterion, we define workers who displayed a strong degree of DNWR as those whose actual wage growth exceeded their potential wage growth during the GFC. Since Japanese regular workers receive periodic pay raises, which reflect their tenure, etc., the potential wage growth of some workers could be positive even during economic downturns such as the GFC.

Table 4 reports the estimation results of the effect of DNWR based on these two alternative criteria.²⁰ The estimation results show that DNWR pushed down significantly the growth of monthly earnings amid the labor market improvement in the 2010s, even when we use alternative criteria for measuring the degree of DNWR.

The effect of DNWR on wage growth at the aggregate level under the alternative criteria is shown in Panel (B) of Figure 6. The figure shows that the impacts of downward pressure due to DNWR were around 0.6 percentage points under the looser criterion and around 0.2 percentage points under the stricter criterion. These estimates are statistically significant. The calculated effect under the looser criterion is larger than that in the baseline, because the estimated coefficient on the effect of DNWR is larger. Under the stricter criterion, while the estimated coefficients are about the same as the baseline, the share of workers who displayed a strong degree of DNWR becomes smaller than that in the baseline. As a result, the calculated effect under the stricter criterion is smaller. From these findings, the conclusion that DNWR of regular workers induced upward rigidity, thereby functioning as a factor for the flattening of the wage Phillips curve amid the improvement of labor market conditions, is robust as a means of measuring DNWR.²¹

²⁰In the estimation based on the looser criterion, we focus on the coefficient of interaction term of the DNWR dummy and the time dummy that displays the period when the unemployment rate declined (Y_t). Note that, since this DNWR dummy can vary over time, we can use an individual fixed effect for this specification. As such, we exclude from the control variables those variables that represent time-invariant characteristics of each worker, and add the individual fixed effect and the DNWR dummy to the control variables. The equation in the stricter criterion is the same as the baseline estimation. We estimate both equations for the period 2004–2017, which is the same as the baseline model.

²¹Note that in the baseline specification, we regard workers added to the sample after 2009 as workers who displayed a low degree of DNWR ($X_i=0$) during the GFC, since there is no information on their wage adjustments during the GFC. To assess the robustness of our result regarding this assumption, Appendix B calculates their degree of DNWR based on the information on their wage

3.4 Estimation results on the two channels

Examination of the backward-looking channel

We examine whether the backward-looking channel did indeed work as a background to the upward rigidity induced by DNWR. More specifically, we focus on the workers who displayed a strong degree of DNWR during the GFC and who inherited the insufficient wage adjustment as identified by their actual wage being higher than their potential. We examine if, as predicted by our theory, the wage growth of this type of worker was lower than that of workers with a low degree of DNWR in the recovery and tightening phases of labor market conditions in the 2010s. The equation is given by

$$\Delta W_{it} = c + \beta_4 X_i \text{Gap}_{it-1} 1_{\{\text{Gap}_{it-1} \geq 0\}} D_{10-17} + \gamma' \mathbf{Z}_{it} + \mu_i + \lambda_t + \epsilon_{it}, \quad (15)$$

where Gap_{it-1} is the deviation rate of the actual wage from the potential wage in the previous year. $\text{Gap}_{it-1} 1_{\{\text{Gap}_{it-1} \geq 0\}}$ is a variable which is positive if the deviation rate is positive and zero otherwise. D_{10-17} is equal to one during 2010–2017, and zero otherwise. μ_i is a fixed effect for each worker.²² The definitions of other variables are the same as those in the baseline estimation.²³ We estimate the equation for the period 2008–2017, in order to focus on the effect of the GFC. If the backward-looking channel had worked, we would have observed that the wage growth rate of the workers who are prone to be affected by the backward-looking channel ($X_i = 1$ and $\text{Gap}_{it-1} \geq 0$) was lower than that of workers whose wage was flexible in the improvement phases of the labor market conditions ($D_{10-17} = 1$). That is, we expect

change after the GFC, and we reestimate the baseline equation (14) using the revised information on DNWR for these workers. Our estimates show that the result is also robust to the treatment of DNWR for workers added to the sample after 2009.

²² $X_i \text{Gap}_{it-1} 1_{\{\text{Gap}_{it-1} \geq 0\}}$ in (15) can vary over time hence is not treated as a fixed effect. Therefore, we employ a fixed effect model to estimate (15).

²³We add $X_i D_{08-09}$, $X_i \text{Gap}_{it-1}$ and $X_i |\text{Gap}_{it-1}| 1_{\{\text{Gap}_{it-1} < 0\}} D_{10-17}$ to the control variables in (14), because we have to control how much the wage growth of workers who displayed a strong degree of DNWR was lower than that of other workers in the sample during the GFC, and how much that of workers with a strong degree of DNWR and without insufficient wage adjustment in the past was lower than workers with a low degree of DNWR. The time-invariant variables are excluded from the control variables because they are included in the fixed effect.

that β_4 takes a negative value.

Table 5 shows the estimation result on monthly earnings. β_4 is negative and statistically significant. This implies that in regard to the workers who are prone to be affected by the backward-looking channel, the channel actually worked in the recovery phase and tightening phase of labor market conditions in the 2010s.

The effect of this channel on wage growth at the aggregate level depends on the proportion of workers who are prone to the backward-looking channel. Figure 7 shows the distributions of the deviation rate of actual wage from potential wage after the GFC, shown separately for workers with a strong or low degree of DNWR. During 2008–2009, the deviation rate of workers with a strong degree of DNWR is biased toward positive territory. This implies that there were many workers with a strong degree of DNWR who received insufficient wage adjustment during the GFC, causing depressed wage growth in the subsequent recovery phase. In the figure, you can also find that the skew of the distribution diminished during 2013–2017. This suggests that the effect of the backward-looking channel gradually diminished as labor market conditions continued to improve after the GFC.

Examination of the forward-looking channel

Finally, we examine whether the forward-looking channel did indeed work after the GFC. In this study, we focus on the workers who displayed a strong degree of DNWR during the GFC, but who received a lower wage than their potential at some point in the subsequent years. We then estimate whether, as our theoretical study predicted, (a) the lower expected growth in the industry to which the workers belong, and (b) the higher uncertainty regarding growth in that industry, are associated with the lower wage growth for these workers, compared with workers who displayed a low degree of DNWR. The estimation equation is given by

$$\begin{aligned} \Delta W_{it} = & c + \beta_5 X_i |Gap_{it-1}| 1_{\{Gap_{it-1} < 0\}} Y_{1t}^j + \beta_6 X_i |Gap_{it-1}| 1_{\{Gap_{it-1} < 0\}} Y_{2t}^j \\ & + \gamma' \mathbf{Z}_{it} + \mu_i + \lambda_t + \epsilon_{it}, \end{aligned} \quad (16)$$

where $|Gap_{it-1}|1_{\{Gap_{it-1}<0\}}$ is a variable which takes the absolute value of the deviation rate of actual wage from its potential only when the deviation rate in the previous year was negative, and zero otherwise. Y_{1t}^j is the index of expected growth by industry and Y_{2t}^j is the uncertainty index by industry. The definitions of other variables are the same as those in (14).²⁴ We estimate the equation for the period 2008–2017. If the forward-looking channel had worked, the wage growth of the workers who are prone to be affected by the forward-looking channel ($X_i = 1$ and $Gap_{it-1} < 0$) would have been lower when expected growth (Y_{1t}^j) declines. Therefore, β_5 is expected to be positive. Moreover, if the forward-looking channel had worked, their wage growth would have been lower, when the uncertainty increases, therefore β_6 is expected to be negative.

We generate the series of the index of expected growth and its uncertainty as follows: the index of expected growth is the profit forecast of firms taken from the Short-Term Economic Survey of Enterprises in Japan (TANKAN), which is a representative survey of firms in Japan. We use the survey results from March 2003 to December 2018, and we remove the short- to medium-term cycle components (5 years or less) of the profit forecasts using the band pass filter of Christiano and Fitzgerald (2003). The value in each year is the average of the trend component among those of the March, June, September and December surveys. We calculate the indexes for the following five industries: manufacturing, wholesale and retail, construction, medical services and welfare, and other non-manufacturing. As for the uncertainty index, we employ the historical standard deviation of daily stock returns for the five industries derived from TOPIX-17.

Table 6 reports the estimation result on monthly earnings. As expected, β_5 is significantly positive and β_6 is significantly negative. This implies that as expected

²⁴We add $X_i D_{08-09}$, $X_i Gap_{it-1}$, $X_i Gap_{it-1} 1_{\{Gap_{it-1} \geq 0\}} Y_{1t}^j$, $X_i Gap_{it-1} 1_{\{Gap_{it-1} \geq 0\}} Y_{2t}^j$, $Gap_{it-1} Y_{1t}^j$, $Gap_{it-1} Y_{2t}^j$ to the control variables used in (14). This is because we aim to control the following: how much the wage growth of workers with a strong degree of DNWR was lower than that of the other workers during the GFC, how much the wage growth of the workers with a strong degree of DNWR and with the insufficient wage adjustment was contained by each index, and the effect of each index on the wage growth through the deviation rate. In addition, we exclude time-invariant variables of each worker from the control variables, as we employ a fixed effect for each worker.

growth declines or its uncertainty increases, the wage increase of workers who are prone to be affected by the forward-looking channel is contained. It is worth noting that in Figure 8, we can observe periods when the index of expected growth was sluggish and when the uncertainty index heightened after 2010.²⁵ These results suggest that there were workers whose wage increase was contained by the forward-looking channel amid the improvement in labor market conditions after the GFC.

The effect of the forward-looking channel on wage growth at the aggregate level seems to have become more significant over time, since the share of workers overpaid has decreased during the same period and that of workers underpaid has increased, as shown in Figure 7. These results provide the empirical ground for the view that firms prioritized the stability of long-term employment over immediate wage increases, since firms were not confident about future growth due to persistent low growth in the past.

4 Conclusion

Among a number of hypotheses, some economists and central bankers have pointed to the significance of the upward wage rigidity induced by DNWR, when interpreting the flattening of the wage Phillips curve. In this paper, we pay particular attention to Japanese regular workers, characterized by their long-term employment contracts, and we examine the validity of the hypothesis that DNWR has contributed to the flattening of the wage Phillips curve from both a theoretical and an empirical perspective.

Our theoretical study, which incorporates long-term employment contracts, suggests that DNWR induces upward wage rigidity, contributing to the flattening of the wage Phillips curve through the following two channels: the mechanism arising from insufficient wage adjustment in the past (the backward-looking channel of DNWR), and the mechanism arising from pay cut risks in the future (the forward-

²⁵Figure 8 (Reference) shows that the similar tendencies are observed in the alternative indexes of expected growth and uncertainty.

looking channel of DNWR). In addition, declines in expected growth and increases in the uncertainty around economic growth strengthen upward rigidity because they increase the risk of future pay cuts.

In line with the theoretical result, our empirical study using the panel data of Japanese regular workers reveals that the slower wage growth of the workers who displayed a strong degree of DNWR pushed down the growth of monthly earnings at the aggregate level by 0.4 percentage points per year (a range of 0.2 to 0.6 percentage points, given uncertainty regarding the identification of DNWR) during the years between 2010–2017. We confirm that both the backward- and forward-looking channels of DNWR contributed to this result. Moreover, the latter channel became relatively stronger in the late 2010s, when a tightening of labor market conditions became notable.

Finally, we suggest two future research topics relevant to our study. First, there remains more room to study the relationship between wage setting and macroeconomic performance. From a theoretical perspective, our model can be extended to incorporate the interaction between wages and prices, and to incorporate monetary policy. From an empirical perspective, assessing the impact of shifts in labor market trends, due for example to population aging, and of fluctuations in the natural rate of unemployment in Japan would enrich our empirical analysis. Second, our findings relate to developments of Japan’s labor market in the 2010s, with our conclusions and the implications of this paper being also based on those observations. To investigate forthcoming labor market fluctuations in the 2020s, following the outbreak of COVID-19, further study is warranted, based on relevant data as they become available. That is, the outbreak could affect wages not only through labor demand shocks at the aggregate level, as examined in this paper, but also through labor force reallocation pressures as they appear heterogeneously among individual industries or regions.²⁶ It will also be important to assess the long-term consequences as well

²⁶Barrero et al. (2020), who examined a U.S. firm survey conducted in April 2020, argued that the outbreak of COVID-19 would lead to a large-scale reallocation in the labor market, since the firms surveyed anticipated job creation to meet new types of demand while mentioning the necessity of massive layoff of the current workforce. For the Japanese economy, Kikuchi et al. (2020) uncovered substantial heterogeneity in the impact of the outbreak of COVID-19 across various characteristics

as the immediate effects of the labor policy introduced following these shocks. Analysis around these points remains future work awaiting the accumulation of sufficient data.

such as industry and employment status.

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Appendix A Estimation of potential wage

When estimating potential wage, we consider the factors of industry and aggregate economy, based on the Mincer wage equation (Mincer 1974), where the potential wage is estimated from the characteristics of workers such as tenure, etc. The estimated potential wage can be interpreted as the average wage level determined by their characteristics as the wage adjustment proceeds in the medium and long term.²⁷ The equation is given by

$$\ln W_{it} = c + \gamma \mathbf{Z}_{it} + \alpha Y_t + \mu_i + \epsilon_{it}, \quad (17)$$

where $\ln W_{it}$ is natural log of the wage level. \mathbf{Z}_{it} is a vector of variables for characteristics of each worker. More specifically, as the characteristics, we consider tenure, square of tenure, age category dummy, title dummy, labor union dummy, firm size dummy, occupation dummy, labor productivity by industry, and CPI by region.²⁸ These variables and specifications are based for the most part on previous studies such as Kawaguchi (2011). We add unemployment rate (Y_t) to capture the effect of aggregate labor market conditions on the wage. μ_i is a fixed effect for each worker. We estimate the equation for the period 2003–2017.

Appendix Table 1 reports the estimation result. The coefficient of tenure is positive and that of square of tenure is negative. This is consistent with previous studies on the Mincer wage equation in Japan such as Kawaguchi (2011) and Kimura et al. (2019). Moreover, that of the unemployment rate whose sign is reversed is positive, showing that the aggregate labor market conditions had a significant effect.

²⁷To eliminate the influence of DNWR from estimation of potential wage, it is possible to limit the sample to workers who displayed a low degree of DNWR. However, in that case, we cannot estimate the potential wage of workers with a strong degree of DNWR, because we cannot obtain their fixed effects. Therefore, in this paper, we conduct the estimation using the sample including the workers who displayed a strong degree of DNWR. Note that the estimated coefficients are close to those when we limit the sample to workers who displayed a low degree of DNWR.

²⁸The definitions of variables other than labor productivity are the same as those in Footnote 17. Labor productivity is calculated by dividing real gross domestic product (classified by economic activities in the National Accounts), by total labor input, which is the number of employed persons (in the Labour Force Survey) multiplied by hours worked per person (in the Monthly Labour Survey).

Appendix B Robustness check on treatment of the sample added after 2009

In the JHPS/KHPS, new cohorts were added in 2007, 2009, and 2012 for reasons such as to compensate for sample loss.²⁹ Regarding the sample added after 2009, information on wage growth during the GFC (2008 and 2009) is unavailable. In the baseline estimation, we define the sample added after 2009 as workers who displayed a low degree of DNWR (DNWR dummy is zero) for convenience. This treatment of the sample added after 2009 can distort the estimation result.

To check the robustness with regard to the sample added after 2009, we calculate the degree of DNWR from the available information on their wage, and estimate the same equation as that in the first half of Section 3.3. More specifically, for the sample before 2008, we use the DNWR dummy based on pay cuts during the GFC as in the baseline. For the sample added after 2009, we define the DNWR index as the period average of the DNWR dummy based on pay cuts in the past three years, which is used as the alternative dummy.³⁰

Appendix Table 2 reports the estimation result. Both β_2 and β_3 take similar values as those in the first half of Section 3.3, and they are significantly negative. This implies that the estimation result in the baseline is robust in its treatment of the sample added after 2009.

²⁹A new sample was added in 2009 because the former Keio Household Panel Survey (KHPS) and the former Japan Household Panel Survey (JHPS) from 2009 were integrated.

³⁰This method assumes that average of the DNWR dummy based on pay cuts in the past three years is an effective alternative variable for the DNWR dummy based on pay cuts during the GFC. In fact, the two dummies are positively correlated, with the correlation around 0.4 for the sample that existed before 2008. This supports the validity of the dummy as an alternative variable.

Table 1: Calibrated parameters

Symbol	Parameters	Values
β	Discount factor	0.950
b	Baseline level of labor intensity	$\exp(1)$
c	Degree of DNWR	1.000
α	Degree of decreasing returns to scale	0.660
δ	Overtime premium	0.250
\tilde{H}/H^{ss}	Statutory working hours	1.000
\underline{H}/H^{ss}	Lower bound of hours worked	0.850
\bar{H}/H^{ss}	Upper bound of hours worked	1.300
π	Inflation rate	0.020
g	Trend productivity growth	0.000
ρ^{agg}	AR (1) coefficient for aggregate component of productivity	0.700
σ^{agg}	S. D. of innovations for aggregate component	0.015
ρ^{id}	AR (1) coefficient for idiosyncratic component of productivity	0.700
σ^{id}	S. D. of innovations for idiosyncratic component	0.150
γ	Probability of no innovations to idiosyncratic component	0.500

Table 2-1: Worker's characteristics

(A) JHPS/KHPS sample used in the current study (regular workers, 2003-2017)

Variables	Share of answers, %					Observation	Individual
Gender	Male 68.0	Female 32.0				40,856	8,423
Type of school last attended	Junior high school 2.1	High School 43.7	Junior college or Technical school 15.5	University 35.1	Graduate school 3.5	37,334	7,628
Region	Hokkaido 4.2	Tohoku 6.7	Kanto 33.5	Chubu 19.2	Kinki 16.9	40,856	8,423
	Chugoku 5.9	Shikoku 3.1	Kyusyu 10.5				
Industry	Construction 7.6	Manufacturing 21.4	Wholesale and Retail 12.2	Medical services and Welfare 12.2	Other non-manufacturing 46.5	40,856	8,423
Firm size	1-29 pers. 21.9	30-99 pers. 16.6	100-499 pers. 22.0	500 pers. or more 30.5	Government 8.9	40,423	8,345

(B) Employment Status Survey (average of 2007, 2012, and 2017 surveys)

Variables	Share of answers, %				
Gender	Male 68.6	Female 31.4			
Type of school last attended	Junior high school or younger 5.3	High School 38.2	Junior college or Technical school 20.1	University 32.6	Graduate school 3.9
Region	Hokkaido 3.9	Tohoku 7.1	Kanto 35.4	Chubu 17.9	Kinki 16.5
	Chugoku 5.8	Shikoku 2.9	Kyusyu 10.6		
Industry	Construction 8.5	Manufacturing 22.0	Wholesale and Retail 13.6	Medical services and Welfare 12.5	Other non-manufacturing 43.4
Firm size	1-29 pers. 24.3	30-99 pers. 13.7	100-499 pers. 17.3	500 pers. or more 31.3	Government, etc. 13.4

Notes: 1. The values shown in Panel (B) are those of regular employees. They are weighted by the number of employees in the 2007, 2012, and 2017 surveys.

2. "Government, etc." shown in firm size in Panel (B) includes national university corporations, independent administrative agencies, and other national and public offices (public schools and public hospitals, etc.), in addition to government offices.

Sources: Ministry of Internal Affairs and Communications; Panel Data Research Center at Keio University.

Table 2-2: Descriptive statistics of key variables

Variables	JHPS/KHPS sample used in the current study (2003-2017)							Basic Survey on Wage Structure (2003-2017)
	Mean	Stdev	10th percentile	Median	90th percentile	Observation	Individual	Mean
Monthly earnings (ten thous. yen)	31.8	14.8	13.7	30.0	50.0	40,004	8,234	32.9
Monthly earnings (y/y % chg.)	2.9	15.1	-14.3	0.0	22.5	28,442	5,800	
Bonuses (ten thous. yen)	80.2	75.7	0.0	61.0	197.0	39,554	8,271	87.7
Bonuses (y/y % chg.)	4.5	47.2	-41.7	0.0	50.0	24,484	5,149	
Hours of paid work (hours/week)	43.4	15.0	20.0	45.0	60.0	38,532	8,220	44.6
Age	43.7	9.4	30	44	51	40,856	8,423	41.4
Tenure (year)	14.5	10.8	2	12	31	37,836	7,854	11.9

- Notes: 1. The statistics of the monthly earnings, bonuses and hours of paid work in the JHPS/KHPS sample exclude samples above the 99th percentile and below the 1st percentile. The calculating growth rates of monthly earnings and bonuses (y/y % chg.) are based on the trimmed sample in terms of level, and we show the numbers that further eliminate outliers (those above the 99th percentile and below the 1st percentile).
2. The values in the Basic Survey on Wage Structure are those of regular employees. They are weighted by the number of employees during 2003-2017.
3. Monthly earnings in the Basic Survey on Wage Structure is "contractual cash earnings." Bonuses are "special cash earnings."
4. Although the growth rates of monthly earnings and bonuses in the Basic Survey on Wage Structure are available, they are not necessarily comparable with the mean of the growth rate of each employee's wage in the JHPS/KHPS, because they are affected by the composition change of workers. Therefore, the table does not show the number for those items.

Sources: Ministry of Health, Labour and Welfare; Panel Data Research Center at Keio University.

Table 3: Overall effects of DNWR

Dependent variables		Monthly earnings	Bonuses
Independent variables		(y/y % chg.)	(y/y % chg.)
β_3	DNWR dummy (X_i) \times	-1.122***	-0.147
	Time dummy for 2013-2017 (D_{13-17})	(0.3681)	(1.4347)
β_2	DNWR dummy (X_i) \times	-1.277***	-2.169
	Time dummy for 2010-2012 (D_{10-12})	(0.3969)	(1.4898)
β_1	DNWR dummy (X_i) \times	6.176***	18.88***
	Time dummy for 2008-2009 (D_{08-09})	(0.4567)	(1.6740)
Number of individuals		4,740	3,984
Number of observations		22,038	18,795
R^2		0.0203	0.0267

- Notes: 1. *** denotes statistical significance at the 1 percent level. Values in parentheses indicate standard errors, clustered at worker level.
2. In addition to the independent variables shown in the table, we include industry dummy \times year dummy, tenure, age category dummy, title dummy, labor union dummy, firm size dummy, gender dummy, dummy for type of school last attended, region dummy, occupation dummy, CPI by region, and hours worked in the previous year (only for the estimation of monthly earnings). We also include a random effect for each worker.
3. Estimation period is from 2004 to 2017.

Table 4: Robustness check

(A) Workers who displayed a strong degree of DNWR are those without any pay cuts in the last three years (looser criterion)

Independent variable	Dependent variable	Monthly earnings (y/y % chg.)
Alternative DNWR dummy (X_{it}) × Dummy for labor market conditions (Y_t)		-1.687*** (0.6426)
Number of individuals		5,220
Number of observations		24,397
R^2		0.0159

(B) Workers who displayed a strong degree of DNWR are those whose actual wage growth exceeded their potential wage growth during the GFC (stricter criterion)

Independent variables	Dependent variable	Monthly earnings (y/y % chg.)
Alternative DNWR dummy (X_i) × Time dummy for 2013-2017 (D_{13-17})		-1.189** (0.4902)
Alternative DNWR dummy (X_i) × Time dummy for 2010-2012 (D_{10-12})		-1.260*** (0.4686)
Alternative DNWR dummy (X_i) × Time dummy for 2008-2009 (D_{08-09})		7.759*** (0.5626)
Number of individuals		4,740
Number of observations		22,038
R^2		0.0199

- Notes: 1. *** and ** denote statistical significance at the 1 and 5 percent levels, respectively. Values in parentheses indicate standard errors, clustered at worker level.
2. In Panel (A), in addition to the independent variables shown in the table, we include industry dummy × year dummy, tenure, age category dummy, title dummy, labor union dummy, firm size dummy, DNWR dummy, CPI by region and hours worked in the last year. We also include a fixed effect for each worker.
3. In Panel (B), in addition to the independent variables shown in the table, we include industry dummy × year dummy, tenure, age category dummy, title dummy, labor union dummy, firm size dummy, gender dummy, dummy for type of school last attended, region dummy, occupation dummy, CPI by region, and hours worked in the previous year. We also include a random effect for each worker.
4. Estimation periods for both estimations are from 2004 to 2017.

Table 5: Backward-looking channel

Independent variable	Dependent variable	Monthly earnings (y/y % chg.)
β_4	DNWR dummy (X_i) \times Positive deviation rate from potential wage (previous year, $Gap_{it-1}1_{\{Gap_{it-1} \geq 0\}}$) \times Dummy for improvement phases (D_{10-17}) (2010-2017)	-0.379*** (0.0892)
Number of individuals		4,400
Number of observations		19,307
R^2		0.0327

- Notes: 1. *** denotes statistical significance at the 1 percent level. Values in parentheses indicate standard errors, clustered at worker level.
2. "Positive deviation rate from potential wage" is a variable that takes the deviation rate of the actual wage from the potential wage in the previous year only if the deviation rate is positive, and zero otherwise.
3. In addition to the independent variables shown in the table, we include industry dummy \times year dummy, tenure, age category dummy, title dummy, labor union dummy, firm size dummy, CPI by region, hours worked in the previous year, DNWR dummy \times time dummy for 2008-2009, DNWR dummy \times deviation rate from potential wage (previous year), and DNWR dummy \times negative deviation rate from potential wage (previous year) \times time dummy for 2010-2017. We also include a fixed effect for each worker.
4. Estimation period is from 2008 to 2017.

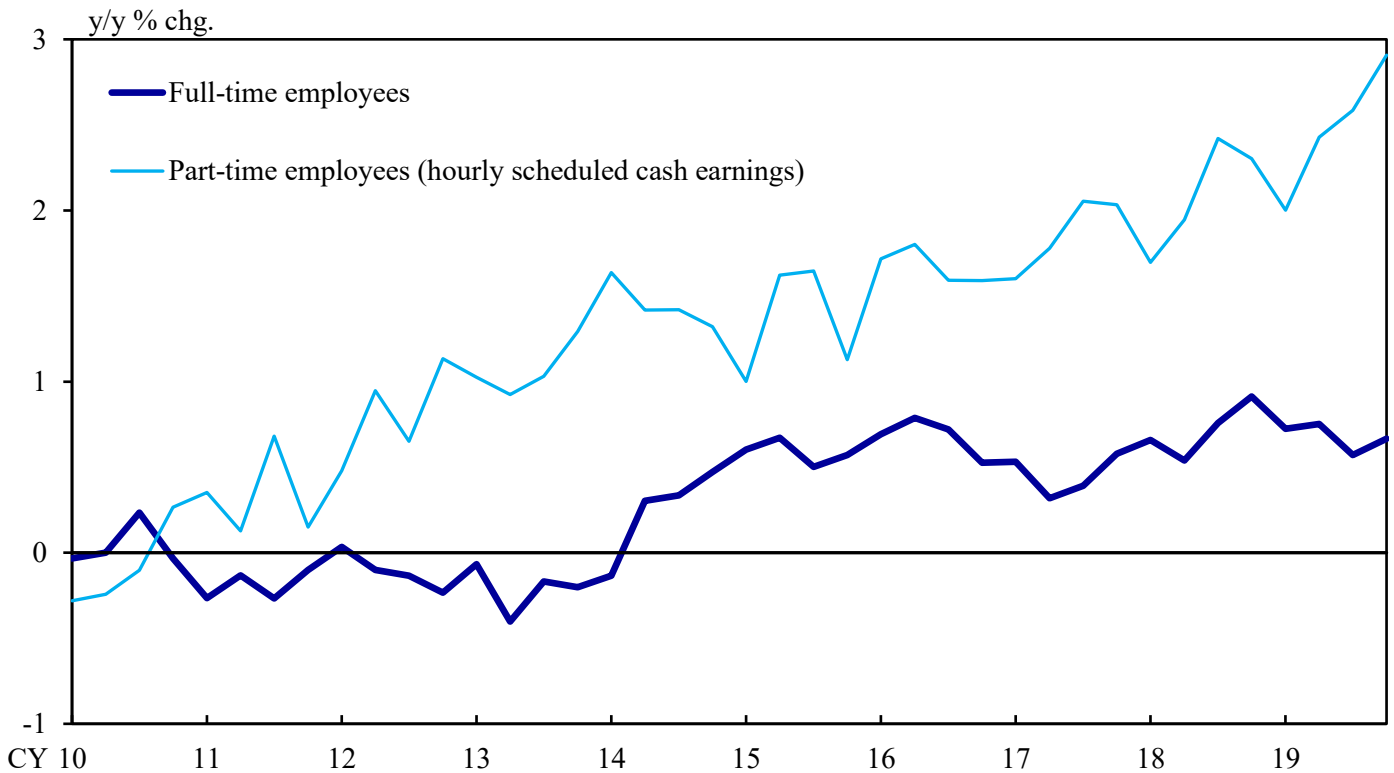
Table 6: Forward-looking channel

Independent variables	Dependent variable Monthly earnings (y/y % chg.)
β_5 DNWR dummy (X_i) \times Negative deviation rate from potential wage (previous year, absolute value, $ Gap_{it-1} 1_{\{Gap_{it-1}<0\}}$) \times Expected growth index (by industry) (Y_{1t}^j)	0.0186* (0.0100)
β_6 DNWR dummy (X_i) \times Negative deviation rate from potential wage (previous year, absolute value, $ Gap_{it-1} 1_{\{Gap_{it-1}<0\}}$) \times Uncertainty index (by industry) (Y_{2t}^j)	-0.662*** (0.0555)
Number of individuals	4,400
Number of observations	19,307
R^2	0.270

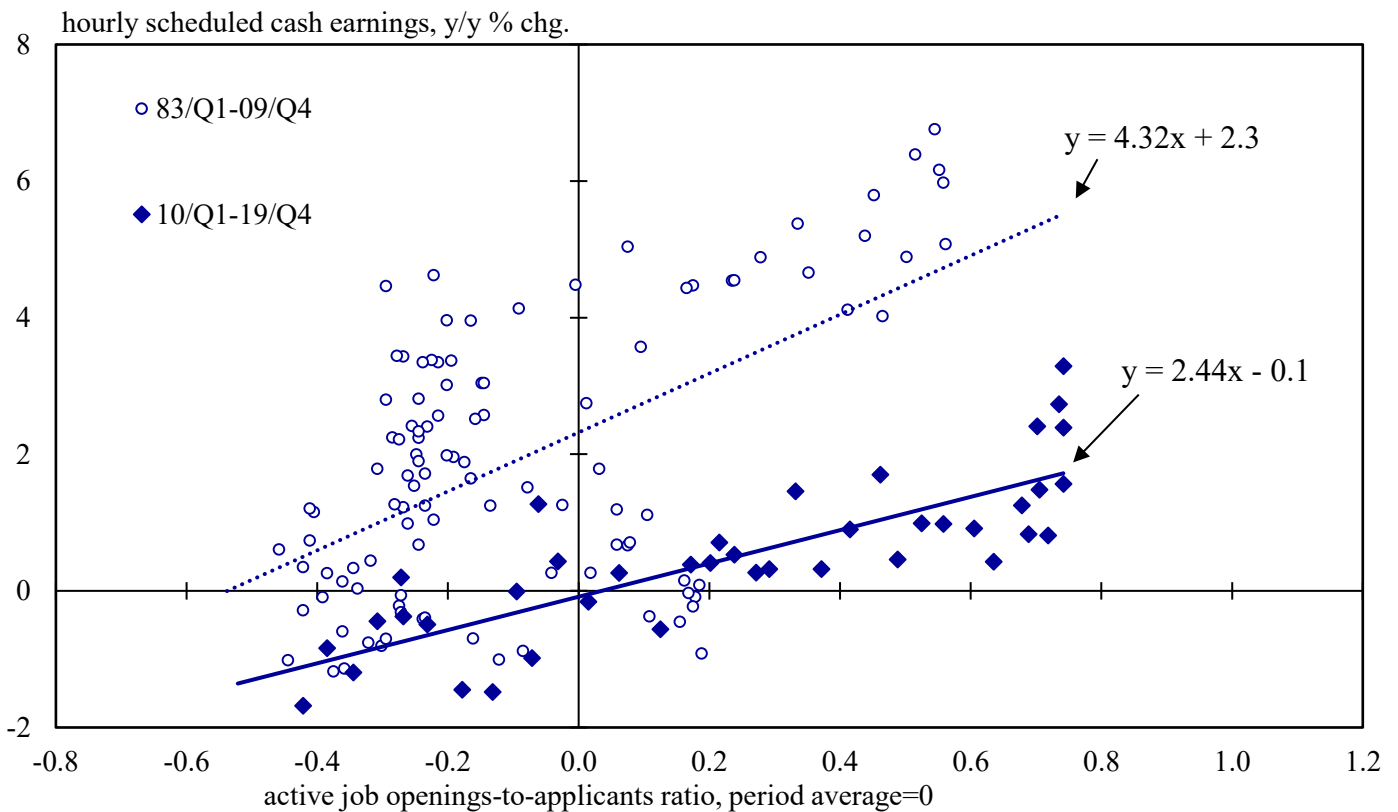
- Notes: 1. *** and * denote statistical significance at the 1 and 10 percent levels, respectively. Values in parentheses indicate standard errors, clustered at worker level.
2. "Negative deviation rate from potential wage" is a variable that takes the absolute value of the deviation rate of the actual wage from its potential only if the deviation rate in the previous year wage is negative, and zero otherwise.
3. In addition to the independent variables shown in the table, we include industry dummy \times year dummy, tenure, age category dummy, title dummy, labor union dummy, firm size dummy, CPI by region, hours worked in the previous year, DNWR dummy \times time dummy for 2008-2009, DNWR dummy \times deviation rate from potential wage (previous year), DNWR dummy \times positive deviation rate from potential wage (previous year) \times each index, and deviation rate from potential wage (previous year) \times each index. We also include a fixed effect for each worker.
4. Estimation period is from 2008 to 2017.

Figure 1: Flattening of wage Phillips curve

(A) Modest growth of scheduled cash earnings for regular workers



(B) Wage Phillips curve



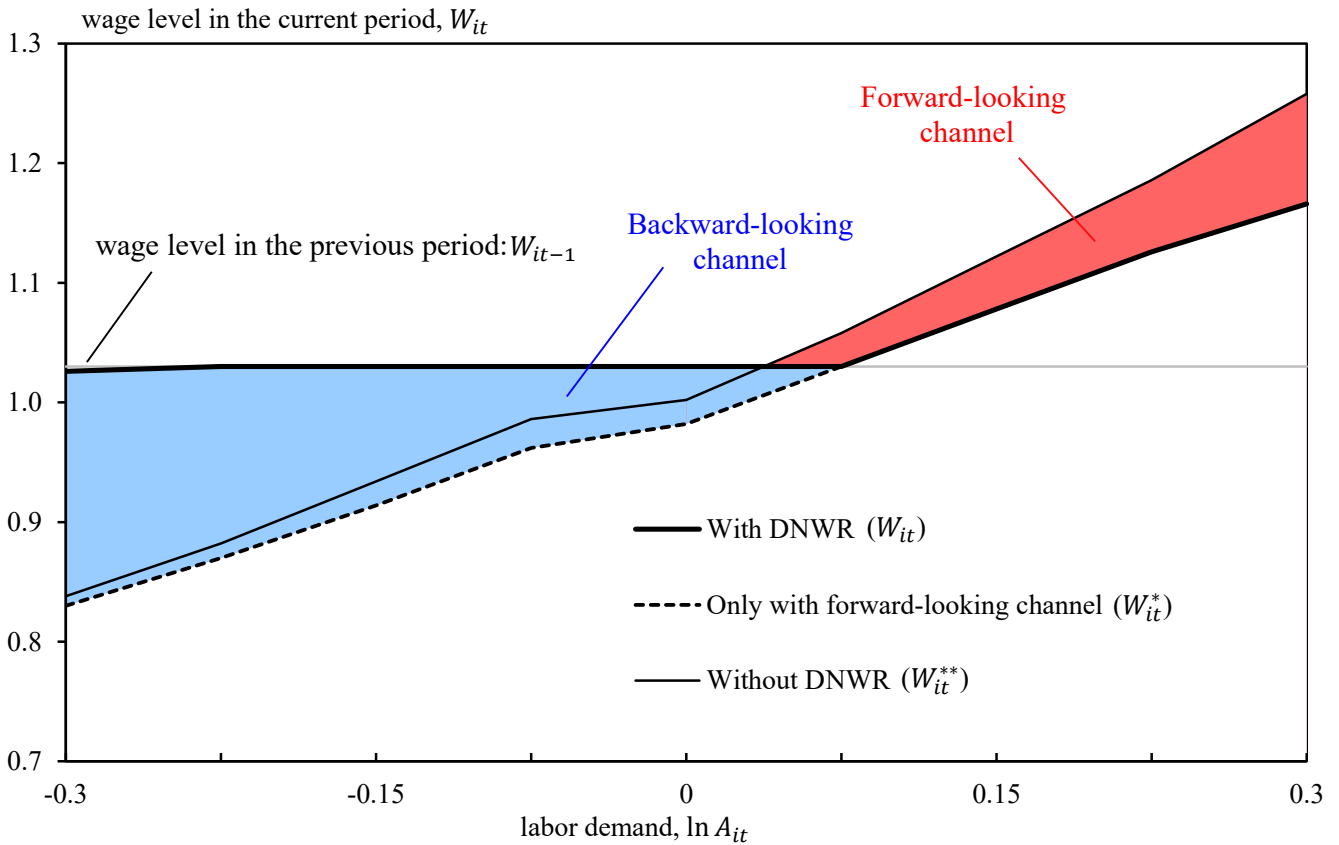
Notes: 1. The definitions of quarters for hourly cash earnings are Q1 = March-May, Q2 = June-August, Q3 = September-November and Q4 = December-February.

2. Figures of the scheduled cash earnings for establishments in Tokyo with 500 or more employees for 2013/Q1-2019/Q1 are corrected data based on sample observations. The figures from 2019/Q2 onward are for all such establishments. Figures from 2016/Q1 are based on continuing observations and the figures before 1990/Q4 are for establishments with 30 or more employees.

Source: Ministry of Health, Labour and Welfare.

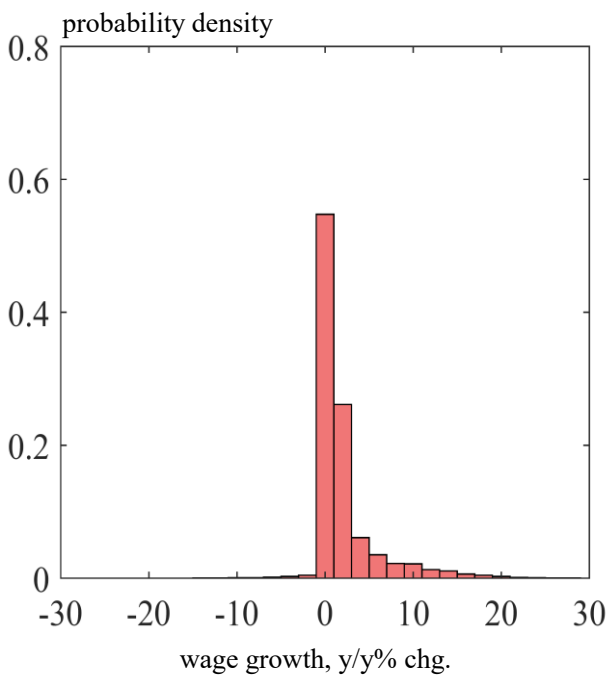
Figure 2: Wage functions for individual workers and cross-sectional wage-growth distributions in calibrated model

(A) Wage functions for individual workers



(B) Cross-sectional wage-growth distributions

(a) With DNWR



(b) Without DNWR

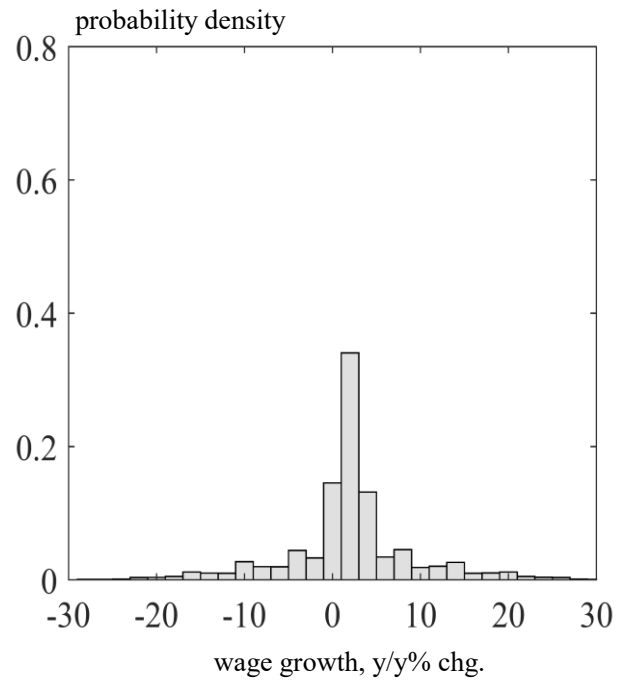
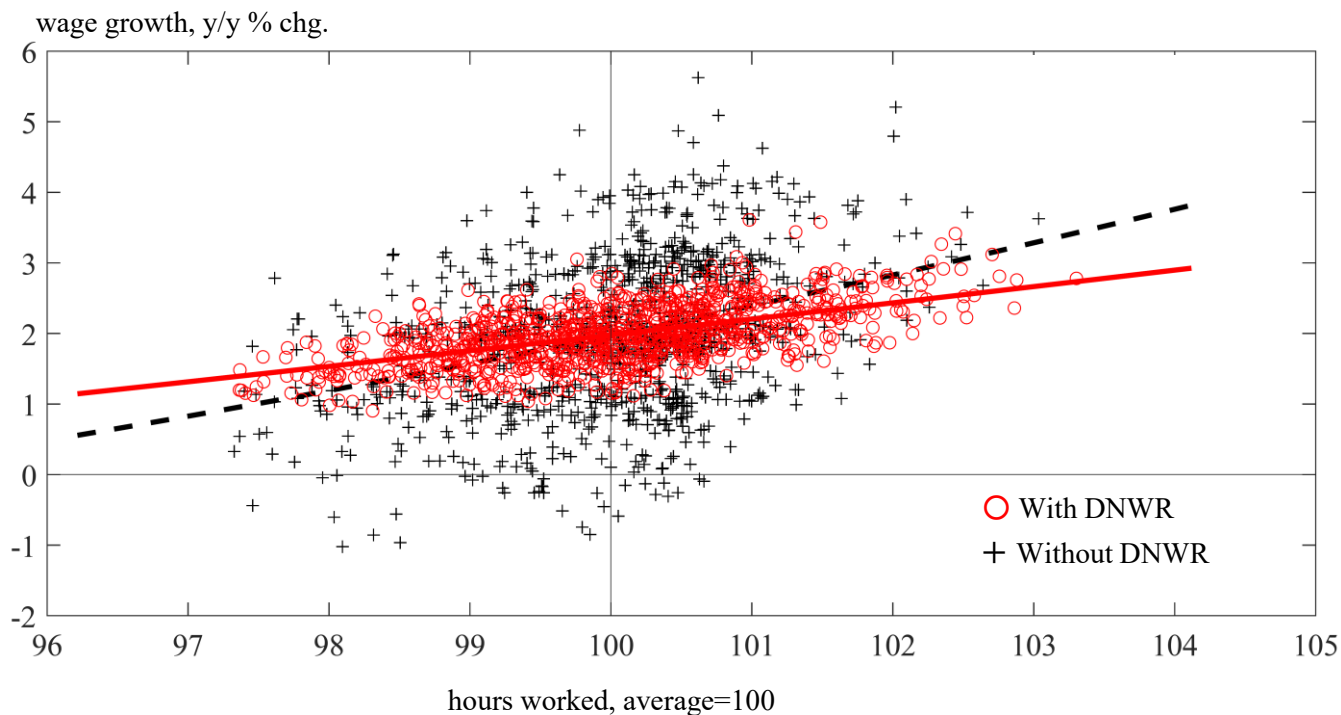
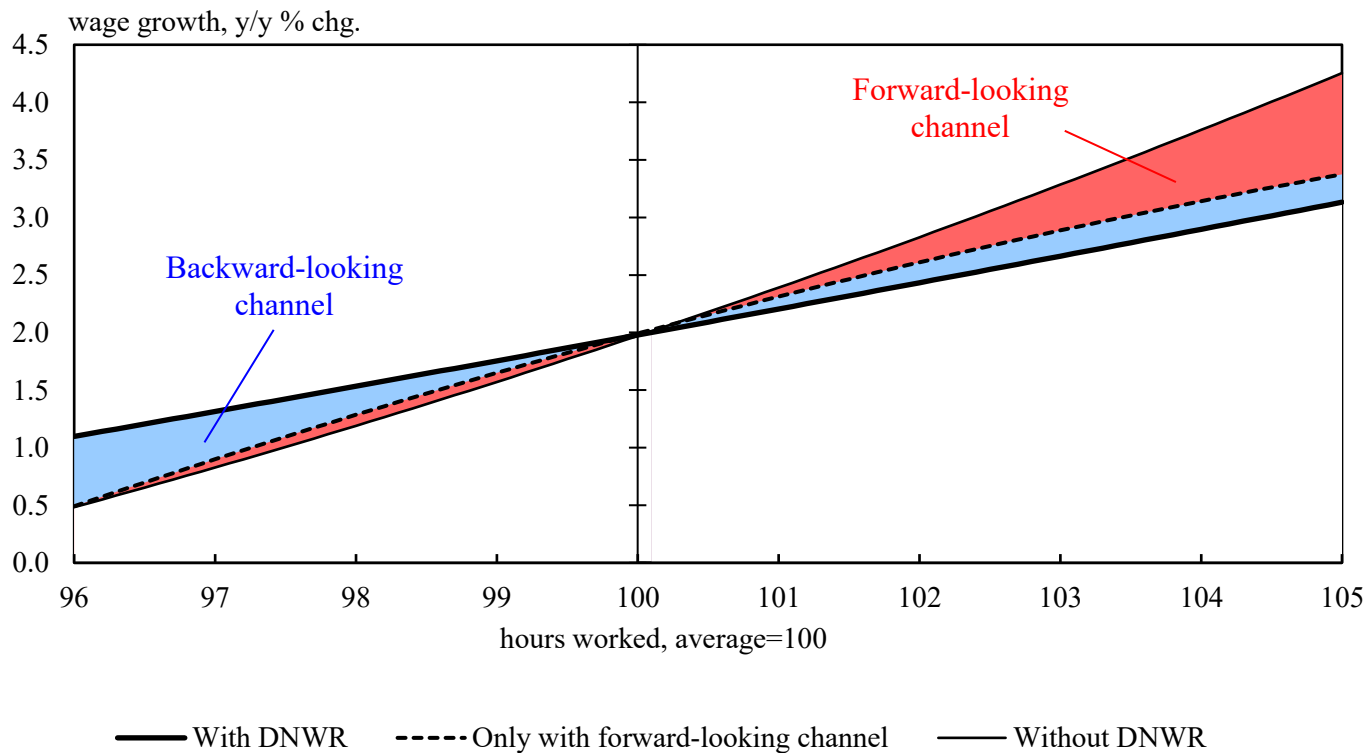


Figure 3: Wage Phillips curve in calibrated model

(A) Wage Phillips curve obtained in stochastic simulation



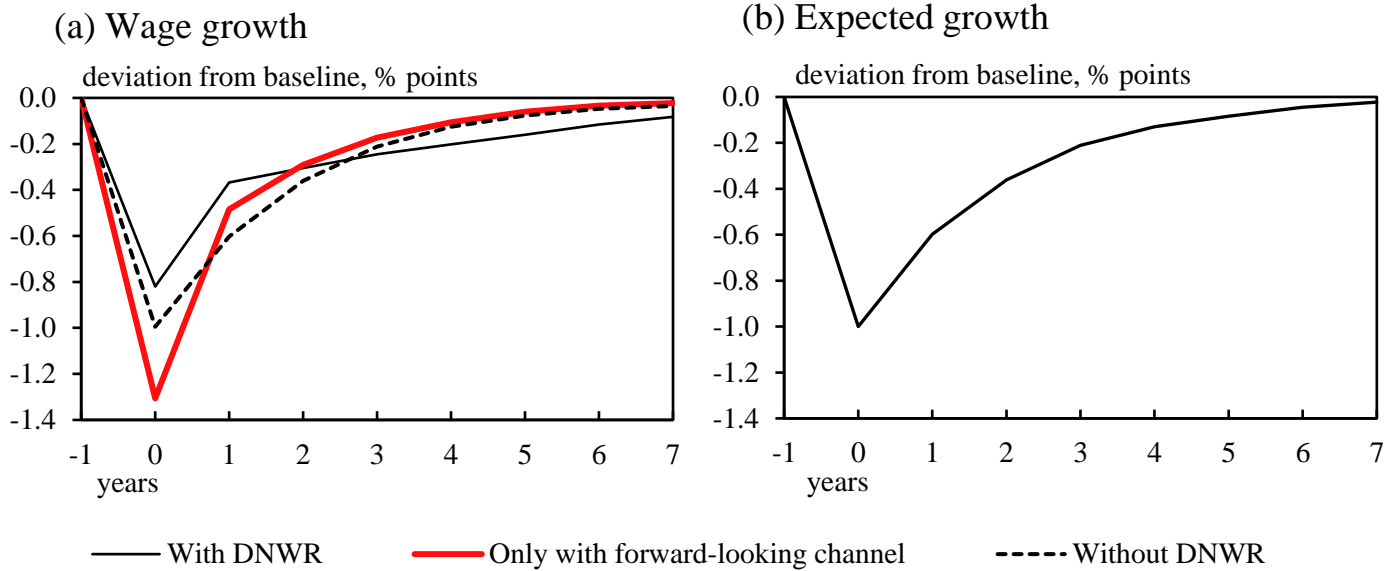
(B) Contribution of the two separate channels to flattening of wage Phillips curve



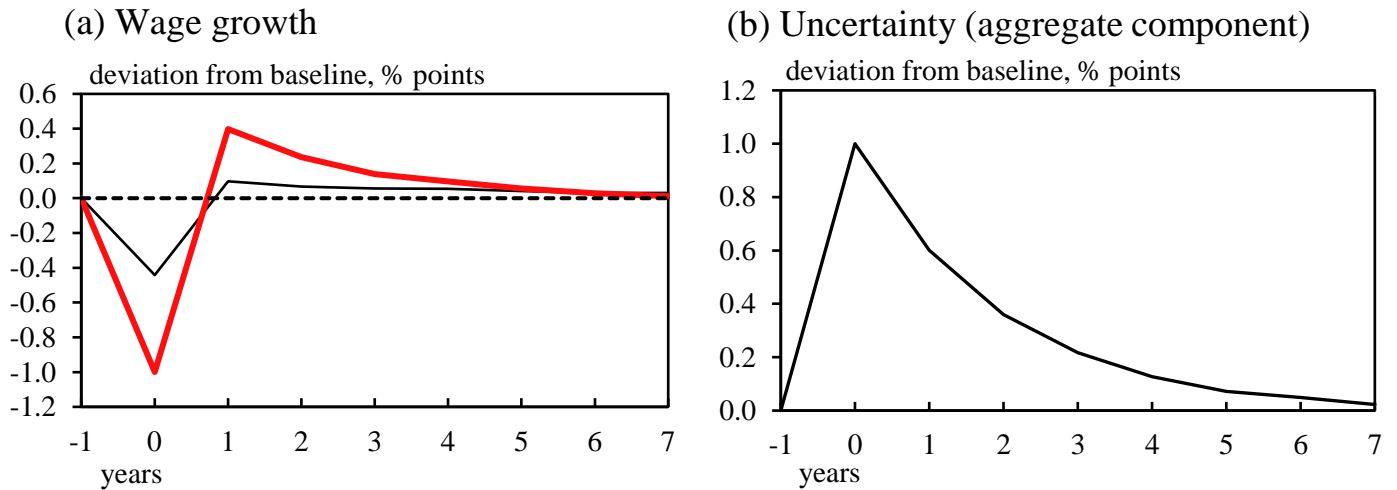
- Notes: 1. Panel (A) shows the scatter plot obtained from the stochastic simulation lasting one thousand periods.
 2. Panel (A) and (B) show the quadratic fitted curves in the stochastic simulation.
 3. The degree of DNWR, c , is equal to one for "with DNWR," while c is equal to zero for "without DNWR."

Figure 4: Generalized impulse responses in calibrated model

(A) Responses of wage growth to an one percentage point decline in expected growth



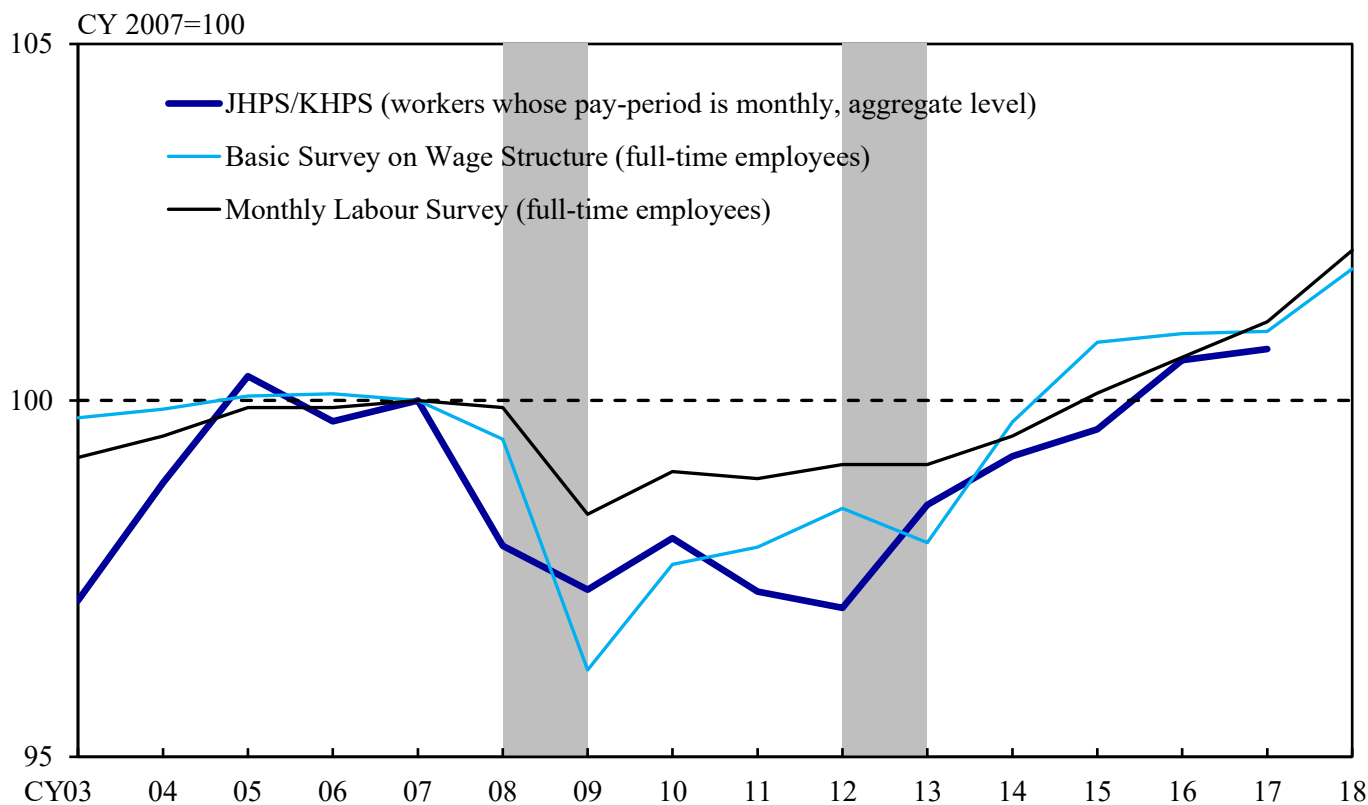
(B) Responses of wage growth to a rise in uncertainty



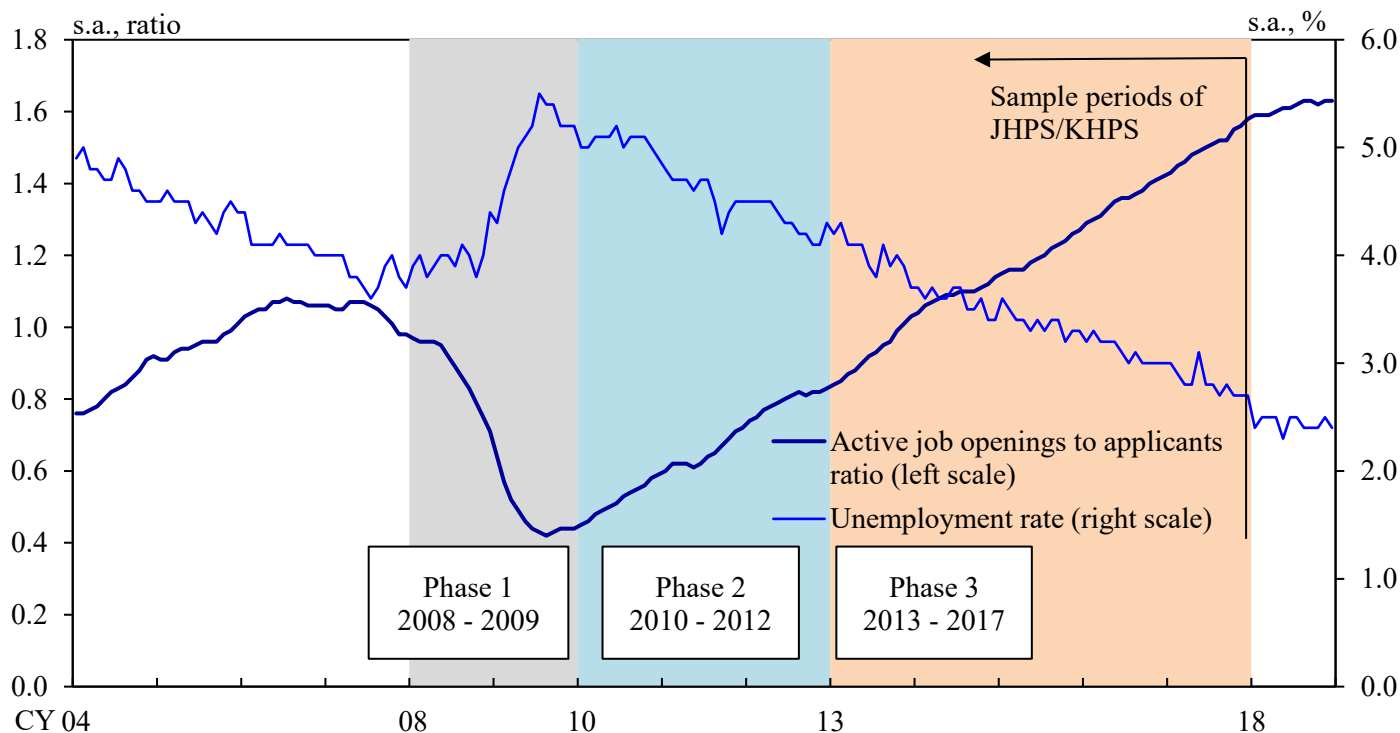
Note: Panel (B) shows the responses to a rise in the standard deviation by 1 percentage point for aggregate component of exogenous productivity and 10 percentage points for idiosyncratic one. These shocks are equivalent to doubling the baseline value of each parameter. The details are described in Footnote 8.

Figure 5: Comparison with the statistics on aggregate wage and three phases of labor market condition after GFC

(A) Average monthly earnings: comparison of JHPS/KHPS and official aggregate statistics



(B) Three phases of labor market condition after GFC

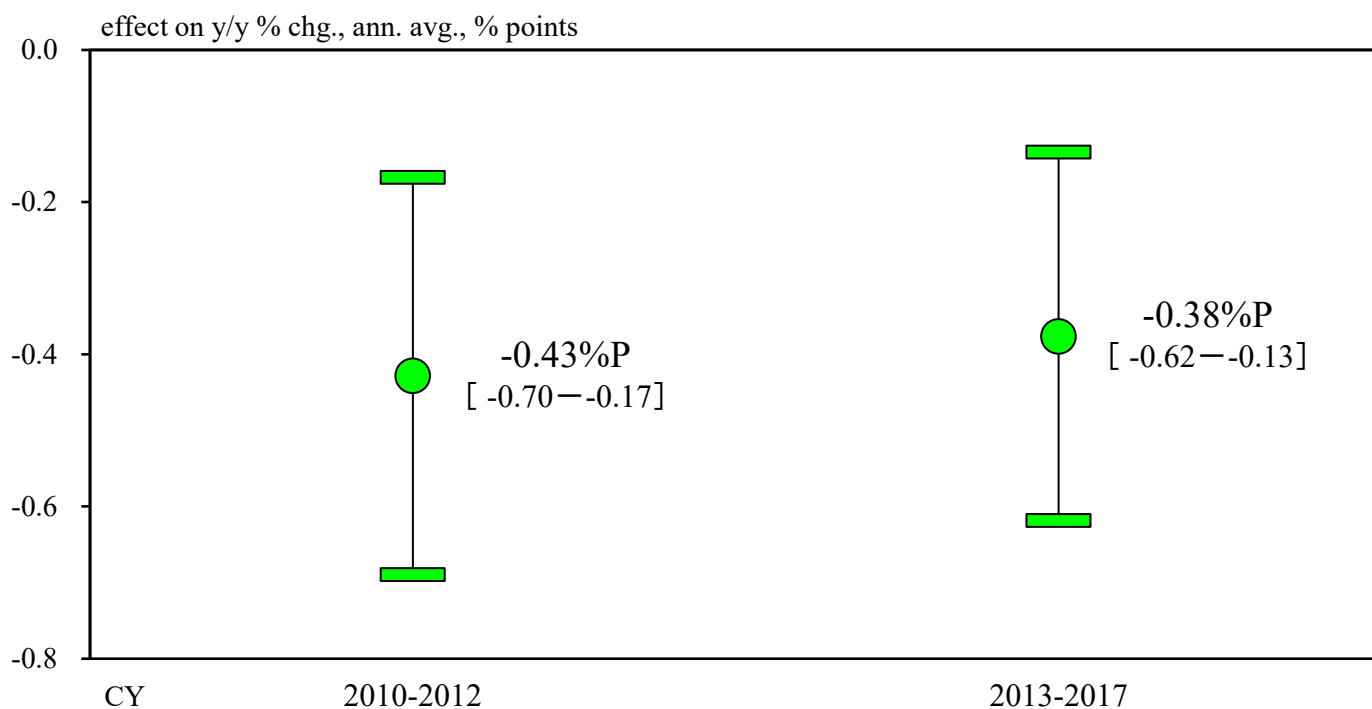


Note: Figures for the JHPS/KHPS are the average among the monthly earnings of workers whose pay-period is monthly. Those for the BSWs are "contractual cash earnings." Those for the Monthly Labour Survey are "contractual cash earnings" and those for establishments in Tokyo with 500 or more employees for 2013-2018 are corrected data based on sample observations. Shaded areas in Panel (A) indicate recession periods.

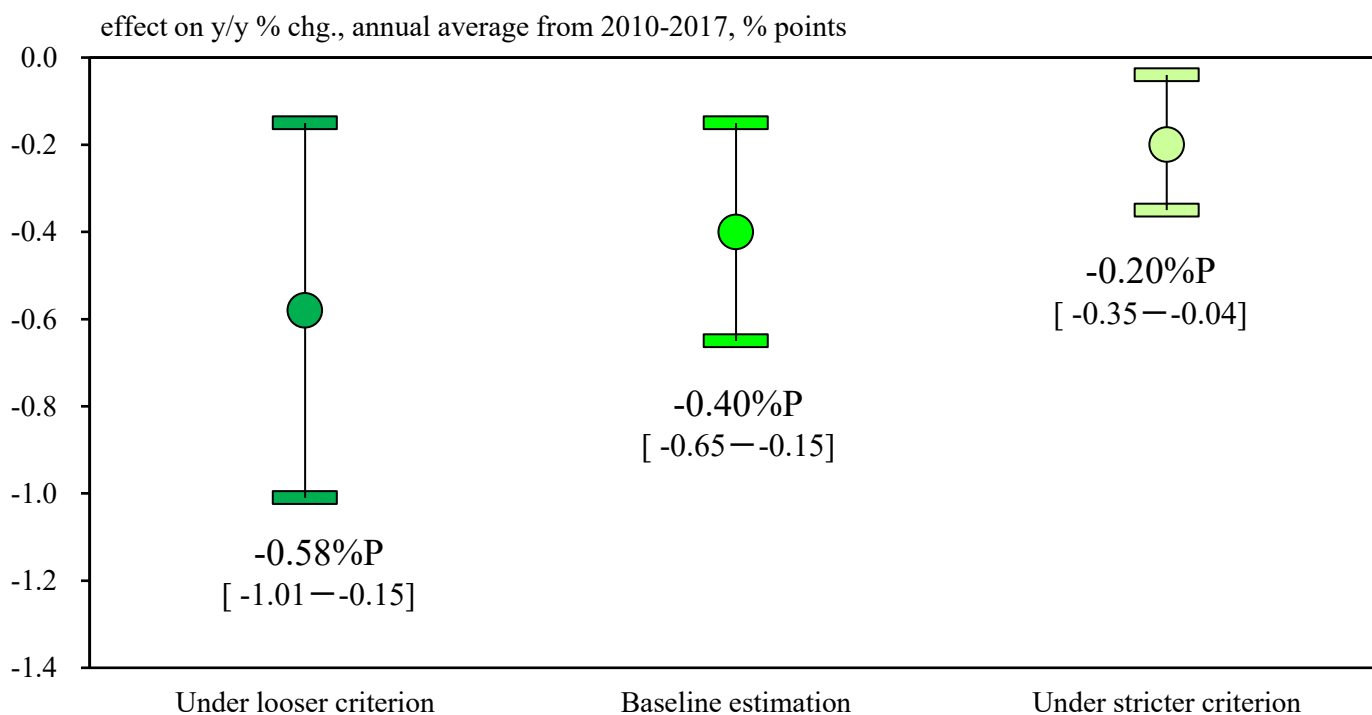
Sources: Ministry of Health, Labour and Welfare; Ministry of Internal Affairs and Communications; Panel Data Research Center at Keio University.

Figure 6: Effect on growth of monthly earnings at aggregate level

(A) Effect on growth of monthly earnings for regular workers at aggregate level



(B) Robustness check

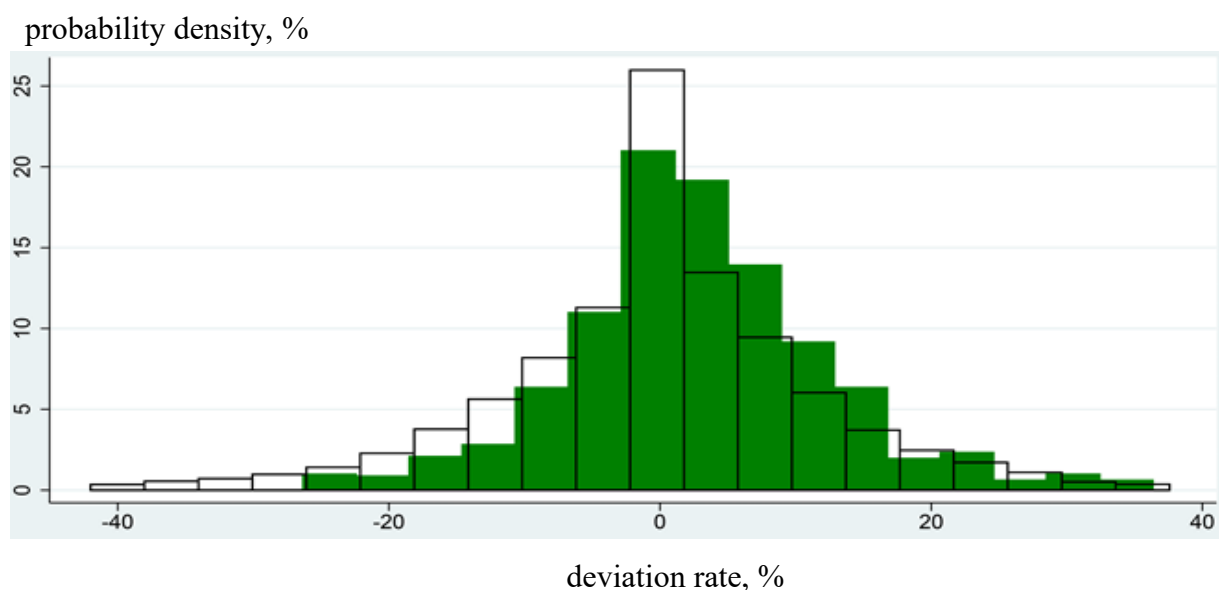


- Notes:
1. The values shown in Panel (A) = coefficients shown in Table 3 × the share of workers who displayed a strong degree of DNWR in the sample during 2008-2009.
 2. The values shown in Panel (B) = coefficients of estimation results × the share of workers who displayed a strong degree of DNWR among the sample. When calculating the values, we use the share in the sample during 2008-2009 in the baseline estimation and the estimation under the "stricter criterion," and use the share in the sample in each year under the "looser criterion."
 3. The values shown in Panel (B) are the weighted averages of the effects during 2010-2012 and those during 2013-2017.
 4. The bars represent the 95 percent confidence intervals of the estimates.

Figure 7: Distribution of deviation rate of actual wage from potential wage

(A) During 2008-2009

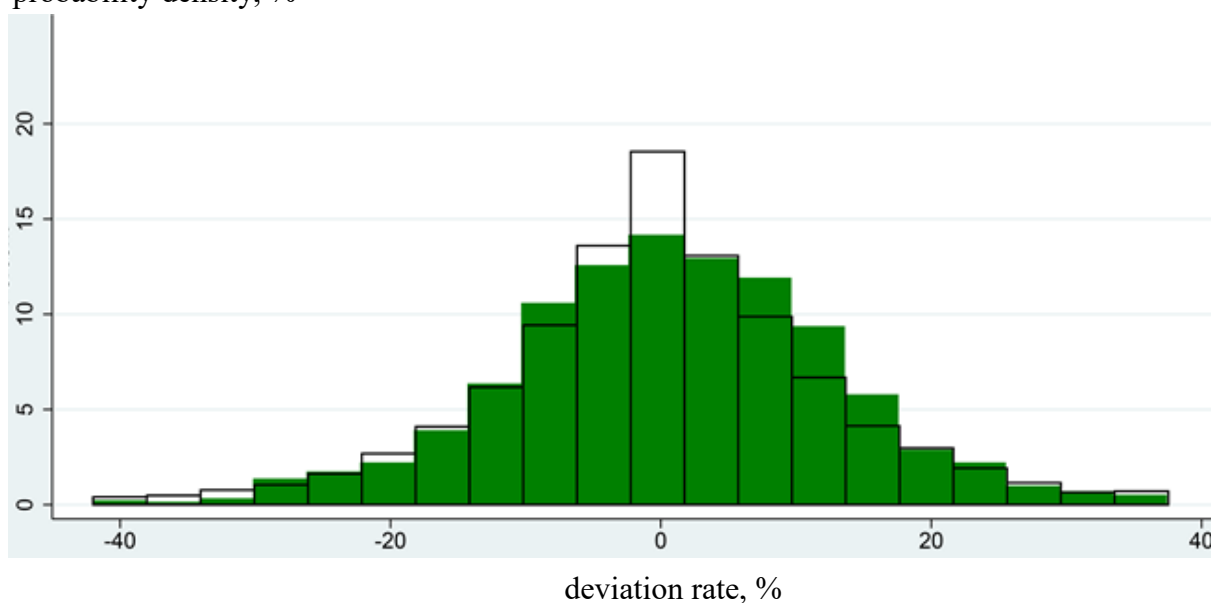
(Green: workers with a strong degree of DNWR, White: workers with a low degree)



2008-2009	Workers with a strong degree of DNWR	Workers with a low degree of DNWR
Average	2.7	-0.1
Skewness	0.3	-0.2

(B) During 2013-2017

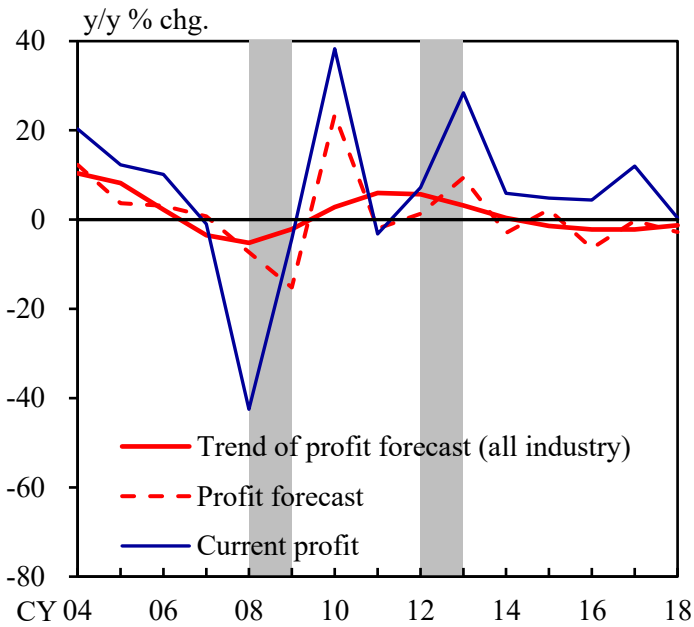
probability density, %



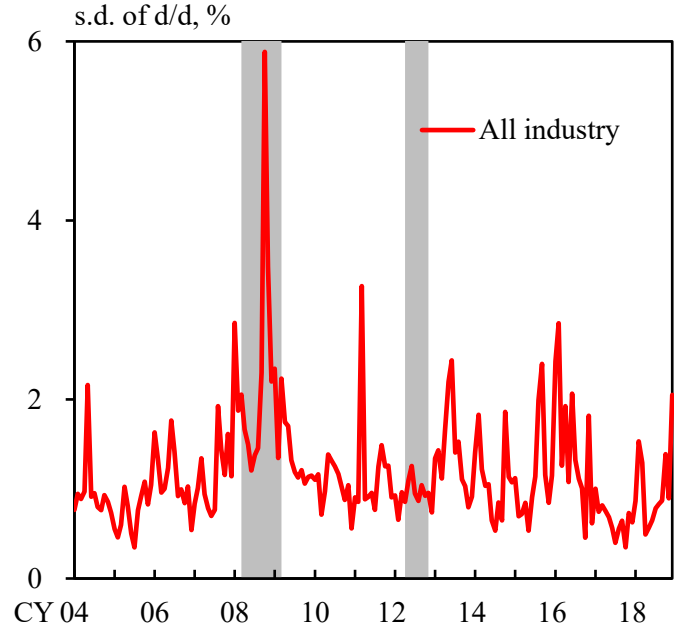
2013-2017	Workers with a strong degree of DNWR	Workers with a low degree of DNWR
Average	0.8	-0.1
Skewness	-0.1	-0.1

Figure 8: Indexes used for estimation on forward-looking channel

(A) Index of expected growth

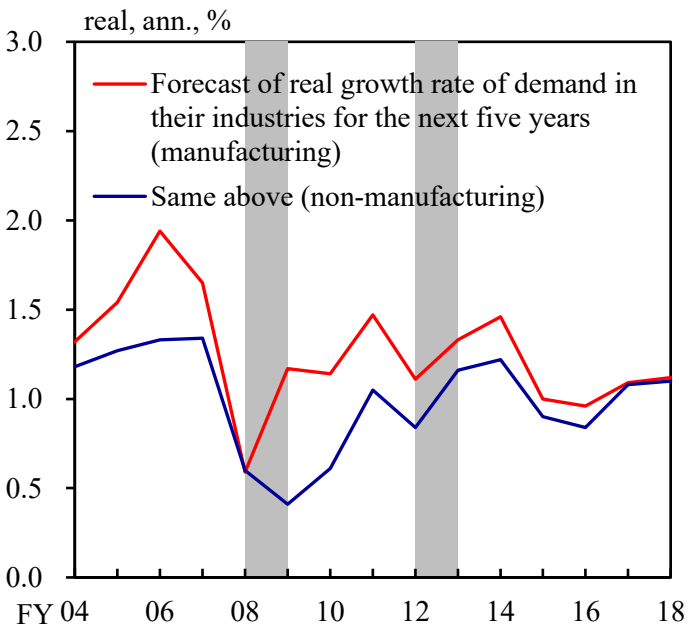


(B) Index of uncertainty

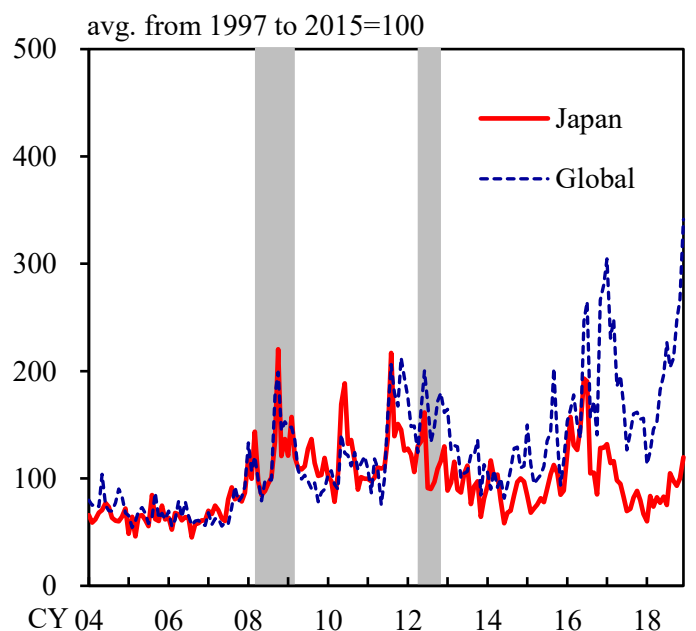


(Reference) Alternative indexes

(A) Annual Survey of Corporate Behavior



(B) Economic Policy Uncertainty Index



- Notes: 1. The index shown in Panel (A) is the profit forecast of firms taken from the Short-Term Economic Survey of Enterprises in Japan. We use the survey results during the March 2003 to December 2018, and we remove the cyclical component (within five years), extracted using the filter by Christiano and Fitzgerald (2003). The value in each year is the average of the trend component among those of the March, June, September, and December surveys. We calculate the index for the following five industries: manufacturing, wholesale and retail, construction, medical services and welfare, and other non-manufacturing.
2. The index shown in Panel (B) is the historical standard deviation of daily stock returns for the five industries derived from TOPIX-17.
3. The global index shown in Panel (Reference)-(B) is the GDP-weighted average of indexes for 20 countries based on PPP-adjusted GDP.
4. Shaded areas indicate recession periods.

Sources: Bloomberg; Cabinet Office; Economic Uncertainty Index; Bank of Japan.

Appendix Table 1: Estimation result of Mincer wage equation

Independent variables	Dependent variable	Monthly earnings (natural log)	
Unemployment rate (reversed-sign, Y_t)		0.0199***	(0.0028)
Tenure		0.0179***	(0.0014)
Square of tenure		-0.000235***	(0.0000)
	25-29 y/o	0.0816***	(0.0161)
	30-34 y/o	0.146***	(0.0202)
Age category dummy	35-39 y/o	0.191***	(0.0222)
(Base = 24 y/o or less)	40-44 y/o	0.227***	(0.0243)
	45-49 y/o	0.254***	(0.0263)
	50-54 y/o	0.255***	(0.0282)
	55-59 y/o	0.228***	(0.0305)
Title dummy (1 = with title)		0.0415***	(0.0042)
Labor union dummy (1 = member)		0.0117**	(0.0059)
	30-99 pers.	0.00865	(0.0083)
Firm size dummy	100-499 pers.	0.0166	(0.0103)
(Base = 1-29 pers.)	500 pers. or more	0.0235**	(0.0120)
	Government	0.0159	(0.0119)
	Service worker	-0.0401***	(0.0100)
Occupation dummy	Manager	0.0236***	(0.0072)
(Base = Others)	Specialized or technical worker	-0.00784	(0.0087)
	Clerical worker	-0.0186***	(0.0069)
	Salesperson	-0.0248***	(0.0086)
	Agriculture, forestry, fishery and mine worker	-0.0185	(0.0590)
	Wholesale and retail	-0.0140	(0.0194)
Industry dummy	Construction	0.0295	(0.0286)
(Base = Manufacturing)	Medical services and welfare	-0.0004	(0.0304)
	Other non-manufacturing	-0.0116	(0.0163)
Labor productivity by industry		-0.00009	(0.0003)
CPI by region		-0.0013	(0.0011)
Number of individuals		7,294	
Number of observations		34,073	
R^2		0.305	

Notes: 1. *** and ** denote statistical significance at the 1 and 5 percent levels, respectively. Values in parentheses indicate standard errors, clustered at worker level.

2. In addition to the independent variables shown in the table, we include a fixed effect for each worker.

3. Estimation period is from 2003 to 2017.

Appendix Table 2: Robustness check on treatment of sample added after 2009

Independent variables	Dependent variable	Monthly earnings (y/y % chg.)
β_3	DNWR index (X_i) \times Time dummy for 2013-2017 (D_{13-17})	-1.075*** (0.3614)
β_2	DNWR index (X_i) \times Time dummy for 2010-2012 (D_{10-12})	-1.346*** (0.3960)
β_1	DNWR index (X_i) \times Time dummy for 2008-2009 (D_{08-09})	6.176*** (0.4568)
	Number of individuals	4,740
	Number of observations	22,038
	R^2	0.0203

Notes: 1. *** denotes statistical significance at the 1 percent level. Values in parentheses indicate standard errors, clustered at worker level.

2. In addition to the independent variables shown in Table, we include industry dummy \times year dummy, tenure, age category dummy, title dummy, labor union dummy, firm size dummy, gender dummy, dummy for type of school last attended, region dummy, occupation dummy, CPI by region, and hours worked in the last year. We also include a random effect for each worker.

3. Estimation period is from 2004 to 2017.

4. For the sample before 2008, we use the DNWR dummy based on pay cuts during the GFC as in the baseline model. For the sample added after 2009, we define the DNWR index as the period average of DNWR dummy based on pay cuts in the past three years.