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The Minimum Wage Effects on Earnings and Sorting*

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Preliminary

Abstract

This paper investigates the effects of the introduction of a nationwide minimum wage in Thailand on earnings and sorting. Using Thai matched employer-employee data, we first show that there is a great degree of mobility differential even among workers with similar wages and this relationship is complex. To evaluate the policy and understand its mechanism, we therefore adopt a flexible semi-parametric framework from Lentz et al. (2023) that allows for double-sided heterogeneity in workers and firms in both wages and mobility. Our results show that there is no disemployment effect on workers who were employed before the policy took place. However, there is an adverse effect on workers who were not employed for a period of time before the policy where their re-employment probability declined. Sorting among new employment matches after the policy became less positive. Low type or less productive firms exited the market and workers reallocated from these firms to more productive ones. Overall, we find that the minimum wage raised earnings for all worker types but with variation in sizes of the gains. We use the model to decompose sources of earnings gains. We find that mobility accounts for a substantial fraction of earnings gains in the short-term, but post policy job-to-job transitions can affect earnings of some worker types negatively. This makes the long-term income implication of the policy unclear as mobility evolves over time. We therefore use the model to simulate the net present value of lifetime income of workers. Despite the negative effect of mobility, the long-term gains on net present value of lifetime income over 20 years are substantial.

Keywords: Minimum wage, Sorting, Mobility, Lifetime income, Double-sided heterogeneity

JEL codes: J31, J60

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1 Introduction

This paper studies the effects of the introduction of a nationwide minimum wage in Thailand on earnings and sorting. The policy involved more than 40 percent increase in minimum wages in Thailand between 2012 to 2013. What are the policy effects along the earnings distribution, particularly on the poorest workers who have low pay and low job stability? What are the mechanisms of these effects? Additionally, how does the policy change matching between workers and firms over time? These questions are crucial for understanding both the short and long-term implications of the policy and its effectiveness at reducing poverty.

To answer these questions, we estimate a semi-parametric model of wages and employment mobility with double-sided heterogeneity of Bonhomme et al. (2019) and Lentz et al. (2023). Our analysis includes both employed and unemployed workers before the policy and estimates worker and firm types using a long panel of matched employer-employee of Thai Social Security data. Latent types in our model reflect differences in both wage and employment patterns. This is crucial for a minimum wage policy evaluation because if workers with similar wages have different employment patterns, then their earnings would be impacted differently by the policy. For instance, two workers who earn the same wage, but face different degrees of job stability could have very different earnings. Indeed, we show that there is a great degree of mobility differential among workers with similar wages and that the relationship between wages and mobility is complex. Further, mobility across different groups may respond differently to the policy as well as may vary across stages of career. Hence, to measure the minimum wage effects, it is vital to use a framework that can allow for flexible interactions between policy periods, stages of career as well as worker and firm types in both wages and mobility.

Using differences by worker type and accounting for pre-trends, we find that the minimum wage has little disemployment effect on workers who were employed before the policy. However, there is an adverse effect on workers who were not employed for at least seven months before the policy. The probability of finding a job for these unemployed workers declined. Sorting among new employment matches after the policy became less positive. This is true across workers of all age groups. Low type or less productive firms exited the market and workers reallocated from these firms to more productive ones. Overall, more productive firms and the formal labor market expanded. Moreover, the minimum wage raised earnings considerably for low-paid workers and there is spillover among high-paid workers. We confirm our findings that even the highest-paid type of workers experience higher earnings from the policy by exploiting spatial variation across provinces in their exposure to the minimum wage policy.

We then use the model to decompose sources of earnings gains one year after the policy. We find that mobility accounts for a substantial part of the earnings gains one year after the policy. However, post policy job-to-job transitions can affect some worker types negatively. This makes the long-term income implication of the policy unclear as the effect of mobility could evolve and accumulate over time. Therefore, to measure the policy impact on workers' lifetime income, we use our model to perform simulations and compute the net present value of lifetime income of workers. Despite some negative effect of mobility, the long-term gains on net present value of lifetime income over 20 years are shown to be substantial for all workers.

Many papers have studied the effects of minimum wage on employment, (e.g. Card and Krueger (1995) and Neumark and Wascher (2008)) and on the wage distribution (e.g. Grossman, 1983; DiNardo et al., 1996; Machin et al., 2003). Studies in developed countries tend to find minimal employment effect and small wage spillover effects (e.g. Lee (1999), Card and Krueger (2000) and Dustmann et al. (2021)). One common approach is to measure minimum wage effects by wage bins where workers are assigned to bins based on their wages before the minimum wage policy (e.g. Harasztosi and Lindner (2019) and Dustmann et al. (2021)). However, as we show in this paper, there is a lot of mobility heterogeneity among workers with similar wages. Analyzing outcomes along the wage distribution without taking mobility into account may not give a complete picture of the policy effects. Moreover, changes in mobility patterns may have an important long-term implication on workers' income.

A second strand of the literature uses a structural modeling approach with varying assumptions on heterogeneity of workers and firms e.g. Van den Berg and Ridder (1998), Flinn (2006) and more recently Engbom and Moser (2022). Using an equilibrium wage posting model, Engbom and Moser (2022) find the minimum wage policy in Brazil to have positive spillovers on wages of other workers up to the 80th percentile. They find that the effects of the minimum wage on employment and output are muted by reallocation of workers to more productive firms. In their model, wages are additive and job-to-job transitions only occur if a wage offer is higher than the present wage. However, we show that job-to-job transitions affect earnings negatively for some workers after the policy and there is a considerable degree of non-linearity in mean wages that a standard linear additive model cannot capture. Therefore, relative to these papers, we analyze the minimum wage effects and changes in worker-firm sorting using a flexible model where wages and mobility parameters can flexibly vary by types of workers and firms. We also quantify the long-term effects of minimum wage lifetime income.

There are previous studies on the minimum wage in Thailand. These studies use the Labor Force survey which are cross-sectional worker data without firm identifiers. Exploiting regional variation, Lathapipat et al. (2016) find that the minimum wage policy in Thailand leads to wage increases with spillovers reaching up to the 60th percentile of the wage distribution. More recently, Samart and Kilenthong (2024) find that the effect of the minimum wage policy to be positive on real labor income with little disemployment effects. We add to these papers by providing a richer analysis of the minimum wage effects and its mechanism at the firm-worker level.

The rest of the paper is organized as follows. Section 2 describes the institution background of the minimum wage policy in Thailand and the data. Section 3 provides descriptive and evidence of mobility heterogeneity. Section 4 describes the model and the estimation procedure. Then, sections 5 and 7 present the estimation results. Section 8 analyzes sources of earnings gains and the long-term implications of the policy, and section 9 concludes.

2 Background and data

2.1 Institution background

The history of minimum wage in Thailand started since the late 1970s where the minimum wage is set by region. The minimum wage is set by the tripartite wage committee consisting of employers, worker representatives and government officials.[1] It is set at the provincial level and at a daily rate so that a minimum daily pay is sufficient for workers' living standard given the social and economic conditions (Labor Protection Act 2008). A day is defined as eight working hours except for occupations potentially imposing danger to employee's health and safety whose hours are limited to 7. The minimum wage policy applies to most occupations except for agricultural workers, fishery, forestry, household workers, those working for not-for-profit employers and government workers.

In November 2011, the Thai government announced the introduction of a nationwide daily minimum wage of 300 bahts. Prior to this policy, the minimum wage rates slightly increased overtime, and by the middle of 2011 the minimum wage ranged between 159 to 221 bahts across 76 provinces. The 300 bahts minimum wage policy was implemented in two phases. In the first phase, minimum wages in all provinces were raised by approximately 40 percent in April 2012. Effectively, this led minimum wages in seven provinces (Bangkok and vicinity plus Phuket province) whose minimum wages were already relatively high to be at 300 bahts right away, whereas the minimum wages in the rest of the country were still below the statutory level of 300 bahts. In the second phrase, January 2013, the statutory minimum wage of 300 bahts per day was applied to the whole nation – the remaining provinces raised their minimum wages to 300 bahts. Figure 1 shows the minimum, maximum and weighted average of the minimum wages across provinces over time. Our analysis focuses on outcomes at the annual level so that the minimum wage hikes in phase one and two would be treated as one major policy event.

Additionally, Thailand has formal and informal labor markets. Workers in the formal sector are defined as those who work in government, state enterprise and private sectors. Informal workers include self-employed and unpaid family workers. Using the Thai Labor Force survey (LFS), over the period of 2008-2015, the total labor force is approximately 37 million people in 2012 and about 10 percent (3.4 million workers) are government or state enterprise workers. Among the rest, about one-third are formal workers, two-third are informal workers and only about 1% are unemployed (defined as those actively seeking and available for work). We examine how the composition and shares of formal and informal sector change before and after the minimum wage policy later in the paper. The downside of the LFS is that it is cross-sectional and hence not suitable for studying worker-firm dynamics of wages and mobility. The main analysis in this paper is based on matched employer-employee data from the Thai Social Security.

[1] Although the differences in minimum wage rates were meant to reflect local costs of living, some study (e.g. Del Carpio et al. (2019)) has argued that the decision to determine the rate may reflect political bargaining power among the three parties rather than the economic conditions.

2.2 Thai Social Security data and baseline sample

The Social Security system in Thailand was introduced in 1991. Originally, the Social Security covered only workers in large establishments with more than 20 employees. However, the coverage for establishments of all sizes started in April 2002 (more than ten years before the 2013 nationwide minimum wage policy). Nevertheless, not all formal workers are part of the Social Security system. Exemptions include government officials, state enterprise workers and workers of foreign entities who have their own pension systems – this accounts for about 10% of the labor force. As mentioned earlier, minimum wages do not apply to agriculture and government workers. Therefore, occupations covered by the minimum wage policy align quite well with the formal workers covered by the Social Security.

The size of the workforce in Thailand rose from 34.7 to 39 million people from 2002 and 2015. During this period, the number of firms registered with the Social Security increased from approximately 240,000 to 390,000 firms, and the number of registered workers increased approximately from six to more than 11 million people. Figure 2 presents the shares of Social Security workers as a proportion of the labor force (excluding government and state enterprise workers which have their own pay and pension schemes), which grew from 21 percent in 2002 to 30 percent in 2015. The social security employee growth rates became noticeably higher in 2013 when the nation-wide minimum wage policy took place.

Specifically, our analysis uses the Thai Social Security data, known as Article 33, which has monthly matched employer-employee data from 1991 until present.[2] We restrict the sample to workers aged 25-50 years old between January 2008 to March 2015, i.e. four years before and two years after the minimum wage policy.[3] This includes 14,602,770 employees where 51% of these workers have moved across establishments 3.6 times on average during the period of study.

We focus on establishments rather than firms as wages vary by establishment, but throughout the paper we refer to establishments as firms. The sample consists of 592,520 firms and 709,396,472 total monthly observations. The Social Security data contains firms' entry and exit dates as well as workers' ages, nationality and monthly salaries. The Social Security maximum contribution wages are capped at 15,000 bahts per month since the launch of the Social Security system. This right censoring affected the top 80th percentile of monthly salary distribution just before the minimum wage policy. For estimation purposes, we resort to the imputation technique in Card et al. (2013) as described in Appendix A. We treat any remaining spell with positive wages as an employment spell, and treat time not observed in the Social Security record as "unemployment" which could include employment in the informal sector. Therefore our *unemployment* term actually refers to non-employment in the formal private sector.

Additionally, the Thai social security data only records monthly salaries without the number of working days per month. Using the Thai Socio-economic panel Survey, in 2012 the majority of workers aged 25-50 years old in the private sector worked 26 days per month.[4] Therefore, the 300 bahts minimum

[2] The Social Security office also has voluntary schemes for informal sectors but the take-up rates are relatively low.

[3] We focus on workers aged below 50 years old since they are unlikely to be affected by the mandatory retirement at 55 years old in the private sector.

[4] The Thai LFS collects information on weekly hours, weeks worked, total monthly salary as well as pay rate by payment

Figure 1: Minimum wages over time in Thailand

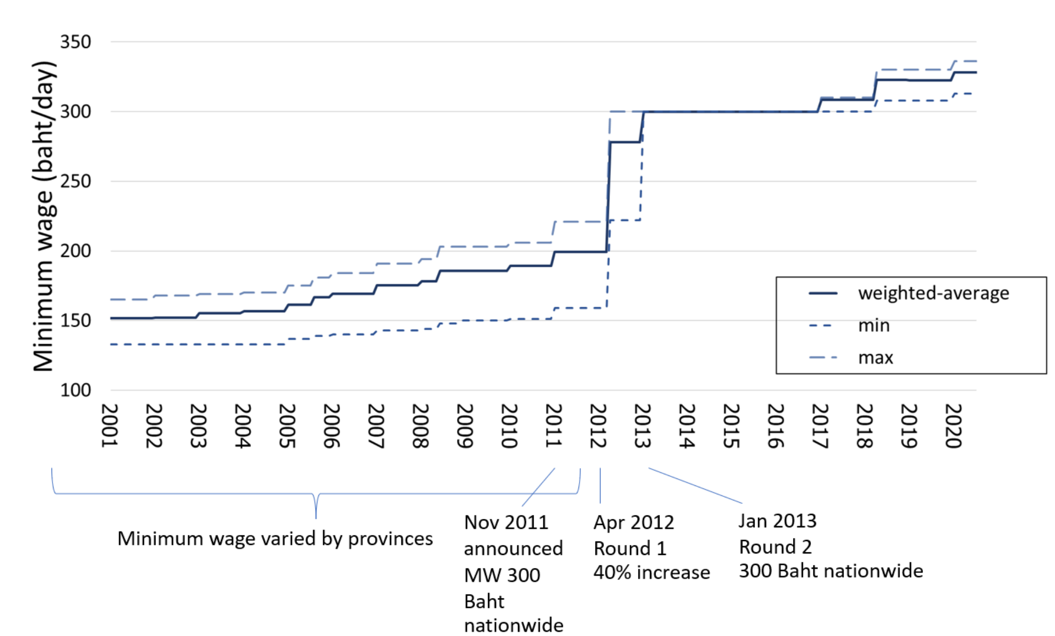
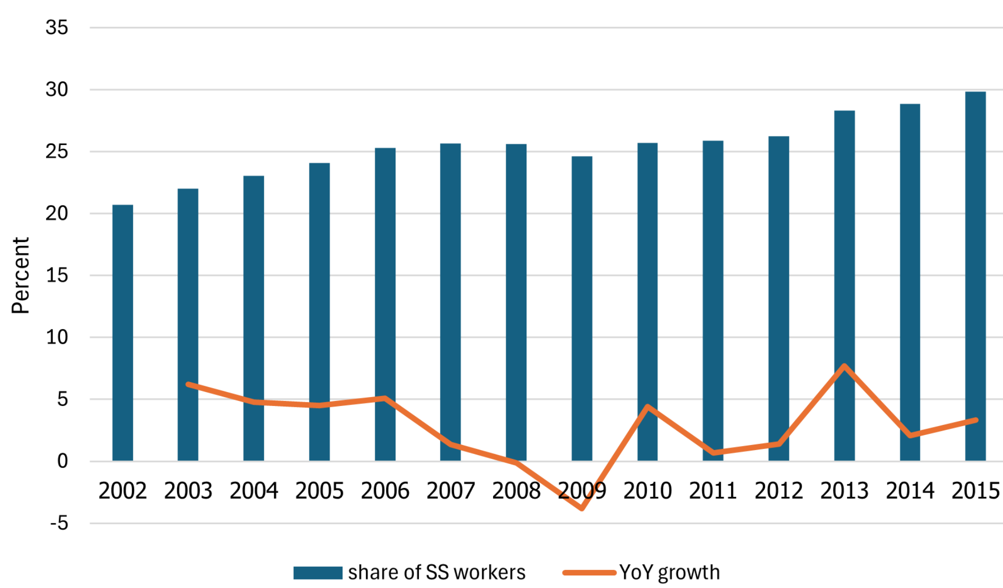
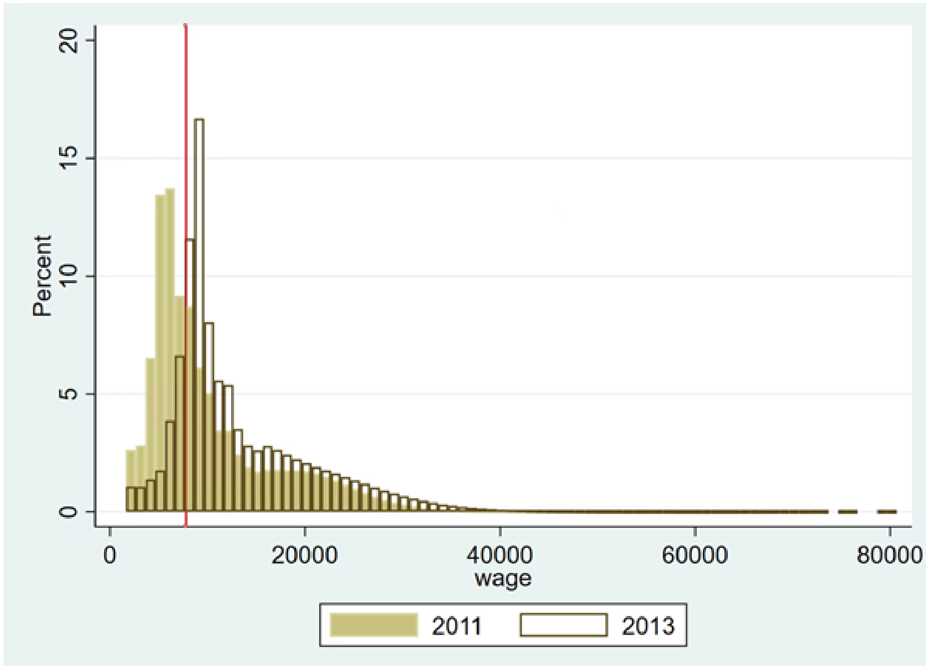


Figure 2: Shares of formal workers who have social security



Notes: Shares of workers reported to have contributed to Social Security system. Source: Social Security data (Article 33) and Labour Force Survey.

Figure 3: Monthly salary distribution over time



Notes: Average monthly salary before the policy in brown bars and after the policy in white bars. Source: Social Security data (Article 33).

wage translated into about 7,800 bahts of monthly salary for most workers. Figure 3 shows the salary distribution in 2011 and 2013 where the vertical line marks salary at 7,800 bahts. The minimum wage policy affected 49 percent of workers before the policy in 2011. After the policy, the percent of workers earning salary above 7,800 bahts increased substantially. We find no bunching and about 22 percent of workers still earned below 7,800 bahts monthly in 2013. This could be a result of part-time working or firms not compiling. We cannot distinguish them but we include all of these workers in our estimation since the fact that some workers still earn relatively low salary is vital for policy evaluation.

3 Mobility heterogeneity in the labor markets

In this section, we provide evidence of heterogeneity in labor market mobility among workers with similar wages. Table 1 shows worker characteristics by their average wage over 4 years before the MW policy. We classify workers into three wage categories: low or minimum wage workers, then medium and high wage. The first three rows of the table shows fractions of workers who never change jobs during the 4-year period before the policy, workers who sometimes move across jobs (2-3 times) and those who frequently move (more than 4 times). Medium and high wage workers tend to move across jobs less than

type: hourly, daily, weekly and monthly. For workers who are paid daily, we can back out the number of working days in a month from their daily pay rate and total monthly salary. Consistent with the Thai socio-economic panel Survey, the implied number of working days from the LFS has a median of 26 days.

Table 1: Worker characteristics before MW

	Low wage <8,000	Medium wage [8,000-12,000)	High wage 12,000+
% Never move (1 job)	0.56	0.65	0.66
% Sometime move (2-3 jobs)	0.32	0.28	0.28
% Frequent move (4+ jobs)	0.11	0.07	0.06
Average unemployment duration in months	15.72	13.26	11.95
% Male	0.50	0.52	0.54
% Movers	0.44	0.35	0.34
% Observations in sample	0.64	0.18	0.18

Notes: sample includes worker observations before the MW policy between January 2008 to March 2012. Wage bins are assigned using individual's average wage over this period. Low wage bin includes average wages below 8,000 bahts per month, middle wage bin includes 8,000-11,999 and high wage bin includes those more than 12,000.

low wage workers, and also have shorter average unemployment duration.

Additionally, figure 4 shows the box plots of 25th, 50th, 75th percentiles and the whisker shows 5th and 95th percentiles of unemployment duration in months. There is a lot of variation in unemployment duration even within a wage-mover category. This is particularly the case among low wage workers whose range between the 5th and 95th percentiles are quite wide. Overall, there is no clear relationship between wages and mobility. The heterogeneity in mobility implies different earnings both in the short and long run of worker's career. Hence, to evaluate the minimum wage effects and to analyze its mechanism, we introduce a framework that allows us to flexibly classify workers and firms by their wage and mobility patterns in the next section.

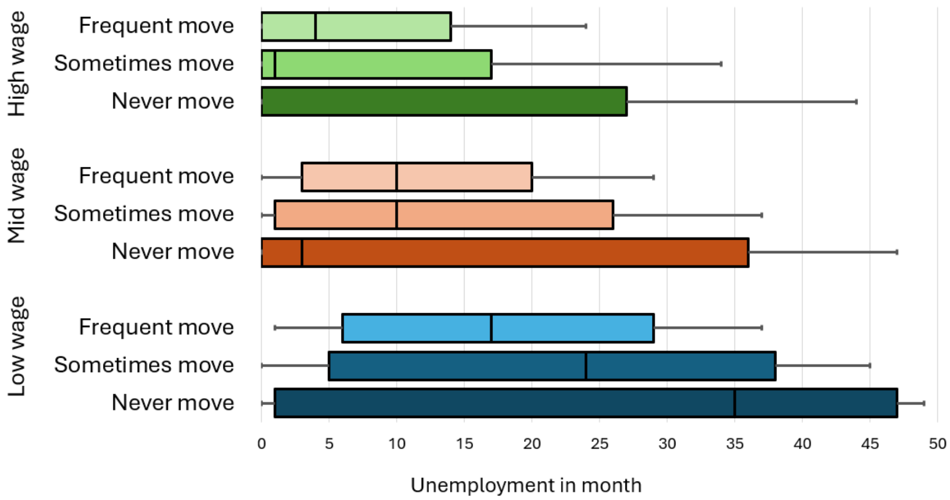
4 Wage-mobility discrete type model

4.1 The Model

The analysis is done at the worker-establishment level, however, we refer to establishments as firms. Workers are indexed by $i \in \{1,...,I\}$ and firms by $j \in \{0,1,...,J\}$, where $j = 0$ reflects non-employment in the formal sector which can partly include employment in the informal sector; however we use the term unemployment throughout the paper. For each worker i, we observe a set of time-invariant characteristics z_i : gender.[5] Firms also differ from each other by a set of observed and fixed characteristics such as dates of entry. Individual trajectories $(w_{it}, j_{it}, x_{it})_{t=1}^{T}$ are recorded at monthly frequency, where $j_{it} \equiv j(i,t) \in \{0,1,...,J\}$ is the employer's ID in the t-th month of observation, x_{it} are observed worker controls

[5] We also observe the immigration status, but the majority of workers in our sample are native.

Figure 4: Unemployment duration by wage and moving frequency



Notes: the box plots shows 25th, 50th, 75th percentiles and the whisker shows 5th and 95th percentiles of unemployment duration in months.

including age, job tenure, calendar year, and w_{it} is the worker's log-nominal wage in month t (or monthly salary).[6] Note that although the number of repeated observations T varies across individuals, we adopt the simplified notation of a balanced panel.

We assume that firms can be clustered into L different groups indexed by $\ell \in \{1,\ldots,L\}$ and that workers can be clustered into K different groups indexed by $k \in \{1,...,K\}$. The index ℓ_j is the type of firm j and k_i is the type of worker i. Unemployment in the formal sector is denoted by $\ell = 0$. Worker and firm type assignments are assumed to be fixed over the duration of estimation sample, but the levels of type-specific parameters can vary by the controls x_{it}. That is, tenure, age, and policy period impact a worker's mobility and wages conditional on a type assignment. Specifically, the vector x_{it} contains workers' age categories: 25-30, 30-35, 35-40 and 40-50 years old. Two statuses of tenure where employment tenure status is short if the worker has been at the same firm for less than one year, otherwise it is long. For unemployment, we define tenure dummy at seven months given the seasonal unemployment pattern in Thailand. There are two policy periods: before the nationwide minimum wage policy and after. Overall, this yields 16 different combinations of controls x's, leading to $K \times L \times 16$ sets for each parameter.

Given a firm classification $F = (\ell_1,...,\ell_J)$, the structure of the likelihood function consists of three parts:

4.1.1 Initial condition

A worker enters the model with their initial experience and tenure x_{i1} which determine a distribution of initial matches $m(k,\ell_{i1}|x_{i1})$. This initial x_{i1} dependence reflects the endogeneity of tenure and matching

[6] We do not have information on education levels.

for the trajectories of workers drawn from the stock. Further, given the worker's time-invariant characteristic, gender, there is a distribution of worker type, $\pi(k|z_i)$. This allows us to map observed individual characteristics to the predicted latent type.[7] Further, the initial employer's ID j_{i1} is drawn given its type with a probability proportional to the relative frequency of the firm type distribution, $1/q(\ell_{i1}|F)$. In other words, we assume that each firm within a firm type is equally likely to be selected. The estimated firm classification is performed subject to this uniform-sampling assumption (along with other parts of the likelihood function). This implies that firms with similar sampling probability will tend to be grouped together.

4.1.2 Wage distribution

Motivated by the shape of the wage (monthly salary) distribution in figure 3 that has no spike or truncation below the minimum wage, we assume wages to be log-normal given a match type. That is

$$w_{it} = \mu\left(k,\ell,x\right) + \varepsilon_{it}, \tag{1}$$

where $\varepsilon_{it} \sim N\left(0,\sigma^2\left(k,\ell,x\right)\right)$. This specification of the log-wage allows for a match-specific mean $\mu_{k\ell}$ and variance $\sigma^2_{k\ell}$ to vary by worker's time variant characteristics x as defined above. For instance, mean wages of long tenure or older workers can be higher than those of the counterparts, or mean wages post the minimum wage policy can be higher than those before the policy.[8] This enables us to capture dynamics of wage variations observed empirically across time. Further, the assumption that conditional on a given match type, the current wage is independent of the past firm type is in line with the literature e.g. Abowd et al. (1999), Bonhomme et al. (2019), Di Addario et al. (2022) and Lentz et al. (2023).

4.1.3 Transition probabilities

We implicitly assume that mobility to ℓ_{t+1} occurs at the end of period t, and hence is conditioned by x_{it}. The probability for a worker of type k with characteristics x_{it} to transition from a firm of type $\ell = 1,...,L$ to a firm of type $\ell' = 1,...,L$ is

$$M(\ell'|k,\ell,x) = \lambda_{k\ell'}(x)P_{k\ell\ell'}(x). \tag{2}$$

Parameter $\lambda_{k\ell'}(x)$ is the worker-type-k-conditional probability of meeting with a different employer of type ℓ' or "chance", whereas $P_{k\ell\ell'}(x)$ is the probability that the meeting results in a transition from ℓ to ℓ'

[7] In theory, we could include the distribution of firm types by industry or some time-invariant characteristics. However, there is a lot of missing in firms' industry information.

[8] A richer model could include an autoregressive component of wages within a firm; however, given our monthly data, this leads to a high order of auto-correlation and would considerably complicate the estimation procedure. We thus leave this to future research.

or “choice”. As in Lentz et al. (2023), we assume a Bradley-Terry specification for $P_{k\ell\ell'}(x)$. That is,

$$P_{k\ell\ell'}(x) = \frac{\gamma_{k\ell'}(x)}{\gamma_{k\ell}(x) + \gamma_{k\ell'}(x)} \tag{3}$$

where $\gamma_{k\ell}(x)$ measures the perceived value of the match (k, ℓ, x) with $\sum_{\ell=1}^{L} \gamma_{k\ell}(x) = 1$.[9] A higher value of $\gamma_{k\ell}(x)$ means a more desirable match. Note that we do not restrict the ordering of $\gamma_{k\ell}(x)$ to be the same as the ordering of mean wages nor to remain the same across policy period. This allows us to assess what kind of firms workers prefer and whether workers move to less desirable firm types after the minimum wage policy.

The unemployment-employment (UE) and employment-unemployment (EU) transitions are unrestricted and denoted by,

$$M(\ell'|k,0,x) = \psi_{k\ell'}(x), \quad M(0|k,\ell,x) = \delta_{k\ell}(x).$$

By convention, $M(0|k,0,x) = 0$. There is no transition from unemployment to unemployment. With this, it follows that the probability of staying unemployed is

$$M(\neg|k,0,x) = 1 - \sum_{\ell'=1}^{L} M(\ell'|k,0,x) = 1 - \sum_{\ell'=1}^{L} \psi_{k\ell'}(x),$$

and for $\ell \geq 1$, the probability of staying with the same employer is

$$M(\neg|k,\ell,x) = 1 - \sum_{\ell'=0}^{L} M(\ell'|k,\ell,x) = 1 - \delta_{k\ell}(x) - \sum_{\ell'=1}^{L} M(\ell'|k,\ell,x).$$

4.1.4 Likelihood

We specify the general form of likelihood for a given firm classification. Let $\ell_{it} = \ell_{j(i,t)}$ denote the type of the firm employing worker i in period t. Let also

$$D_{it} = \begin{cases} 1 & \text{if } j_{i,t+1} \neq j_{it}, \\ 0 & \text{if } j_{i,t+1} = j_{it}, \end{cases}$$

indicate an employer change between t and $t+1$.

For the given firm classification $F = (\ell_1, ..., \ell_J)$, let f, M, π and m, respectively, denote parametric versions of the wage density function; $f(w_{it}|k, \ell_{it}, x_{it})$, the transition probability $M(\ell_{i,t+1}|k, \ell_{it}, x_{it})$, the worker type probability $\pi(k|z_i)$, and the distribution of initial employer types $m(\ell_{i1}|k, x_{i1})$. For a value $\beta = (f, M, \pi, m)$ of the parameters and a classification F of firms, the likelihood for worker i – i.e. of

[9] If the worker draws a same-type job, with no loss of generality, since $\lambda_{k\ell'}(x)$ is unrestricted, we assume that the worker moves with probability 1/2.

$(w_{it}, j_{it}, x_{it})_{t=1}^{T}$ conditional on (z_i, x_{i1}) is

$$L_i(k|\beta,F) = m(\ell_{i1}|k,x_{i1})\,\pi(k|z_i)\prod_{t=1}^{T} f(w_{it}|k,\ell_{it},x_{it}) \\ \times \prod_{t=1}^{T-1} M(\neg|k,\ell_{it},x_{it})^{1-D_{it}}\,(M(\ell_{i,t+1}|k,\ell_{it},x_{it}))^{D_{it}}, \tag{4}$$

where $M(\neg|k,\ell,x) = 1 - \sum_{\ell'=0}^{L} M(\ell'|k,\ell,x)$ is the probability of staying with the same employer, and assuming that for the last observation period we do not know whether a mobility occurs or not by the end of it.

4.2 Identification

Bonhomme et al. (2019) provides an identification proof of this type of models. They show that at least three wage observations are sufficient to identify mixtures models for matched employer-employee data. Additionally, Lentz et al. (2023) provides a complementary proof in their appendix. The basic idea is the following: first, to identify the firm classification, firms must be sufficiently different in terms of their observed differences in wages and mobility patterns. Second, all transitions, conditional on type assignments, are realized with positive probability. Finally, wage densities are linearly independent with respect to worker types.

We use a monthly panel over four years for our estimation. We choose the number of firm types to satisfy the first assumption that firms are different across types in terms of their wage and mobility characteristics. Essentially, we perform k-means clustering based on firms' observed wage distributions, sizes, entry and exit rates, and choose an optimal cluster number of firm types such as firms are different across types. The second and third assumption can be checked if all the estimated transitions are non-empty and mean wages are linearly dependent in worker types. These three assumptions essentially require the data in workers' and firms' differences to be sufficiently rich given the number of types.

Finally, the identification of Bradley-Terry specification for $P_{k\ell\ell'}(x)$ in (3) follows directly from Lentz et al. (2023). First, if the worker draws a same-type job, then the worker moves with probability $1/2$. So $M(\ell'|k,\ell,x) = \lambda_{k\ell'}(x) \times 1/2$ where $\ell = \ell'$ pins down $\lambda_{k\ell'}(x)$. Then the ratio of different types of moves $M(\ell'|k,\ell,x)$ and $M(\ell|k,\ell',x)$ where $\ell \neq \ell'$ pin down $\gamma_{k\ell}(x)$ with a restriction that $\sum_{\ell=1}^{L} \gamma_{k\ell}(x) = 1$. See Lentz et al. (2023) for further discussion.

4.3 The Estimation Procedure

We assume firm types to be fixed effects and worker types to be random effects as in Bonhomme et al. (2019) and Lentz et al. (2023). This is because it is infeasible to evaluate the likelihood function for the formulation of the model where a firm's type is a random effect. Worker mobility across different firm types makes it impossible to separate the complete log-likelihood (i.e. $\sum_i \ln \mathscr{L}_i(\beta|k,F)$) across firm types. Consequently, the estimation delivers a point estimate for each firm type instead of a posterior probability distribution over it as is the case for worker types.

For a given firm classification F and a value of $\beta = (f, M, \pi, m)$, the posterior probability of worker i to be of type k given all wages and controls (all the available information) is

$$p_i(k|\beta,F) \equiv \frac{L_i(k|\beta,F)}{\sum_{k=1}^{K} L_i(k|\beta,F)}. \tag{5}$$

Then, define

$$Q_i(f|\beta^{(m)},F) = \sum_{k=1}^{K} p_i(k|\beta^{(m)},F)\left[\sum_{t=1}^{T} \ln f(w_{it}|k,\ell_{it},x_{it})\right] \tag{6}$$

as the expected log-likelihood of worker i's wages for a given value $\beta^{(m)}$ of the parameter. The worker posteriors are determined by the model parameters and firm classification $\left(\beta^{(m)},F\right)$, where the superscript m is used to denote a given EM-algorithm iteration. Also, let

$$H_i(M|\beta^{(m)},F) = \sum_{k=1}^{K} p_i(k|\beta^{(m)},F)\left[\sum_{t=1}^{T-1}\left\{(1-D_{it})\ln M(\neg|k,\ell_{it},x_{it}) + D_{it}\ln M(\ell_{i,t+1}|k,\ell_{it},x_{it})\right\}\right] \tag{7}$$

be the expected log-likelihood of worker i's mobility history conditional on the first state ℓ_{i1}.

Since we are interested in classifying both worker and firm types based on their wage and mobility information, we adopt a Classification Expectation Maximization (CEM) algorithm from Lentz et al. (2023), which allows us to estimate firm types jointly with worker types using the full likelihood information on wage and mobility history.[10] The algorithm involves three steps with the standard EM algorithm and the additional classification step of firm types. For a given firm classification F, the EM algorithm iterates the following steps:

E-step For $\beta^{(m)} = (f^{(m)}, M^{(m)}, \pi^{(m)}, m^{(m)})$ and F, calculate posterior probabilities $p_i(k|\beta^{(m)},F)$.

M-step Update $\beta^{(m)}$ by maximizing $\sum_i p_i(k|\beta^{(m)},F)\ln L_i(k|\beta,F)$ subject to $\sum_k \pi(k|z) = 1$ for all z and

[10] An alternative estimation procedure is to use k-means to classify firm types then proceed to use the EM algorithm to estimate worker types. However, it is difficult to summarize all mobility information into matrices for k-means inputs.

$\sum_{\ell_1} m(\ell_1|k,x_1) = 1$ for all k,x_1, that is

$$f^{(m+1)} = \arg\max_f \sum_{i=1}^{I} Q_i(f|\beta^{(m)},F), \tag{8}$$

$$M^{(m+1)} = \arg\max_M \sum_{i=1}^{I} H_i(M|\beta^{(m)},F), \tag{9}$$

$$\pi^{(m+1)}(k|z) = \frac{\sum_{i=1}^{I} p_i(k|\beta^{(m)},F)\,\mathbf{1}\{z_i = z\}}{\#\{i : z_i = z\}}, \tag{10}$$

$$m^{(m+1)}(\ell|k,x_1) = \frac{\sum_{i=1}^{I} p_i(k|\beta^{(m)},F)\,\mathbf{1}\{x_{i1} = x_1, \ell_{i1} = \ell\}}{\sum_{i=1}^{I} p_i(k|\beta^{(m)},F)\,\mathbf{1}\{x_{i1} = x_1\}}. \tag{11}$$

The M-step updating formulas for wage distributions are the usual posterior probability-weighted mean, variance and autocorrelation for Gaussian mixtures. See the appendix of Lentz et al. (2023) for the formulas.

C-step Given an initial value $(\widehat{\beta}^{(s)}, F^{(s)})$, where $\widehat{\beta}^{(s)}$ is obtained given $F^{(s)}$ using the previous EM algorithm, we update $F^{(s)}$ as

$$F^{(s+1)} = \arg\max_F \sum_{i=1}^{I} \sum_{k=1}^{K} p_i(k|\widehat{\beta}^{(s)}, F^{(s)}) \ln \mathscr{L}_i(\widehat{\beta}^{(s)}|k, F^{(s)}). \tag{12}$$

In practice, we only search for and update a firm reclassification that increases the likelihood. Start with any firm, we find $\ell_1^{(s+1)}$ such that it maximizes the criterion in equation (12), keeping all other firm types equal to their values in $F^{(s)}$. Then, we find $\ell_2^{(s+1)}$ given $\ell_1^{(s+1)}$, $\ell_3^{(s)}, \ldots, \ell_J^{(s)}$, and so on until $\ell_J^{(s+1)}$. Thereafter, we return to the EM iterations with the updated $F^{(s+1)}$ and iterate between the C and EM steps until convergence.

4.4 Choice of period of data and group numbers K, L

Our estimation sample consists of seven years of data including four years before the minimum wage policy (pre-MW) and three years after (post-MW). In order to evaluate the minimum wage effects along the distribution of worker types, without confounding type characteristics with endogenous outcomes and keeping the composition of workers clean, we estimate worker and firm types in the E and C steps using only the pre-MW data.

However, the estimation of model parameters in the M-step uses the full sample of data, both before and after the policy. Recall that our model parameters vary by workers' controls x which include age, tenure status and policy periods. While we exclude new workers entering the sample after the policy from the M-step parameter estimation for the reasons explained above, we cannot simply exclude new firms. This is because if we drop new firms then this would be equivalent to dropping employment observations

Table 2: Average characteristics by worker type

			Pre-MW				
k	earnings	women	wage	var	EU	UE	EE
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1	47,365	0.48	8.476	0.080	0.048	0.005	0.028
2	57,110	0.53	8.511	0.060	0.026	0.006	0.013
3	81,440	0.45	8.834	0.037	0.012	0.005	0.009
4	127,154	0.50	9.249	0.039	0.009	0.005	0.009
5	218,516	0.50	9.800	0.065	0.006	0.008	0.011
6	304,336	0.40	10.128	0.067	0.007	0.007	0.020

Notes: the table shows average characteristics of each worker type in pre-MW period, weighted by their matching probabilities $p(k,\ell,x)$. See text for explanation.

overstating the unemployment rate. We show that our results on sorting are not sensitive to the inclusion of new firms since they represent a small fraction of pre-existing firms before the policy.[11]

For the numbers of types, as in Lentz et al. (2023), we use k-means to cluster firms and workers, separately, based on wage and mobility information similar to the likelihood function and select the values of K and L associated with the highest Calinski-Harabasz index, which is the ratio of the between-cluster and the within-cluster sum-of-squares. We select $K = 6$ for worker types and $L = 10$ for firm types. Finally, there may be local maxima in the EM estimation. In practice, we use many different starting values of parameters, and we choose the set of results with the highest likelihood value.

5 Characteristics of worker and firm types

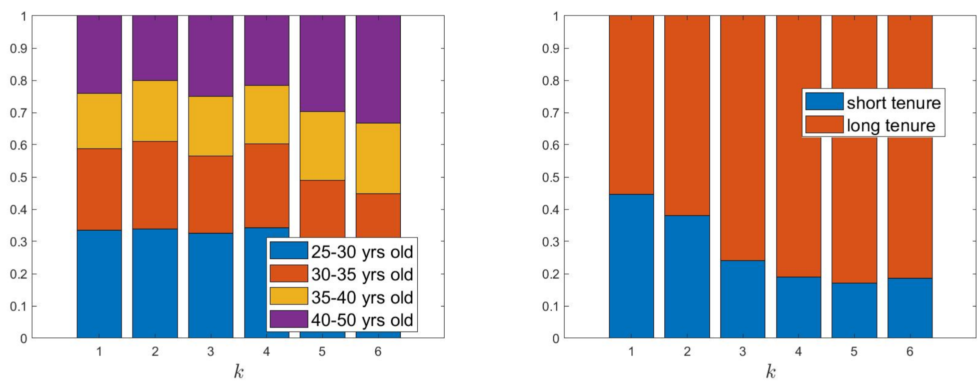
In this section, we describe the characteristics of worker and firm types before the policy. The estimation essentially gives us classifications of workers and firms. We assign labels to these groups in a way that we can understand how the minimum wage policy affects workers differently along the earnings distribution. We re-label k by the ordering of average annual earnings of worker type in one year before the policy. Similarly, we re-label ℓ by the ordering of average annual earnings of firm type before the policy.

5.1 Worker types

Table 2 shows the average characteristics of each worker type before the policy. The first column is worker type and the second column is the average annual earnings in Bahts in 2011 before the policy which is increasing in worker type given our re-labeling of k as explained above. The second column is fraction of women in each type. Columns four to eight are the average parameters of each worker type weighted by their matching probabilities $p(k,\ell,x)$ across ℓ and x. This includes mean wages ($\mu_{k\ell}(x)$) in

[11] An alternative modeling approach is to assign new firms to additional types. However, this would increase the number of parameters and also makes the counterfactual exercises complicated.

Figure 5: Pre-MW age group (left) and tenure fraction (right) by worker type



column three, wage variance within type ($\sigma_{k\ell}(x)$) in column four, monthly employment-unemployment or EU rate ($\delta_{k\ell}(x)$) in column six, re-employment rate or UE ($\psi_{k\ell}(x)$) in column seven, and job-to-job transition rate or EE ($M_{k\ell\ell'}(x)$) in column eight.[12]

First, it can be that there are relatively fewer women in the high-earning types. Second, average wages correspond with the ordering of earnings therefore our re-labeling of types would be unchanged whether we use wages or annual earnings. At the new minimum wage of 300 bahts per day, a worker who works full-time throughout the year would have their average annual earnings around 93,600 bahts – therefore worker types 1 and 2 are relatively low wage workers whose earnings were below the nationwide minimum wage. The main difference between worker type 1 and 2 is that workers of type 1 tend to leave their jobs much more often, both to another job and to unemployment, as shown in their higher EU and EE rates. We can regard type 1 as low wage job hoppers who have the lowest earnings and type 2 as low wage job holders who have slightly higher earnings due to a stronger attachment to their jobs. Types 3 and 4 are medium wage workers with type 3 having slightly higher chance of changing jobs. Finally, types 5 and 6 are high wage workers. Note that these transition rates are averages across firm types. A particular worker type might be more likely to make transitions to a certain firm type. We analyze sorting in the later section.

In terms of age composition, defined by age at the first observed spell and shown in the left panel of figure 5, the composition looks similar among the first four worker types, whereas the two highest types have more older workers. Low-earning or lower types also have more short tenure workers than higher type workers as shown in the right panel of figure 5.

[12]The UE rate is estimated to be considerably lower than the EU rate. This is because unemployment in our definition also includes working in the informal sector. The inflow into the formal sector also tend to be young workers aged below 25 years old which are not in our primed-age estimation sample, while older workers gradually move to the informal sector.

Table 3: Average characteristics by firm type

				Pre-MW						
ℓ	earnings	women	size	no.firms	wage	var	EU	UE	EE	<MW%
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
1	36,413	0.44	2.83	67,164	8.011	0.035	0.027	0.002	0.001	0.99
2	46,920	0.45	31.35	8,900	8.262	0.069	0.037	0.004	0.010	0.98
3	54,498	0.43	7.18	47,117	8.446	0.038	0.025	0.003	0.003	0.98
4	66,074	0.46	61.09	12,042	8.567	0.058	0.029	0.006	0.013	0.91
5	83,776	0.49	5.00	108,984	8.829	0.039	0.022	0.004	0.005	0.65
6	90,118	0.49	116.69	10,563	8.824	0.053	0.019	0.006	0.019	0.71
7	93,259	0.47	34.32	18,804	8.921	0.044	0.018	0.004	0.009	0.50
8	134,208	0.45	113.42	11,163	9.215	0.057	0.014	0.006	0.018	0.29
9	150,482	0.46	21.12	44,151	9.336	0.051	0.013	0.005	0.012	0.20
10	256,637	0.49	17.22	36,752	9.910	0.066	0.008	0.008	0.020	0.05

Notes: the table shows average characteristics of each firm type in pre-MW period, weighted by their matching probabilities $p(k,\ell,x)$. See text for explanation.

5.2 Firm types

Similar to worker types, we relabel firm types by the ordering of the average annual earnings of workers in each firm type in the year before policy, this is shown in the second column of Table 3 . The third column shows fractions of women ranging between 0.4-0.5 with no clear pattern. The forth column displays the average number of employment spells in each firm type. Overall, higher paid firms tend to be bigger than lower paid firms. Columns six to ten are the average model parameters of each firm type weighted by their matching probabilities $p(k,\ell,x)$ across k and x. This includes, respectively, means wages ($\mu_{k\ell}(x)$), wage variance within firm type ($\sigma_{k\ell}(x)$), monthly employment-unemployment or EU rate ($\delta_{k\ell}(x)$), re-employment rate or UE ($\psi_{k\ell}(x)$), and job-to-job outflow rate by firm type or EE ($M_{k\ell\ell'}(x)$).[13] Wages are mostly lined up with the ranking of annual earnings with an exception of a few firm types where the difference in job stability (EU rate) dominates the difference in wage e.g. firm type 5 has a higher average wage than firm type 6, but has a shorter duration of jobs leading firm type 6 to have a higher average earnings. The overall trend shows that higher paid or higher type firms tend to offer more stable jobs and they also provide a higher chance of job-to-job transition opportunity.

Finally, the last column shows fractions of workers earning below the minimum wage before the policy. Low type firms (1-4) have almost of all their workers earning below the minimum wage. We would expect more impacts on them. The middle types (5-7) have 50-70 percent of their workers affected by the policy, while the high types (8-10) have much fewer affected workers. We show how employment matches distribute differently across worker and firm types before and after the policy in the next section.

[13] We study how EE destination of firm types reveal preferences in section 6.3.

Table 4: Changes in average model parameters by worker type

	Pre-MW				Post-MW			
k	wage	EU	UE	EE	$\triangle$wage	$\triangle$EU	$\triangle$UE	$\triangle$EE
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1	8.476	0.048	0.005	0.028	0.459	-0.020	0.001	-0.005
2	8.511	0.026	0.006	0.013	0.461	-0.008	0.000	-0.002
3	8.834	0.012	0.005	0.009	0.347	-0.001	0.000	0.001
4	9.249	0.009	0.005	0.009	0.288	0.000	0.000	-0.001
5	9.800	0.006	0.008	0.011	0.203	0.000	-0.001	0.000
6	10.128	0.007	0.007	0.020	0.175	0.000	0.001	-0.003

Notes: the table shows changes in average model parameters of each worker type between pre-MW and post-MW periods, weighted by their respective matching probabilities $p(k,\ell,x)$. See text for explanation.

6 Changes in worker and firm characteristics and sorting

In this section, we first show how the model parameters change by worker and firm types on average. We then examine how firms' labor market shares, their sizes, numbers, entry and exit rates evolve over time. Finally, we measure sorting and analyze how the allocation of workers to firms has changed after the policy.

6.1 Worker types in post-MW policy period

We first show how the model parameters change over time by worker type aggregating over firm types, age groups and tenure statuses. The right panel of table 4 shows the changes in average wages and transition probabilities by worker type between pre-MW and post-MW periods, while the left panel shows the pre-MW baseline parameters from table 2 for a reference. Mean wages increase quite substantially for worker types 1-2 and gradually decline in worker type. Overall, there is sizable spillover on wages. In terms of transition rates, workers of type 1-3 have lower EU rates i.e. they hold on to their jobs longer, while the same rate is unchanged for higher type workers. The UE rates minimally change while the EE rates decline for some worker types. The changes in wages and transition rates jointly affect the overall earnings. We present heterogeneity in earnings gains and decompose sources of the gains in later section.

The distribution of matches by worker type before and after the policy is shown in figure 6. Workers of types 1-4 are more predominant than the higher paid types 5-6. The shares of employment increased slightly for medium wage workers or types 3-4 while remain roughly the same for other types. Recall that we only focus on pre-MW workers in the benchmark sample – however, the match distribution of post-MW workers looks similar to that of the pre-MW workers. As shown in figure 7, the additional 2,680,981 workers are predominantly workers of types 1-3. The majority of them, represented in the blue bars, are young workers at age 25 years old who are likely to have transitioned from school or training given their age, whereas other bars are older workers who are likely to have transitioned from the informal sector.

Figure 6: Aggregate employment shares by worker type

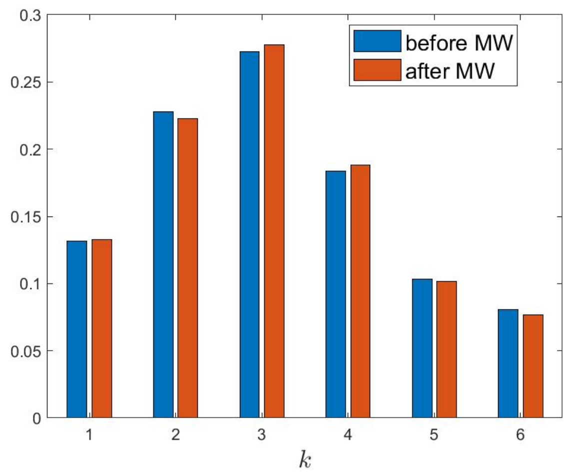


Figure 7: Types of new workers in the post-MW period

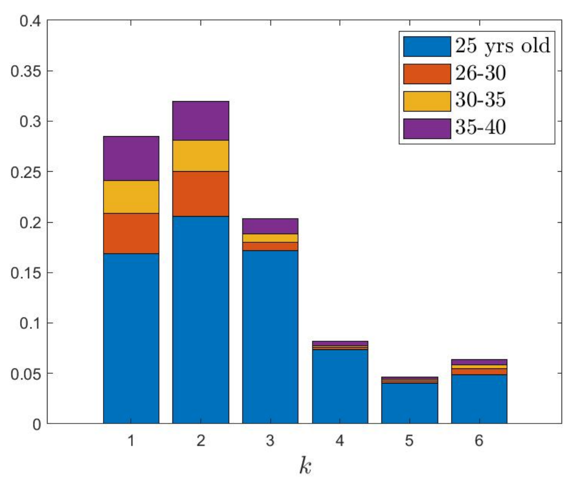


Table 5: Changes in average model parameters by firm type

	Pre-MW				Post-MW			
ℓ	wage	EU	UE	EE	$\triangle$wage	$\triangle$EU	$\triangle$UE	$\triangle$EE
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1	8.011	0.027	0.002	0.001	0.346	-0.007	0.000	0.003
2	8.262	0.037	0.004	0.010	0.456	-0.011	0.000	0.002
3	8.446	0.025	0.003	0.003	0.351	-0.007	0.000	0.007
4	8.567	0.029	0.006	0.013	0.397	-0.008	0.000	-0.006
5	8.829	0.022	0.004	0.005	0.327	-0.003	0.001	0.000
6	8.824	0.019	0.006	0.019	0.351	-0.005	0.000	-0.007
7	8.921	0.018	0.004	0.009	0.296	-0.003	0.000	0.002
8	9.215	0.014	0.006	0.018	0.282	-0.003	0.000	-0.003
9	9.336	0.013	0.005	0.012	0.239	-0.002	0.000	-0.001
10	9.910	0.008	0.008	0.020	0.160	-0.001	-0.001	0.002

Notes: the table shows changes in average model parameters of each firm type between pre-MW and post-MW periods, weighted by their respective matching probabilities $p(k,\ell,x)$. See text for explanation.

6.2 Firm characteristics post policy

Table 5 shows the changes in model parameters by firm type after the policy, aggregating over worker types, age groups and tenure statuses. The right panel shows the changes between pre-MW and post-MW periods, while the left panel shows the pre-MW baseline parameters presented in table 3 for a reference. Mean wages increase more among firm types 1-6 and gradually fall. The average EU rates also fall across the board, but at a smaller magnitude than the same reduction by worker type. This suggests that employment-unemployment transitions are more worker specific. Both the UE and EE rates minimally change. These changes jointly impact workers' overall earnings and we analyze this in section 7.1.

Figure 8 shows the distribution of matches by firm type. The employment shares of firms of types 1-6 fall except for type 5 whose share is roughly unchanged. At the same time, the shares of firm types 7-10 expanded. This is consistent with Dustmann et al. (2021) and Engbom and Moser (2022) in that the low productive firms tend to exit and high productive firms enter and expand in response to a minimum wage policy. We illustrate this explicitly in section 6.3.

The expansion of firms' labor market shares could come from existing firms expanding and new firms entering the labor market. We show in figure 9

Figure 8: Aggregate employment shares by firm type

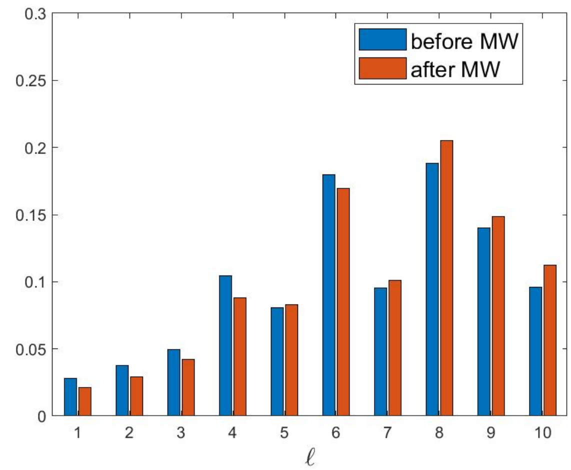
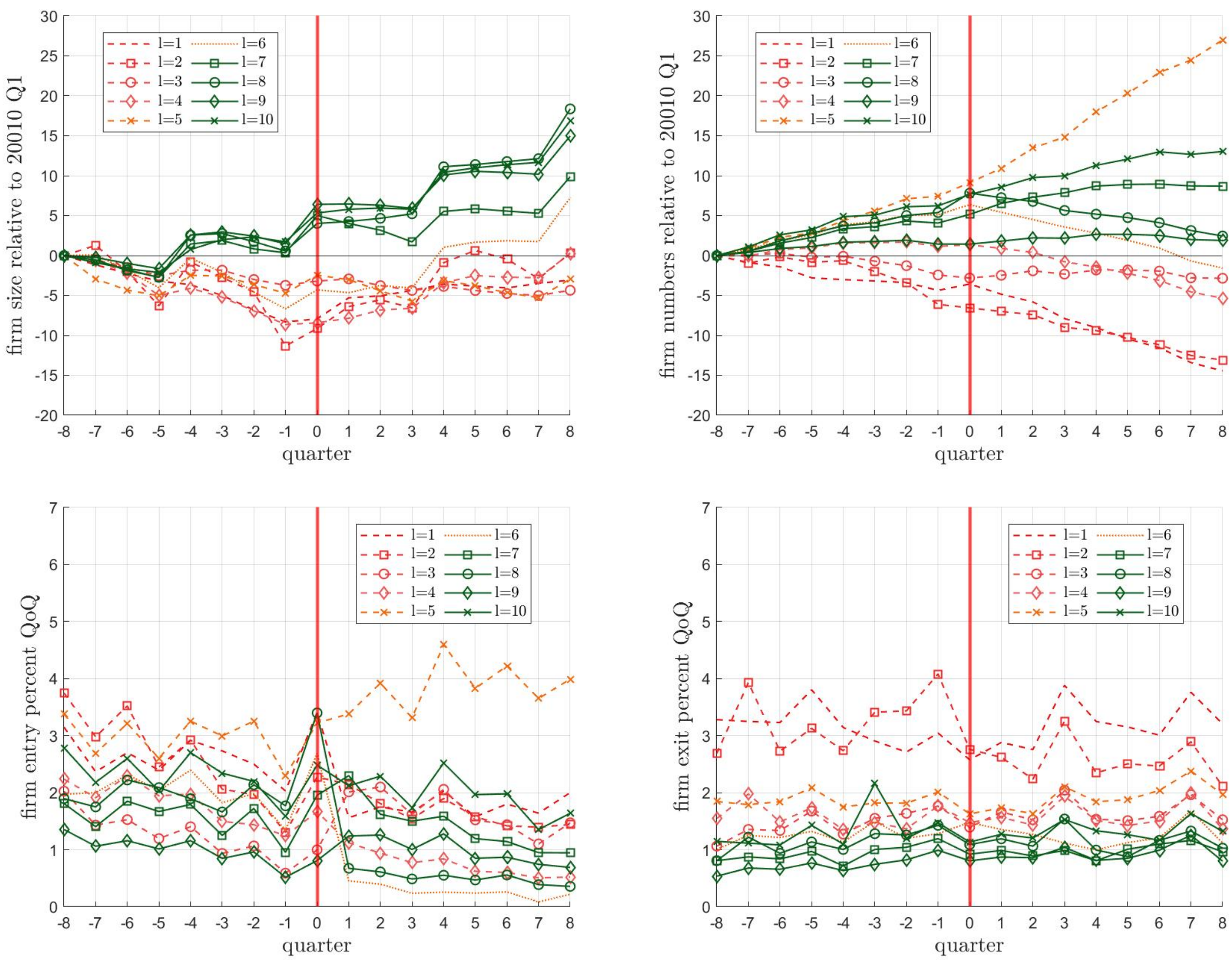
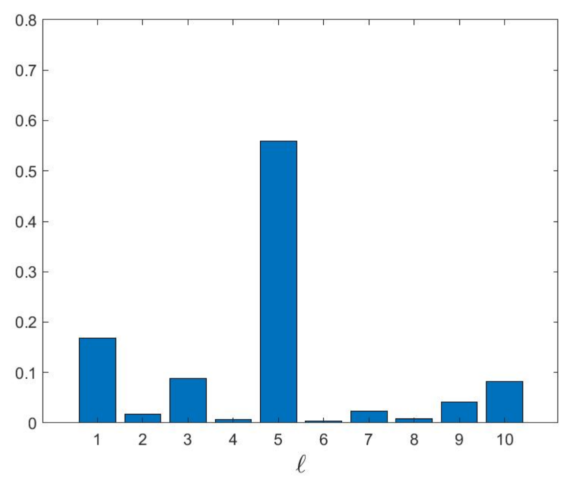


Figure 9: Dynamics of firm growth, number, entry and exit



that the expansion of the high types' labor market shares come from both firm size increase and more firms entering the labor market. This is shown in the top panel where both firm sizes and numbers are relative to the initial level in 2010 rise for firms of types 7-10. While the average size of firms of type 5 has dropped, we can see the entry rate of type 5 has considerably increased in the bottom left graph – this opposing forces lead the overall labor market share of firms of type 5 to remain roughly the same after the policy. The entry rates have declined for all other types and the exit rates have trended up, however the exit rates remain lower than the entry rates for types 7-10 resulting in higher number of firms overall. Finally, as the entry rate graph also implies, most new firms are firms of type 5 (see figure 10).

Figure 10: Types of new firms in the post-MW period



6.3 Sorting over time

To measure the dynamics of sorting between worker and firm types over time, we use the Mutual Information (MI).[14] This index measures the dependence between two variables, say X and Y, without imposing any structure. Specifically, it is the Kullback-Leibler distance between a bidimensional distribution and the product of its margins:

$$I(X,Y) = d_{KL}(p(X,Y)||p(X)p(Y)) = \sum_{x,y} p(x,y) \ln\left(\frac{p(x,y)}{p(x)p(y)}\right).$$

[14]One commonly used measure of sorting in the literature is a correlation between worker and firm wage fixed effects. However, as pointed out in Lentz et al. (2023), there may be dependencies between worker and firm types that the correlation of fixed effects are missing e.g. due to non-linearity in mean wages. Furthermore, there may be non-wage factors that drive sorting patterns that are not captured by wage fixed effects.

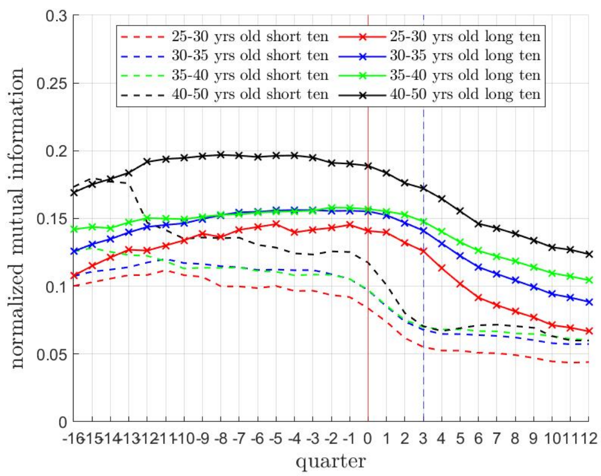
It measures the distance between observed and independent matching. As in Lentz et al. (2023), we use the following normalized MI,

$$\tilde{I}(X,Y) = \frac{I(X,Y)}{\min\left[H(X), H(Y)\right]},$$

where the denominator contains the minimum of the entropy of X, $H(X) = -\Sigma_x p(x)\ln(p(x))$, and the entropy of Y, $H(Y) = -\Sigma_y p(y)\ln(p(y))$. In the extreme case of perfect dependence where X and Y are the same random variable, then $\tilde{I} = 1$, and in the other extreme case of independence, $\tilde{I} = 0$.

Figure 11 shows the normalized MI indexes for each experience and tenure category by quarter where

Figure 11: Mutual information

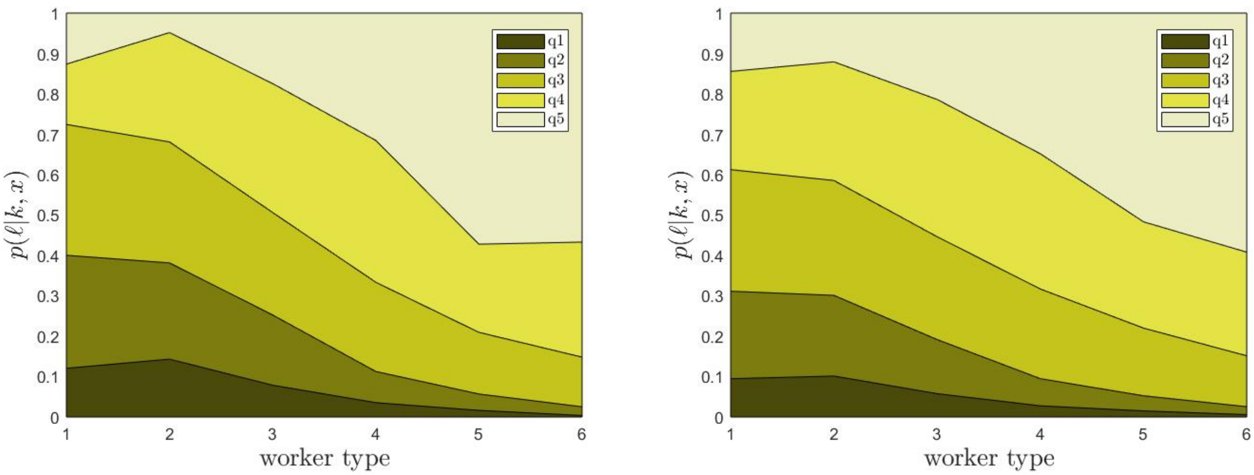


time zero on the horizontal axis denotes the second quarter of 2012 when the first minimum wage hike occurred and the second vertical dashed line marks the second minimum wage hike in the first quarter of 2013. Short-tenure employment are matches that have been formed for less than a year, while long-tenure are worker-firm matches that last for more than a year. First, we can see that long-tenure matches have a higher level of MI i.e. they are more sorted compared to short tenure matches. As one would expect, bad matches do not last and surviving or long-tenure matches hence involve more sorting. Further, both short and long tenure matches have become less sorted – the degree of dependence dropped substantially for the short tenure or new matches formed within one year after the policy.

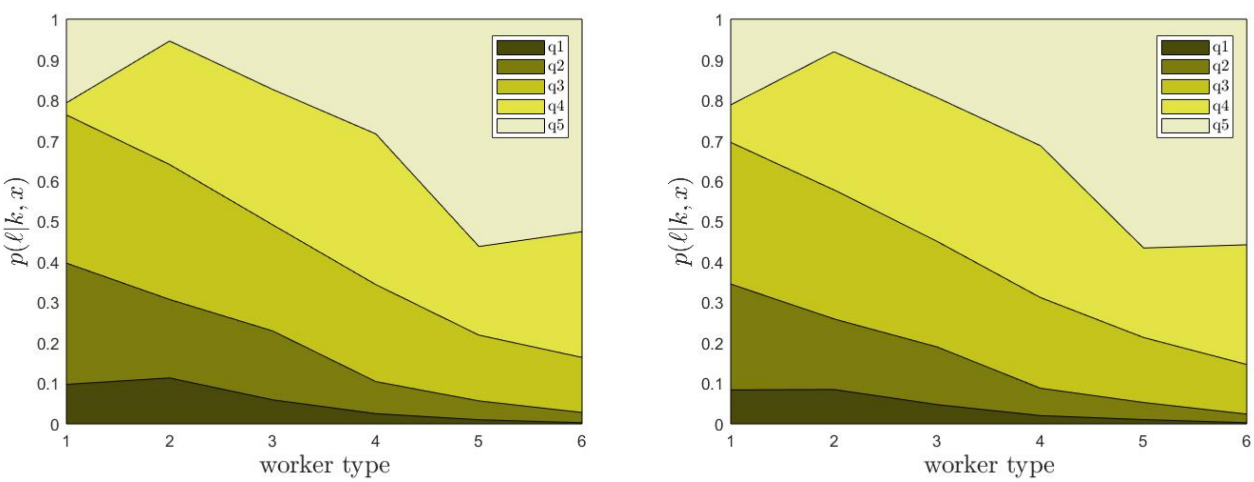
A drawback of the standard MI index is that it does not say if the matching is positive or negative assortative, but the direction of matching can be easily learned from a graphical illustration of worker type composition across firm types. To understand if the changes in MI reflects more positive or negative assortative matching, we depict the area charts of the probability of firm matching conditional on worker type and tenure status, $p(\ell|k,x)$ in figure 12. For legibility of graphs, we aggregate over age groups since there is little difference between them and we also group firm types into quintiles where q_1 includes firm types 1 and 2,..., q_5 includes firm types 9 and 10. The top (bottom) panel shows $p(\ell|k,x)$ of short (long) tenure matches before the policy (left) and after the policy (right). There are proportionately more of low-type workers working at low-type firms and similarly for high-type workers and high-type firms. There is clear evidence of positive sorting in both short and long tenure matches before the policy. However, after the policy, the proportion of low-wage workers (types 1-2) working at the bottom two quintile firms have dropped. We illustrate where these low-wage workers reallocate to using spider plots in figures 13 for short tenure matches and figure 14 for long tenure matches. The blue web represents the probability of matching with each firm quintile conditional on worker type, $p(\ell|k,x)$, that is the edges sum to one. The orange web shows the same probability after the policy. Among short-tenure matches, workers of types 1-2 have moved from firms in the bottom three quintiles to the top two, as shown by the orange web being shifted towards the top firm types. Workers of type 3 also move in the same direction but at a lessor extent while high-wage workers of types 4-5 who are less affected by the policy keep more or less the same allocation. The pattern is similar but less pronounced among long-tenure matches which is consistent with a smaller drop in the MI indices in figure 11.

Figure 12: Firm type composition at each worker type by tenure status

(a) Short-tenure: before MW (left) after MW (right)



(b) Long tenure: before MW (left) after MW (right)



Notes: the area charts display the probability of firm matching conditional on worker type and tenure status, $p(\ell|k,x)$. For presentation purposes, we aggregate over age groups and we divide firms into quintiles with two firm types per quintile where q_1 includes types 1 and 2,..., q_5 includes types 9 and 100.

Figure 13: Distribution of worker types across firm types: short tenure

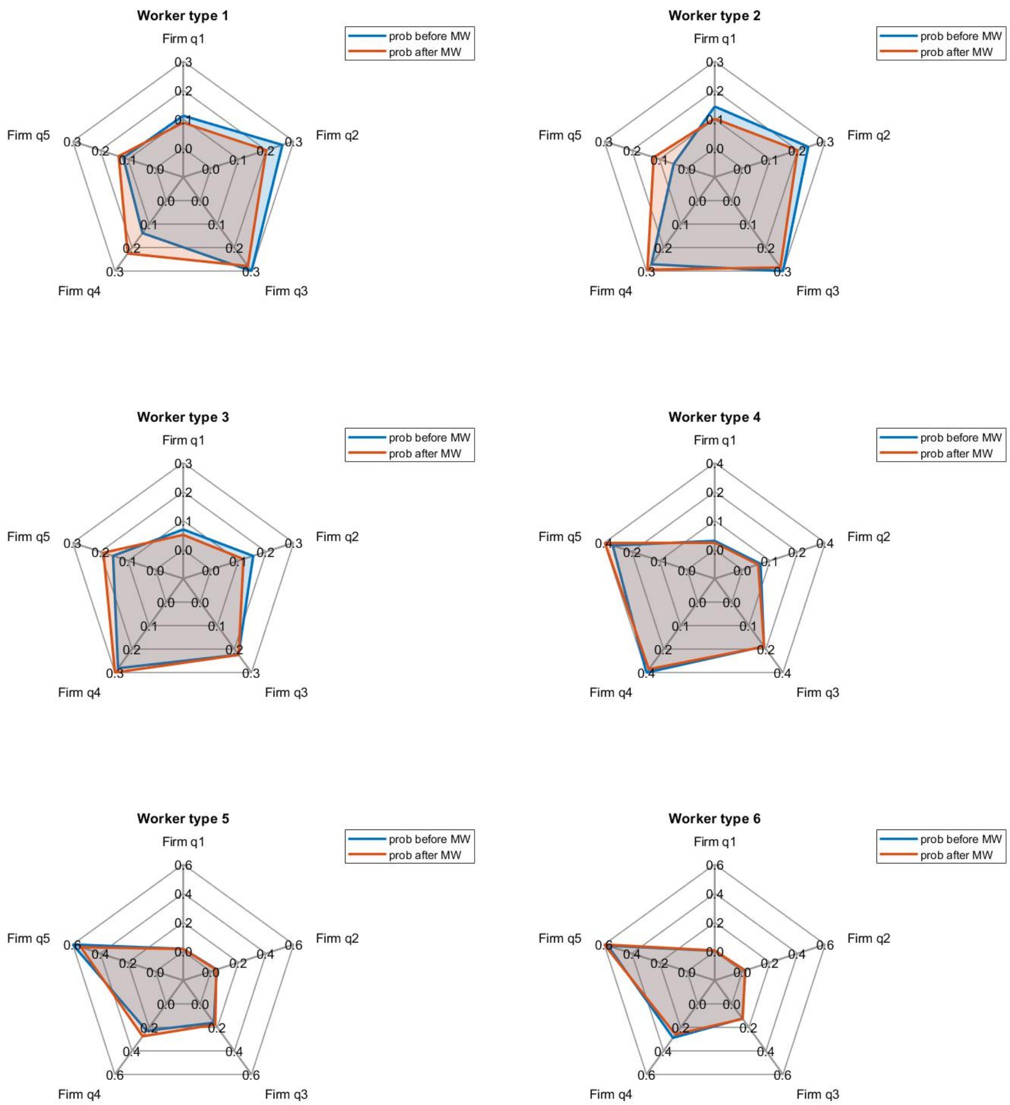
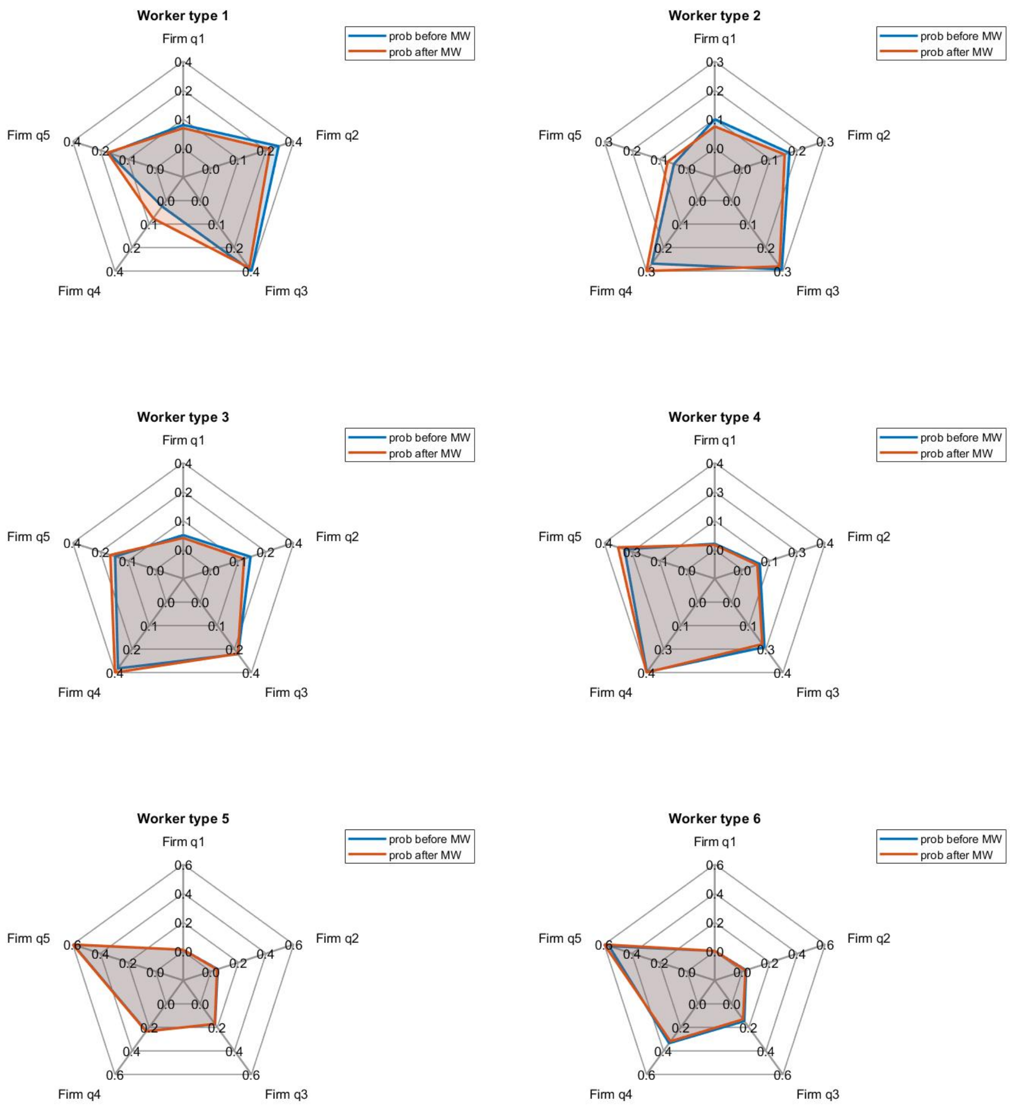


Figure 14: Distribution of worker types across firm types: long tenure



7 The effects of minimum wage on earnings, unemployment and informal sector

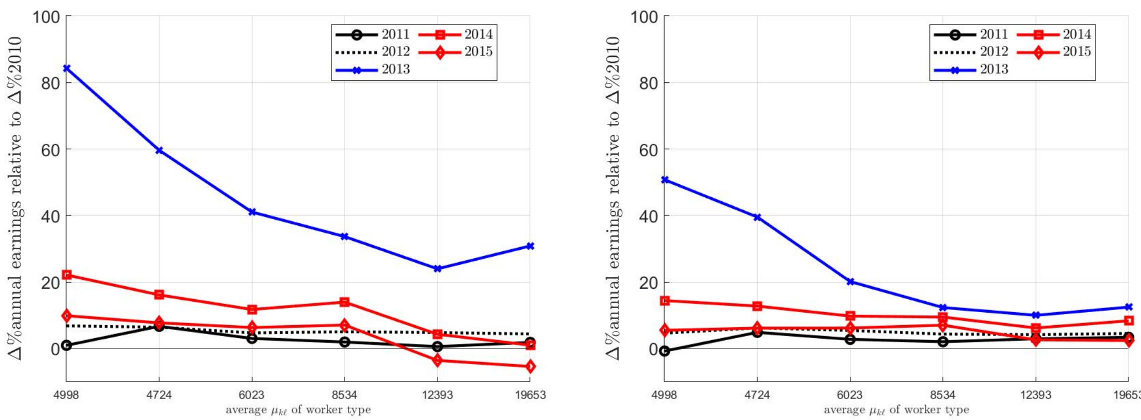
In this section, we first show the effects of the minimum wage policy on earnings and unemployment probability, accounting for pre-trends. We argue that given the size of the policy, there is no pure control group in this case. We then confirm our findings at the national level by using a spatial variation approach. Finally, we examine the labor market shares of formal and informal sectors.

7.1 Earnings

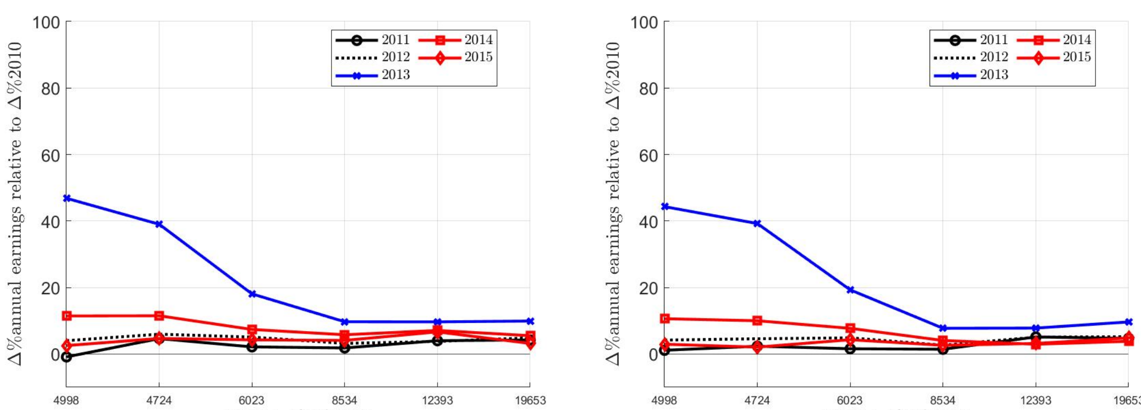
The average annual earnings growth rates relative to the growth rate in 2009-2010 (before the policy) are shown in figure 15. The horizontal axis shows the expected mean wage $\mu_{k\ell}$ of each k type. Results

Figure 15: Annual earnings growth by average $\mu_{k\ell}$ of worker type

(a) 25- 30 yrs old (left) and 30-35 yrs old (right)



(b) 35-40 yrs old (left) and >40 yrs old (right)



are similar whether we assign workers to the most likely type or take average earnings weighted by the posterior probability, $p_i(k)$. Overall, there are larger gains among low-type workers and some spillover on the earnings of high-type workers. There are differences in the earnings gains across worker types. We decompose the sources of these gains in section 8.

One way to quantify the effects of the minimum wage policy is to perform differences-in-differences, assuming the highest earning-type is the control group e.g. as in Dustmann et al. (2021). However, we argue that given the size of the policy, there is no pure control group in this case. We confirm this using a spatial variation analysis in section 7.4.

7.2 Unemployment

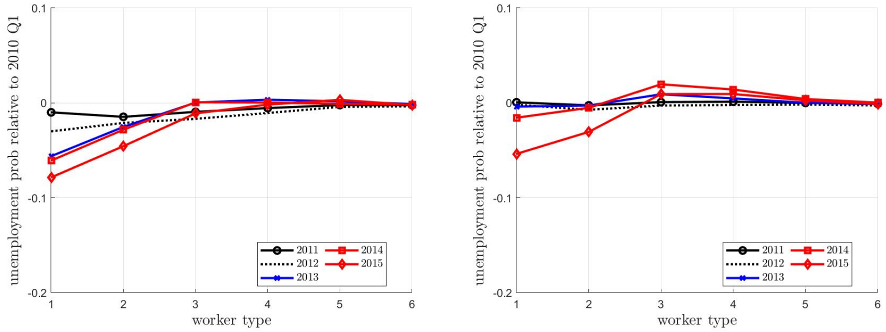
A number of papers in the minimum wage literature have found little disemployment effects of minimum wages, e.g. Card and Krueger (2000). Most papers focus on workers who are employed before the policy and find that these workers are not any more likely to lose their jobs after the policy than before. However, workers who have been unemployed for some time before the policy may have a harder time finding jobs if there are fewer vacancies due to a lower separation of existing matches.

To better understand the minimum wage effects thoroughly, we divide our outcomes into two categories: the probability of remaining unemployed for workers who were unemployed less than seven months at a given point in time and the probability of remaining unemployed for workers who were unemployed for more than seven months ago. Figure 16 shows the unemployment probabilities of each worker type, $p(k, \ell = 0|x)$ relative to their respective unemployment probability in 2010 where the left panel are outcomes of workers who were unemployed less than seven months (held jobs recently) and the right panel are those who were unemployed for more than seven months ago.

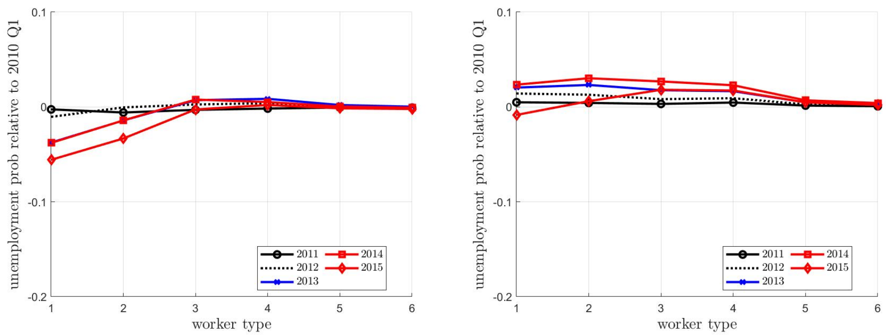
We can see that among workers with a short duration of unemployment (left panel), their probabilities of remaining unemployed after the minimum wage policy in 2013 becomes lower for workers of type 1-2 and similar to that of the prior years for other types. These workers with short unemployment duration (relatively high attachment to the labor market) leave the unemployment pool faster. This is consistent with Dube et al. (2016) and Gittings and Schmutte (2016) who find that minimum wages can lower separate rates. In contrast, if we look at the right panel which shows the probability of remaining unemployed among those who have been unemployed for at least 7 months aged 30 and above, then we see that these workers with relatively low labor force attachment are more likely to remain unemployed after the minimum wage policy in 2013. Thus, while there is little disemployment effect on workers who were employed before the policy, there is a substantial adverse effect on the re-employment probability of workers older than 30 years old who have a relatively long unemployment spell.

Figure 16: Change in unemployment prob YoY in Q1 by worker type

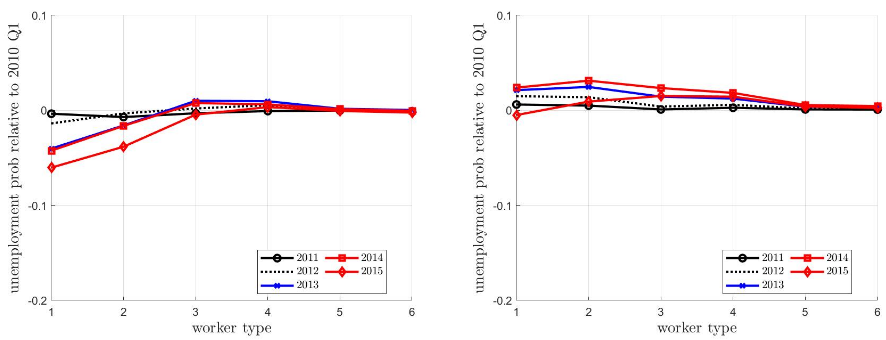
(a) 25- 30 yrs old: short tenure (left) long tenure (right)



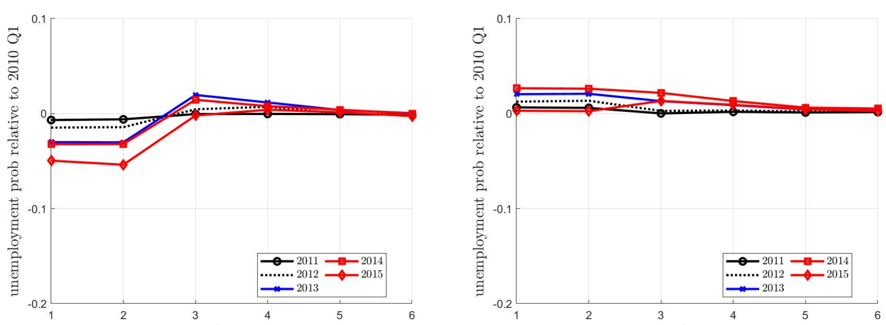
(b) 30-35 yrs old: short tenure (left) long tenure (right)



(c) 35-40 yrs old: short tenure (left) long tenure (right)



(d) >40 yrs old: short tenure (left) long tenure (right)



7.3 Formal and informal labor markets

Previous studies document that the Thai formal and informal sectors are connected. For instance, a non-trivial fraction of formal workers is observed moving in-and-out during the agricultural season (Wasi et al. (2021)). The minimum wage policy could affect the transition between the two sectors. We show the time trends of workers in the formal and informal sectors using the Thai LFS. Workers in the formal sector are defined as those who work in the private sector – we exclude government and state enterprise workers since this sector has their own pay and pension schemes and do not tend to move across sectors – they account for about nine percent of the labor force. Informal workers include self-employed and unpaid family workers. Unemployed workers include those who are not working and seeking for jobs.

Among those aged 25-50 years, over the period of 2008-2015, the share of formal workers increased from 38 to 42 percent. The increase is more pronounced after the policy.[15] The composition by age and education groups also changed. Figure 17 plots the shares of workers in the three statuses: formal, informal and unemployed by age groups and education from 2008-2015 where the solid vertical line is the first round of minimum wage hike and the dashed line is the second round. Among workers aged 25-34 years old who have primary and high school education in panel (a), there is a noticeable increase in their shares in the formal sector after the minimum wage hike at the start of 2013, and a decrease in their shares in the informal sector. We also see a similar trend but less pronounced among primary and high school workers aged 35-44 years old. The time trends appear minimally changed for all other age and education groups.

Overall, figure 17 suggests that the formal sector has expanded, while the informal has contracted after the minimum wage policy. This is in line with Magruder (2013) also finds that employment in the formal sector increased while that the informal sector decreased in response to the minimum wage policy in Indonesia.

7.4 Spatial variation approach

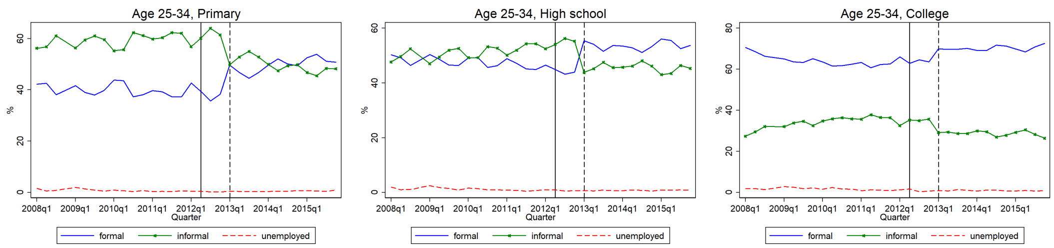
Given that previous minimum wages vary by province, we exploit spatial variation in the exposure to the nationwide minimum wage in this section. The continuous measure for each province's exposure to the minimum wage depends on both the share of workers in the province who earn less than the minimum wage, and the difference between their wages and the minimum wage. We follow Dustmann et al. (2021) by defining

$$GAP_{pt} = \frac{\Sigma_{i\in p}\max\{0, MW - w_{it}\}}{\Sigma_{i\in p} w_{it}}$$

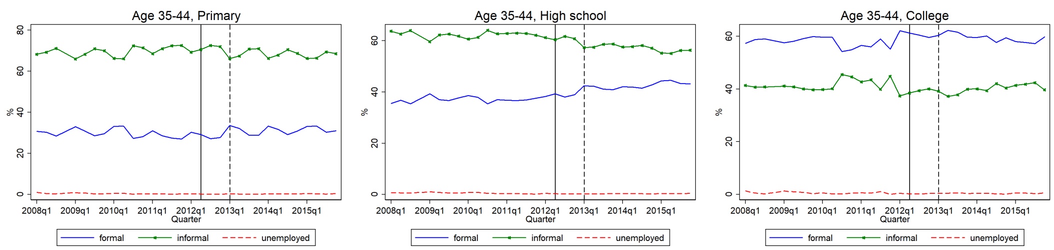
[15]Using the LFS, Samutpradit (2024) finds that one percent increases in minimum wages reduced the employment in the covered sector (formal sector) by 0.1-1.1 percent. However, her sample focuses on primary educated workers aged 15-60 years old. Our analysis focuses on primed age workers, 25-50 years old since some workers aged below 25 years old might still be in training or school and there is a mandatory retirement at 55 years old in the private sector.

Figure 17: Shares of workers across sectors

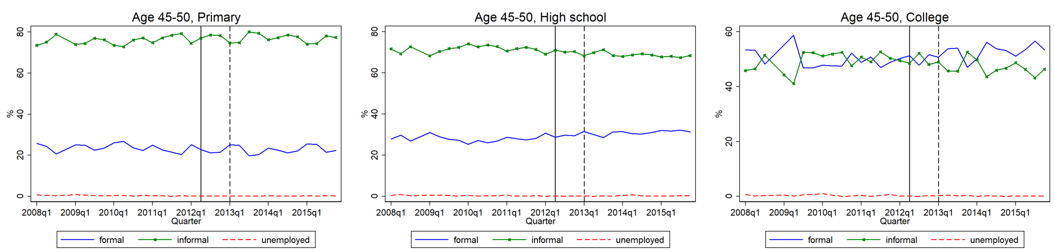
(a) 25-34 years old by education level



(b) 35-44 years old by education level



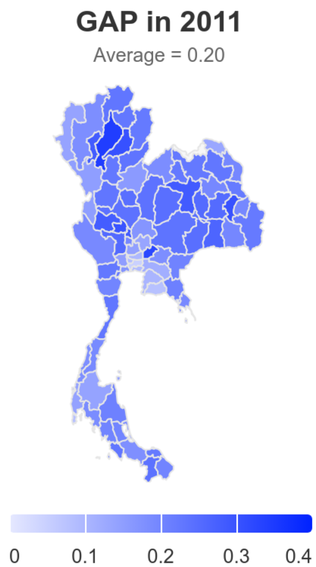
(c) 45-50 years old by education level



where p denotes a province, t is year and i indexes workers. GAP equals zero means there is no worker with wage below minimum wage. Provinces with high GAP reflects either a higher number of workers with wage below the minimum wage or the gap between the current and minimum wage or both.

We compute GAP for 77 provinces in Thailand and calculate GAP during year 2011. The average GAP in 2011 is 0.20 where large provinces such as Bangkok and metropolitan area have lower GAP, and small provinces such as the north eastern provinces have larger GAPs. Figure 18 shows variation in GAP across provinces.

Figure 18: Spatial variation in exposure to the MW policy



We first estimate the effects of the minimum wage policy on the overall employment and earnings including both pre and post-MW workers. The specification is

$$Y_{pt} = \alpha_p + \theta_t + \delta_{post} GAP_{p,2011} POST_t + \beta_p time_t + \varepsilon_{pt}$$

where Y_{pt} is the outcome of interest in province p year t, α_p is province fixed effect, θ_t is time fixed effect, $POST_t$ is an indicator variable equal to 1 for the post-MW policy years, and $time_t$ is a linear time trend that can vary across provinces. The key parameter of interest is δ_{post}. Table 6 shows the estimates of δ_{post} under various specifications when the outcome variable is employment, earnings and wage. The effect on employment is sensitive to the specification. It is not statistically different from zero in specification 1 when not controlling for provincial level linear trend, but becomes negative, though not very precisely estimated, when controlling for the linear trend. The effects on wage and earnings are all statistically significant and positive implying that comparing the provinces less affected by MW (GAP close to zero) to provinces more affected by MW, wages or earnings of the latter increase by 0.4-0.5 percent when GAP increases by 1 percent.

Table 6: GAP regression results

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variables:	Employment	Employment	Earnings	Earnings	Wage	Wage
GAPxPost	-0.056	-0.219*	0.521**	0.491**	0.515**	0.46**
	(0.13)	(0.11)	(0.04)	(0.04)	(0.03)	(0.03)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Province linear trend	No	Yes	No	Yes	No	Yes
R^2	0.999	0.835	0.995	0.959	0.996	0.965
N	539	539	539	539	539	539

Notes: standard errors in parenthesis and clustered at the province level. * and ** denote statistical significance at 5% and 1% levels, respectively.

Next, we estimate the minimum wage effect on earnings by type. We assign workers to types most probable types based on their $p_i(k)$. As can be seen in table 7, the minimum wage effects remain positive on all types even the highest type. This confirms the size of spillover we found in figure 15.

Table 7: GAP regression results on log earnings by worker type

Worker type:	1	2	3	4	5	6
GAPxPost	0.095**	0.54**	0.061**	0.296**	0.126**	0.013**
	(0.05)	(0.04)	(0.05)	(0.08)	(0.05)	(0.05)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Province linear trend	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.971	0.983	0.989	0.939	0.866	0.912
N	539	539	539	539	539	539

Notes: standard errors in parenthesis and clustered at the province level. * and ** denote statistical significance at 5% and 1% levels, respectively.

8 Decomposition

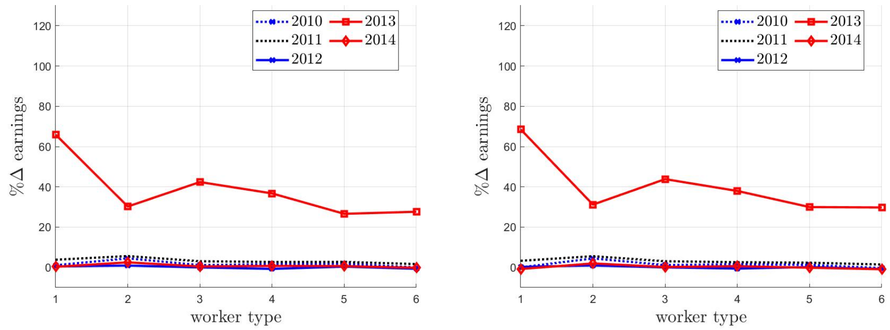
In this section, we use simulation to perform decomposition of sources of earnings gains as well as compute the net present value of life-time income over 20 years from the policy. We first simulate each age group's earnings in the pre-MW policy model environment then counterfactually set each parameter to the post-minimum wage policy to quantify the contribution of each channel in section 8.1. To understand the long-term implications of the policy, we simulate individuals as new entrants in the labor market in the pre and post-MW environments over the course of 20 years and compare their net present value of lifetime income in section 8.2.

8.1 Earnings decomposition

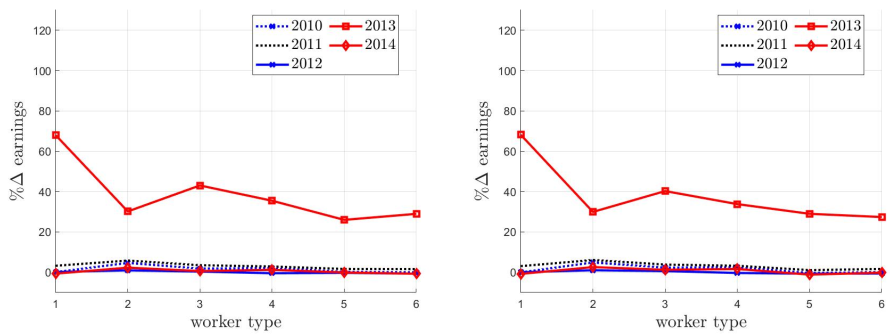
In this first exercise, we simulate individuals of each age group drawn from the initial match distribution for five years in the pre and post-MW environments. We hold age categories fixed in each five year simulation, but tenure and matching allocation evolve according to the estimated transition rates. Figure 19 shows the simulated earnings and 20 shows the simulated mutual information in the benchmark which

Figure 19: Simulated earnings: benchmark model

(a) 25- 30 yrs old (left) and 30-35 yrs old (right)



(b) 35-40 yrs old (left) and >40 yrs old (right)

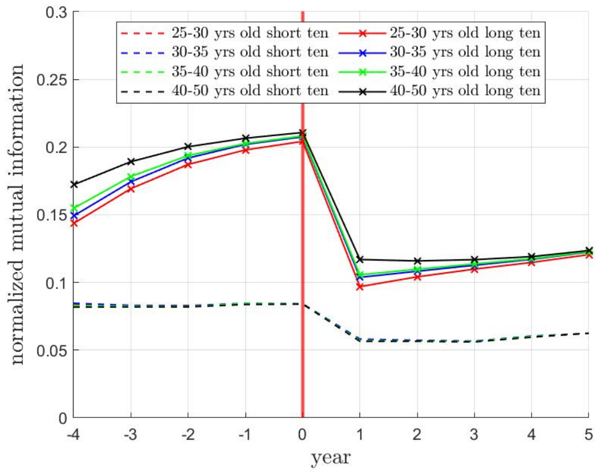


reasonably match their data counterparts in figures 15 and 11, respectively.

We focus on decomposing the sources of earnings growth between 2012 and 2013, one year after the policy since this is where the year-on-year gains are largest. Table 8-11 show the decomposition for workers of each age group where column 1 is the overall earnings growth between 2012-13 by worker type. We first decompose the overall earnings growth into the wage and mobility effects in columns 2 and 6, respectively. The wage effect is the counterfactual earnings growth holding all mobility parameters $(\lambda_{k\ell'}, \gamma_{k\ell}, \delta_{k\ell}, \psi_{k\ell})$ fixed at the pre-policy level. The mobility effect is the counterfactual earnings growth holding all wage parameters $(\mu_{k\ell}, \sigma_{k\ell})$ fixed at the pre-policy level. The mobility effect accounts for a small part of the earnings gains for workers of types 3-6, but plays a substantial role on the earnings gains of type-1 workers. Interestingly, it has a negative effect on the earnings of workers of type 2.

To better understand the mobility effect, we decompose mobility into changes in the EE moves through changes in the chance and choice parameters: $\lambda_{k\ell}(x), \gamma_{k\ell}(x)$ in column seven and EUE moves through changes in $\psi_{k\ell}(x)$ and $\delta_{k\ell}(x)$ in column 8. Overall, after the policy, most workers make larger gains from EE moves than before with an exception of workers of types 1 and 2. The negative effect of

Figure 20: Benchmark mutual information



mobility on type-2 workers' earnings comes predominantly from the EE moves, rather than transitions involving unemployment or EUE.

Furthermore, as firms may try to save labor costs by paying workers more now, but giving them a smaller raise later on the job. That is, the returns to tenure may be proportionately lower leading to a tradeoff between initial and later wages for some workers. We further decompose the wage effect into (i) an increase in wages for new entrants or short-tenure workers, and (ii) a wage adjustment for long-tenure workers. Column four presents the initial wage effect which is counterfactual earnings gains if the short-tenure wages are at the post-policy level, but the return to long-tenure employment and all mobility parameters had counterfactually stayed at the pre-policy level. We attribute the difference between this counterfactual earnings in column four and the overall wage effect in column two as the later wage effect in column five. The positive gains in both columns four and five show that workers gain from both initial and later wages. There is no evidence of tradeoff between the initial and later wages faced by workers.

Table 8: Percent change in annual earnings between 2012-2013 for 25-30 years old

Worker type	Full effect (1)	Wage effect (2)	Initial Wage (4)	Later Wage (5)	Mobility effect (6)	EE effect (7)	EUE effect (8)
1	65.93	48.42	45.95	2.47	17.50	-3.86	21.36
2	30.22	45.70	32.80	12.90	-15.47	-12.39	-3.09
3	42.38	41.26	31.26	10.00	1.13	1.74	-0.61
4	36.74	34.44	23.66	10.77	2.30	5.37	-3.07
5	26.61	29.15	22.50	6.65	-2.54	4.15	-6.69
6	27.63	28.86	22.21	6.65	-1.23	2.39	-3.63

Table 9: Percent change in annual earnings between 2012-2013 for 30-35 years old

Worker type	Full effect (1)	Wage effect (2)	Initial Wage (4)	Later Wage (5)	Mobility effect (6)	EE effect (7)	EUE effect (8)
1	68.53	48.31	45.85	2.46	20.22	-3.79	24.01
2	31.18	45.71	32.74	12.97	-14.54	-12.50	-2.04
3	43.84	41.32	31.38	9.95	2.51	1.71	0.81
4	37.96	34.45	23.65	10.80	3.51	5.48	-1.98
5	29.96	29.13	22.52	6.60	0.83	3.94	-3.11
6	29.76	28.92	22.22	6.70	0.84	2.28	-1.44

Table 10: Percent change in annual earnings between 2012-2013 for 35-40 years old

Worker type	Full effect (1)	Wage effect (2)	Initial Wage (4)	Later Wage (5)	Mobility effect (6)	EE effect (7)	EUE effect (8)
1	68.02	48.41	46.04	2.37	19.61	-3.88	23.49
2	30.18	45.79	32.91	12.87	-15.61	-12.14	-3.46
3	43.06	41.45	31.62	9.82	1.61	1.79	-0.18
4	35.48	34.42	23.70	10.72	1.06	5.71	-4.64
5	26.00	28.91	22.64	6.27	-2.91	3.65	-6.56
6	28.98	28.96	22.23	6.72	0.03	2.12	-2.10

Table 11: Percent change in annual earnings between 2012-2013 for 40-50 years old

Worker type	Full effect (1)	Wage effect (2)	Initial Wage (4)	Later Wage (5)	Mobility effect (6)	EE effect (7)	EUE effect (8)
1	68.21	48.37	46.05	2.32	19.84	-3.88	23.72
2	29.94	45.87	33.12	12.76	-15.93	-11.89	-4.05
3	40.27	41.49	31.77	9.72	-1.22	1.91	-3.13
4	33.80	34.40	23.73	10.68	-0.60	5.84	-6.44
5	29.00	28.75	22.70	6.05	0.25	3.34	-3.09
6	27.40	28.99	22.22	6.77	-1.58	1.99	-3.57

8.2 Net present value of lifetime income

Given, that effect of mobility could evolve over time, we simulate net present value (NPV) of lifetime income of young workers entering the labor market over 20 years in the pre versus post-policy environments. Table 12 shows the gains in terms of the level of NPV over 20 years and the percentage change in NPV. Overall, workers gain substantially in both short and long runs in terms of earnings from this policy.

Table 12: Change in net present value of lifetime income over 20 years of young workers

Worker type	NPV levels (1)	NPV %△ (2)
1	455,208	71.27
2	426,515	45.98
3	525,746	49.63
4	721,327	43.02
5	860,768	31.18
6	1,203,750	29.07

Notes: Simulation of new entrants at age 25 years old forward for 20 years. Column 1 shows the difference between NPV of lifetime income between pre and post-minimum wage policy environments and column 2 shows the corresponding percentage change.

9 Conclusion

In this paper, we estimate the effects of the introduction of a nation-wide minimum wage in Thailand on earnings and sorting using the Thai matched employer-employee Social Security data. First, we show that there is a great degree of mobility differential among workers with similar wages. Hence, it is crucial to analyze the impact of the minimum wage policy in a framework that can incorporate both employed and unemployed workers as well as taking mobility versus wage heterogeneity into account. To this end, we adopt the semi-parametric model of wages and employment mobility with two-sided heterogeneity of Bonhomme et al. (2019) and Lentz et al. (2023).

We find that while the minimum wage had little disemployment effect on workers who were employed before the policy, there is an adverse effect on workers who were not employed for at least seven months before the policy. The probability of finding a job for these unemployed workers declined. Sorting among new employment matches after the policy became less positive. Low type or less productive firms exited the market and more productive firms expanded. Workers reallocated from less to more productive firms. The minimum wage raised earnings considerably for low paid workers and there is also positive spillover on high-paid workers. To understand what drives the earning effects, we use our model to decompose sources of earnings gains in one year after the policy. We find that mobility accounts for a considerable fraction of earnings gains in the short-term. However, some workers face a negative mobility effect on earnings through their job-to-job moves making the long-term implications ambiguous. We therefore simulate the net present value of lifetime income of workers. Despite some negative mobility effect, the gains on net present value of lifetime income over 20 years are estimated to be substantial for all workers.

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APPENDIX

A Wage Imputation

The Social Security taxable salary is capped at 15,000 bahts since the start of the Social Security system. In our sample, out of 503,694,802 employment observations, 20 percent of employment observations are right censored at the cap. The censoring rates are higher over time, from about 10 percent in 2009 to 30 percent in 2015. We adopt the imputation technique from Card et al., 2013 by fitting a series of Tobit model. From 2009 to 2015, we fit a total of 840 Tobit models separately by month-year, gender, and 5-year age range (25-29, 30-34, 35-39, 40-44, 45-50 years old). Worker, firm, and job characteristics are included in the model.

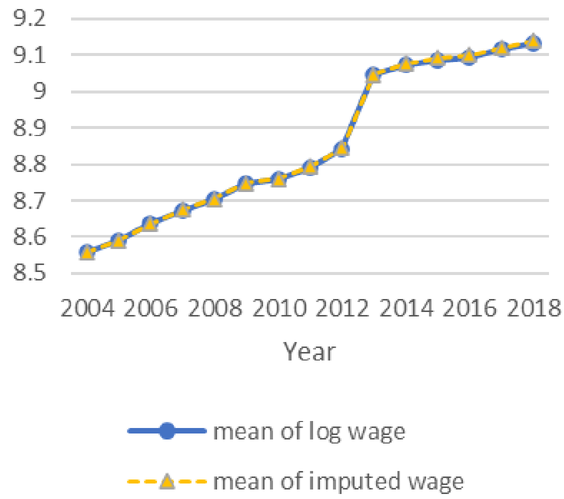
We have no information on the workers' education levels. However, the age at which they first registered with the Social Security is a proxy for their education. Those who joined the labor market when young, say 18, are likely to obtain a lower level of education. Workers' time-varying characteristics include mean log wages in the past 12 months, a fraction of months with censored wages from the whole sample period, and months being unemployed in the past 12 months. For workers who are observed only once in the sample, we include a dummy for such workers in the tobit model. Their mean past log wages are set to the sample mean by age and gender, and their fraction of months with censored wages are set to the sample mean.

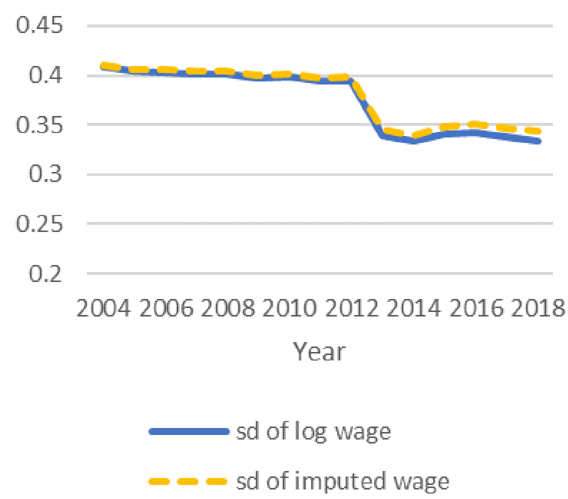
Variables that reflect firm characteristics include firm sizes (and squared), mean log wages of co-workers, fraction of male workers at the firm, fraction of co-workers with censored wages, and median log wages of all workers at the firm. For firms with one worker, sample mean log wages of workers with the same gender and cohort are used instead of mean log wages of co-workers.

The imputed log uncensored wages from the Tobit model are then calculated from the predicted wage and a random draw from the associated right-censored distribution. Specifically, let $y \sim N\left(X'\beta, \sigma^2\right)$ be an uncensored log wage distributed as normal with mean $X'\beta$ and standard deviation σ. For the censored observations, $y \geq c$, the uncensored value, y^u is then calculated as $y^u = X'\beta + \sigma\Phi^{-1}\left[k + \mu\left(1-k\right)\right]$, where $k = \mu\Phi\left[\frac{c-X'\beta}{\sigma}\right]$ is a normal CDF and $\mu \sim U\left[0,1\right]$ is a draw from a standard uniform distribution, and σ is estimated from the Tobit model

To assess how well our model performs in imputing the upper tails of monthly wages, we implement a validation exercise. We create an artificial censoring data where truth is actually observed, and impute wages using the above model, then compare the mean and standard deviation of the real and imputed wages over time. We use the sample of male age 25-29 whose censoring rate in the data ranges from 0.82 percent in 2004 to 5.1 percent in 2018 for the exercise. We create an artificial censoring at 14,000 bahts (the actual censoring wage is at 15,000 bahts). The means and standard deviations of imputed and the actual wages are shown in figure A.1. As we can see, the means and standard deviations of imputed wages line up with the actual wage data quite well.

Figure A.1: Imputation validation exercise





B Wage inequality and variance decomposition

Wage inequality has declined after the minimum wage policy which is consistent with our findings in figure 15 that earnings growth are higher for low type or low wage workers. Table A.1 reports wage variance decomposition over time. The first row clearly shows that the variance of log wages became lower. We then decompose the log-wage variance as follows:

$$
\begin{aligned}
\mathrm{V}(w_{it}) &= \mathrm{E}[V(w_{it}|k_i,\ell_{it},x_{it})] + \mathrm{V}[\mathrm{E}(w_{it}|k_i,\ell_{it},x_{it})] \\
&= \mathrm{E}[\sigma^2(k_i,\ell_{it},x_{it})] + \mathrm{V}[\mu(k_i,\ell_{it},x_{it})],
\end{aligned}
$$

and

$$
\begin{aligned}
\mathrm{V}[\mu(k_i,\ell_{it},x_{it})] = {} & \mathrm{V}[\overline{\mu}(x_{it})] + \mathrm{V}[a(k_i)] + \mathrm{V}[b(\ell_{it})] \\
& + \mathrm{V}[\widetilde{\mu}(k_i,\ell_{it},x_{it})] + 2\,\mathrm{Cov}[\overline{\mu}(x_{it}), a(k_i)] \\
& + 2\,\mathrm{Cov}[\overline{\mu}(x_{it}), b(\ell_{it})] + 2\,\mathrm{Cov}[a(k_i), b(\ell_{it})],
\end{aligned}
$$

where expectation operators (and variance and covariance) are with respect to distribution $p(k,\ell,x)$.

We have higher within variation and lower between variation after the minimum wage policy. The contribution of variation in the person effect on the variance has reduced slightly after the minimum wage policy. The degree of wage sorting as measured by the correlation between worker and firm wage fixed effects has declined minimally. However, as discussed earlier, the mutual information which is a more

Table A.1: Unconditional variance decomposition

		Before MW	After MW
Variance w		0.36	0.26
Percent contribution:			
Residual	$E\sigma^2$	13.32	28.50
Between-var	Var(μ)	86.68	71.50
Person effect	Va	24.93	22.36
Firm effect	Vb	27.65	24.00
Cross effect	2Cov(a,b)	17.68	15.07
Match effect	V$\tilde{\mu}$	12.28	7.08
	Vβ	2.56	1.87
Observed het.	2Cov(a,β)	1.10	0.89
	2Cov$(b,\bar{\beta})$	0.48	0.23
Sorting	Corr(a,b)	0.34	0.33

flexible measure of dependence between matches tells us that sorting has declined substantially after the minimum wage policy.