

Wage and Productivity Differentials in Japan: The Role of Labor Market Mechanisms

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Abstract. This paper aims at explaining two stylized facts of the Lost Decade in Japan: rising wage inequalities and increasing firm-level productivity differentials. We build a model where firms can choose between efficiency wages with endogenous effort and competitive wages, and show that it can replicate those facts. Using Japanese microeconomic data, we find support for the existence of efficiency wages in one group of firms and competitive wages in the other group. Based on those results, a simulation shows that the share of firms using efficiency wages has declined, within sectors, during the Lost Decade, as predicted by the model.

1. Introduction

Although the Japanese economy is famous for the deflation it has experienced in the last 10 years, less attention has been given to the real side of the economy. Two major stylized facts characterized Japan during the Lost Decade (1992–2004): rising wage inequalities and increasing productivity differentials at the firm level. Both evolutions occurred against the backdrop of a slowdown in aggregate productivity. This paper proposes an explanation for those real developments. We argue that wage inequalities are the flip side of productivity differentials, which themselves originated from choosing different models of work organization as a reaction to the productivity slowdown.

Our contribution is twofold. First, we build a simple efficiency wage model with two types of firms differing by their compensation scheme and associated incentive mechanisms. We show that a negative aggregate productivity shock leads to different reactions of both types of firms and, consequently, to increasing productivity and wage differentials. Second, we conduct an empirical investigation with a Japanese matched employer–employee data set. We show that firms can be divided into two groups: one group with efficiency wages, and another paying competitive wages, consistent with the model.

Substantial increases in wage inequalities have been observed for more than two decades in a wide range of countries, including the USA, the UK, and many other OECD countries. This has given birth to a sizable literature, which first reached the consensus that skill-biased technological change was the main factor driving inequalities in the late 1990s and the early

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2000s. As emphasized by Machin (2008), the topic has seen a recent renewal of interest as a result of several developments. Among them, the fact that some countries, previously characterized by relatively stable wage structures, have started to experience rising wage inequalities certainly deserves a new generation of research.

Together with Germany, Japan is one of these countries. Whether income inequalities have really widened in Japan during the 1990s and onward has first been the subject of a debate but recent evidence shows that wage inequalities across male workers with similar characteristics have increased (Kambayashi *et al.*, 2008).

To explain these rising ‘within-group’ inequalities, it is natural to turn to firms’ characteristics. A well-established stylized fact in Japan is indeed the increased dispersion of productivity at the firm level (Fukao and Kwon, 2006; Ito and Lechevalier, 2009). Surprisingly, these two facts have never been connected in the literature. This paper tries to fill the gap. We adopt a perspective similar to Faggio *et al.* (2010) or Mortensen (2003) and analyse the link between rising wage inequalities and increasing productivity dispersion at the firm level.

Our explanation for rising wage inequalities focuses on labor market mechanisms and firms’ heterogeneity with regard to the choice of their organizational structure. By doing so, we abstract from other factors such as the impact of technical progress or the internationalization of the economy. In the model, firms can choose between two types of work organizations, a complex structure with workers’ involvement and job security where the productivity of workers depend on their effort (type-I firms), and a simple competitive structure where workers have an exogenous productivity (type-II firms).¹ A key ingredient of the model is that type-I firms endogenously generate a continuous effort function, contrary to the standard efficiency wage model where effort is a discrete variable. With this assumption, adjustment to the productivity slowdown in type-I firms can take place through increased effort, consistent with the intensification of work that we document for Japan. The core mechanism we emphasize is the interaction between this endogenous effort and the free choice of the organizational structure. A decrease in aggregate productivity leads to a smaller share of type-I firms, whose employees provide a higher effort, get a higher wage premium and make these firms overall more productive in relative terms.

In the empirical part of the paper, we match for the first time the Basic Survey on Wage Structure (BSWS) and the Employment Trend Survey (ETS) for the years 2005–9, in order to build a rich employer–employee data set that allows us to disentangle individual and firm determinants of wage inequalities.² We test for the presence of efficiency wages by looking for a negative correlation across firms between job flows and the firm-specific wage premium, as predicted by the model. We find that the existence of such a correlation on average is not contradicted by our data. Next, we divide our sample of establishments into two groups by using the unknown regime switching regression *à la* Dickens and Lang. We find that a group of establishments can be characterized by efficiency wage mechanisms, whereas the other group cannot. This confirms the key mechanism underlying our explanation for the rising wage and productivity differential. Our identification assumption in the regime switching relies on differences between gross flows of male and female workers, which we argue is a good indicator of the extent to which (male) workers enjoy job security in Japanese firms. On the Japanese labor market, female workers are usually not part of the regular workforce but are used by firms as a buffer, making them a natural benchmark for the flexible labor input that we associate with the competitive work organization. Our results are robust to an alternative specification based on the share of part-timers. We also do robustness checks to rule out alternative explanations of the correlation between wage premia and job flows, such as on-the-job search. Finally, we use the regime switching equation to simulate the evolution of

the share of type-I firms and find that it decreased, within sector, at the beginning of the Lost Decade, consistent with the prediction of the model. These results suggest that our explanation based on efficiency wages and the heterogeneity of firms' organizational structure is a plausible candidate to account for the recent joint rise in productivity and wage differentials in Japan.

The rest of the paper is built as follows. In the next section, we describe some stylized facts that characterized the Japanese economy from the early 1990s on, focusing on the real side of the economy, in particular the rising wage and productivity differentials. Section 3 then discusses the recent literature that aimed at connecting wage and productivity differentials. Section 4 builds an efficiency wage model with the endogenous choice of organizational structure and shows that it accounts well for the stylized facts. Section 5 tests whether the efficiency wage mechanism embedded in the model is present in the data and identifies the two types of firms with an unknown regime switching regression. The final section concludes.

2. Stylized facts: the Japanese Lost Decade viewed from the real side of the economy

The Lost Decade in Japan (1992–2004) has been infamous for the long-lasting effect of the burst of the financial and real estate bubbles and the inability of successive governments to deal with a crisis that has turned into a deflation (Mikitani and Posen, 2000). But the Lost Decade has also witnessed several important developments in the real side of the economy. This section reviews the major stylized facts (SF) that motivate our analysis.

SF1: Aggregate productivity has slowed down during the Lost Decade

Although it is less known outside Japan than the deflationist episode, a major feature of the Lost Decade is the productivity slowdown at the aggregate level, which has been the focus of a lively academic debate in Japan. Between 1995 and 2004, the annual average gross value-added growth has been 0.7 per cent in Japan against 3.7 per cent in the USA, with a contribution of total factor productivity (TFP) growth of 0.4 and 1.7 respectively, whereas during the period 1980–95 gross value-added growth was 3.6 per cent in Japan and 2.9 per cent in the USA with a contribution of TFP growth of 1.2 and 0.5 respectively (Fukao and Miyagawa, 2007).³

Hayashi and Prescott (2002) also conducts a growth accounting. Using their data, we can decompose the loss of 3.1 points of growth in per capita income between the periods 1983–91 and 1991–2000 into a loss of 2.2 points in TFP growth and a loss in 0.9 points in number of hours worked per capita, whereas the ratio of capital to hours worked slightly decreased (by 0.1 point).

SF2: Productivity differentials across firms have increased, even after controlling for firm size and sector

Recent studies on Japan, using different data sets and different methodologies, have found an increasing productivity dispersion among Japanese firms during the 'Lost Decade' (Fukao and Kwon, 2006 or Ito and Lechevalier 2009, 2010, among others). Moreover, whereas Japan has been characterized by size and sector productivity differentials that were relatively higher than in other developed countries (Yoshikawa, 2008), these recent studies have emphasized productivity differentials for firms of similar size and belonging to the same narrowly defined sectors, which have also observed in other countries (Dosi *et al.*, 2010).

Ito and Lechevalier (2009) test whether the introduction of information and communication technologies had an effect on the evolution of productivity differentials at the sectoral level. They find no statistically significant effect, which casts doubt on the popular technology-based explanation according to which innovation explains productivity differentials,⁴ thus leaving room for other possible explanations.

SF3: Wage inequalities have substantially increased for workers with similar characteristics and between firms of the same size

Japan has experienced a significant increase of inequalities to become one of the most unequal countries of the OECD, when inequalities are measured through the Gini coefficient (OECD, 2006). This statement, now widely accepted, has first been the subject of an intense academic debate: until recently, there was no consensus regarding whether income inequality really widened during the 1990s and onward. For example, Tachibanaki (2005) claimed that income inequalities substantially rose during the 1980s and 1990s, with a Gini coefficient increasing from 0.278 in the mid-1980s (OECD average: 0.286) to 0.314 in early 2000s (OECD average: 0.307). On the contrary, Ohtake (2005) argued that this observed increase in income inequalities was a statistical artifact largely driven by the aging population. Focusing on labor income, Kambayashi *et al.* (2008) reconciled both sides of the debate. Using micro data, they showed that the distribution of wages remained apparently stable as a result of two opposing trends: (i) declining between-group (defined by education, experience, tenure, and establishment size) wage inequality; but (ii) increasing within-group inequality among male workers.

The first candidate to explain this increasing wage gap is the introduction of individual performance-based systems, but it does not seem to have played an important role in Japan even though such systems have been experimented with.⁵ The second candidate is related to the wage differential between regular and non-regular workers. The rising share of non-regular workers, which has more than doubled in 20 years to reach more than a third of the workforce, has been indeed a popular explanation of rising inequalities in Japan, especially within firms (Ota, 2005). A peculiarity of the Japanese labor market is that non-regular workers are mostly female whereas regular workers are mostly male, a fact that we will use later in our identification strategy.⁶

However, the higher share of non-regular workers does not explain why wage inequalities have also increased between firms (Ito and Lechevalier, 2009; Tachibanaki, 2005). This has first gone unnoticed since the literature has first focused on firms of different size and found that firm-size differential does not explain the increasing wage gap (e.g. Kambayashi *et al.*, 2008).⁷

SF4: Work intensity has increased, especially in firms that adopted Toyota-style flexible production systems

Although labor productivity growth has tended to slowdown, there is some evidence that work intensity has increased. Signs of rising work intensity can be captured through indicators such as accidents, depressions, and, in the most extreme cases, suicides on the work place.⁸ For example, according to a Governmental Report on Workers' Accident Compensation (2011), the number of claims of industrial accidents per 10,000 workers has increased from 0.149 in 2001 to 0.317 in 2010. Moreover, since 2007, the number of claims related to psychological diseases corresponds to more than 50 per cent of the total number of claims, whereas it was only one-third of the total number of cases in 2001. Finally, although it has not been

systematically investigated yet, the anecdotal evidence suggests that these problems concern more particularly firms who adopted new human resource practices and work organizational models, such as the Toyota-style flexible production system (Lechevalier, 2005).

Given those stylized facts, it is tempting to explain the rising wage inequalities (SF3), especially between firms, by the increased between-firm productivity differentials (SF2), as it has been done by the existing literature in the case of other countries (see next section). The present paper aims at studying this link in a way that is consistent with the two other stylized facts. Surprisingly, there has been no recent investigation of between-firms wage dispersion in connection with productivity differentials. One reason for the absence of this type of study might be the assumption of friction-less labor markets, which does not allow for any connection between wage differential and productivity differential other than human capital. Another possible reason is the concern for within-firm wage differential between regular and non-regular workers described above, or the fact that studies that have looked at between-firm inequality have focused on firms with different sizes, which failed to explain the increasing wage gap as mentioned above.

3. Review of the literature on productivity and wage differentials

In addition to the stylized facts described above, this paper is motivated by a large body of literature, both empirical and theoretical, that investigated the relationship between productivity and wage differentials.

On the empirical side, several studies have shown that variations in wages can be explained by cross-firms differences in wage policy and productivity, using Danish, US, or UK data (Dunne *et al.*, 2004; Faggio *et al.*, 2010; Mortensen, 2003). The correlation between wage and productivity differentials in different countries is now a well-established stylized fact.

Several theoretical mechanisms have been suggested to generate this link between productivity and wage differentials. A first and obvious explanation relies on differences in human capital (Haltiwanger *et al.*, 1999).

A sizable literature focuses instead on the role of technology. Caselli (1999) explains the growing wage differential by different rates of technological adoption. He builds a model where the adoption of new technologies together with different learning abilities of workers results in both different wages and different capital–labor ratios. In Leonardi (2007), the falling price of equipment results in a more dispersed distribution of capital–labor across firms. This, together with a search model of the labor market, generates an increased dispersion of wages for *ex ante* identical workers. Empirical work by Dunne *et al.* (2004) for the USA and Faggio *et al.* (2010) for the UK have confirmed the link between wage and productivity differentials on the one hand and the rate of technology adoption on the other hand. Leamer (1999) builds a two-sector Heckscher–Ohlin model with variable effort from workers and shows that effort and wages are higher in the more capital-intensive sector.

Finally, many papers explain this link by labor market mechanisms. Layard *et al.* (2005) review a range of models of imperfect labor markets that are able to generate wage and productivity differentials — union bargaining, efficiency wage, rent-sharing, or search-based.

Although the mechanisms described above are relevant for many OECD countries, they do not fit well the Japanese stylized facts described in Section 2. According to SF3, wage inequalities are found across individuals with similar characteristics and are therefore unlikely to be explained by differences in human capital or in learning abilities as in Haltiwanger *et al.* (1999) or Caselli (1999). According to SF2, productivity differentials have been observed for

firms of similar size and within narrowly defined sectors. Thus, explanations relying on sectoral differences (e.g. different capital–labor ratio as in Leamer, 1999) are not sufficient to account for them. The mechanism proposed by Leonardi (2007) for the USA is able to generate an increased dispersion of wages and productivity within sectors but implies an increase in the capital–labor ratio of firms. As documented in SF1, the capital–labor ratio slightly slowed down in Japan during the Lost Decade. The adoption of better technologies should also be associated with a higher aggregate productivity whereas productivity growth has slowed down in Japan (SF1). More generally, in the case of Japan, wage inequalities are better explained by the characteristics of the labor market (Tachibanaki, 2005) than by differences in technology (Ito and Lechevalier, 2009). Finally, few of the models mentioned above, included those on labor market mechanisms, are able to generate the intensification of effort suggested by SF4.

In the next section, we build an efficiency wage model where productivity and wage differentials stem from the endogenous choice of work organization by otherwise similar firms. This model is consistent with the four stylized facts described in Section 2 and therefore overcomes the limits of the existing theoretical literature when applied to Japan.

The increased diversity of human resources and management practices and its impact on effort and productivity differentials has been documented by Bloom and Van Reenen (2007, 2011) for the USA and Europe, and Valeyre (2004) for France. Green (2004) shows that, in the case of the UK, technological and organizational changes on the one hand, the use of high-commitment human resources policies on the other hand, explain work intensification better than the reduction of union power or rising job insecurity.

A prediction of the model that will play an important role in the empirical part of the paper is the correlation between wages and employment flows. This correlation has also been documented in other OECD countries. Using data from the State of Washington, Abowd *et al.* (2006) show that idiosyncratic wage policies of firms are closely related to observed patterns of worker and job flows at the firm level. Lazear and Shaw (2008) show that a negative correlation between workers' flows and wage levels is a widespread stylized fact among 10 OECD countries. On-the-job search offers an alternative theoretical explanation for this negative correlation, as in Mortensen and Pissarides (1994): workers in more productive establishments do not have any incentive to search for another job, because they receive enough match-specific benefits. Therefore, voluntary quits in such establishments are lower, resulting in a negative correlation between gross flows and productivity. Although this mechanism is relevant for voluntary quits, our efficiency wage mechanisms concerns involuntary quits. In Japan, the share of voluntary quits has drastically dropped since the mid-1990s. In the empirical section, we show that our results are robust even when controlling for voluntary quits.

4. An efficiency wage model with endogenous choice of organizational structure

This section describes a plausible mechanism to account for the stylized facts described in Section 2. It introduces a simple efficiency wage model with endogenous effort and the endogenous choice of organizational structure. The model is able to reproduce all the stylized facts described above. Unfortunately, the lack of data makes it impossible to directly test all its predictions. However, the empirical part of the paper (Section 5) will provide some support to the model by testing its main feature, the existence of efficiency wages in one group of firms.

The framework we use is a simple extension of the classical model proposed by Shapiro and Stiglitz (1984), with two types of firms as in Bulow and Summers (1986).⁹ This dualism

corresponds to two alternative organizational structures. Some firms (type-I firms) implement a complex organizational structure with job security and where productivity depends on specific efforts from workers, whereas other firms (type-II firms) behave competitively on the labor market and implement a simple organizational structure where workers have constant marginal productivity regardless of their effort. We assume that one firm equals one job.¹⁰ Hence, the levels of employment in the two types of firms, L_1 and L_2 , stem from the distribution of firms across the two productive models, which will be endogenous.

Jobs in type-I firms require workers' implication and efforts. Productivity in type-I firms, m_1 , is a concave function of the effort e . In order to get closed-form solutions, we assume a constant elasticity:

$$m_1(e) = \frac{1}{\eta} A e^\eta \quad \eta < 1, \quad [1]$$

where A is the economy-wide aggregate productivity. Type-I firms choose both the wage and the effort required to maximize profits, taking into account the possibility that workers can choose to shirk and not provide any effort. Shirkers are detected and fired with probability q . Non-shirkers enjoy job security: they only lose their job when the firm is hit by an exogenous separation shock, which happens with probability s . Then, the worker becomes unemployed and the firm exits the economy. The wage is used as an incentive mechanism to ensure that workers do not shirk.

In type-II firms, no incentive is required: workers always have an exogenous productivity $m_2 = A\mu$. Contrary to type-I firms that offer job security, type-II firms are perfectly competitive. Workers freely choose between supplying their labor to type-II firms on the competitive spot labor market or being unemployed. Only unemployed workers can look for a job in a type-I firm; they succeed with probability a , which has to satisfy:¹¹

$$aU = sL_1, \quad [2]$$

where U is the number of unemployed.

Unemployment benefits w_u are financed by a tax raised on wages, with the following budget constraint:

$$w_u U = t(w_1 L_1 + w_2 L_2). \quad [3]$$

The tax rate t is exogenous. The total labor force is N , with:

$$N = L_1 + L_2 + U. \quad [4]$$

Firms are free to choose their productive model, type I or type II. We also assume free entry of firms in the economy.

The model is solved in three steps:

- Step 1: type-I firms choose the wage and the effort that maximize the value of the firm.
- Step 2: workers not employed in type-I firms freely choose between unemployment and a job in type-II firms, which determines wages in type-II firms.
- Step 3: firms freely enter the economy and choose their productive model (type I or type II), which determines employments in type-I and type-II firms, as well as the hiring rate a .

Table 1. Variables of the model

Variable	Definition
w_1, w_2	Wage in type-I and type-II firms
L_1, L_2	Number of type-I firms and of type-II firms
N, U	Total labor force, total unemployment
w_u	Unemployment benefits
e	Effort of workers in type-I firms
η	Elasticity of a worker's productivity with respect to its effort
a, s	Hiring and firing rates in type-I firms
$V_1^S, V_1^{NS}, V^U, V_2$	Utilities of shirker in type-I firms, of non-shirker in type-I firms, of unemployed, and of worker in type-II firms
J_1, J_2	Values of a type-I and a type-II firm
t	Tax rate raised on wages
m_1, m_2	Productivity in type-I and type-II firms
q	Probability of detecting shirker
r	Interest rate
μ	Idiosyncratic productivity in type-II firms
A	Aggregate productivity

As the efficiency wage block of the model (step 1) is standard, we put some of the derivations of the results in Appendix A and keep here only what is necessary to our demonstration. The definition of all variables is summarized in Table 1.

Step 1: incentives and effort in type-I firms

Type-I firms choose an efficiency wage to make sure that workers will not shirk (see Appendix A):

$$w_1 = \frac{e(a+s+r+q)}{q(1-t)} + \frac{w_u}{1-t}. \quad [5]$$

Then, they choose the level of effort that maximizes the value of the firm subject to this efficiency wage schedule. The value of a type-I firm J_1 is given by:

$$J_1 = \frac{m_1 - w_1}{r+s}. \quad [6]$$

Profits' maximization yields an endogenous effort function:

$$\frac{dJ_1}{de} = \frac{\partial m_1}{\partial e} - \frac{\partial w_1}{\partial e} = 0, \quad [7]$$

$$e = \left[\frac{(1-t)Aq}{a+s+r+q} \right]^{\frac{1}{1-\eta}}. \quad [8]$$

At the optimum, the positive effect on profits of a marginal increase in effort, and therefore productivity, would be exactly offset by the higher efficiency wage needed to get that higher

effort. The fact that effort and productivity are endogenously determined by firms is a crucial aspect of the model. In contrast, standard models like Shapiro and Stiglitz (1984) assume that effort is exogenous.

Taken together, the efficiency wage [5] and the optimal level of effort [8] imply a wage schedule given by:

$$w_1 = \left[\frac{(1-t)q}{a+s+r+q} \right]^{\frac{\eta}{1-\eta}} A^{\frac{1}{1-\eta}} + \frac{w_u}{1-t}. \quad [9]$$

Step 2: equilibrium wage in type-II firms

Because type-II firms are perfectly competitive, workers can freely choose to either supply their labor to type-II firms or be unemployed. In equilibrium, the wage paid by type-II firms adjusts to make workers indifferent between unemployment and a job in a type-II firm (see Appendix A):

$$w_2 = \frac{ae}{q(1-t)} + \frac{w_u}{1-t}. \quad [10]$$

From [5] and [10], we can derive the expression of the wage differential:

$$w_1 - w_2 = \frac{e(s+r+q)}{q(1-t)}. \quad [11]$$

The wage premium paid by type-I firms over type-II firms increases with the effort required from workers in type-I firms.

Step 3: productive model and employment

Finally, firms choose their productive model. In equilibrium, they should be indifferent between both models so that the value of a type-I firm should equal that of a type-II firm: $J_1 = J_2$, where:

$$J_2 = \frac{m_2 - w_2}{r}. \quad [12]$$

As there is free entry, this value is driven down to 0. We have $J_1 = J_2 = 0$, which gives:

$$m_1(e) = w_1, \quad [13]$$

$$m_2 = w_2. \quad [14]$$

We can now define an equilibrium of the model.

Definition: An equilibrium is an allocation vector (L_1, L_2, U, e) , a price vector (w_1, w_2, w_u) , and a hiring rate a , satisfying the flow equilibrium condition [2], the budget constraint [3], the labor resource constraint [4], the free entry conditions [13] and [14], the efficiency wage schedule

[5], such that type-I firms choose optimally the level of effort [8] and workers are indifferent between unemployment and jobs in type-II firms [10].

The following proposition describes the equilibrium of the model.

Proposition 1 (Equilibrium): There is a unique $\bar{A} > 1$, such that for all A satisfying

$$1 < \left[\frac{\eta\mu}{1-\eta} \right]^{\frac{1-\eta}{\eta}} \frac{(1-t)q}{s+r+q} A < \bar{A} \text{ there exists a unique equilibrium with } L_1 > 0 \text{ and } L_2 > 0. \text{ In this}$$

$$\text{equilibrium, } \frac{\partial a_1}{\partial A} > 0, \frac{\partial e}{\partial A} < 0, \frac{\partial(m_1 - m_2)}{\partial A} < 0, \frac{\partial(w_1 - w_2)}{\partial A} < 0, \text{ and } \frac{\partial(L_1/L_2)}{\partial A} > 0.$$

Proof: See Appendix A.

The lower (upper) bound on A is necessary to get strictly positive employment in type-I (type-II) firms L_1 (L_2).

Discussion of the results

In our framework, the productivity slowdown of the Lost Decade that we documented in SF1 can be modeled as a decrease in the aggregate productivity A . The proposition shows that this leads to lower hiring flows into type-I firms, a higher effort in type-I firms, and larger wage and productivity differentials between type-I and type-II firms, consistent with SF2, SF3, and SF4.

The intuition for this result is the following. In a partial equilibrium framework, i.e. for a given hiring flow a , the direct effect of a lower aggregate productivity A is to lower the effort at the firm level (see equation [8]), which would depress the firm-level productivity $m_1(e)$ in type-I firms even further than in type-II firms. However, there is a general equilibrium effect going in the opposite direction. Lower profits in type-I firms indeed lead to a reallocation of firms from a type-I to a type-II productive model. With a lower share of type-I firms, the hiring rate a then decreases (equation [2]). This in turns lowers the value of unemployment as it is now harder to find a job in type-I firm, making it profitable for type-I firms to increase the effort required. Indeed, equation [8] shows that the optimal effort is a decreasing function of the hiring rate. What proposition 1 shows is that this general equilibrium effect dominates so that the effort e increases when A decreases. This is consistent with SF4, which documents an increase in the intensification of work.

From equation [11], a higher level of effort then means a larger wage differential, consistent with SF3, as well as a larger productivity differential between type-I and type-II firms, consistent with SF2.

To sum it up, a decrease in aggregate productivity leads to a smaller number of type-I firms, providing a higher effort, getting a higher wage premium and making these firms overall more productive in relative terms. The fact that the relative productivity of type-I firms increases following the crisis is due to the interaction between the general equilibrium effect and the endogenous intensification of work in these firms.

Although this main result is consistent with the stylized facts presented in Section 2, whether our efficiency wage mechanism is a satisfying model of the Japanese labor market is a matter of empirical investigation.¹² The empirical section of this article focuses on detecting efficiency wages in type-I firms and competitive wages in type-II firms. According to equation [9], conditional on macro variables, efficiency wages in type-I firms are a decreasing function of the separation rate s . Although the rate of inflow a is a macroeconomic variable (the probability for an unemployed to find a job in any type-I firm), the rate of outflow s is an

idiosyncratic variable specific to each type-I firm.¹³ Therefore, if the separation rate varies across firms, we expect to find a decreasing relationship between wages and separation rates in the cross-sectional dimension of micro data for type-I firms. On the contrary, type-II firms are perfectly competitive: their wage is pinned down by their exogenous productivity, which is unrelated to employment flows.¹⁴ Therefore, we do not expect any cross-sectional relationship between wages and employment flows for type-II firms.

Finally, firms in the model all have the same size and belong to the same sector. Therefore, the predictions of the model should be understood as holding *within groups of sector and size* and not for the entire economy. For example, the share of type-I firms could decrease within sectors and for firms of the same size but increase overall in the economy. This would be the case if a sector with a large share of type-I firms becomes larger relative to the rest of the economy.

5. An empirical investigation with Japanese micro data

5.1 Empirical strategy and data set

According to the model of the previous section, we should find a negative relationship between flows and wages in type-I firms (as in equation [9]), whereas there should be no such correlation in type-II firms. The goal of this empirical part is to try to explain the stylized facts mentioned in Section 2, in particular productivity and wage differentials, by applying this dichotomy to the Japanese economy.

Ideally, we would like to test the model by using a micro panel data set including data on wages and employment flows. Unfortunately, to our knowledge, such a database is not publicly available in Japan. However, we had access to the BSWS and the ETS between the years 2005 and 2009. The first survey provides information on wages and the second on employment flows. By matching those two data sets at the establishment level for each year, we get an employer–employee data set with 9,007 establishments, a well-known type of data to address the question we are interested in (Abowd *et al.*, 1999; Abowd and Kramarz, 2001). The appendixes describe the two initial databases, explain the matching process (Appendix B), and provide summary statistics (Appendix C).

Using this repeated cross-sectional data, we detect efficiency wages by showing the existence of a negative correlation between flows and wages. To do this, we first estimate a Mincerian wage equation for male regular workers with fixed effects on establishment. The dependent variable is the logarithm of hourly ‘base’ wage rate of each worker (see below) and the explanatory variables are individual characteristics such as education, tenure, as well as dummies for prefectures (Kambayashi *et al.*, 2008). The establishment fixed effect can be interpreted as the establishment-specific wage premium. According to the model, this fixed effect should be negatively correlated with the magnitude of outflows in type-I establishments.

In a second step, we use the unknown regime switching technique (Dickens and Lang, 1985; Ishikawa and Dejima, 1994) to decompose the economy into two types of establishments. This methodology allows us not to set any explicit *a priori* criterion to define which establishment belongs to which type of firm. This is a crucial point, as productivity dispersion has increased within groups of firms sharing similar characteristics such as size and industry (SF2). After having identified these two groups of firms, we can check whether there is a negative correlation between wage premia and flows in type-I firms, and no such correlation in type-II firms.

In a third step, we use the result of this estimation and public data with a longer time span to simulate the evolution of the share of type-I firms in the economy. This will allow us to confirm an additional prediction of the model.

5.2 Detecting the existence of efficiency wage schemes

We start by checking whether there is a negative correlation between wage premia and employment flows in the data, as predicted by the model when firms adopt efficiency wage schemes.

First, according to a conventional procedure in the usage of the BSWs, we define an hourly ‘base’ wage w_{ijt} as the wage, excluding various allowances, paid per scheduled hour worked by worker i , in establishment j at time t . The base wage thus excludes bonus payments and overtime work, which avoids a potential bias coming from unobservable temporary labor demand shocks. If the wage were computed using the total wage bill instead, such shocks would affect both the estimated wage premium and the labor flows.¹⁵

Second, we limit the sample to regular male workers in private firms with more than 30 employees, and exclude the construction industry, to keep the comparability to public data.¹⁶

Third, we regress year by year the log of the base wage on individual characteristics of human capital (such as educational level, age, tenure), and prefecture dummies (X_{ijt}), in addition to an establishment fixed effect (u_{jt}). Following the standard Mincerian equation, the specification is:

$$w_{ijt} = \alpha_t + X_{ijt}\beta_t + u_{jt} + e_{ijt} \quad (t = 2005, \dots, 2009). \quad [15]$$

Here e_{ijt} is the normally distributed error term given X_{ijt} and u_{jt} . If the human capital market is perfect, the establishment fixed effects u_{jt} of [15] can be interpreted as the unobserved wage premium that a worker can enjoy just because he/she belongs to a specific establishment.

The next step is to look at the relationship between the predicted wage premium \widehat{u}_{jt} and employment flows. Table 2 shows the negative statistical relationship between the predicted establishment effects and several kinds of flow ratios at the establishment level, controlling for industries, firm size, and overtime ratio. This supports the predictions of [9] for the whole sample of firms.

Table 2. OLS estimates of the effect of flow structure on establishment fixed effects (1) sample: 2005–9 BSWs and ETS matched sample

	(2a)	(2b)	(2c)	(2d)
Dependent variables	Predicted establishment fixed effect			
Inflow ratio	-0.052 (0.013)***			
Outflow ratio		-0.074 (0.017)***		
Gross flow ratio			-0.038 (0.008)***	
Excess flow ratio				-0.025 (0.010)***
Observations			9,007	
R-squared	0.27	0.27	0.27	0.27

Notes: Standard errors in parentheses, and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Other explanatory variables include the average overtime ratio, four firm size dummies, nine industry dummies, and a constant. The inflow (outflow) ratio is the number of employees hired (fired) during a year divided by total employment at the beginning of the year. The gross flow ratio is the sum of the inflow and the outflow ratios. The excess flow ratio is the difference between the gross flow ratio and the absolute value of the employment growth rate.

Although these results confirm the existence of an efficiency wage mechanism on average, the negative correlation may not be universal. This leads us to further investigate this issue by dividing the sample into two categories, type-I and type-II firms.

5.3 Identifying two types of firms: a switching regression approach

To divide the sample of firms into two tiers, a possibility would be to set up an *a priori* criterion such as firm size or industry. However, adopting such an *a priori* classification might lead to misclassify some firms. More importantly, it rules out by assumption the possibility of within-group heterogeneity, e.g. the possibility that two firms with similar size or belonging to the same sector may choose different wage schemes and organizational structure. Allowing for within-group heterogeneity is important if one considers that previous studies, which have tried to link increasing productivity differentials to strategic choices of firms (such as investment in R&D or export behavior) have shown its importance (Ito and Lechevalier, 2010).

This is why we adopt the unknown regime switching regression *à la* Dickens and Lang (1985),¹⁷ With this methodology, sample separation is *a priori* unknown and the choice between two sectors becomes endogenous (Sousa-Poza, 2004). The system of estimation is, suppressing time dimension, as follows:

$$\begin{cases} \widehat{u}_{j,I} = \theta_I + \gamma_I s_{j,I} + Z_{j,I} \delta_I + \varepsilon_{j,I} \\ \widehat{u}_{j,II} = \theta_{II} + \gamma_{II} s_{j,II} + Z_{j,II} \delta_{II} + \varepsilon_{j,II} \\ \mu_j = \theta_3 + \gamma_3 K_j + Z_j \delta_3 + \varepsilon_{j3} \end{cases}$$

and

[16]

$$u_j = \begin{cases} \widehat{u}_{j,I} & \text{if } \mu_j \geq 0 \\ \widehat{u}_{j,II} & \text{if } \mu_j < 0 \end{cases},$$

where

- $\widehat{u}_{j,k}$ is the predicted fixed effect of establishment j of type k (I: type I, II: type II);
- s_j is the separation rate of establishment j ;
- Z_j are control variables;
- μ_j is a latent variable that splits the sample into two types of firms;
- K_j provides the key to identify the two types of firms.

Because $\widehat{u}_{j,k}$ is the predicted fixed effect of establishments and can be interpreted as a wage premium, industry and firm size should matter. Therefore, we include nine industry dummies, four firm size dummies, and year dummies as controls. As previously discussed, $\widehat{u}_{j,k}$ may also be affected by unobserved temporary demand shocks, causing omitted variable bias. This potential bias is already limited by the fact that we estimate the wage premium using the base wage, not the total wage bill (see above). In addition, we introduce the average overtime ratio within establishments to directly control for temporary demand shocks.

The main issue, before estimating the system of equations [16], is to define the key to identify the two sectors, K_j . We propose to use the difference between gross flows of male and female employees. The reason for this identification strategy is the following. First, a distinctive feature of the Japanese labor market is that female workers are usually not part of the regular workforce but are used by firms as a buffer (Abraham and Houseman, 1989; Houseman and Abraham, 1993). Accordingly, we identify female employees as a benchmark for the most

flexible type of labor input. Then, if the gross flow of male employees is large compared with that of female employees belonging to the same firm, male workers are considered as a flexible labor input as well and the firm is classified as a type-II firm with a competitive work organization. If, on the contrary, the gross flow of male employees is low compared with that of female employees, male workers are considered as enjoying job security and the firm is classified as a type-I firm.

This identification strategy relies on the specificity of the Japanese labor market with regards to the dichotomy between male and female employees. Discrimination against female workers in Japan has been documented by the existing literature (Tachibanaki, 2005; Wakisaka, 1997). The gender gap in the labor market in Japan is one of the highest among OECD countries (OECD, 2010, table 1.1, p. 37). The fact that female workers are used as a buffer and thus displays larger gross flows is confirmed in our data set: the gross flow rate is higher on average and more volatile for female than for male regular workers (Appendix D).

Another option for the identification strategy may be to use the difference between gross flows of part-timers and full-timers within the same establishment. In this case, we would assume that an establishment that uses part-timers more flexibly than its full-timers is more likely to treat their full-timers as quasi-fixed input and could be considered as a type-I firm. However, using part-timer flows drastically limits the sample size and creates biases in the estimated results, because the use of part-timer is heavily concentrated on some establishments (small establishment and/or belonging to the service industry). The share of establishments that do not use female regular worker is at most 12 per cent, whereas the share without any part-timers is 44 per cent. This makes it easier to econometrically identify the two types of firms that we theoretically distinguished using the dichotomy between male and female workers than the dichotomy between part-time and full-time workers. In addition, the category of full-time workers does not necessarily coincide with that of regular workers, as full-time workers can also be used as a buffer to protect the core workforce. Indeed, many female workers who work fulltime are treated as non-regular workers (so-called ‘quasi-part-timers’; OECD, 1998). That being said, we will use this alternative identification strategy as a robustness check (Section 5.5.1).

After having chosen our identification strategy, we run the estimation based on equation [16]. The estimated results are shown in Table 3. Column (2a) is the same as in Table 2, in which we can find a weakly negative correlation between separation rates and the predicted establishment fixed effect on average. When we divide the sample into two parts, following the switching equation reported in column (3c), this negative relation becomes stronger and gains statistical significance in type-I firms (3b), whereas it becomes rather small and statistically insignificant in type-II firms (3a). These results imply that we cannot reject the hypothesis that type-I firms resort to efficiency wages, whereas type-II firms do not.

The estimation is also consistent with the identification strategy: the difference between male and female gross flows affects the establishments’ probability to belong to the type-I firms negatively as well as significantly in the switching equation (column (3c) in Table 3), as expected. The estimation is also consistent with the existing literature on wage premium and firm size: male workers enjoy larger wage premium in larger firms regardless of their organizational structure, type I or type II (columns (3a) and (3b)). Interestingly, the estimated switching equation (column (3c)) implies that smaller firms are less likely to belong to type-I firms (compared with the largest firms), and that firms in the service industry are more likely to be of type I (compared with those in the manufacturing industry).

As the switching equation (column (3c) in Table 3) is a type of Probit model, we cannot distinguish the magnitude of the marginal effect of variables directly. Instead, Table 4

Table 3. Estimated results of switching regression: effect of flow structure on predicted establishment fixed effect 2005 BSWS and ETS matched sample

		(2a)	(3a)	(3b)	(3c)
		Full sample OLS	Type-II firms	Type-I firms	Switch
Dependent variables		Predicted establishment fixed effect			(latent)
Out flow ratio		-0.074 (0.017)***	-0.016 (0.012)	-0.156 (0.043)***	
Gross flow ratio difference between male and female					-0.048 (0.006)***
Overtime ratio		-0.584 (0.046)***	-0.226 (0.036)***	-1.204 (0.117)***	
Firm size dummies	(Over 1000)			Base	
	(300–999)	-0.161 (0.007)***	-0.134 (0.005)***	-0.2 (0.015)***	0.091 (0.007)***
	(100–299)	-0.278 (0.007)***	-0.275 (0.005)***	-0.26 (0.019)***	-0.839 (0.008)***
	(30–99)	-0.346 (0.009)***	-0.342 (0.007)***	-0.329 (0.021)***	-0.79 (0.010)***
Industry dummies	(Mining)	0.161 (0.023)***	0.139 (0.014)***	0.363 (0.050)***	0.53 (0.025)***
	(Manufacturing)			Base	
	(Electric and utilities)	0.203 (0.013)***	0.204 (0.007)***	0.117 (0.036)***	-1.945 (0.015)***
	(Transportation and communication)	0.122 (0.009)***	0.245 (0.007)***	0.07 (0.020)***	2.062 (0.010)***
	(Retail, wholesales, and restaurants)	-0.03 (0.010)***	-0.066 (0.006)***	0.053 (0.022)**	0.96 (0.010)***
	(Finance and insurance)	0.179 (0.012)***	0.156 (0.008)***	0.216 (0.025)***	1.127 (0.014)***
	(Real estates)	0.095 (0.016)***	0.255 (0.012)***	0.009 (0.017)***	2.377 (0.018)***
	(Service)	0.109 (0.007)***	0.064 (0.005)***	0.124 (0.017)***	2.139 (0.008)***
Constant		0.171 (0.008)***	0.12 (0.006)***	0.275 (0.021)***	-1.131 (0.007)***
Observations				9,007	
R-squared		0.27	0.47	0.13	0.94

Notes: Standard errors in parentheses, and *** p < 0.01, ** p < 0.05, * p < 0.1. Estimation includes year dummies. Gross flow ratio means inflow ratio plus outflow ratio.

decomposes the sample according to the *ex post* estimated probability to be type I, and confirms the difference of firm characteristics between more-likely-to-be-type-I firms and less-likely-to-be-type-I firms. As expected, the average wage premium is much larger in the more-likely-to-be-type-I firms. The difference between gross flows of male and female workers is also smaller in the more-likely-to-be-type-I firms. It is also apparent that there are less small firms among the more-likely-to-be-type-I firms. For example, among the firms whose probability to belong to type I is more than median, the smaller firms (under 299 employees) represent 22.7 per cent against 26.3 per cent in less likely firms. The table also suggests that the relation between firm size and type of firm is non-monotonous, implying that an *a priori*

Table 4. Average attributes between more-likely-to-be-type-II firms and more-likely-to-be-type-I firms

Variable	Less than median of Prob. of type-I		More than median of Prob. of type-I	
	Mean	Std. Dev.	Mean	Std. Dev.
Predicted establishment fixed effect	0.030	0.232	0.088	0.307
Outflow ratio	0.116	0.104	0.158	0.185
Gross flow ratio difference between male and female	-0.027	0.243	-0.081	0.654
Overtime ratio	0.090	0.056	0.070	0.058
Firm size dummies	(Over 1000)	0.610	0.511	
	(300–999)	0.130	0.262	
	(100–299)	0.163	0.147	
	(30–99)	0.100	0.080	
Industry dummies	(Mining)	0.020	0.006	
	(Manufacturing)	0.876	0.140	
	(Electric and utilities)	0.076	0.000	
	(Transportation and communication)	0.000	0.172	
	(Retail, wholesales, and restaurants)	0.027	0.142	
	(Finance and insurance)	0.002	0.092	
	(Real estates)	0.000	0.052	
Year dummies	(Service)	0.000	0.397	
	2005	0.154	0.285	
	2006	0.272	0.145	
	2007	0.204	0.202	
	2008	0.185	0.150	
Observation	0.186	4,504	0.217	4,503

classification of type of firm would not have been appropriate. As for the industries, manufacturing industries have a low probability of being type I whereas high probability firms are characterized by a high share of service industry.

Overall, the estimation of the system of equations supports the existence of efficiency wages in type-I firms and competitive wages in type-II firms. This result shows the usefulness of the unknown switching regression methodology *à la* Dickens and Lang.

5.4 Implication for the evolution of the share of type-I firms

A key mechanism of the theoretical model is the reallocation of firms from a type-I to a type-II organization when the economy is hit by a negative aggregate productivity shock (see Proposition 1). This section uses the result of the estimation to simulate the evolution of the share of type-I firms.¹⁸ To do this, we feed the switching regression estimate (column (3c) in Table 3) with public data from 1981 to 2005 to compute the probability to be a type-I firm.

The probability of being a type-I firm is calculated as:

$$F(\widehat{\theta}_3 + \widehat{\gamma}_3 K_j + Z_j \widehat{\delta}_3), \quad [17]$$

where F is the cumulative distribution function of the standard normal distribution, K_j is the difference between gross flows of male and female workers, and Z_j are dummies for industry and firm size. In the sample used for the estimation, the mean (median) over the 9,007 establishments of this probability is 31 per cent (13 per cent). By using the number of male regular workers as weights, we can compute the share of type-I firms in the economy, measured by the number of male regular workers. In our sample, it is equal to 19 per cent.

To determine the evolution of the share of the type-I firms over time, we feed [17] with published ETS data that provide semi-aggregated worker flows by gender, firm size, and industry since 1981. If we assume that the switching equation has been stable over time, we can deduce the probability for the average firm to belong to type I in a certain industry, for a certain size class and in a certain year. As the model predicts a shrinking share of type-I firms within a homogenous sector and for a given size (normalized to 1), the simulation has to abstract from changes in the composition of sector and size. To do this, we fix the composition of industry and firm-size as it was in 1981. More precisely, denote S_{t1981} the average share of type-I firms at year t , based on the number of male regular workers of industry-firm size k in the year 1981, which we denote M_{k1981} . K_{kt} is the difference between aggregate gross worker flow of male and female, and Z_{kt} are dummies for industry and firm size. S_{t1981} is defined as follows:

$$S_{t1981} = \frac{\sum_k F(\hat{\theta}_3 + \hat{\gamma}_3 K_{kt} + Z_{kt} \hat{\delta}_3) M_{k1981}}{\sum_k M_{k1981}}. \quad [18]$$

We refer to this first simulation as the *within-group transition* and report our result in Figure 1a. To be complete, we also report in Figure 1b the total share of type-I firms when allowing the composition of industry and size to evolve over time (*total transition*).¹⁹ In this second simulation, the evolution of the total share is affected by the distributional shift of workers from sector to sector and from size to size. As, according to our results, firms in the service sector are more likely to adopt the efficiency wage scheme, the increasing share of the service industry over time is likely to lead to a larger total share of type-I firms.

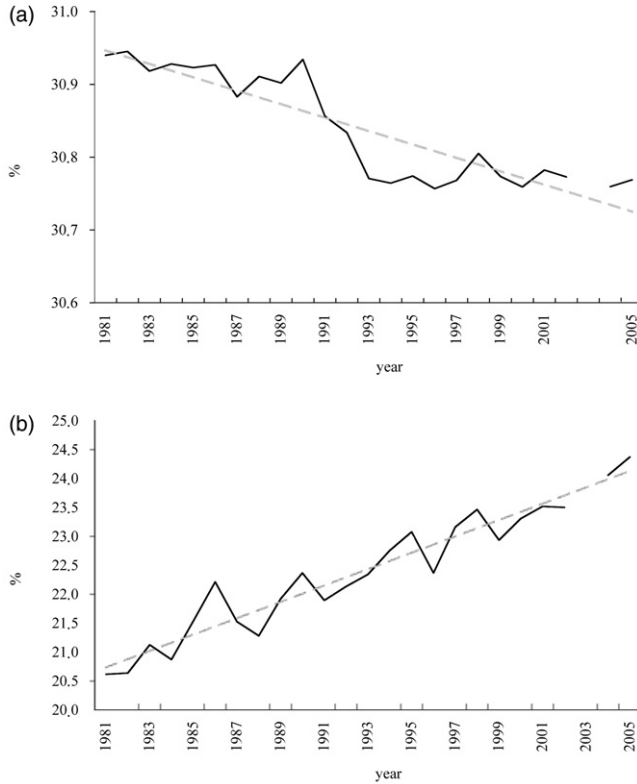
Figure 1a shows the evolution of the simulated share of type-I firms between 1981 and 2005 based on a fixed sectoral and size composition (S_{t1981}).²⁰ The simulated share of type-I firms has decreased within group at the beginning of the Lost Decade, which confirms the prediction of the model.

Figure 1b shows the evolution of the simulated total share of type-I firm when allowing for changes in the industry-size composition. The total share in the simulation is about 25 per cent in 2005, which is slightly higher than the share directly computed with the micro data, 19 per cent. This difference, which could be due to aggregation errors, should make us cautious when interpreting the simulated probability based on aggregate data. The figure shows that changes in the composition of industry and firm-size led to an overall increase in the share of type-I firms within whole economy. Although the first simulation provides an explanation for the rise of within-group wage differentials, this second simulation could explain widening between-group wage differentials.

5.5 Robustness of switching regression

The existence of efficiency wages is not contradicted by our estimations so far. However, it is necessary to conduct some robustness checks to make this conclusion stronger. We first

Figure 1. Predicted share of type-I firms worker: (a) within group transition; (b) total transition



discuss the robustness of the switching equation, especially with regard to the identification strategy; then we discuss the robustness of the wage premium equation.

5.5.1 Gross flow difference between regular workers and part-timers. An alternative choice for the variable K_j in equation [16] is to use the gross flow difference between regular workers and part-timers. As we already explained, the drawback of this approach is the drastic decrease of the sample size. Table 5 shows the distribution of part-timer ratio.

The sample mean of part-timer ratio per establishment is about 23 per cent. However 44 per cent of establishments do not use part-timers at all. Some service industries such as hotels and restaurants uses part-timers much more than manufacturing industries do. Moreover, part-timers are likely to be concentrated in the very large and very small firms.²¹ Therefore, if we use the difference between gross flows of full-timers and part-timers, we lose much of the sample size and the remaining sample will be biased towards some particular sectors.

Regardless of these drawbacks, Table 6 displays the estimated results of equation [16], when using the difference between gross flows of full-timers and part-timers. As we expected, with one third less of sample size, the resulting estimation does not distinguish as well as before type-I from type-II firms. However, results from of pooled ordinary least

Table 5. Distribution of part-timer ratio (BSWS 2005–9)

	Obs.	Mean	Std. Dev.	Min.	Median	Max.	Fraction of zero
Total	266,563	0.232	0.315	0	0.059	1	0.439
Industry							
Manufacturing	50,980	0.115	0.207	0	0	1	0.541
Hotels and restaurants	33,411	0.623	0.328	0	0.737	1	0.099
Firm size							
Over 5000	29,725	0.326	0.390	0	0.075	1	0.411
100–299	38,945	0.180	0.268	0	0.049	1	0.454
5–9	38,765	0.249	0.326	0	0.111	1	0.488

Table 6. Summary of estimated results of switching regression: effect of gross flow difference between regular workers and part-timers: 2005–9 BSWS and ETS matched sample

Dependent variables	(6d)	(6a)	(6b)	(6c)
	Pooled OLS	Type-II firms	Type-I firms	Switch (latent)
Outflow ratio	-0.096 (0.020)***	-0.030 (0.013)**	-0.202 (0.067)***	
Gross flow ratio difference between regular and part-timer				-0.228 (0.002)***
Constant	0.152 (0.010)***	0.109 (0.007)***	0.202 (0.025)***	-1.059 (0.008)***
Observations			5,898	
R-squared	0.27	0.46	0.16	0.97

Notes: Standard errors in parentheses, and *** p < 0.01, ** p < 0.05, * p < 0.1. Estimation includes industry, firm size, year dummies, and overtime ratio. Gross flow ratio means inflow ratio plus outflow ratio.

squares (OLS) (6d) still show the slightly negative relation between the inflow ratio and the wage premium as a whole. The switching equation (6c), which uses the gross flow difference between regular workers and part-timers, yields a similar result as in Table 3. Contrary to the results we showed in Table 3, the outflow ratio in type-II firms now also negatively affects the wage premium in (6a). Nonetheless, the magnitude of the effect is much smaller than for type-I firms. Overall, the change of the identification key does not substantially alter our results.

5.5.2 *Wage premium equation: on-the-job search and composition effect.* The estimation of the wage premium equation may have been affected by two other mechanisms. First of all, as recalled in Section 3, a mechanism of on-the-job search may also explain the observed negative relation between wage premium and gross flows at the micro level. Because incumbents can look for a job elsewhere, employers have an incentive to retain them with higher wages, which results in both a higher wage premium and a lower labor flow. To control for

Table 7. Robustness check of switching regression: 2005–9 BSWs and ETS matched sample

Dependent variables	(7a)	(7b)	(7c)	(7d)
	Type-II firms	Type-I firms	Type-II firms	Type-I firms
	Predicted establishment fixed effect			
Outflow ratio	−0.018 (0.012)	−0.150 (0.042)***	−0.010 (0.013)	−0.105 (0.031)***
Difference of average age	−0.001 (0.001)	0.009 (0.002)***		
Ratio of voluntary quit			−0.040 (0.005)***	−0.071 (0.011)***
Constant	0.123 (0.006)***	0.241 (0.024)***	0.132 (0.006)***	0.239 (0.014)***
Observations			9,007	
R-squared	0.46	0.16	0.47	0.17

Notes: Standard errors in parentheses, and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Other explanatory variable includes overtime ratio, four firm size dummies, nine industry dummies, and year dummies. The probability weight to belong to each sector is re-estimated as in (3c).

this potential bias, we use the outflow ratio of voluntary quits as an additional control variable.

Second, in the actual workplace, fluctuations in gross flows may introduce a change in the composition of the company's workforce; for example, when hiring decreases, the average age and tenure of workers may increase as a result of reducing younger new-comers. In the estimation, we assume that the observable attributes of human capital solely determine the hourly base wage, and any change in the workforce composition does not affect the residual of wage equations. However, if the company uses deferred payment schemes, in which workers receive wage premium in the later period of career, any temporal decrease of younger workers' share in hiring will cross-sectionally produce a higher average wage premium, even though this change in the composition of the workforce will not alter the aggregated wage premium through lifetime. As our data set is built on cross-sectional survey, the unobservable deviation of each establishment from the cross-sectional mean may come from a temporal imbalance of workers' composition. To account for this, we use the difference between the average age of stock and inflows.

Results are shown from columns (7a) to (7d) of Table 7. It appears that extra variables, which control for on-the-job search incentives and potential composition change, do not alter the main part of the results. The coefficients of gross inflow remain negative in type-I firms and close to zero in type-II firms. In (7b), the coefficient of the composition effect is positive, which means that when incumbents are older than newly hired employees, the average wage premium grows. Interestingly, the estimated coefficient is only statistically significant in type-I firms, showing that this effect matters only for a specific type of firms. This finding is consistent with the long-term employment practices in Japan (Ishikawa and Dejima, 1994). The ratio of voluntary quits negatively affects the wage premium, which is consistent with on-the-job search models. After controlling for on-the-job search incentives, gross inflow still affects the wage premium negatively and significantly in type-I firms. Overall, these results show the robustness of our estimation.

6. Conclusion

In this paper, we have proposed a framework aiming at connecting two major stylized facts that characterized the Japanese economy during the Lost Decade (1992–2004): rising wage inequalities and increasing productivity differentials. After having documented these stylized facts and having reviewed possible theoretical explanations, we have proposed a simple efficiency wage model with one sector but two types of firms of similar size: in one type of firms, which provide job security and adopt an efficiency wage scheme with endogenous effort, the productivity is assumed to depend on the effort provided by workers, whereas in the other type of firms, characterized by a competitive labor market, productivity is exogenous. The prediction of the model is that a negative aggregate productivity shock produces increasing productivity and wage differentials, as well as a falling share of type-I firms.

The core of our paper is then an empirical investigation of the Japanese labor market with micro data. For the first time, we merge two databases, the BSWs and the ETS for the years 2005–9. This matched worker-firm cross-sectional data set allows us to get information on (hourly) wages, hiring, and separation rates and provides many control variables for firms (size, sector) and for workers (age, gender, education). The existence of efficiency wages mechanisms on average, detected by a negative correlation between the firm-specific wage premium and workers flows, is not contradicted by our data. Moreover, in dividing our sample of establishments into two groups by using the unknown regime switching regression *à la* Dickens and Lang, we find that one group of establishments can be characterized by efficiency wages, whereas the other group cannot. Further robustness checks and a simulation confirm that efficiency wages and the heterogeneity of firms with regards to their work organization is a plausible explanation for the joint rise in productivity and wage differentials in Japan in recent years.

Important implications can be drawn from this paper. First of all, we confirm that rising wage inequalities in Japan can be related to increasing productivity dispersion among firms. Second, we show that developments related to the labor market can generate rising wage inequalities, without resorting to hypotheses regarding skill-biased technical change or globalization.

At the same time, several limitations of the paper open future avenues for research. First, data availability limited our study to cross-sectional data and prevented us to directly observe the evolution of between-firm wage and productivity differential. Second, although the paper focuses on between-firm wage differentials, a future extension should decompose precisely the overall wage differentials into within-firms and between-firms components. Last, the aim of the simple model we introduced in this paper was to illustrate how an efficiency wage mechanism may generate productivity and wage differentials in the case of an exogenous aggregate shock. A natural next step would be to conduct a quantitative analysis in an extended and more realistic model. This is left for future studies.

Appendix A: Derivation of some results of the model

Wages in type-I and type-II firms

Here, we display dynamic equations for the utilities of shirking (V_1^S) and non-shirking workers (V_1^{NS}) employed in type-I firms, along with the utilities of the unemployed (V^U) and workers employed in type-II firms (V_2):

$$rV_1^{\text{NS}} = w_1(1-t) - e + s(V^U - V_1^{\text{NS}})$$

$$rV_1^{\text{S}} = w_1(1-t) + (s+q)(V^U - V_1^{\text{S}})$$

$$rV^U = w_u + a[\max(V_1^{\text{NS}}, V_1^{\text{S}}) - V^U]$$

$$rV_2 = w_2(1-t).$$

As it is optimal for firms that workers never shirk (otherwise, production would be zero), they choose a wage such that $V_1^{\text{NS}} = V_1^{\text{S}}$. From this no-shirking condition, we obtain the standard incentive-compatible real wage schedule (the efficiency wage) applying to workers in type-I firms:

$$w_1 = \frac{e(a+s+r+q)}{q(1-t)} + \frac{w_u}{1-t}.$$

Because jobs in type-II firms are perfectly competitive, workers are indifferent between working in a type-II firm or being unemployed. Therefore, $V^u = V_2$, which gives:

$$w_2 = \frac{ae}{q(1-t)} + \frac{w_u}{1-t}.$$

Proof of proposition 1

The free entry conditions [13] and [14], together with the expression of the wage differential [11] give the following equation:

$$m_1(e) - m_2 = \frac{e(s+r+q)}{q(1-t)}, \quad [\text{A1}]$$

where e , which is a function of a , follows from [8]. Equation [A1] determines the equilibrium value of a . To solve it, it is useful to introduce the following reduced variables:

$$\tilde{A} = \left[\frac{\eta\mu}{1-\eta} \right]^{\frac{1-\eta}{\eta}} \frac{(1-t)q}{s+r+q} A$$

$$\tilde{a} = \frac{a}{s+r+q}.$$

Then, substituting [8] into [A1] and using the definition of the reduced variables gives:

$$\tilde{A} = \left[\frac{1}{1-\eta} (1+\tilde{a})^{-\frac{\eta}{1-\eta}} - \frac{\eta}{1-\eta} (1+\tilde{a})^{-\frac{1}{1-\eta}} \right]^{\frac{1-\eta}{\eta}}.$$

This equation implicitly defines a function f such that $\tilde{a} = f(\tilde{A}) - 1$. It is easy to show that f is strictly increasing and maps $(1, +\infty)$ into $(1, +\infty)$. When $\tilde{A} > 1$, the hiring rate \tilde{a} is strictly positive and so is employment in type-I firms, L_1 . In addition, $\frac{f(\tilde{A})}{\tilde{A}}$ is also strictly increasing.²²

Then, from [8], the effort is given by:

$$e = \left(\frac{\eta}{1-\eta} \mu \right)^{\frac{1}{\eta}} \left[\frac{f(\tilde{A})}{\tilde{A}} \right]^{\frac{1}{1-\eta}},$$

which is a decreasing function of \tilde{A} (and hence of A). The wage rates w_1 and w_2 follow from [13] and [14]. From [11], the wage differential $w_1 - w_2$, which is also equal to the productivity differential $m_1 - m_2$, is strictly increasing in e and therefore strictly decreasing in A .

The unemployment allowance w_u follows from [9] and can be shown to be equal to $(1 - t)(1 - \eta)w_1$. Finally, L_1 , L_2 , and U follow from [2], [3], and [4]. In particular, we have:

$$\frac{L_2}{L_1} = \frac{1}{1-\eta} \left[\frac{f(\tilde{A})}{\tilde{A}} \right]^{\frac{\eta}{1-\eta}} \left[\frac{1-t}{t} (1-\eta) \frac{s}{s+r+q} \frac{1}{f(\tilde{A})-1} - 1 \right].$$

The second factor on the right-hand side is strictly decreasing and goes to $+\infty$ when \tilde{A} goes to 1 and to -1 when \tilde{A} goes to $+\infty$. Therefore, it has a unique zero \tilde{A} on $(1, +\infty)$. When $\tilde{A} < \tilde{A}$, L_2 is strictly positive. The ratio L_2/L_1 is a strictly decreasing function of \tilde{A} on $1, \tilde{A}$, so that L_1/L_2 is strictly increasing in \tilde{A} and A .

Appendix B: The data set-matching BSWS individual survey and ETS establishment survey

The key issue in the construction of our matched employee–employer data set is the size of the sample after matching.

BSWS individual survey is a sample survey of individual workers conducted by MHLW (Ministry of Labor, Health, and Welfare), once a year, at the end of June. It covers private establishments over five employees and public establishments over 10 employees. All industries other than agriculture are surveyed. Workers are re-sampled within an establishment. The sample size is about 78,000 establishments and 1.6 million workers per year. The most important feature for us is rich data on wages.

ETS is an establishment survey conducted by MHLW, twice a year, at the end of June and December. It covers public and private establishments with more than five employees in all industries, except agriculture. Individual recently separated and newly hired workers (within the sampling period) are re-sampled within an establishment. The sample size is about 10,000 establishments, with 80,000 hirings and 90,000 separations per year. The survey gives detailed information on new entrants and separations.

We match these two surveys, year by year, at establishment level by using a key provided by the Ministry. Although the size of the matched sample is 12,100, we found some possible inconsistencies in the data. The data point of BSWS is the end of June, and that of the second

wave of ETS is the beginning of July (day following the data point of BSWS). We proceed to a sample restriction as follows:

- 9 establishments are excluded due to the negative employment stock at the beginning of July;
- 1,209 establishments are excluded due to the inconsistency of industry classification between BSWS and the second ETS;
- 1,747 establishments are excluded due to the inconsistency of firm size and establishment size classifications between BSWS and the second ETS;
- 126 establishments are excluded due to the inconsistency of employment data between the first and the second ETS.
- 2 establishments are excluded due to perfectly predict success or failure in the dependent variable along with their associated observations. Dropping perfectly predicted observations has no effect on the likelihood or estimates of the remaining and increases the numerical stability of the optimization process.

As a result, the final size of the matched sample is 9,007 establishments. For the BSWS, the matching rate is only 3.4 per cent but from the point of view of ETS, it is 15.9 per cent, which is quite acceptable. Finally, please note that this restriction is very conservative in that there is a possibility for an establishment to move to another classification at the beginning of July.

Appendix C: Summary statistics for the data set

Variable	Full sample used in the regression			
	Mean	Std. Dev.	Min.	Max.
Predicted establishment fixed effect	0.060	0.274	-1.250	1.641
Outflow ratio	0.137	0.153	0.000	6.000
Gross flow ratio difference between male and female	-0.054	0.502	-16.000	9.414
Overtime ratio	0.080	0.058	0.000	0.446
Firm size dummies				
(Over 1000)	0.558		0	1
(300–999)	0.196		0	1
(100–299)	0.155		0	1
(30–99)	0.090		0	1
Industry dummies				
(Mining)	0.013		0	1
(Manufacturing)	0.508		0	1
(Electric and utilities)	0.038		0	1
(Transportation and communication)	0.086		0	1
(Retail, wholesales, and restaurants)	0.084		0	1
(Finance and insurance)	0.047		0	1
(Real estates)	0.026		0	1
(Service)	0.198		0	1
Year dummies				
2005	0.219		0	1
2006	0.219		0	1
2007	0.204		0	1
2008	0.168		0	1
2009	0.202		0	1
Observation	9,007			

Appendix D: Summary statistics for gross flow rate by gender, 2005–9 BSWs and ETS matched sample

	Obs.	Mean	Std. Dev.	Min.	Median	Max.
Male	9007	0.278	0.312	0	0.212	12
Female	9007	0.332	0.570	0	0.237	16

Notes

¹ Thus, the difference between the two types of firms corresponds to different organizational models, as in Oi (1983), rather than to different monitoring technologies, as in Bulow and Summers (1986).

² For the sake of simplicity, in this paper, we indifferently use the terms ‘firms’ and ‘establishments’, although we are aware of the differences between these two units of analysis.

³ There have been debates on the origin of the productivity slowdown — demand (Yoshikawa, 2008) versus supply side (Hayashi and Prescott, 2002) — and its extent — manufacturing (Fukao *et al.*, 2004) versus non-manufacturing (Yoshikawa, 2008).

⁴ As in Caselli (1999). See the next section for other references.

⁵ First, not all firms have tried to introduce such systems. Second, among those who have tried, many have abandoned them after a while because of negative externalities. For example, in the case of Fujitsu, the introduction of individual performance-based scheme has been detrimental to the overall performance of the company due to the fact that individual performance is all the more difficult to observe in a working environment characterized by the pre-eminence of team work. The current attempts at reforming the wage system focus less on setting individual performance-based wage schemes than on modifying deferred compensation schemes to allow employees to get short-term reward for their engagement in the firm, in a context of rising risks and uncertainty (Fujimura, 2003).

⁶ According to 2007 Employment Status Survey, female workers represented 74.3 per cent of non-regular workers aged 15–59 and 30.3 per cent of regular workers.

⁷ The focus on wage differential between firms of different size is understandable in a country that has been (and still is to a certain extent) characterized by a dual structure along the firm size.

⁸ The increased number of hours has sometimes been proposed as an alternative proxy for work effort. This has been criticized by various authors, including Green (2004) or Askenazy (2004), who point out that a reduction in working hours can actually be associated with the intensification of work effort. This is particularly relevant for Japan. The typical response of Japanese firms to negative shocks is indeed labor hoarding and reduction of working hours (Abraham and Houseman, 1989), as has been observed during the Lost Decade. Using the number of hours worked as a proxy for effort would lead to the conclusion that work effort has decreased whereas our indicators suggests the opposite.

⁹ Our main inspiration is Amable and Gatti (2004).

¹⁰ The model then abstracts from the size of firms. As explained in Section 2, the wage differential is not explained by heterogeneity between firms of different sizes.

¹¹ To write this equation, we have already taken into account the fact that workers will not shirk in equilibrium, hence the flow out of type-I firms is equal to $sL1$.

¹² The empirical strategy to detect efficiency wages may drastically vary depending on the exact nature of the model. For example, Abe and Ohashi (2004) confirm the existence of efficiency wage model in Japan by analysing the steepness of wage profiles (the idea is that firms raise not only wage levels but also the steepness of wage profiles to prevent workers from shirking); Fuess and Millea (2002) use the Geweke linear feedback method to overcome a basic identification problem regarding the direction of causality between productivity gains and wage hikes.

¹³ The rate of inflow a affects the efficiency wage through the value of unemployment, and hence stands for the probability of finding a job in *any* type-I firm, whereas the rate of outflow s affects the efficiency wage through the probability that the *current* employment relationship ends, and hence stands for the probability of being fired from by the *current* employer. See Appendix A.

¹⁴ From the assumption of perfect mobility between type-II firms and unemployment, transitions between jobs in type-II firms and unemployment occur at a potentially infinite rate.

¹⁵ The Japanese legal regulation requires almost every employer to prepare ‘Workplace Rule’ (*Shugyo Kisoku*), which specify *ex ante* the base wage and the number of hours worked in a written contract. Because it is not easy to modify the written contracts, *ex post* adjustments to temporary shocks are usually made by using bonus payments and overtime work. The base wage and hours reported in the survey are based on the wage and hours of the Workplace Rule. Therefore, the hourly base wages in our data are not directly affected by temporary shocks.

¹⁶ Construction industry was not covered by ETS until 1990. In published tables, the disaggregated employment flows for different industries and -firm sizes are only available for firms with more than 30 employees.

¹⁷ A well-known limit of this classical methodology, which has been already applied to the Japanese labor market by Ishikawa and Dejima (1994), is that it provides a test for dual labor markets and does not recognize the possibility of three segments. For the question we address in this paper, it is not a problem as we explicitly focus on the difference between two types of productive models.

¹⁸ Because of the lack of data, it is not possible to simulate the evolution of other variables such as wage differentials.

¹⁹ The total share S_t is defined as
$$\frac{\sum_k F(\hat{\theta}_3 + \hat{\gamma}_3 K_{kt} + Z_{kt} \hat{\delta}_3) M_{kt}}{\sum_k M_{kt}}.$$

²⁰ Data for 2003 are missing.

²¹ This result is confirmed by the *Diversification of Employment Forms survey*, an establishment-based administrative survey conducted by the MHLW in 1994 and 2007. In the 75 per cent of establishments in which full-time regular employees are the major form of employment, they account for 92 per cent of the total employment; in the 20 per cent of establishments where part-time employees constitute the major form of employment, they account for almost two-thirds of the establishment employment. To put it differently, part-time workers are concentrated on few establishments.

²² A formal proof is available from the authors upon request.

References

- Abe M. and Ohashi I. (2004) ‘Inter-industry and Firm Size Effects on Wage Differentials and Efficiency Wages in Japan’, Hi-Stat Discussion Paper Series No. 25, Hitotsubashi University.
- Abowd J. M., Finer H. and Kramarz F. (1999) ‘Individual and Firm Heterogeneity in Compensation: An Analysis of Matched Longitudinal Employer–Employee Data for the State of Washington’ in Haltiwanger J., Lane J., Spletzer J. and Troske K. (eds.) *The Creation and Analysis of Employer–Employee Matched Data*, Amsterdam: North-Holland: 3–24.
- Abowd J. M. and Kramarz F. (2001) ‘Inter-industry Wage Differentials in France and in the United States’, Cornell University Working Paper.
- Abowd J. M., Kramarz F. and Roux S. (2006) ‘Wages, Mobility, and Firm Performance: Advantages and Insights from Using Matched Worker–Firm Data’, *Economic Journal* 116: 245–285.
- Abraham K. and Houseman S. N. (1989) ‘Job Security and Work Force Adjustment: How Different Are U.S. and Japanese Practices?’, *Journal of the Japanese and International Economies* 3(4): 500–521.
- Amable B. and Gatti D. (2004) ‘Product Market Competition, Job Security and Aggregate Employment’, *Oxford Economic Papers* 56(4): 667–686.
- Askenazy P. (2004) ‘Shorter Work Time, Hours Flexibility, and Labor Intensification’, *Eastern Economic Journal* 30(4): 603–614.
- Bloom N. and van Reenen J. (2007) ‘Measuring and Explaining Management Practices across Firms and Countries’, *Quarterly Journal of Economics* 122(4): 1351–1408.
- Bloom N. and van Reenen J. (2011) ‘Human Resource Management and Productivity’ in Ashenfelter O. and Card D. (eds.) *Handbook of Labor Economics*, Vol. 4B, Amsterdam: North Holland: 1697–1767.

- Bulow J. I. and Summers L. H. (1986) 'A Theory of Dual Labor Markets with Application to Industrial Policy, Discrimination and Keynesian Unemployment', *Journal of Labor Economics* 4(3): 376–414.
- Caselli F. (1999) 'Technological Revolutions', *American Economic Review* 89(1): 78–102.
- Dickens W. T. and Lang K. (1985) 'A Test of Dual Labor Market Theory', *American Economic Review* 75(4): 792–805.
- Dosi G., Lechevalier S. and Secchi A. (2010) 'Inter-firm Heterogeneity: Nature, Sources and Consequences for Industrial Dynamics. An Introduction', *Industrial and Corporate Change* 19(6): 1867–1890.
- Dunne T., Foster L., Haltiwanger J. and Troske K. (2004) 'Wage and Productivity Dispersion in the US Manufacturing: The Role of Computer Investment', *Journal of Labor Economics* 22(2): 397–430.
- Faggio G., Salvanes K. G. and Van Reenen J. (2010) 'The Evolution of Inequality in Productivity and Wages: Panel Data Evidence', *Industrial and Corporate Change* 19(6): 1919–1951.
- Fuess S. M. and Millea M. (2002) 'Do Employers Pay Efficiency Wages? Evidence from Japan', *Journal of Labor Research* 23(2): 279–292.
- Fujimura H. (2003) 'Changes in the Spring Wage Offensive and the Future of the Wage Determination System in Japanese Firms', *Japan Labor Bulletin* 42(5): 6–12.
- Fukao K. and Kwon H. U. (2006) 'Why Did Japan's TFP Growth Slow Down in the Lost Decade? An Empirical Analysis Based on Firm-level Data of Manufacturing Firms', *Japanese Economic Review* 57(2): 195–228.
- Fukao K. and Miyagawa T. (2007) 'Productivity in Japan, the US, and the Major EU Economies: Is Japan Falling Behind?', RIETI Discussion Papers Series No. 2007-046.
- Fukao K., Inui T., Kawai H. and Miyagawa T. (2004) 'Sectoral Productivity and Economic Growth in Japan, 1970–98; an Empirical Analysis Based on the JIP Database' in Ito T. and Rose A. K. (eds.) *Growth and Productivity in East Asia*, National Bureau of Economic Research-East Asia Seminar on Economics, Vol. 13, Chicago: University of Chicago Press: 177–227.
- Green F. (2004) 'Why Has Work Effort Become More Intense?', *Industrial Relations. A Journal of Economy and Society* 43(4): 709–741.
- Haltiwanger J. C., Lane J. I. and Spletzer J. R. (1999) 'Productivity Differences Across Employers: The Roles of Employer Size, Age and Human Capital', *American Economic Review* 89(2): 94–98.
- Hayashi F. and Prescott E. C. (2002) 'The 1990s in Japan: A Lost Decade', *Review of Economic Dynamics* 5(1): 206–235.
- Houseman S. N. and Abraham K. (1993) 'Female Workers as a Buffer in the Japanese Economy', *American Economic Review* 83(2): 45–51.
- Ishikawa T. and Dejima T. (1994) 'The Dual Structure of Labor Markets' in Ishikawa T. (ed.) *The Distribution of Wealth and Income in Japan*, Tokyo: The University of Tokyo Press: 169–209 (in Japanese).
- Ito K. and Lechevalier S. (2009) 'The Evolution of Productivity Dispersion of Firms. A Reevaluation of Its Determinants in the Case of Japan', *Review of World Economics* 145(3): 405–429.
- Ito K. and Lechevalier S. (2010) 'Why Some Firms Persistently Out-perform Others? Investigating the Interactions between Innovation and Exporting Strategies', *Industrial and Corporate Change* 19(6): 1997–2039.
- Kambayashi R., Kawaguchi D. and Yokoyama I. (2008) 'Wage Distribution in Japan, 1989–2003', *Canadian Journal of Economics/Revue canadienne d'économie* 41(4): 1329–1350.
- Layard R., Nickell S. and Jackman R. (2005) *Unemployment: Macroeconomic Performance and the Labour Market*, Oxford: Oxford University Press.
- Lazear E. P. and Shaw K. L. (2008) *The Structure of Wages. An International Comparison*, NBER, Chicago, IL: The University of Chicago Press.
- Leamer E. E. (1999) 'Effort, Wages, and the International Division of Labor', *Journal of Political Economy* 107(6): 1127–1162.
- Lechevalier S. (2005) *Will Toyota Save Japan (and the World...)?*, Jouy en Josas: HEC Eurasia Institute.

- Leonardi M. (2007) 'Firm Heterogeneity in Capital/Labor Ratios and Wage Inequality', *Economic Journal* 117(518): 375–398.
- Machin S. (2008) 'An Appraisal of Economic Research on Changes in Wage Inequality', *Labour* 22(s1): 7–26.
- Mikitani R. and Posen A. S. (eds.) (2000) *Japan's Financial Crisis and Its Parallels to US Experience*, Washington, DC: Institute for International Economics: Special report 13.
- Mortensen D. T. (2003) *Wage Dispersion*, Cambridge: MIT Press.
- Mortensen D. T. and Pissarides C. A. (1994) 'Job Creation and Job Destruction in the Theory of Unemployment', *Review of Economic Studies* 61(3): 397–415.
- OECD (1998) 'Labour Policies for Part-time Workers in Japan: Changing Labour Market and Gender Equality: The Role of Policy', Manuscript for conference in Norway, Oslo, 12 and 13 October 1998.
- OECD (2006) *Economic Survey of Japan*, Paris: OECD.
- OECD (2010) 'Activation Policies in Japan', OECD Social, Employment and Migration Working Papers No. 113.
- Ohtake F. (2005) *Inequality in Japan*, Tokyo: Nihon Keizai Shimbun (in Japanese).
- Oi W. Y. (1983) 'Heterogeneous Firms and the Organization of Production', *Economic-Inquiry* 21(2): 147–171.
- Ota K. (2005) 'Rise in Labour Income Inequality with Increasing Numbers of Freeters', ESRI Discussion Paper Series No. 140 (in Japanese).
- Shapiro C. and Stiglitz J. (1984) 'Equilibrium Unemployment as a Worker Discipline Device', *American Economic Review* 74(3): 433–444.
- Sousa-Poza A. (2004) 'Is the Swiss Labor Market Segmented? An Analysis Using Alternative Approaches', *Labour* 18(1): 131–161.
- Tachibanaki T. (2005) *Confronting Income Inequality in Japan: A Comparative Analysis of Causes, Consequences, and Reform*, Cambridge: MIT Press.
- Valeyre A. (2004) 'Forms of Work Intensification and Economic Performance in French Manufacturing', *Eastern Economic Journal* 30(4): 643–658.
- Wakisaka A. (1997) 'Women at Work' in Sako M. and Sato H. (eds.) *Japanese Labour and Management in Transition: Diversity, Flexibility and Participation*, London: Routledge: 131–150.
- Yoshikawa H. (2008) *Japan's Lost Decade*, Tokyo: I-House Press.