in Section 6. Section 7 discusses possible interpretations of the results. Section 8 concludes.

2 Background

Several previous studies have examined the relationships between participation and wages using cross sectional data for the U. S., based on a labor supply framework. Juhn et al. (1991) and Juhn (1992) estimate the relationships between the employment-population ratio and wages for men from 1968 to 1988 when the participation of less-educated men fell significantly. Juhn (1992) reports that the wage elasticity of participation of less-educated men is positive and significant, and furthermore, the wage change explains most of the fall in participation of white men. Pencavel (1998) estimates labor supply elasticity of women from 1974 to 1994 using cell-mean data created from cross-sectional data of the Current Population Survey, reporting own-wage elasticity estimates that are mostly positive. Pencavel (2002) estimates labor supply elasticity for men using data from 1968 to 1999. He shows that the estimates for intertemporal substitution elasticity are positive while those for uncompensated elasticity are negative, and argues that estimates obtained by Juhn et al. (1991) and Juhn (1992) are close to intertemporal substitution elasticity. Blau and Kahn

(2007) show that wage elasticity of married women's labor supply fell between 1980 and 2000.[5] Studies that relate regional variation in wages of wage growth to participation in the U.S. are Juhn et al. (1991) and Devereux (2004). Our specification in this article is close to theirs because we relate regional differences in employment growth to regional variations in wage growth.

In most of the studies using U.S. data for recent periods, estimates of wage elasticity of labor supply are positive, except for Pencavel (2002)'s estimates for men's uncompensated elasticities. While the specification employed in this article is similar to some of the papers above, our coefficient estimates of log wage growth using data for the employment-population ratios of less-educated young men and women in Japan are significantly negative, which differ sharply from most of the results from studies using recent U.S. data.[6]

One study closely related to our work is that of Kuroda and Yamamoto (2008), in which the authors estimate wage elasticity of labor supply using aggregate data for Japan. Our framework differs from that of Kuroda and Yamamoto in several ways. First,

[5] Although Blau and Kahn (2007) mainly analyze hours of work rather than participation, in one specification they analyze participation, the estimates of wage elasticity are positive but become smaller over time.
[6] According to Pencavel (2002)'s argument, our specification is more likely to yield positive elasticity estimates because we do not include controls for nonwage income or higher order polynomials of age. The fact that we still obtain large negative estimates for the young people suggests that the wage elasticity patterns for the U.S. and Japan are quite different.

we analyze the extensive margin of labor supply by education level. While focusing only on extensive margin is certainly a limitation, it comes with a substantial benefit in that we are able to analyze the data disaggregated by education.[7] Kuroda and Yamamoto (2008) use data aggregated over education levels, and use samples that pool age groups (ages 20-64) together. On the other hand, our analysis is based on the less-educated sample and we estimate separate coefficients for different age groups (ages 25-39 and ages 40-59). The level and time-series variations for the employment-population ratios differ sharply depending on education and age, as shown in Figures 1 and 2 (also see Abe 2008). The separate estimation by age groups is motivated by the age-twist pattern found in the data.

Second, our analysis is more focused on regional patterns of employment than that of Kuroda and Yamamoto (2008) do. We explicitly show the differing employment patterns in the high-wage and low-wage regions, and consider how such patterns might be related to policies such as minimum wage.

Finally, our specification estimating the impact of wage growth on changes in

[7] In empirical labor supply literature, education is considered an important piece of information. There are arguments over whether or not education should be included in the labor supply equation (e.g., Pencavel, 2002). However, even in the case when it is not included in the labor supply equation, it is used as an important instrumental variable for predicting wage. In this article, we take an approach that education directly affects labor supply. Separate estimation by education is also motivated by the fact that the value of labor supply elasticity could differ across skill levels. For example, Juhn (1992) shows that participation is more elastic to wage for workers at the lower end of the wage distribution.

the employment-population ratios do not include many of the control variables Kuroda and Yamamoto (2008) employ, such as population share or regional industrial structure.[8] Aside from wage growth, we include only age dummies in the first-difference specification. Our specification is close to many of the labor supply models estimated using U.S. data (e.g., Juhn 1992, Pencavel 1998, 2002).

3 Data

3.1 Employment data

The employment data used in this article are from the published version of the Census in 1990 and 2000 (Statistics Bureau, Ministry of Internal Affairs and Communications of Japan). We use data classified by education (junior high school graduates, senior high school graduates, junior college graduates, and university graduates or above), age group (5-year intervals) and sex for 47 prefectures. In order to minimize the possible impact of school enrollment at young ages and retirement at old ages on participation, we focus on the population aged 25-59 years.

[8] Some of these variables are the ones that affect the labor demand side, and not the labor supply side. In a narrow sense, labor supply is affected by the demand side variables only through its impact on wages: Ham and Reilly (2002) explain this as wage being a "sufficient statistic" of demand-side factors in a labor supply model. The implication is that if we include wage variables in the labor supply equation, other demand side variables should not affect labor supply, as long as choices observed in the data are on the labor supply curve.

3.2 Average wage data

For wages, we use aggregate data of the Basic Survey of Wage Structure (BSWS, Ministry of Health, Labour and Welfare of Japan). This data set contains mean earnings and working hours for full-time employees for each prefecture by age groups defined by 5-year intervals; the data are not available separately by education. Full-time wages are defined as monthly salary (shoteinai kyuyo) divided by monthly hours.[9] This is an hours-weighted measure of hourly wages.[10]

Mean hourly wages for male and female part-time employees are available for each prefecture, aggregated over all age and education groups. We use wages for female part-time employees to form an instrumental variable in the regression analysis reported in Section 6. The mean part-time wages published in the BSWS are the mean of hourly wages and are not weighted by hours worked. The sampling errors of part-time wages are rather large for prefectures with a small population. The wages of full-time employees are less likely to suffer from large sampling errors.

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[9] Here, the earnings figure in the numerator does not include bonuses.

[10] Since the mean hourly wages of individual full-time workers are not reported in the published BSWS data, hourly wages are calculated by dividing mean earnings by mean hours in each cell. The resulting measure is an hours-weighted measure of hourly wages: see Abe and Tanaka (2007) for an explanation. On the other hand, for part-time workers, average hourly wages that are not weighted by hours worked are reported in the published version of the BSWS.

4 Patterns of wage growth across regions from 1990 to 2000

In this section, we report hourly wage changes from 1990 to 2000 for each prefecture to gauge the pattern of wage growth by region. In some of the following analysis, 47 prefectures are classified into the high- and the low-wage regions based on the four minimum wage ranks (A to D) in 1990.[11] The classification in 1990 is referred to as the "minimum wage rank" in the rest of the article. The Rank A region is the set of highest-wage prefectures, while the Rank D region corresponds to the lowest-wage prefectures. To examine the growth in wage rates by sex and region, we calculate the growth rate of hourly wages as

$$\Delta LogWage_a = ln(hw_{a,2000}) - ln(hw_{a,1990}), \qquad (1)$$

where $hw_{a,t}$ is the hourly wage for age group a in year t.[12] These growth rates are calculated for each pair of prefecture, age group, and sex. Figure 2 plots wage growth for full-time employees defined by Equation (1) against age for the four regions classified by the minimum wage rank, separately for men and women.[13]

[11] The minimum wage ranks are the classification of prefectures used for the minimum wage setting in Japan: see Kawaguchi and Yamada (2007) for a detailed explanation of minimum wage setting and the minimum wage ranks. The prefectures classification into minimum wage rank is shown in Table A1.

[12] We do not deflate wages by regional price level. Prefecture-level Consumer Price Index (CPI) data are available for the capital of each prefecture. We performed the analysis presented below using the data deflated by regional CPI, and find that the results are very similar to the ones obtained using the wage data without regional CPI adjustment.

[13] For aggregating the wage growth at prefectural level into the four regions, the weight used in the regression analysis in Section 5 is used.

The most notable feature of wage growth during this period is that it was much lower in the high-wage regions than in the low-wage regions. Wage growth rates in the regions were in the order Rank A≤Rank B≤Rank C≤Rank D. This pattern holds true for almost all age groups for both sexes, although the profiles of different regions almost coincide for certain age groups (e.g., male employees aged 45-59). Full-time wage growth was higher for females than for males during this period, but regional differences in wage growth are quite similar.[14] The growth of part-time wages was also higher in the low-wage regions than in the high-wage regions (results are not shown).

Unfortunately, wage measures are not available by education level in the published version of the BSWS. It is possible that the educational composition of the workforce changed during the analysis period, which may have affected the wage growth pattern shown in Figure 2. To partially address this concern, we calculate the wage growth rates for very small firms (firms with 5 to 9 employees) and plot them against age in Figure 3.[15] In Japan, the less-educated are more likely to work in very small firms than others, and thus wage growth in such firms is likely to reflect the wage growth pattern of the less-educated, which is the focus of the subsequent analysis.

[14] In fact, female full-time wages grew more than the minimum wage, while male full-time wages did not grow as fast as the minimum wage for most regions; the minimum wage growth during this period was almost uniform for all prefectures.

[15] For the aggregation here, we use the weight created from the total hours supplied by the workers in firms with 5-9 employees in the two years (1990 and 2000).

While sampling errors of wage data for very small firms are larger than sampling errors for wage data for all firm sizes, and the variations by age in Figures 2 and 3 are different, the basic pattern of differential regional wage growth holds here as well: wage growth is higher in the low-wage regions than in the high-wage regions.[16]

It must be kept in mind that sampling errors of the mean wage measures here are rather large, and sampling errors in the growth rates of the wages are even larger. To account for measurement error in the wage growth variable, we use region dummy variables (the minimum wage rank dummies or the prefecture dummies) as instruments in the regression analysis reported in Section 6. The differential wage growth across regions means that the region dummies are correlated with wage growth.

5 Patterns of employment across regions from 1990 to 2000

For analysis of regional patterns in employment, we begin with a simple

[16] It is possible that regional wage growth observed in Figure 2 is partly due to worker migration across regions. For example, if the proportion of university graduates among workers in the low-wage regions increased relative to that in the high-wage regions, high wage growth in the low-wage regions from 1990 to 2000 can be explained by changes in the educational composition of workers. To check for such possibility, we look at changes in the educational composition of workers in the four minimum wage ranks using the census data. The proportion of university graduates among male workers aged under 40 increased slightly more in the low-wage regions compared to the high-wage regions. For older men, however, the proportion of university graduates increased more in the high-wage regions. For women aged 25-59, the proportion of university graduates generally increased more in the high-wage regions than in the low-wage regions. The higher concentration of more educated workers in the high-wage regions tends to increase wage differentials across regions, rather than compressing them. Accordingly, it is unlikely that migration is the major cause of differential wage growth across regions reported here.

tabulation of the employment-population ratios by sex, education, age group, and region. Figure 4 shows the level of employment-population ratios from the census data, by minimum wage rank, sex, education, and year (1990 and 2000).

The employment-population ratio for men increases with age until the late 40s and then starts to decline. Male participation is highest in the Rank B region and lowest in the Rank D region for almost all age groups; participation by men is somewhat low in the highest wage regions (Rank A). This pattern is particularly apparent for older men in 2000.

For women, the employment-population ratio increases in their 30s and 40s, and then starts to decline. The increase for those in their 30s corresponds with the move toward the second peak in the M-shaped labor force participation profiles for women in Japan.[17] It is also notable that regional differences in participation are large for women. Female participation is highest in the low-wage regions (Rank D) and lowest in the high-wage region (Rank A). This pattern is consistent with the findings of Abe et al. (2008).

Figure 5 shows the changes in the employment-population ratios (defined as the difference in the employment-population ratios between 1990 and 2000) for junior

[17] The profiles for junior high school graduate women in Figure 4 are not M-shaped partly because they are plotted for over age 25. When we plot them from age 15, they are close to an M-shape.

high school graduates in a similar manner as in Figure 4. Reflecting a secular decline in participation by men and a secular increase in participation by women, changes in male participation in Figure 5 are mostly negative and those for female participation tend to be positive, although there are significant variations across age groups and regions.

The most notable changes in participation of male junior high school graduates between 1990 and 2000 in Figure 5 is the "age twist," which refers to the fact that the employment-population ratios fell more (or grew less) for those aged 25-39 living in the low-wage regions than for those living in the high-wage regions, while for those aged 40-59, the decline was larger (or the growth was smaller) in the high-wage regions than in the low-wage regions (Figure 1). While decline in participation by less-educated men occurred for both the young and the middle-aged (Genda 2006; Abe 2008), regional patterns of the decline differed sharply depending on age.

For female junior high school graduates, the regional differences in the increase in participation are quite large for the 25-39 age group. The regions where there was increase in participation by young women are the ones where female participation was low (Ranks A and B); these regions include the large metropolitan areas. The regional differentials in women's participation shrank remarkably for this age group: in the panels of the third row of Figure 4, the profiles of the employment-population ratio for the four regions are located in closer positions in 2000 than in 1990. For female junior high school graduates aged 40-59, there are small regional differences in the increase in participation. Thus, the age twist is less apparent for female than for male junior high school graduates.

The changes in the employment-population ratios of other educational groups are summarized as follows (graphs are not shown). For male university graduates, regional differences in employment changes are much smaller than those for less-educated men. For male senior high school graduates and university graduates, differences across age groups are minimal. The employment-population ratios fell more or less uniformly for both the 25-39 and 40-59 age groups. For female senior high school graduates, age twist is observed. For female university graduates, employment rose more for those living in the high-wage regions than for those in the low-wage regions for both age groups. Statistical significance of the age-twist patterns is confirmed by the regression analysis below.

6 Regression Results[18]

We now turn to regression analysis of the regional patterns in changes in

[18] Here and in the rest of the article, we use the words "insignificant" and "significant" to denote a statistical test at the 5% level.

employment, using prefecture-level cell-mean data. The unit of observation for the cell-mean data is a cell defined by sex, education, age group (5-year interval), and prefecture. In the following, we confine our attention to male and female junior and senior high school graduates. First, we report the results for the age-twist pattern, and then examine the extent to which the age-twist pattern is related to the differential regional wage growth reported in Section 4.

6.1 Age twist

We begin by estimating the age-twist pattern using the following regression equations:

$$\Delta EPR_j = \beta_1 \cdot (\textit{Minimum wage rank Dummies}) + X\eta + u\,, \qquad \text{(2a)}$$

$$\Delta EPR_j = \beta_2 \cdot LogWage_{1990,j} + X\eta + u\,, \qquad \text{(2b)}$$

where ΔEPR_j is the change in the employment-population ratio between 1990 and 2000 in the cell j (a cell defined by age group and prefecture), $LogWage_{1990,j}$ is the log of hourly wage in year 1990 for full-time employees in cell j, and X is a set of age dummies. The base group for the minimum wage rank dummies in Equation (2a) is the Rank A region (the highest wage region). We estimate Equation (2a) and (2b) separately for each sex and education. We further estimate (2a) and (2b) separately for the 25-39 and 40-59 age groups, for each sex-education pair. Regression equations are weighted by $\{(pop_{j,1990})^{-1} + (pop_{j,2000})^{-1}\}^{-1}$, where pop_{jt} is the population of cell j in year t.[19]

The age-twist hypothesis suggests that β_1's for the low-wage regions (i.e., Ranks C and D) take small values for the 25-39 age group, and large values for the 40-59 age group. It also suggests that estimates for β_2 are positive for the younger but negative for the older age group. The estimates for Equation (2a) are shown in Panel A of Table 1, and those for Equation (2b) are shown in Panel B of Table 1. The results show that the age-twist hypothesis clearly holds for male junior high school graduates and female senior high school graduates. It holds weakly for female junior high school graduates: for this group, while the decline in employment for young women is significant in the low-wage regions, changes for older women exhibit small regional differences. Age twist is not observed for male senior high school graduates, for whom differences across age groups are minimal.

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[19] To motivate this weight, note that the variance of EPR_{jt} is $EPR_{jt}(1-EPR_{jt})/pop_{jt}$. If we ignore the heteroscedasticity due to the term $EPR_{jt}(1-EPR_{jt})$ in the numerator, the variance of EPR_{jt} is proportional to the inverse of pop_{jt}. Then, the variance of $\Delta EPR_j (= EPR_{2000} - EPR_{1990})$ is $(pop_{j,1990})^{-1} + (pop_{j,2000})^{-1}$, the inverse of which is the weight used here. The standard errors are corrected for heteroscedasticity. For the regressions reported in Section 6.2, we experimented with a feasible generalized least-squares (GLS) procedure that takes into account the heteroscedasticity due to $EPR_{jt}(1-EPR_{jt})$.

6.2 Age twist and wage growth

Next, we assess whether the age-twist pattern confirmed above is explained by regional wage growth. The basic specification we estimate is as follows:

$$\Delta EPR_{j,s} = \alpha \Delta LogWage_j + X\phi + u, \qquad (3)$$

where $\Delta EPR_{j,s}$ is the change in the employment-population ratio between 1990 and 2000 for cell j and education level s, $\Delta LogWage_j$ is the wage growth measure defined by the log-difference in wages between 1990 and 2000 for cell j, and X is a set of age dummies. Equation (3) is estimated separately for men and women, for education, and for two age groups (ages 25-39 and 40-59).[20]

The specification of Equation (3) is close to that of Juhn et al.'s (1991) regression that estimates labor supply elasticity using regional variation in wage growth (Juhn et al. 1991, Table 9), with the following differences. First, our data consist of two-period (1990 and 2000) while Juhn et al.'s (1991) data are annual data of 1970-89: thus we take the first difference between the two years. Second, Juhn et al. (1991) estimate regression equations separately for various percentiles of wage distribution,

[20] We consider that the first-differenced specification of Equation (3) is preferable to the level specification in which the dependent variable is the employment-population ratio in levels and wages are measured in levels for the following reason. Since we wish to focus on the impact of differential wage growth across regions from 1990 to 2000, it is important to "difference out" the permanent factors in wage and participation levels in the regression analysis. The easiest way to do this is to take the first difference. This is particularly relevant for women, for whom the regional differences in participation are large (Figure 2).

while our aggregate data do not permit such estimation: instead, we confine attention to the less-educated (i.e., junior and senior high school graduates). Our specification is also close to that of Devereux (2004) who uses 1980 and 1990 U.S. census data and takes the first differences to estimate labor supply elasticity, using regional variations in wage growth.

Note that we are not relating changes in the employment-population ratio of the same cohort to their wage growth, as the cohort ages. In that sense, our specification is not consistent with the life-cycle labor supply framework. The reason we do not take a cohort approach here is that, in the presence of migration across regions, cohort can not be defined precisely in aggregate data.[21] Devereux (2004) takes a similar approach and relates the difference of labor supply of the same age (not same cohort) group to the regional wage changes.

Separate estimation for the two age groups is motivated by our focus on the age-twist pattern. To account for measurement error in $\Delta LogWage_j$, we estimate Equation (3) by three different sets of instrumental variables: (1) part-time wage rates in the region; (2) three dummy variables for the minimum wage rank in 1990; and (3) 46

[21] People aged A in year 1990 in a prefecture may have moved outside of the prefecture between 1990 and 2000. Therefore, comparing outcome of those aged A+10 in year 2000 in region R to that of those aged A in 1990 in region R may not directly correspond to the life-cycle evolution in behavior.

prefecture dummy variables (excluding the base group).[22] As for the age-twist regressions, the regressions are weighted by $\{(pop_{j,1990})^{-1}+(pop_{j,2000})^{-1}\}^{-1}$.[23] Results are reported in Table 2. The IV estimates using the 46 prefecture dummies as instruments yield results that are close to the weighted least squares estimates.

Estimates for α are negative for the 25-39 age group except for male senior high school graduates, while they are positive for the 40-59 age group, except for female junior high school graduates. Positive α means that higher wage growth is correlated with higher participation (or, a smaller decline in participation), while negative α means that higher wage growth is negatively correlated with participation.[24]

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[22] A possible concern for using this instrumental variable (IV) procedure is the problem of weak instruments. Among the IV regressions, we consider the one that uses 46 prefecture dummies as the preferred specification. For this specification, the R^2 coefficient from the first stage regression is about 0.87 and the F-statistic is above 12 for the four samples for men (junior and senior high school graduates aged 25-39 and 40-59). For female junior and senior high school graduates aged 25-39, the R^2 coefficient is about 0.83 and the F-statistic is around 9. For female junior and senior high school graduates aged 40-59, the instruments have lower explanatory power and the R^2 coefficient is about 0.58 and the F-statistic is around 3. Therefore, instruments have reasonable explanatory power for men and young women, while there is a possible concern for weak instruments for older women.

[23] We also experimented with a feasible GLS procedure to take into account the heteroscedasticity due to $EPR_{jt}(1-EPR_{jt})$ (see footnote 19). To apply a feasible GLS, it is necessary to obtain a consistent estimate of EPR_{jt}. We ran a cross-sectional regression for each year for which the dependent variable is EPR_{jt} and the explanatory variables include log wage for the sex-age-region in the corresponding year and age dummies. Let the predicted value of the dependent variable from these regressions be $E\hat{P}R_{jt}$. Then, $\{E\hat{P}R_{j,1990}(1-E\hat{P}R_{j,1990})/pop_{j,1990}+E\hat{P}R_{j,2000}(1-E\hat{P}R_{j,2000})/pop_{j,2000}\}^{-1}$ is used as the weight. This feasible GLS procedure yields results that are similar to the ones reported in Table 2. Although this procedure has the advantage of taking into account the heteroscedasticity due to the $EPR_{jt}(1-EPR_{jt})$ term, the cross-sectional regressions in the first step are specified in a somewhat arbitrary way.

[24] If Equation (3) is understood as a labor supply function measuring participation (extensive margin), the coefficient α is a labor supply elasticity. Kuroda and Yamamoto (2008) estimate labor

Clearly, the relationship between wages and employment differs across age groups. For the younger group, wage growth has a negative effect on employment, while for the older group, wage growth promotes employment. It should be kept in mind that the wage data are regional aggregates across all education levels, so we are not relating the wage growth for each education group to their participation changes.

6.3 Does age twist remain after controlling for wage growth?

The coefficients shown in Table 2, together with the wage growth patterns in Figure 2, suggest that the age-twist pattern is partly explained by wage growth. Higher wage growth in the low-wage regions than in the high-wage regions is associated with lower employment growth in the low-wage regions through the negative α for the 25-39 age group. At the same time, a similar wage growth pattern is associated with higher employment growth in the low-wage regions through the positive α for the 40-59 age group.[25] These opposite signs of α could create the age-twist pattern in employment growth. The next question is whether the age-twist remains after controlling for wage growth.

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supply elasticities using aggregate data for Japan and find that they are generally positive.

[25] Figures 2 and 5 indicate that there is an age twist in changes in participation, while no twist is observed for wage growth. Therefore, we have opposite signs for α for the younger and the older groups.

To understand the extent to which age twist is explained by regional differences in wage growth, residuals from Equation (3) are regressed on the minimum wage rank dummies or on the log wage in 1990, and the estimates are compared to those in Table 1 (estimates from Equations (2a) or (2b)). Specifically, let $\hat{u}_j$ be the residuals from Equation (3). Then the following equations are estimated:

$$\hat{u}_j = \gamma_1 \cdot (\textit{Minimum wage rank Dummies}) + \varepsilon \, , \quad \text{(4a)}$$

$$\hat{u}_j = \gamma_2 \cdot LogWage_{1990\,j} + \varepsilon \, . \quad \text{(4b)}$$

The coefficients of the minimum wage rank dummies in Equations (2a) and (4a), β_1 and γ_1, are compared: if the coefficients change significantly, age twist is mostly explained by the differential regional wage growth and responses to it. Likewise, the coefficients of the log wage in 1990 (β_2 and γ_2) are compared to investigate whether the age twist is explained by differential wage growth. In this subsection, we report results for male and female junior high school graduates and female senior high school graduates, for whom the age-twist is most apparent. For the dependent variables of Equations (4a) and (4b), $\hat{u}_j$, we use residuals from two specifications of Equation (3): the weighted least squares regression and the IV regression that uses 46 prefecture dummies as instruments.

Results from the regressions of (4a) and (4b) are reported in Panel A and Panel

B of Table 3, respectively. Age twist is a combination of a relative decline in employment for the younger group and a relative increase for the older group in the low-wage regions compared to the high-wage regions. Thus we first discuss whether the larger fall in employment for the younger group in the low-wage regions is explained by wage growth, and then discuss the pattern for the older group.

Results for men and women in the 25-39 age group are shown in the left portion of Table 3. For male junior high school graduates aged 25-39, the fall in employment in the low-wage regions is explained by higher wage growth (Columns (1)-(3)). The coefficient of the Rank D dummy in Equation (4a) is close to zero, while it is -0.008 (with a standard error of 0.005) in Equation (2a). High employment growth in the Rank B region relative to Rank A region cannot be explained by wage growth, because the coefficient of the Rank B dummy ranges from 0.011 to 0.013 for all specifications. When the $LogWage_{1990}$ is included, the estimate of β_2 in Equation (2b) is positive (0.035), but the estimate of γ_2 in Equation (4b) is close to zero.

For female junior and senior high school graduates aged 25-39, wage growth explains a large part of the low employment growth in the low-wage regions (Columns (4)-(6) and (13)-(15)). The negative coefficients of Rank C and Rank D dummies become small in magnitude (in absolute value) in Equation (4a) compared to those in

Equation (2a). The positive coefficients of the log wage in 1990 are less than 0.06 for Equation (4b) while they are greater than 0.16 for Equation (2b). Yet, the estimates of γ_1 and γ_2 are not quite close to zero, implying that regional differences in decline of employment for young women remain even after wage growth is accounted for.

The results for the 40-59 age group are shown in the right panel of Table 3. For male junior high school graduates aged 40-59, the smaller decline in employment in the low-wage regions is partly explained by higher wage growth there (Columns (7)-(9)). For male junior high school graduates, the estimates of γ_2 in Equation (4a) are smaller in magnitude than the estimates of β_2 in Equation (2a). For female junior high school graduates aged 40-59, the regional variations in employment growth are small in the first place (Columns (10)-(12)). For female senior high school graduates, on the other hand, wage growth explains less of the regional differences in employment growth. The coefficients on the minimum wage ranks or the log wage in 1990 do not differ much between the regression Equations of (2b) and (4b) (Columns (16)-(18)).

Taken as a whole, the larger fall or lower growth in employment for 25-39-year-old men and women in the low-wage regions than in the high-wage regions is explained by the higher wage growth in the former. This means that high wages in low-wage regions had an effect to reduce employment of young people. On the other