Investigating the Effects of Minimum Wages on Employment, Unemployment, and Labour Participation in Java Indonesia: A Dynamic Spatial Panel Approach

INTRODUCTION

Despite the vast number of studies on the topic, economists have yet to reach a consensus on the employment effects of minimum wages. Numerous studies in minimum wages varying in data, quantitative approach, target industries, and countries have been conducted in order to understand the workings of labour markets (Card and Krueger 1995; Brown 1999; Neumark and Wascher 2008). While various empirical literatures support the standard theory of a negative employment impact of minimum wages (Brown et al 1982; Neumark and Wascher 1992), others show that there is barely an effect (Card and Krueger 1995; Dube et al 2010). A few even show the opposite, where a rise in minimum wages is expected to increase employment (Card and Krueger 1994).

Among the reasons for the variation in the empirical results are the differences in methodologies and underlying assumptions used when modelling the labour market. For example, many studies assume full coverage of the minimum wage, meaning that the minimum wage law applies to all workers. However, in the real economy, especially in developing countries, coverage of the minimum wage policy may be low. The presence of economic sectors which do not respect the minimum wage policy complicate the effects of minimum wages, as workers who failed to obtain formal employment due to minimum wage hikes may move to the informal sector where they could work for lower pay than the minimum wage. As a result, the employment impact of minimum wage increases may become indistinguishable from zero or even positive depending on the coverage of the minimum wage and the size of the informal sector[1].

Moreover, previous studies usually assume labour markets to be geographically independent from one another. However, in reality, this may not be the case. For example, a job vacancy is rarely posted with the condition that nobody outside the immediate geographical vicinity is ineligible to apply. Furthermore, a spatially located phenomenon, such as an increase in a city's minimum wage level, might not only affect workers in that city but also workers in neighbouring towns. Consequently, workers from other cities might be attracted to relocate to areas with higher minimum wages to get a better paying job.

Therefore, we allow labour markets to be geographically correlated. In doing so, we use spatial panel econometric methods, as standard econometric techniques frequently fail in the presence of spatial autocorrelation commonly found in geographic datasets (Anselin 2001). This is important, as estimating a model using geographical data under the assumption of non-spatially related units, when they are indeed spatially related, may result in biased estimates (LeSage and Pace 2009). As a comparison, we also estimate our model using a non-spatial model. Furthermore, we also analyse the effects separately by gender, as previous studies have shown disproportionate effects of minimum wages between genders (Suryahadi et. al. 2003, Chun and Khor 2010, and Comola and de Mello 2011).

We contribute to existing literature not only by incorporating informal sector employment, but also by relaxing the assumption of spatial independence. To our knowledge, this is the first paper to investigate the consequences of minimum wage increases in a two-sector labour market whilst considering spatial correlation among districts in Indonesia.

We focus our analysis on the island of Java, Indonesia. Java provides an opportunity to analyse how minimum wage increases might affect workers not only in the district where it was increased, but also those in neighbouring districts, as many districts have their own minimum wage level. Moreover, most internal migration in Indonesia occurs in Java (Ilmiawan

[1] Definitions of formal and informal sectors in this study are discussed in more details in the upcoming section *Overview of Minimum Wages and Labour Market in Java*.

2019). With its relatively advanced infrastructure and transportation modes, movement costs within Java are likely to be lower compared to that in outer islands, making it more plausible for workers to be affected by minimum wage differences across districts.

The results of this study highlight the need to account for spatial dependence when modelling formal sector employment, unemployment, and labour participation, as we found those variables to be correlated, at least across districts in Java. We show that after allowing labour markets to be geographically correlated, the negative impact of minimum wages on formal sector employment in the district where the minimum wage was increased became statistically nonsignificant. We also found that the effects of minimum wages on employment and unemployment in neighbouring districts are negligible. Conversely, we found that an increase in a districts minimum wage level is associated with a rise in the labour participation of that district and a decline in the labour participation of neighbouring districts. This hints at the possibility of labour mobility from areas with a lower minimum wage to areas with a higher minimum wage, although further research is necessary.

The remaining parts of this paper are as follows. In the second section, we provide a brief overview of the Indonesian minimum wage legislation as well as the labour market conditions in Java. We then review existing literature in the impact of minimum wages on labour outcomes in section three. The fourth section discusses the data and methodology. The fifth and final sections provide the estimation results, discussion and conclusions of this study.

OVERVIEW OF MINIMUM WAGES AND LABOUR MARKET IN JAVA

Minimum Wages in Java

Minimum Wage Trends

Although Indonesia has implemented the minimum wage policy since the 1970s, it received little attention until late 1980s when it was aggressively increased in order to stop sweatshop employment. Initially, minimum wages in Indonesia were set by the central government. However, in line with the fiscal decentralization in 2001, minimum wage setting responsibilities were transferred to the provincial government. Although most provinces set only province level minimum wages, most provinces in Java, as well as few others outside Java, set district level minimum wages. Minimum wages in Java has been on an increasing trend both in nominal and real terms (Figure 1.1).

The official purpose of the establishment of minimum wages is to meet the adequate living standard needs *(Kebutuhan Hidup Layak/*KHL) of a single worker. KHL is calculated based on a yearly survey[2]. Different minimum wage levels are set for different districts partly to reflect the variations in living costs and price levels. Thus, in Figure 1.2, we show the ratio of district minimum wages to the district consumer price index (CPI)[3]. Districts which do not have their own CPI are assigned the CPI of their nearest neighbouring district. Although we can see some cluttering, especially in western Java where minimum wages are relatively higher, in the eastern parts of Java, the ratios are relatively dispersed where districts with high real minimum wage levels share borders with districts with lower minimum wage levels. Consequently, workers might be attracted to move to areas where minimum wages are relatively higher.

Figure 1. Minimum Wages in Java

Figure 1.1 Average Minimum Wages, 2001 - 2015

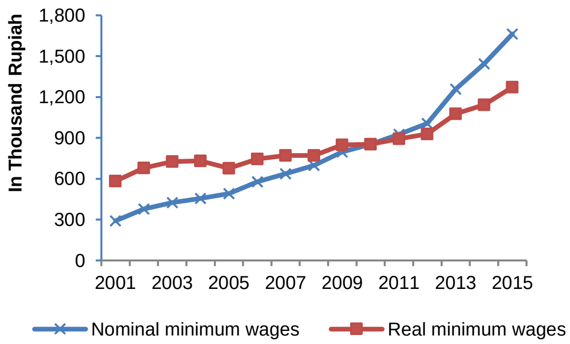
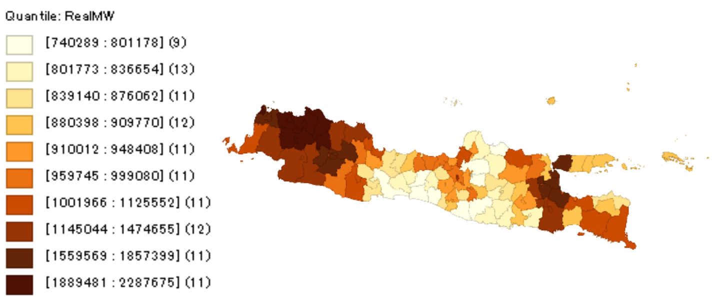


Figure 1.2 Ratio of Minimum Wages to CPI in Java by Districts, 2015



Source: Author's calculations based on minimum wages and expenditure data 2015 obtained from BPS.
Note: Both figures: Real minimum wages values were calculated using 2010 prices.
Figure 1.1: Average minimum wage is obtained by taking the average of the minimum wages of all districts in Java.
Figure 1.2: The numbers in the brackets on the right-hand side of the minimum wage levels show the number of districts with the said minimum wage level.

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[2] Indonesian Law on Manpower Affairs 2003 articles 88 and 89.
[3] Due to data limitation, we use CPI instead of KHL.

Coverage of the Minimum Wage Policy

The Indonesian minimum wage policy is applied following the classification of workers defined by the Indonesian Bureau of Statistics (*Badan Pusat Statistik/*BPS) which is formulated based on workers' occupational sectors and statuses[4]. The minimum wage provision covers all sectors and statuses, where *entrepreneurs* are prohibited from paying their *employees* lower than the minimum wage[5]. However, because most workers in Indonesia are not classified as *employees,* the number of workers not covered by the minimum wage law is relatively large. Even in the covered sector, compliance with the minimum wage law is quite low. In 2015, 47% of regular wage employees were paid lower than the minimum wage (Ginting et al. 2018).

Given the magnitude of workers earning less than the minimum wage, it is important to consider them in analysing the effects of minimum wages. Therefore, we incorporate activities in the informal sector where the minimum wage law does not apply and the formal sector where the minimum wage regulation is enforced. We consider workers with the statuses of *employees* and *employers with permanent workers* as workers in the formal sector. Meanwhile, workers with other statuses are assumed to be employed in the informal sector. Note that this is a simplification of BPS's classification of formal and informal sectors which also considers workers' occupational sectors (agriculture, manufacturing, trade, etc.). However, this will not change our findings meaningfully as we only focus on urban areas where agriculture work, where the minimum wage does not apply, is less extensive. Comola and de Mello (2011) also analysed the impact of minimum wages on urban formal and informal employment and found that including agricultural salaried workers either in the formal or informal sector did not cause significant changes to their results. The sign and magnitude of the coefficients estimated by both classifications are comparable to one another.

[4] The classification of workers' status by BPS is as follows: own-account workers, self-employed, employers with permanent workers, regular wage employees, casual employees in agriculture, casual employees not in agriculture, and unpaid workers.
[5] Based on the Act of the Republic of Indonesia Number 13 Year 2003 Concerning Manpower.

Regional Labour Markets in Java Indonesia

Figure 2 shows formal sector employment, informal sector employment, unemployment, and labour force participation rates by districts in Java. Employment in the formal sector is high in cities *(kota)*, while informal employment is rampant in regencies *(kabupaten)*. We can also see dark shaded areas surrounded by a lighter-shaded area. This shows that districts with high formal sector employment are surrounded by districts with high informal sector employment (Figure 2.1) and vice versa (Figure 2.2). Such pattern is common in Indonesia, where *kota* is surrounded by *kabupaten*

Conversely, we can suspect clustering in unemployment rate (Figure 2.3) and labour participation rate (Figure 2.4). This suggests that districts with high unemployment rates and low labour participation rates are located near each other.

Figure 2. Employment and Unemployment Rates in Java by Districts, 2015 (%)

Figure 2.1: Formal Sector Employment

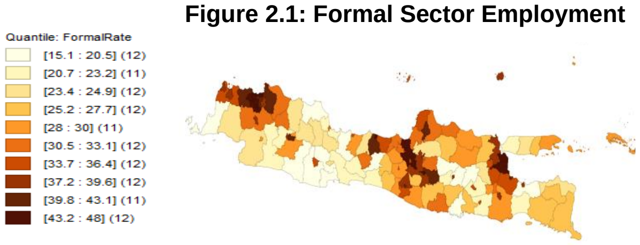


Figure 2.2: Informal Sector Employment

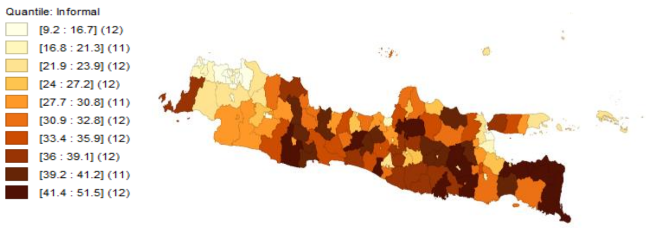


Figure 2.3: Unemployment

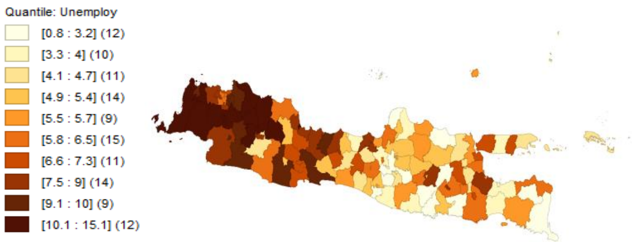
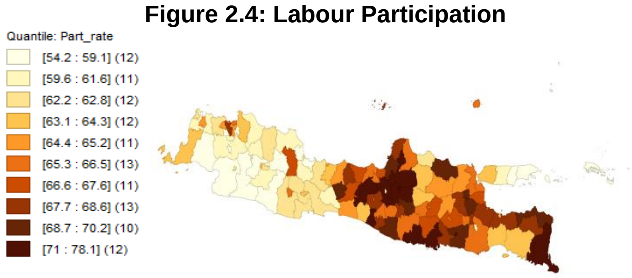


Figure 2.4: Labour Participation



Source: Author's calculations based on Sakernas 2015
Note: Figures are in percentage. Formal sector employment is defined as the number of workers working as: regular wage employees and employers assisted with permanent workers, divided by the number of working age population. On the other hand, informal sector employment is defined as workers with the remaining working statuses divided with the number of working age population. Unemployment is defined as the number of people unemployed divided by the labour force. Labour participation rate is defined as the number of people in the labour force divided by working age population.

Do Workers Cross Borders?

Before analysing the impacts of minimum wage increases on neighbouring areas, we first need to identify the possible channels of such spill overs, which in our case is the geographic movement of workers. Therefore, we briefly review literature on internal migration in Indonesia.

In 2010, the average distance covered by migrants in Indonesia is 673 km (Wajdi et al. 2017). Data from 2010 population census also show that 11.7% of the population resides in a province different from their province of birth and 2.4% had lived in a different province in the previous five years[6]. Based on the inter-census population survey 2015, the main reasons for recent migrants to relocate were family related (40%), work duties (27%) and job seeking (12%). When divided by educational attainment, roughly 40% of recent migrants who are working had a high school diploma as their highest educational attainment, while 43% of migrants had a junior high school diploma or less. Among recent migrants who are employed, 65% work in the formal sector, while the remaining 35% are informally employed. Given that 12% of recent migrants relocate in order to find work in addition to their relatively low educational attainment, a significant portion of them may settle for low-wage jobs in the destination provinces. This argument is supported by Manning and Pratomo (2013) who concluded that migrants, specifically very recent migrants and recent migrants, are more likely to work in the informal sector than non-migrants[7]. On the other hand, Pardede and Listya (2013) showed that migrants who relocate due to work-related motives are more likely to work in the formal sector than those who moved due to family-related reasons.

PREVIOUS STUDIES ON THE EMPLOYMENT IMPACT OF MINIMUM WAGES

Many recent studies on the employment effects of minimum wages found a negative relationship between minimum wages and employment, while others found the relationship to

[6] Migrants who are currently residing in a province different from their province of birth are defined as lifetime migrants whereas recent migrants are defined as those whose current place of residence (at the time of survey) is different from their place of residence five years ago.
[7] Manning and Pratomo (2013) divided migrants into three groups: very-recent migrants (those who moved to their current place of residence during 2003–09); recent migrants (those who moved to their current place of residence during 1998–2002); and long-term migrants (those who moved to their current place of residence before 1998).

be statistically nonsignificant or even positive (as surveyed in Card and Krueger 1995; Neumark and Wascher 2008). Nevertheless, only few studies account for the fact that labour market outcomes are spatially correlated. Kalenkoski and Lacombe (2008, 2013) found evidence of spill over effects of minimum wages on employment in the United States. Based on their findings, a 10% increase in a state's minimum wage level is expected to lower employment in that state by 1.7%. When combined with the impact on neighbouring states, the estimated drop in employment becomes 2%. Similarly, Dolton et. al. (2015) and Lopez-Tamayo et. al. (2017) found evidence of spatial spill over effects of minimum wages on employment in the United Kingdom and Spain, respectively. Dolton et. al. (2015) found the expected negative impact of minimum wages on employment, but the estimates became insignificant when the time lag of employment was included. Likewise, Lopez-Tamayo et. al. (2017) found no significant impact of minimum wages on total population. When divided by age groups, the authors found a negative and significant impact of minimum wages only for the 20-24 age group, while the results for other age groups were nonsignificant.

However, unlike Indonesia, those studies were conducted in countries where compliance with the minimum wage policy is high. While many studies on the employment impact of minimum wages in Indonesia only focus on the formal sector (Islam and Nazara 2000; Rama 2001; Suryahadi et al. 2003), others have also considered the informal sector (Chun and Khor 2010; Magruder 2013; Hohberg and Lay 2015; Comola and de Mello 2011; Siregar 2020). Chun and Khor (2010) found a negative impact on formal sector employment but no significant impact of minimum wages on total employment. Comola and de Mello (2011) found that minimum wages have negative impacts on both male and female workers in the formal sector. They also found positive effects for both male and female employment in the informal sector. Regarding the unemployment rate, the authors found a negative impact on total unemployment and for female unemployment, but the impact on male workers was nonsignificant. Siregar (2020) found that an increase in minimum wages lead to lower employment in both the formal and informal sectors. The author also found that a minimum wage hike is associated with lower unemployment, as labour participation declined. Like the findings of Comola and de Mello (2011), females were also found to be disproportionately affected by minimum wage hikes.

Conversely, Hohberg and Lay (2015) argued that a minimum wage increase would raise the possibility of being employed in the formal sector and lower the possibility of becoming employed in the informal sector. The authors provided two reasons for their results. First, minimum wage increases in their period of study, 1997-2007, were relatively moderate. Second, there is a possibility of other channels of adjustment which are not included in the traditional model. For example, given a minimum wage hike, employers may opt to reduce nonwage benefits, training, profit or turnover, and increase prices or efficiency which may dampen the effects on employment.

Similarly, Magruder (2013) also found a positive impact of minimum wages on formal sector employment and a negative effect on informal sector employment[8]. The author also considered spatial heterogeneity among districts and argued that a minimum wage hike pushes up local product demand which then increases labour demand.

DATA AND METHODOLOGY

Conceptual Framework

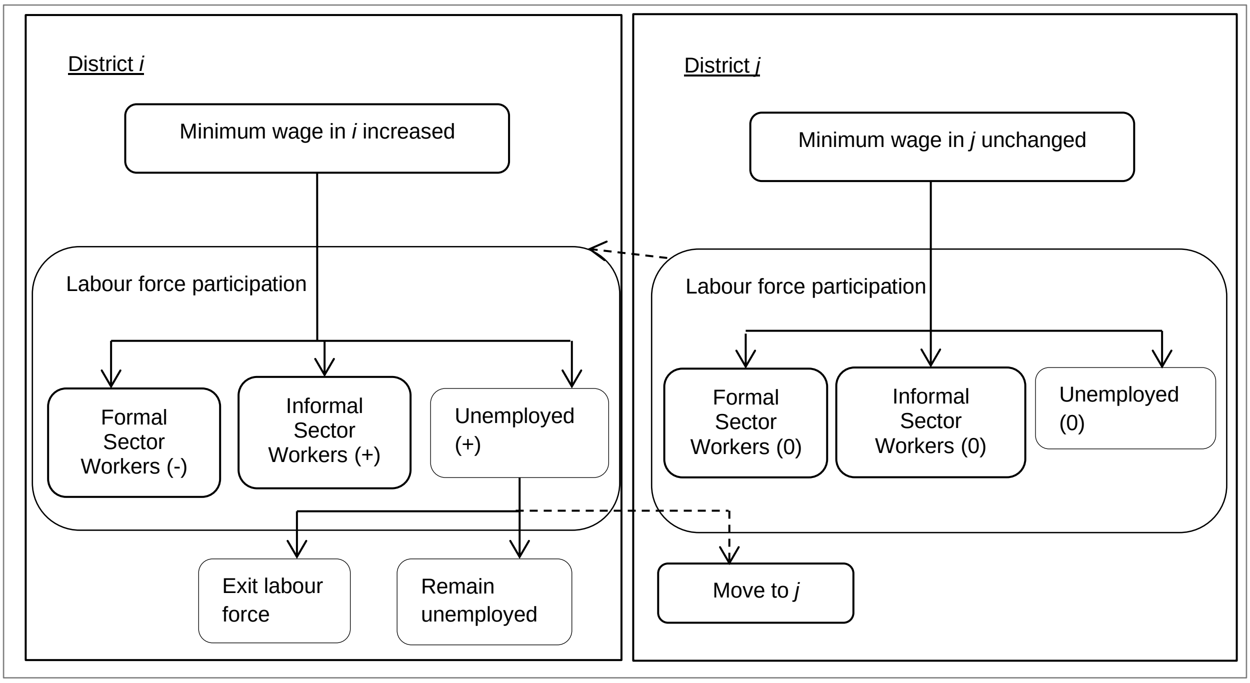
Based on our literature review, we construct the conceptual framework of this study (Figure 3). Assume Java only consists of two districts, district *i* and district *j*. Each district has its own minimum wage level and consists of two employment sectors, the formal sector where compliance to the minimum wage is high and the informal sector where compliance is low. If *i* increases its minimum wage level while *j* leaves its minimum wage level unchanged, there may be several outcomes on workers within *i* depending on whether they are formal or informal sector workers. The increase in *i*'s minimum wage will raise the labour cost of firms in the formal sector. Consequently, there may be workers who got laid off. Similarly, new entrants to

[8] The positive impact of minimum wages on formal sector employment occurs for industries which are both non-tradable (or at least with high cost of trade) and has the potential for formalization. Conversely, for industries which are tradable and has low potential for formalization, a minimum wage increase is expected to lower formal sector employment and increase informal sector employment (Magruder 2013).

the labour market may not be able to obtain formal sector employment. Therefore, we expect a minimum wage hike in *i* to lower the number of workers employed in the formal sector, as shown by our (-) sign in the ‘formal sector employment’ box in district *i*. Because there are no unemployment benefits in Indonesia, many of those workers would not be able to afford being unemployed for long and may resort to employment in the informal sector. Consequently, we expect the relationship between minimum wage and informal sector employment in *i* to be positive. Other workers may become unemployed or move out of the labour force altogether.

However, the impact of *i*’s minimum wage increase may transcend borders and affect workers in *j*. Due to the possibility of geographical movement, workers in *i* who were negatively affected by the minimum wage hike may choose to move to *j* in search of better employment opportunities. Still, workers in *j* may also be attracted by the relatively higher wage rate in *i* and choose to relocate there. Studies on the effect of income on internal migration in Indonesia is mixed. Wajdi et al (2017) found that migration in Indonesia is directed towards provinces with a higher GDP per capita. Similarly, van Lottum and Marks (2012) also found that provinces of origin with a higher income relative to destination provinces is associated with lower migration. However, the authors also stated that in Indonesia, wage differentials between origin and destination provinces is not an important determinant of migration compared to other factors, such as population, contiguity (whether two provinces share borders), and distance. Therefore, although there may be workers who move from *i* to *j,* given the disemployment effects of the minimum wage increase in *i,* we also expect movement of laborers from *j* to *i,* as workers may be enticed by the relatively higher wage in *i.*

Figure 3. Conceptual Framework



Note: the signs in the brackets show our expected results. (+) means we expect minimum wages to have a positive relationship with the variable; (-) means we expect minimum wages to have a negative relationship with the variable; (0) means we expect minimum wages to have a nonsignificant relationship with the variable.

Data

Data on district level minimum wages were collected from BPS, whereas data on labour market indicators were obtained from the Indonesia Labour Force Survey (*Survey Tenaga Kerja Nasional/*Sakernas) which are also available at BPS. The main information collected from Sakernas include data on individual characteristics, such as gender and education level; employment, including types of occupation and employment status; unemployment, and working age population.

The spatial unit of analysis is district (*kabupaten* or *kota*). We dissolved the districts of Jakarta into one district because Jakarta only has a province level minimum wage. Following Suryahadi et. al. 2003, Comolla and de Mello 2011, Pratomo 2011, we also limit our scope to urban areas, as compliance to the minimum wage regulation is low in rural areas.

We start our analysis from 2011 because Sakernas changed its classification method of rural and urban areas in 2010[9]. Furthermore, due insufficient sample size, Sakernas 2016 can only be used for analysis at the province or national level. Therefore, our period of analysis is

[9] Based on *Peraturan Kepala Badan Pusat Statistik Nomor 37 Tahun 2010*.

2011-2015. To prevent seasonality problems, we use data from the Sakernas surveys conducted in August[10].

Empirical Model

Our study is done by two methods, a non-spatial dynamic panel model and a spatial dynamic panel model. Both models contain the same variables, as described in Table 1.

The dependent variables are formal sector employment, informal sector employment, unemployment, or labour participation. Following Dube et al (2010), Meer and West (2015), Pratomo (2011), and Wursten (2013), we use the absolute values of the labour market outcome instead of shares[11]. Moreover, the variables are used in their logarithmic form, so our estimation results show the elasticity of our dependent variable with respect to the minimum wage.

Our main variable of interest is real minimum wage. The selection of our minimum wage variable is in line with Pratomo (2011) which showed that for Indonesia, the log of real minimum wages is superior compared to other minimum wage measures commonly used in literature[12]. Moreover, like Pratomo (2011), Suryahadi et. al. (2003), and Rama (2001), we assume minimum wages to be exogenously determined with employment. As discussed previously, the main component in the setting of minimum wages is KHL. Rama (2001) stated that there is no evidence for the endogeneity of minimum wages, as the KHL is not directly affected by the labour market. Pratomo (2011) also found empirical evidence that real minimum wages are exogenously determined with employment at the provincial level. Although the unit of analysis in this study is districts, we also assume exogeneity of minimum wages with employment, as the district level minimum wage is also set by the provincial government, albeit after receiving recommendations from the district level government.

[10] Sakernas is done every February and August.
[11] Dube et al (2010), Pratomo (2011), Meer and West (2013), and Wursten (2013) used number of employees instead of employment to working age population ratio as their dependent variables.
[12] Other minimum wage variables widely used in literature include: the Kaitz index (the ratio of minimum wage to average wage), the fraction affected by the minimum wage, the fraction at the minimum wage, and the fraction below the minimum wage (Lemos 2004; Pratomo 2011)

Table 1. Definitions of Variables

Variable	Definition
Dependent Variables:	
Formal Sector Employment	Number of people employed in the formal sector
Informal Sector Employment	Number of people employed in the informal sector
Unemployment	Number of people unemployed
Labour Participation	Number of people aged 15 years old or higher who are in the labour force
Minimum Wage Variable:	
Real Minimum Wage	Annual minimum wage (Rupiah/month) at the district level deflated by consumer price index (CPI). For districts that do not have their own CPI level, the nearest available district's CPI level is used.
Control Variables:	
High school	Share of working age population with a high school degree but not higher
College	Share of working age population with at least college degree
Population	Working age population
Real GDP	Nominal GDP deflated by the CPI. For districts that do not have their own CPI level, the nearest available district's CPI level is used.
Productivity	Real GDP divided by the number of workers
District fixed effects	Fixed effects used to control for district-specific characteristics
Time fixed effects	Fixed effects used to control for year-specific characteristics

The control variables include factors that affect labour supply, such as educational attainment and working age population, as well as labour demand, such as regional GDP and labour productivity. District and time fixed effects are included to control for district characteristics that do not vary over time and yearly effects that have an impact on all districts in any given year, respectively. We exclude district specific time trends because the inclusion of it is typically based on the hypothesized omitted variables that underlie such trends (Neumark 2019). Therefore, we incorporate more control variables which includes shifters of labour supply and labour demand, unlike many studies of minimum wages which use a parsimony set of controls (Neumark 2019). Furthermore, when we ran a regression of the equations including time trends, the coefficients of the trends were statistically nonsignificant, justifying our decision to exclude them. Table 2 presents the summary statistics of our variables of interest.

Table 2. Summary Statistics

Variable	Obs.	Mean	Median	Min	Max
Dependent Variables					
Total					
Formal	565	189,027	362,861	6,827	3,491,452
Informal	565	145,408	159,117	16,236	1,417,298
Unemployment	565	27,036	51,156	474	555,408
Participation	565	361,472	557,447	33,296	5,368,572
Male					
Formal	565	122,236	234,914	4,664	2,189,771
Informal	565	87,528	96,923	8,263	848,527
Unemployment	565	16,845	30,560	170	298,381
Participation	565	226,609	351,039	18,484	3,192,879
Female					
Formal	565	66,790	129,019	2,163	1,352,057
Informal	565	57,881	64,113	7,685	630,149
Unemployment	565	10,191	21,108	167	257,027
Participation	565	134,862	208,359	14,812	2,222,130
Real minimum wage (IDR)	565	1,013,704	903,470	671,213	2,320,589

Source: Author's calculations

Non-Spatial Model

We adopt the dynamic fixed effect model from Siregar (2020). The time lag of the dependent variable is included to account for the hysteresis nature of the dependent variables. Moreover, we also incorporate the time-lagged value of our variable of interest, real minimum wage, as previous studies have shown that the employment effects of minimum wages take at least a year to be evident, presumably because of the time it takes for employers to adjust factor inputs (Neumark and Wascher 1992; Baker et al. 1999; Neumark and Wascher 2008, Siregar 2020). Furthermore, Neumark and Wascher (1992) found evidence that not including the lagged values of minimum wages may result in biased estimates of the employment effects of minimum wages. To avoid confusion with the spatial-lag of the variables (which will be used in the spatial models), we refer to the time-lagged minimum wage variable as the *past* minimum wage. The estimation equation is as follows:

$$Y_{it} = \beta_0 + \beta_1 Y_{it-1} + \beta_2 mw_{it} + \beta_3 mw_{it-1} + \theta X_{it} + \gamma_i + \delta_t + \varepsilon_{it} \quad (1)$$

Where:

Y = formal sector employment, informal sector employment, unemployment, or labour force participation (depending on model)

mw = real minimum wage

X = control variables (as listed in Table 1)

γ = district fixed effects

δ = time fixed effects

i = district

t = year

ε = error term

The dependent and independent variables are estimated in their natural logarithmic form.

Spatial Model[13]

Next, we employ the spatial Durbin model (SDM). The variables used are the same as those in Equation (1). However, to account for the relationship between districts, this model contains the spatial weight matrix *W*. For simplicity, we omit the *i* subscripts and include the fixed effects and error term in *R*. Our spatial model is as follows:

$$Y_t = \beta_1 Y_{t-1} + \rho W Y_t + \beta_2 mw_t + \beta_3 mw_{t-1} + \beta_4 W mw_t + \beta_5 W mw_{t-1} + \theta X_t + \sigma W X_t + R \quad (2)$$

The coefficient of WY (ρ) is referred to the spatial autocorrelation coefficient. ρ shows the spatial interdependencies between the district of reference and its neighbours. In other words, ρ shows the impact of changes in neighbouring districts' Y (WY) on the dependent variable (Y). For example, if our dependent variable is employment level, then ρ shows the impact of changes in *j*'s employment level on *i*'s employment level. Similarly, β_4 , β_5, and σ show the impact of neighbouring districts' minimum wages and other control variables (Wmw and WXs) on Y. However, as we will discuss shortly, unlike ρ , we cannot directly interpret β_4 , β_5, and σ.

Moreover, note that we do not include the spatial lag of past Y (WY_{t-1}) in our model. Following Elhorst (2010, 2012), we restrict the coefficient of (WY_{t-1}) to equal 0 in order to avoid identification problems. A more detailed explanation of the derivation of our spatial model is given in Appendix A.1.

[13] A brief discussion on the derivation our spatial model is given in the Appendix.

To estimate dynamic spatial panel data models, three methods have been developed, namely quasi-maximum likelihood (QML) estimator, instrumental variables or generalized methods of moments (IV/GMM), and Bayesian Markov Chain Monte Carlo (MCMC) approach (Elhorst 2012). Here, we estimate our model using the biased corrected QML estimator approach for dynamic spatial panel data model developed by Yu, et al (2008) which can be used when the variable WY_{t-1} is eliminated from the model (Elhorst 2012).

In selecting the spatial model to use, we follow LeSage and Pace (2009) by starting with an SDM followed by testing the joint significance the estimates of WX. If the estimates of WX are nonsignificant, SDM can be simplified into a spatial autoregressive (SAR) model, which is as follows[14]:

$$Y_t = \beta_1 Y_{t-1} + \rho W Y_t + \beta_2 mw_t + \beta_3 mw_{t-1} + \theta X_t + R \quad (3)$$

Consequently, we conducted an LR test for all equations, but the results differ between models. For example, SDM is found to be best fitting for our formal sector employment model while SAR is better for our informal sector employment model. In order to enable us to make reliable comparisons for all employment outcomes, we selected the SDM model, as it is the best fitting model for total employment (formal sector and informal sector employment combined)[15].

Spill Over Measures: Direct, Indirect, and Total Effects

In the standard OLS model, the marginal effect of a variable is its coefficient estimate. However, for spatial models, the coefficient estimate (in our case, the β_4 , β_5, and σ in Equation (2)) do not equal the marginal effects because there are feedbacks (spill over effects) induced by the data generating process. Therefore, it is necessary to calculate the direct, indirect, and total effects which consider the feedback effects. The direct effect describes the effect of a change in *x* on *y* in district *i*. On the other hand, the indirect effect describes the

[14] In our case, the SAR model is preferred when β_4 , β_5, and σ in Equation (2) is statistically nonsignificant.
[15] Results of the SAR model and LR test (SDM vs. SAR) are given in the Appendix.

effect of a change in *x* in district *j* on *y* in district *i*. Finally, the total effect is the sum of direct and indirect effects. Mathematically, the effects can be written by rewriting Equation (2) as:

$$Y_t = (I - \rho W)^{-1}(\beta_1 I)Y_{t-1} + (I - \rho W)^{-1}(\theta X_t + \sigma W X_t) + R \quad (4)$$

For simplification, we include the minimum wage variables (*mw*) in *X*. Because we are estimating a dynamic model, we can obtain the short term and long-term marginal effects. The short term and long-term effects can be expressed through the partial derivatives of Y with respect to the k^{th} explanatory variable of X from unit 1 to unit *N* at time *t*. The short-term effects can be written as follows:

$$\left[\frac{\delta Y}{\delta x_{1k}} \cdots \frac{\delta Y}{\delta x_{Nk}}\right]_t = (I - \rho W)^{-1}[\theta_k I_N + \sigma_k W] \quad (5)$$

Whereas the long-term effects are as follows:

$$\left[\frac{\delta Y}{\delta x_{1k}} \cdots \frac{\delta Y}{\delta x_{Nk}}\right] = [(I - \beta_1)I - \rho W]^{-1}[\theta_k I_N + \sigma_k W] \quad (6)$$

The direct effect is the average of the diagonal elements of the matrix on right-hand side of equations (5) and (6), whereas the indirect effect is the average of the row sums or column sums of the non-diagonal elements of those matrices (LeSage and Pace 2009).

Construction of the Spatial Weights Matrix

One of the main issues in applying spatial econometric methods is the selection of the spatial weights matrix as it is chosen before carrying out the estimation and may affect the estimation.

Defining ‘neighbours’

The two most common criteria used to determine whether two areas are spatially related are ‘contiguity’, which defines neighbours as geographic areas with a common border, and ‘distance’, which places a distance band for neighbouring areas. Here, we use contiguity, which can be classified into rook contiguity and queen contiguity. When we use the rook contiguity criterion, area 5’s neighbours would be areas 2, 4, 6, and 8 (Figure 4). On the other hand, when we apply the queen contiguity matrix, area 5 would be neighbours with areas 1, 2, 3, 4, 6, 7, 8, and 9. Because area 10 does not share a border with other regions, it has no neighbours.

There are no isolated districts (such as area 10) in Java, except *Kabupaten Kepulauan Seribu* islands in Jakarta. However, because we dissolved all districts in Jakarta as one district, *Kabupaten Kepulauan Seribu* did not cause any problems in our model.

Figure 4. Contiguity

1	2	3		10
4	5	6		
7	8	9		

Choosing the spatial weights matrix

In selecting the spatial weights matrix, we follow Vega and Elhorst (2014) by choosing the matrix which yielded the lowest Akaike Information Criteria (AIC) values. We test the AIC values of the queen contiguity matrix and the rook contiguity matrix. The AIC was computed for an SDM model with total employment (the sum of formal sector and informal sector) as the dependent variable and all the independent variables stated in Table 1. Based on the results, the queen contiguity matrix is the best fitting matrix for our model[16]. However, we also run the regression using the rook contiguity matrix and the inverse distance matrix as a robustness test, which are presented in the robustness check section[17].

[16] AIC results are not presented here but are available upon request.

[17] Other than the contiguity matrices, we also experimented with the inverse distance matrix. Unlike in the contiguity matrix where neighbours are assigned the value 1 if they are neighbours, using the inverse distance matrix, neighbours are assigned the value of the distance between the districts (in km). The values are inversed to account for the diminishing effect of distance.

RESULTS AND DISCUSSION

Non-Spatial Model Estimation Results

In estimating our non-spatial dynamic model, we follow Siregar (2020) in using difference generalized methods of moments (GMM) developed by Arellano and Bond (1991). By using GMM, we can control for the endogeneity of the lagged dependent variable. The remaining regressors are assumed to be exogenous. We first discuss our main results for total sample before analysing males and females separately (Table 3). However, we will not go into a detailed discussion, as our focus is on the spatial models results while this section serves as a comparison to the findings from our spatial models.

The minimum wage variables have the expected negative coefficient on formal sector employment although the estimate of past minimum wages is nonsignificant. Based on the results, a 10% increase in minimum wages is expected to lower formal sector employment in urban areas in Java by 2.3%. This estimate is in the range found by Suryahadi et al. (2003), Comola and de Mello (2011), and Pratomo (2011) which varies from, -1.1% to -3.0%.

We found minimum wages to have a nonsignificant impact on informal sector employment, which is contradictory with what we expected and what others have concluded (Siregar 2020 and Comola and de Mello 2011 who found positive and significant results, as well as Magruder 2013 and Hohberg and Lay 2015 who found negative and significant results).

On the other hand, unemployment is found to be negatively affected by minimum wage hikes. However, the coefficient is positive for past minimum wage, suggesting that there is a lag in the effects of minimum wages on unemployment. Based on the magnitude of the coefficients, the results suggest that a minimum wage hike lowers unemployment, in line with Comolla and de Mello (2011). The decline in the number of unemployed could be a result of lower labour participation, as suggested by the negative and significant estimate of the contemporaneous minimum wage variable for our labour participation equation.

Table 3. Non-Spatial Model Estimation Results

	Total				Male				Female			
	Formal	**Informal**	**Unempl.**	**Part.**	**Formal**	**Informal**	**Unempl.**	**Part.**	**Formal**	**Informal**	**Unempl.**	**Part.**
Lag of dependent variable	-0.010	0.005	**-0.216****	**-0.225****	-0.058	-0.163	-0.119	-0.061	**0.282****	0.221	0.046	**0.601*****
	(0.127)	(0.151)	(0.100)	(0.092)	(0.163)	(0.164)	(0.111)	(0.108)	(0.134)	(0.149)	(0.302)	(0.222)
Minimum wage	**-0.233****	0.072	**-0.538****	**-0.147*****	-0.097	0.112	**-0.518***	-0.032	**-0.266****	0.046	-0.256	-0.104
	(0.104)	(0.065)	(0.224)	(0.046)	(0.131)	(0.077)	(0.278)	(0.021)	(0.121)	(0.113)	(0.350)	(0.076)
Past minimum wage	-0.061	-0.038	**0.365***	0.010	-0.096	0.073	**0.617*****	0.025	0.029	-0.168	0.421	-0.075
	(0.052)	(0.068)	(0.187)	(0.032)	(0.059)	(0.082)	(0.231)	(0.022)	(0.093)	(0.116)	(0.368)	(0.090)
High school	**0.265*****	**-0.221*****	**0.557*****	0.001	**0.203*****	**-0.232*****	**0.342***	**-0.027***	**0.275*****	-0.043	0.055	0.066
	(0.083)	(0.069)	(0.149)	(0.029)	(0.071)	(0.058)	(0.175)	(0.012)	(0.082)	(0.074)	(0.230)	(0.045)
College	**0.156*****	**-0.139*****	-0.074	-0.009	**0.102*****	**-0.130*****	0.009	**-0.025*****	**0.270*****	**-0.151*****	0.011	0.040
	(0.025)	(0.027)	(0.065)	(0.008)	(0.025)	(0.031)	(0.084)	(0.007)	(0.031)	(0.031)	(0.135)	(0.027)
Population	**0.595*****	**1.553*****	**1.062****	**1.052*****	**0.704*****	**1.513*****	**1.194***	**1.113*****	**0.423***	**1.294*****	**1.165****	**0.694*****
	(0.201)	(0.163)	(0.495)	(0.063)	(0.230)	(0.174)	(0.619)	(0.039)	(0.237)	(0.249)	(0.527)	(0.224)
GDP	**0.492****	0.856	-0.541	0.222	0.283	0.269	-1.063	**0.250****	0.572	**1.884*****	-0.209	1.162***
	(0.247)	(0.310)	(0.486)	(0.224)	(0.302)	(0.296)	(0.697)	(0.096)	(0.349)	(0.664)	(0.134)	(0.370)
Productivity	**-0.322****	**-1.007*****	0.654	**-0.425*****	-0.115	**-0.657*****	0.504	**-0.370*****	**-0.824*****	**-1.610*****	0.223	**-1.204*****
	(0.149)	(0.185)	(0.465)	(0.154)	(0.185)	(0.201)	(0.605)	(0.080)	(0.278)	(0.255)	(0.141)	(0.178)
AR (2) p-value	0.808	0.440	0.760	0.097	0.530	0.778	0.162	0.480	0.331	0.312	0.624	0.147
Hansen test p-value	0.174	0.560	0.171	0.105	0.190	0.344	0.642	0.200	0.561	0.642	0.232	0.358
No. of groups	113	113	113	113	113	113	113	113	113	113	113	113
No. of observations	339	339	339	339	339	339	339	339	339	339	339	339

Notes: Standard errors (in parentheses) are robust to heteroscedasticity. All equations contain both time and individual fixed effects.
***: p-level < 0.01, **: p-level < 0.05, and *: p-level < 0.1.

When divided by gender, we found that in general, the negative impact of minimum wages on formal sector employment is higher for females than for males. This is also in line Siregar (2020), Comolla and de Mello (2011), Chun and Khor (2010), and Suryahadi et. al. (2003) which conclude a disproportionate effect of minimum wages on female employment compared to male.

Spatial Model Estimation Results

The results of our spatial model estimation are given in Table 4. The coefficients of the spatial lag variables suggest the presence of spatial spill overs, both from changes in neighbouring districts' employment, unemployment, and labour force participation levels (WYs) and their minimum wage levels (WXs). We obtained positive and significant estimates of WY for formal sector employment and unemployment. This means that if neighbouring district's formal sector employment and unemployment levels increased, formal sector employment and unemployment levels of the district of reference are also expected to increase, and vice versa.

A possible explanation for the significance of WY for formal sector employment is that both formal sector workers and firms are attracted to areas with efficient trade services and lower formalization costs (Yuwei et. al. 2017). As the local formal economy develops, firms in both formal and informal sectors become more profitable, so more enterprises move in to increase revenue. Other studies also show evidence of the clustering of the manufacturing sector which accounts for a majority of formal sector work (Rothenberg et. al. 2017, Santoso and Wilantari 2017). Rothenberg et. al. (2017) attribute the clustering of manufacturing sectors in Indonesia to natural resources and supply chain linkages.

Table 4. Spatial Model Estimation Results

		Total				Male				Female			
		Formal	**Informal**	**Unempl.**	**Part.**	**Formal**	**Informal**	**Unempl.**	**Part.**	**Formal**	**Informal**	**Unempl.**	**Part.**
X	Lag of dependent variable (L.Y)	-0.074	0.057	**-0.121***	**-0.096*****	0.051	0.068	**-0.120***	**-0.141*****	-0.046	-0.029	**-0.136*****	-0.047
		(0.056)	(0.054)	(0.064)	(0.035)	(0.067)	(0.067)	(0.064)	(0.034)	(0.034)	(0.045)	(0.035)	(0.038)
	Minimum wage	-0.096	0.103	-0.153	-0.028	-0.125	0.178	-0.253	**-0.044***	-0.030	0.023	-0.455	0.004
		(0.079)	(0.086)	(0.268)	(0.026)	(0.120)	(0.113)	(0.301)	(0.025)	(0.114)	(0.118)	(0.782)	(0.065)
	Past minimum wage	0.044	-0.058	**0.491****	**0.065****	0.013	-0.109	**0.747*****	**0.070****	0.109	-0.078	-0.125	0.028
		(0.077)	(0.091)	(0.246)	(0.031)	(0.095)	(0.115)	(0.282)	(0.030)	(0.111)	(0.155)	(0.533)	(0.079)
	High school	**0.261*****	**-0.221*****	0.425	-0.015	**0.226*****	**-0.256*****	0.217	**-0.026***	**0.260*****	-0.044	0.477	0.051
		(0.068)	(0.073)	(0.158)	(0.026)	(0.070)	(0.061)	(0.144)	(0.014)	(0.051)	(0.069)	(0.545)	(0.041)
	College	**0.169*****	**-0.131*****	-0.091	-0.008	**0.106*****	**-0.121*****	0.001	**-0.017*****	**0.261*****	**-0.136*****	0.038	0.013
		(0.026)	(0.024)	(0.071)	(0.008)	(0.028)	(0.030)	(0.069)	(0.005)	(0.033)	(0.024)	(0.117)	(0.016)
	Population	**0.394****	**1.620*****	**1.350*****	**1.054*****	**0.589*****	**1.548*****	**1.020****	**1.091*****	0.091	**1.507*****	3.153	0.859
		(0.169)	(0.165)	(0.493)	(0.052)	(0.200)	(0.172)	(0.490)	(0.039)	(0.207)	(0.236)	(2.038)	(0.115)
	GDP	**0.443****	**0.377****	**-1.687*****	**0.320*****	**0.477****	-0.036	**-2.220*****	**0.182*****	**0.526***	**0.950****	-1.755	0.627
		(0.193)	(0.221)	(0.610)	(0.077)	(0.240)	(0.258)	(0.771)	(0.060)	(0.297)	(0.370)	(1.407)	(0.192)
	Productivity	**-0.360*****	**-0.867****	**1.001****	**-0.500*****	-0.136	**-0.541*****	0.664	**0.043*****	**-0.872*****	**-1.388*****	**2.809****	-0.912
		(0.114)	(0.148)	(0.447)	(0.055)	(0.149)	(0.169)	(0.486)	(-6.41)	(0.170)	(0.192)	(1.273)	(0.106)
Spatial Lag Y (WY)		**0.101***	0.040	**0.085***	0.072	0.072	0.076	0.039	0.037	0.070	0.016	0.057	**0.144*****
		(0.050)	(0.063)	(0.047)	(0.052)	(0.060)	(0.066)	(0.044)	(0.047)	(0.064)	(0.058)	(0.077)	(0.054)
Spatial lag X (WX)	Minimum wage	0.007	0.059	-0.323	0.002	0.073	0.035	-0.160	0.042	-0.1976	0.086	-0.254	-0.053
		(0.100)	(0.121)	(0.282)	(0.031)	(0.154)	(0.152)	(0.344)	(0.032)	(0.130)	(0.161)	(0.730)	(0.077)
	Past minimum wage	**-0.141***	-0.061	0.256	**-0.067***	-0.139	0.006	-0.083	**-0.067***	-0.181	-0.054	1.188	-0.027
		(0.085)	(0.098)	(0.326)	(0.036)	(0.118)	(0.136)	(0.350)	(0.035)	(0.132)	(0.165)	(0.751)	(0.085)
	High school	-0.054	**0.166****	-0.250	0.035	-0.005	0.091	**-0.614****	-0.009	**0.143****	0.018	0.444	0.055
		(0.073)	(0.078)	(0.225)	(0.029)	(0.087)	(0.093)	(0.267)	(0.020)	(0.070)	(0.091)	(0.548)	(0.045)
	College	**0.058***	**-0.064***	**0.172***	-0.011	-0.010	0.001	**0.295*****	-0.003	**0.135*****	**-0.084***	-0.143	-0.014
		(0.032)	(0.037)	(0.092)	(0.014)	(0.030)	(0.040)	(0.104)	(0.008)	(0.039)	(0.045)	(0.221)	(0.024)
	Population	0.241	0.019	-1.091	**-0.162***	0.172	0.241	-1.199	-0.037	0.039	-0.174	-1.555	-0.205
		(0.221)	(0.321)	(0.676)	(0.094)	(0.262)	(0.365)	(0.754)	(0.082)	(0.299)	(0.430)	(1.647)	(0.211)
	GDP	**-0.901****	-0.213	0.866	**-0.545*****	-0.621	0.353	2.734	-0.001	**-0.930***	-0.876	-1.181	**-1.303*****
		(0.431)	(0.660)	(1.699)	(0.187)	(0.609)	(0.762)	(1.818)	(0.178)	(0.557)	(1.101)	(4.202)	(0.468)
	Productivity	-0.085	0.278	0.142	0.083	-0.245	0.492	**-1.334***	-0.009	0.325	-0.015	1.869	0.200
		(0.181)	(0.257)	(0.581)	(0.087)	(0.261)	(0.337)	(0.706)	(0.064)	(0.252)	(0.303)	(1.362)	(0.179)
Within R-sq		0.315	0.470	0.154	0.394	0.351	0.257	0.109	0.865	0.438	0.342	0.075	0.465
No. of observations		452	452	452	452	452	452	452	452	452	452	452	452

Note: Standard errors (in parentheses) are robust to heteroscedasticity. All equations contain both time and individual fixed effects.
***: p-level < 0.01, **: p-level < 0.05, and *: p-level < 0.1.

Similarly, the significant estimate of WY for unemployment is in line with Patacchini and Zenou (2007), Vega and Elhorst (2016), and Oktafianto et. al. (2019) which found evidence of spatial spill over effects of unemployment. Another interesting finding is a highly significant estimate for WY of female labour force participation. This result is consistent with Fogli and Veldkamp (2011) which stated that in the US, females learn to participate in the labour market by observing employed females in neighbouring regions.

Next, we discuss the results of our main variable of interest, minimum wage. However, as discussed previously, interpretation of the estimates of X and WX variables from spatial models are done by analysing their marginal effects. Estimates of the direct effect include feedback effects that arise as a result of impacts passing through neighbouring districts and then back to the district of origin. Similarly, estimates of the indirect effects also include feedback effects. These are precisely the reason for the differences between the direct effects and the estimates of X variables, and between the indirect effects and the estimates of the WX variables shown in Table 4 (Vega and Elhorst 2014)[18]. Given the limited space, we only report the marginal effects of the minimum wage variables (Table 5). Furthermore, because the results are consistent between short and long term, we will only discuss the short-term effects. In general, the effects tend to fade out over time (the estimates obtained are higher in magnitude for short term than for long term), except for informal sector employment where the increase becomes more pronounced over time.

Before discussing employment, unemployment, and participation equations separately, we point out that the indirect effects of our employment equations and unemployment equation are all nonsignificant. This suggest that the impacts of minimum wage changes on formal sector employment, informal sector employment, and unemployment are local. In other words, the impacts of changes in neighbouring districts' minimum wages on the levels of employment and

[18] For example, the short run direct effects minimum wages on formal sector employment is -0.100 while its coefficient estimate (in Table 3) is -0.096. The difference of 4% is the feedback effect.

unemployment in the district of reference are negligible. However, because we found significant WY estimates, particularly for formal sector employment and unemployment, estimating those equations using a non-spatial model are likely to result in biased estimates.

Going into details, for formal sector employment, we found the impact of minimum wages to be nonsignificant, be it in the district of reference (direct effect), in neighbouring districts (indirect effect), or in both combined (total effects). This is contrary to the findings from our non-spatial model which suggests a negative effect (although in the non-spatial model the estimate does not contain feedback effects from neighbouring districts). Our spatial model estimation results suggest that once we allow districts to be correlated, the negative impact of minimum wages on formal sector employment disappears, implying that there was a downward bias when we ignored spatial dependence. This argument is also supported by the fact that when we run the regression with a SAR model (thus, ignoring WX), the negative direct effect of minimum wages on formal sector employment becomes statistically significant at the 5% confidence level, as is obtained from our non-spatial model[19]. We can also conclude that when we allow labour markets to be spatially correlated, the Indonesian labour market is relatively less elastic than what was concluded by previous studies.

Our findings are in line with Dolton et. al. (2015) and Lopez-Tamayo et. al. (2017) which found nonsignificant effects of minimum wages on employment once they considered spatial correlation and past employment (Y_{t-1}). Both studies also suggest that failing to incorporate spatial dependence in estimating the employment impacts of minimum wages lead to the negative effects mostly found in the literature.

[19] SAR results are given in Appendix A.3.

Table 5. Marginal Effects: Direct, Indirect (Spill over), and Total Effects

			Total				Male				Female			
			Formal	Informal	Unempl.	Part.	Formal	Informal	Unempl.	Part.	Formal	Informal	Unempl.	Part.
Short Run	Direct Effect	Real mw	-0.100	0.099	-0.169	-0.029	-0.132	0.173	-0.267	**-0.045***	-0.032	0.018	-0.484	0.001
			(0.079)	(0.084)	(0.256)	(0.025)	(0.119)	(0.112)	(0.289)	(0.025)	(0.112)	(0.114)	(0.751)	(0.062)
		Past real mw	0.056	-0.048	**0.524****	**0.067****	0.027	-0.099	**0.779*****	**0.073****	0.124	-0.061	-0.045	0.036
			(0.076)	(0.089)	(0.233)	(0.030)	(0.094)	(0.113)	(0.270)	(0.029)	(0.108)	(0.149)	(0.503)	(0.074)
	Indirect Effect	Real mw	0.023	0.065	-0.345	0.002	0.089	0.034	-0.143	0.045	-0.174	0.101	-0.251	-0.053
			(0.100)	(0.119)	(0.284)	(0.032)	(0.153)	(0.150)	(0.343)	(0.031)	(0.126)	(0.158)	(0.756)	(0.082)
		Past real mw	-0.140	-0.063	0.307	**-0.067***	-0.141	0.006	-0.073	**-0.071****	-0.188	-0.069	1.207	-0.030
			(0.085)	(0.102)	(0.348)	(0.037)	(0.118)	(0.140)	(0.370)	(0.035)	(0.133)	(0.168)	(0.818)	(0.092)
	Total Effect	Real mw	-0.077	**0.164****	**-0.514****	-0.027	-0.043	**0.207****	-0.410	0.000	**-0.205****	0.119	-0.735	0.006
			(0.051)	(0.076)	(0.251)	(0.030)	(0.075)	(0.091)	(0.290)	(0.025)	(0.085)	(0.118)	(0.707)	(0.083)
		Past real mw	-0.084	-0.111	**0.831*****	0.001	-0.114	-0.092	**0.705***	0.002	-0.064	-0.129	**1.162***	0.006
			(0.060)	(0.081)	(0.286)	(0.032)	(0.084)	(0.116)	(0.329)	(0.029)	(0.102)	(0.119)	(0.644)	(0.083)
Long Run	Direct Effect	Real mw	-0.093	0.105	-0.150	-0.026	-0.139	0.185	-0.238	-0.040*	-0.031	0.017	-0.425	0.001
			(0.073)	(0.090)	(0.228)	(0.023)	(0.125)	(0.120)	(0.258)	(0.022)	(0.107)	(0.111)	(0.661)	(0.059)
		Past real mw	0.052	-0.051	**0.467****	**0.062****	0.028	-0.106	**0.695*****	**0.064****	0.118	-0.059	-0.041	0.035
			(0.070)	(0.094)	(0.208)	(0.027)	(0.099)	(0.122)	(0.241)	(0.025)	(0.103)	(0.144)	(0.443)	(0.071)
	Indirect Effect	Real mw	0.021	0.069	-0.303	0.002	0.094	0.035	-0.126	0.039	-0.166	0.098	-0.216	-0.050
			(0.093)	(0.127)	(0.252)	(0.029)	(0.161)	(0.161)	(0.306)	(0.028)	(0.120)	(0.154)	(0.660)	(0.078)
		Past real mw	-0.130	-0.066	0.267	**-0.061***	0.148	0.007	-0.068	**-0.062****	-0.179	-0.067	1.055	-0.029
			(0.079)	(0.108)	(0.308)	(0.034)	(0.125)	(0.151)	(0.329)	(0.031)	(0.128)	(0.163)	(0.713)	(0.087)
	Total Effect	Real mw	-0.072	**0.174****	**-0.453****	-0.024	-0.045	**0.221****	-0.365	0.000	**-0.197****	0.115	-0.641	-0.050
			(0.047)	(0.080)	(0.221)	(0.027)	(0.078)	(0.097)	(0.258)	(0.022)	(0.081)	(0.115)	(0.615)	(0.073)
		Past real mw	-0.079	-0.118	**0.733*****	0.001	-0.120	-0.099	**0.627****	0.002	-0.061	-0.126	**1.013***	0.005
			(0.056)	(0.086)	(0.251)	(0 .029)	(0.088)	(0.124)	(0.292)	(0.026)	(0.098)	(0.116)	(0.558)	(0.078)

Notes: results for other explanatory variables are not shown but available upon request. Standard errors (in parentheses) are robust to heteroscedasticity.
***: p-level < 0.01, **: p-level < 0.05, and *: p-level < 0.1

For informal sector employment, we found no significant direct and indirect effects although the signs and significance of the direct effect estimates are consistent with the findings from our non-spatial model. However, total effects estimates are significant, with an estimated elasticity of 0.16. This means that a 10% increase in minimum wages is associated with a 1.6% rise in informal employment. As our results suggest, the rise in informal sector employment may not be obvious when we look at the district of reference and its neighbours separately. Only when we look at the total effects, the rise in informal sector employment becomes apparent. The positive impact of minimum wages on informal sector employment is in line with Comolla and de Mello (2011) which argued that there is a shifting of those who were unemployed to the informal sector. Indeed, we also found a negative total effect of the contemporaneous minimum wage variable on unemployment.

However, the impact of past minimum wages on unemployment is positive which is what we expected. The positive total effects of past minimum wages is higher than the negative estimate of the contemporaneous minimum wage variable, indicating that overall, rises in minimum wages increase unemployment. One might think that the higher unemployment level is due to lower formal sector employment. But the impact on formal sector employment we found is indistinguishable from zero. The reason behind the rise in unemployment becomes clear when we consider labour participation. The rise in the pool of labour in the district of reference, as shown by the positive direct effects, is what causes the surge in unemployment. However, we cannot say whether the increase in those unemployed are migrants from neighbouring districts or people who were already residents of the district of reference.

Our direct and indirect effects of past minimum wages on labour participation suggest that a 10% hike in minimum wages is expected to raise labour participation in the district of reference by 0.67%. On the other hand, labour participation in neighbouring districts is expected to fall by 0.67%. There are two possible explanations for this result. First, a minimum wage hike motivates people in that district who were previously inactive to participate in the labour force of that district.

This could explain the positive direct effect on labour participation but fails to explain the negative indirect effect. Second, there are workers who moved from neighbouring districts to the district where the minimum wage was raised. This explains both the positive direct effect and negative indirect effect. The latter explanation is supported by the findings of van Lottum and Marks (2012) which show that wage differentials play an important factor for internal migration in Indonesia.

Our findings are in contrast with studies on the migration impact of minimum wages which found that low-skilled migrants tend to move to areas with lower minimum wages (Martin and Termos 2015, Cadena 2014, and Orrenius and Zavodny 2008). Nevertheless, their studies are on the US where compliance with minimum wages is high and labour demand is relatively elastic. According to Monras (2019), if local labour demand elasticity is above 1, workers are expected to leave regions that increase minimum wages[20]. The author also stated that if a region decides to introduce minimum wages and unemployment benefits are effectively paid by workers unaffected by the policy, the introduction of minimum wages lead to higher wages, lower employment, and more low-skilled population in that region even when disemployment effects are large.

Our results conform to the findings of Monras (2019) as Indonesia has a relatively lower labour demand elasticity and no unemployment benefits. Tadjoeddin and Chowdury (2012) show that the Indonesian labour demand for the manufacturing sector (the sector highly affected by minimum wages) is around 0.41, while the average of the labour demand for all sectors are 0.64. Moreover, Chun and Khor (2010) and Hoghberg and Lay (2015) found that minimum wage increases pushes up formal sector wages but leaves informal sector wages unchanged. Therefore, workers may still be attracted to relocate to the district where the minimum wage was increased. This argument is also supported by Magruder (2013) who found supporting evidence that in a district where the minimum wage was increased, in-migration rises while out-migration were not significantly affected.

[20] Monras (2019) estimated the labour demand elasticity for low-skilled labour in the US to be around 1. Therefore, low skilled migrants there tend to relocate to areas with lower minimum wages.

Like our nonspatial model results, when divided by gender, we conclude that minimum wage hikes affect males and females disproportionately. The negative total effects of minimum wages on formal sector employment is significant only for female workers. Moreover, only males experience a significant increase in informal sector employment (total effects). This is unfortunate because there are significantly fewer females, especially in the formal sector, to begin with (Table 2). Moreover, the increase in unemployment is higher and only significant for females (total effect). Labour participation of males is also found to be significantly affected by minimum wage changes, while female labour participation is not.

Robustness Check

For robustness check, we re-run the estimation using two other spatial matrices, namely the rook contiguity matrix and an inverse distance matrix. Furthermore, we also re-run the estimation with the previously used queen contiguity matrix. However, we drop Jakarta from our dataset as it is found to strongly influence internal migration patterns in Indonesia (van Lottum and Marks 2012). Because the main rationale for the spill over effects of minimum wages in our study is labour movement (internal migration), there is possibility that the inclusion of Jakarta might affect our estimation results.

By comparing the results in Table 6 with Table 5, it is evident that all our variables of interests yield estimated marginal effects with the same signs[21]. Nevertheless, the significance level is different, especially for the estimates obtained by using the inverse distance matrix. The direct and total effects of minimum wages on the formal, informal, and unemployment equations become statistically significant. The magnitudes of the variables are also higher, presumably because we ignore the WXs. On the other hand, the effects on labour participation are

[21] For simplicity we only show the results for short run effects. Like our main results, we obtained similar short-run marginal effects and long-run marginal effects.

nonsignificant. A possible explanation for the non-significance on labour participation is that by using an inverse distance band, all districts are considered neighbours while the queen contiguity matrix results in the average number of neighbours of 4.3. Therefore, the migration which occurs, especially those over large distances, may mainly be done by relatively higher skilled workers who are unaffected by minimum wage changes. Because the cost of migrating goes up with distance, lower-skilled workers affected by minimum wage changes may be deterred from relocating.

Finally, we show that our results are robust to the inclusion or exclusion of Jakarta. The estimates found are similar to our main results. The negative indirect effect of minimum wage increase on labour participation is just shy of statistical significance (p-value = 0.104).

Table 6. Robustness Check: Marginal Effects

		Rook Contiguity (SDM)				Inverse Distance (SAR)				Queen Contiguity (excluding Jakarta, SDM)			
		Formal	**Informal**	**Unempl.**	**Part.**	**Formal**	**Informal**	**Unempl.**	**Part.**	**Formal**	**Informal**	**Unempl.**	**Part.**
Direct Effect	Real mw	-0.099	0.095	-0.152	-0.030	**-0.111****	**0.148*****	**-0.378***	-0.034	-0.091	0.107	-0.193	-0.026
		(0.079)	(0.084)	(0.256)	(0.025)	(0.046)	(0.056)	(0.211)	(0.022)	(0.078)	(0.084)	(0.255)	(0.025)
	Past real mw	0.055	-0.046	**0.516****	**0.068****	-0.063	-0.084	**0.741*****	0.008	0.052	-0.058	**0.551****	**0.065****
		(0.076)	(0.089)	(0.232)	(0.030)	(0.055)	(0.068)	(0.182)	(0.024)	(0.076)	(0.089)	(0.235)	(0.030)
Indirect Effect	Real mw	0.022	0.072	-0.371	0.005	0.023	-0.021	0.088	0.000	0.012	0.046	-0.340	-0.005
		(0.100)	(0.120)	(0.284)	(0.032)	(0.016)	(0.016)	(0.070)	(0.007)	(0.099)	(0.120)	(0.283)	(0.032)
	Past real mw	-0.137	-0.066	0.325	**-0.067***	0.012	0.013	**-0.174***	-0.001	-0.137	-0.051	0.329	-0.060
		(0.085)	(0.102)	(0.350)	(0.037)	(0.013)	(0.014)	(0.093)	(0.004)	(0.086)	(0.102)	(0.348)	(0.037)
Total Effect	Real mw	-0.077	**0.167****	**-0.524****	-0.026	-0.089**	0.127**	**-0.290***	-0.034	-0.079	**0.153****	**-0.533****	-0.031
		(0.051)	(0.076)	(0.252)	(0.030)	(0.038)	(0.050)	**(0.171)**	(0.023)	(0.051)	(0.077)	(0.249)	(0.031)
	Past real mw	-0.082	-0.113	**0.841*****	0.001	-0.051	-0.071	**0.567*****	0.007	-0.084	-0.108	**0.880*****	0.005
		(0.060)	(0.081)	(0.290)	(0.031)	(0.046)	(0.059)	(0.162)	(0.024)	(0.061)	(0.083)	(0.286)	(0.032)
WY		**0.102****	0.037	**0.095****	0.067	**-0.276***	-0.187	**-0.341****	-0.038	**0.102****	0.035	**0.080***	0.070
		(0.050)	(0.063)	(0.048)	(0.051)	(0.149)	(0.124)	(0.172)	(0.150)	(0.050)	(0.063)	(0.047)	(0.052)

Note: For equations using the inverse distance matrix, the LR test for all equations failed to reject the assumption that WX=0. So SAR is preferred for all equations
Results are for total (male and female) workers. Standard errors are robust to heteroscedasticity. All equations include time and individual fixed effects.
***: p-level < 0.01, **: p-level < 0.05, and *: p-level < 0.1.

CONCLUSION

We focus our analysis on the impacts of minimum wage changes on employment, unemployment, and labour participation in Java Indonesia. Unlike previous studies, we relax the assumption of spatial independence among districts and estimate how an increase in minimum wages may affect not only the district where the minimum wage was raised, but also neighbouring districts.

Once we allow districts to be spatially correlated, we found that minimum wage increases have no discernible effect on formal sector employment, be it in the district of reference or in neighbouring districts. However, an increase in minimum wages is expected to raise informal sector employment and unemployment in total (the district of reference and neighbouring districts combined). Interestingly, we also found evidence that a minimum wage hike is associated with higher labour participation in the district of reference, and lower labour participation in neighbouring districts.

Therefore, we draw the following conclusions. First, the effects of a minimum wage hike on employment (both formal and informal) and unemployment are relatively local, meaning that the impact on neighbouring districts (as shown by indirect effects) are negligible. Second, because we found evidence of spatial interdependence for formal sector employment, unemployment, and labour participation, failing to account for the spatial dependence when estimating a model of those variables may result in biased estimates. Third, our results indicate that minimum wage hikes induce workers to relocate to the districts with an increased minimum wage level. Nevertheless, we did not explicitly test the impact of minimum wages on migration.

The implications from our study is as follows. First, we show that labour participation responds to minimum wage hikes. Therefore, analysing the impacts of minimum wage increases on migration or the number of workers who commute between districts (without failing to consider spatial dependence) may yield interesting results.[22] Second, our results highlight the need for

[22] Given Java's relatively more advanced infrastructure as well as the proliferation of motorcycle use which keeps commuting costs low (depending on distance), many workers may opt to commute inter-district rather than to relocate.

researchers and policymakers to realize that policies designed to affect a single labour market will likely have spill over effects on neighbouring markets. In the case of minimum wages or similar programs which increase a worker's expected income, more migrants are likely to be attracted to the district where the policy will be implemented. Future research on labour market policies should explicitly examine the mobility incentives the policies create.

APPENDIX

A.1 Derivation of the spatial model

Spatial autocorrelation is formally defined by Anselin and Bera (1998) as follows:

$$cov(y_i, y_j) = E(y_i, y_j) - E(y_i)E(y_j) \quad for\ i \neq j \qquad \text{(A.1)}$$

Where y_i and y_j are observations of a random variable at locations *i* and *j*. The subscripts *i* and *j* refer to geographic designations. According to Elhorst (2010), three types of interaction effects may explain why an observation in one area may be affected by observations in other areas. Assuming *i* and *j* are neighbouring districts, the interaction effects are as follows:

1. Endogenous interaction effects, where the dependent variable *y* in *i* is correlated with the dependent variable *y* in *j*.
2. Exogenous interaction effects, where the dependent variable *y* in *i* is correlated with the independent variable *x* in *j*.
3. Interaction effects in the error term, error terms *u* in *i* is correlated with the error term *u* in *j*.

A panel model with all interaction effects can be represented by the following equation (Elhorst 2011)[23]:

$$Y_{it} = \rho \sum_{j=1}^{N} W_{ij} Y_{jt} + \theta X_{it} + \sigma \sum_{j=1}^{N} W_{ij} X_{ijt} + \gamma_i + \delta_t + u_{it} \qquad \text{(A.2)}$$

$$u_{it} = \lambda \sum_{j=1}^{N} W_{ij} u_{it} + \varepsilon_{it}$$

[23] For simplicity, we include mw variables from our main equations (Equations 1-3) in X.

Special cases can be applied to Equation (A.2) by restricting parameters. For example, by setting both σ =0 and λ=0, we have a SAR model which exhibits spatial dependence only in the dependent variable ($\rho \neq 0$). Conversely, the spatial error model (SEM) is used when there is spatial dependence only in the error term (ρ =0 and σ =0). Lastly, putting the restriction λ =0 results in the spatial Durbin model (SDM), which is our main model.

The spatial panel model in Equation (A.2) may also be extended into a dynamic model by adding time lags of Y and WY. For simplicity, we omit the *i* and *j* subscripts as well as the fixed effects. Thus, the equation becomes:

$$Y_t = \beta_1 Y_{t-1} + \rho W Y_t + \eta W Y_{t-1} + \theta X_t + \sigma \mathrm{W} X_t + u_t \qquad \text{(A.3)}$$

Similarly, time lags of the variables X and WX as well as that of the error terms u and Wu may be included in the model. A complete dynamic SDM contains both the contemporaneous lag, the spatial lag, and the contemporaneous and spatial lags of the dependent variable. However, Anselin (2008) criticizes this model because it is prone to suffer from identification problems. To avoid such problems, the following four restrictions could be imposed: $\sigma = 0$, $\rho = 0$, $\eta = \beta_1 \rho$, and $\eta = 0$ (Elhorst, 2012). Following Elhorst (2010, 2012) and Franseze and Hays (2007), we impose the restriction where $\eta = 0$. Elhorst (2012) also stated that restricting $\eta = 0$ seems to be the least restrictive model compared to the other three restrictions. Therefore, the equation we estimate in this study is Equation (2) (shown in the main text). Moreover, after running several regressions including WY_{t-1}, we found its coefficient estimates to be mostly statistically insignificant, which also validates our restriction. In other words, past values of neighbouring districts' employment levels are found to not have a significant impact on the employment levels of the district of reference.

A.2. Results of LR test for model selection

Equation		p-value	Preferred model
Total	Formal	0.0131	SDM
	Informal	0.1429	SAR
	Unemployment	0.3035	SAR
	Labour Participation	0.0006	SDM
Male	Formal	0.6588	SAR
	Informal	0.4678	SAR
	Unemployment	0.0003	SDM
	Labour Participation	0.6343	SAR
Female	Formal	0.0000	SDM
	Informal	0.5865	SAR
	Unemployment	0.1700	SAR
	Labour Participation	0.0310	SDM

Note: The null hypothesis (H0) = WX variables are jointly indistinguishable from 0

A.3 Results of SAR model estimation: Marginal Effects

			Total				Male				Female			
			Formal	Informal	Unempl.	Part.	Formal	Informal	Unempl.	Part.	Formal	Informal	Unempl.	Part.
WY			-0.048	-0.048	0.066	0.025	-0.059	-0.080	-0.001	-0.059	0.075	0.028	0.073	0.133*
			(0.042)	(0.063)	(0.049)	(0.050)	(0.055)	(0.073)	(0.042)	(0.040)	(0.048)	(0.057)	(0.078)	(0.069)
Short Run	Direct Effect	Real mw	-0.111**	0.152***	-0.379*	-0.034	-0.100	0.225***	-0.511**	-0.028	-0.133*	0.052	-0.543	-0.037
			(0.046)	(0.057)	(0.211)	(0.022)	(0.064)	(0.074)	(0.249)	(0.019)	(0.079)	(0.084)	(0.643)	(0.050)
		Past real mw	-0.067	-0.091	0.699***	0.009	-0.082	-0.081	0.818***	0.037*	-0.041	-0.118	0.520	-0.036
			(0.055)	(0.067)	(0.179)	(0.024)	(0.064)	(0.089)	(0.229)	(0.021)	(0.083)	(0.108)	(0.357)	(0.060)
	Indirect Effect	Real mw	0.005	-0.007	-0.030	-0.001	0.006	-0.016	-0.003	0.002	-0.011	0.001	-0.038	-0.007
			(0.005)	(0.010)	(0.031)	(0.002)	(0.007)	(0.017)	(0.026)	(0.002)	(0.011)	(0.006)	(0.090)	(0.011)
		Past real mw	0.003	0.003	0.055	0.000	0.004	0.003	0.004	-0.002	-0.004	-0.003	0.043	-0.005
			(0.004)	(0.008)	(0.043)	(0.002)	(0.006)	(0.010)	(0.036)	(0.002)	(0.009)	(0.010)	(0.061)	(0.011)
	Total Effect	Real mw	-0.107**	0.145***	-0.409*	-0.035	-0.094	0.209***	-0.514**	-0.027	-0.144*	0.053	-0.581	-0.044
			(0.044)	(0.052)	(0.230)	(0.023)	(0.059)	(0.069)	(0.254)	(0.018)	(0.086)	(0.087)	(0.695)	(0.059)
		Past real mw	-0.064	-0.088	0.754***	0.009	-0.078	-0.077	0.821***	0.034*	-0.045	-0.121	0.563	-0.042
			(0.053)	(0.066)	(0.201)	(0.025)	(0.062)	(0.086)	(0.235)	(0.020)	(0.091)	(0.111)	(0.388)	(0.069)
Long Run	Direct Effect	Real mw	-0.106**	0.161***	-0.343*	-0.031	-0.106	0.241***	-0.474**	-0.025	-0.130*	0.051	-0.475	-0.036
			(0.044)	(0.060)	(0.191)	(0.020)	(0.068)	(0.080)	(0.231)	(0.017)	(0.077)	(0.081)	(0.563)	(0.049)
		Past real mw	-0.063	-0.096	0.632***	0.008	-0.087	-0.090	0.759***	0.032*	-0.040	-0.114	0.455	-0.035
			(0.053)	(0.071)	(0.162)	(0.022)	(0.068)	(0.096)	(0.213)	(0.019)	(0.081)	(0.104)	(0.312)	(0.057)
	Indirect Effect	Real mw	0.004	-0.008	-0.024	-0.001	0.007	-0.018	-0.003	0.001	-0.011	0.001	-0.029	-0.006
			(0.005)	(0.011)	(0.025)	(0.002)	(0.008)	(0.020)	(0.022)	(0.001)	(0.010)	(0.006)	(0.067)	(0.010)
		Past real mw	0.003	0.003	0.044	0.000	0.004	0.004	0.003	-0.002	-0.004	-0.003	0.032	-0.005
			(0.004)	(0.009)	(0.035)	(0.001)	(0.007)	(0.012)	(0.031)	(0.002)	(0.009)	(0.009)	(0.045)	(0.010)
	Total Effect	Real mw	-0.101**	0.153***	-0.367*	-0.032	-0.100	0.224***	-0.476**	-0.024	-0.141*	0.051	-0.503	-0.0421
			(0.042)	(0.055)	(0.206)	(0.020)	(0.063)	(0.074)	(0.235)	(0.016)	(0.084)	(0.084)	(0.601)	(0.057)
		Past real mw	-0.061	-0.093	0.675	0.008	-0.082	-0.083	0.762***	-0.024*	-0.044	-0.117	0.487	-0.040
			(0.050)	(0.070)	(0.179)	(0.023)	(0.065)	(0.092)	(0.217)	(0.016)	(0.089)	(0.107)	(0.335)	(0.066)

Notes: results for other explanatory variables are not shown but available upon request. Standard errors (in parentheses) are robust to heteroscedasticity.
***: p-level < 0.01, **: p-level < 0.05, and *: p-level < 0

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