The Minimum Wage and Occupational Mobility *

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Abstract

This paper quantifies the effect of minimum wages on workers' occupational mobility. I show that minimum wages decrease younger, less-educated workers' occupational mobility and are associated with more mismatch. A search-and-matching model highlights two channels by which the minimum wage decreases occupational mobility. First, it compresses wages and reduces the gain from switching, leading to lower occupational mobility and more mismatch. Second, it decreases vacancy posting. Calibrating the model to the US economy, the results suggest that a 15 dollar minimum wage can damp aggregate output by 0.4 percent, of which the wage compression channel accounts for 80 percent.

JEL Classification: J38, J62, E64

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1 Introduction

In recent years, many states, counties, and cities have imposed minimum wage increases, spurring ongoing debate about the potential effects of the minimum wage.[2] I analyze how the minimum wage affects workers' incentives to search for jobs. My results revealed a novel effect of minimum wage increases: reduced occupational mobility. By examining how the minimum wage affects workers' search incentives, I explore the implications of the reduced occupational mobility on occupational mismatch and aggregate output.

I construct occupational mobility using Current Population Survey (CPS) data for 2005 to 2016. The baseline regression shows that a 10% minimum wage increase leads to a 3% decline in the occupational mobility of the younger, less-educated workers but no significant effect on the occupational mobility of the older, more-educated workers. The results are robust to tests of spatial confounds (e.g. Dube et al. (2010)) and treatment timing confounds (e.g. Meer and West (2016); Goodman-Bacon (2021)).

The decline in occupational mobility might be due to increased difficulty in finding jobs or to reduced incentives to switch occupations. To test the former possibility, I analyze the effect of the minimum wage on the younger, less-educated workers' job-finding rate, which is a proxy for difficulty in finding jobs. The results suggest that the minimum wage has little effect on the job-finding rate of the younger, less-educated workers.

Incentives to switch occupations can be related to the switching cost or to a change in the quality of the match between workers and jobs. If there are occupational switching costs (e.g., Cortes and Gallipoli (2018)), a minimum wage increase reduces the wage gain obtained from switching occupations, leading to a decrease in occupational mobility. On the other hand, if the match quality improves after a minimum wage increase, workers have less incentive to switch occupations. Both explanations imply increased job tenure, but they differ by their implication on match quality. The former implies that the average

[2]See e.g. Card and Krueger (2015), Neumark and Wascher (2008).

match quality is lower after the minimum wage increase, because workers stay longer in occupations with lower match quality.

To see the relation between the minimum wage and match quality, I use data from Guvenen et al. (2020) to measure mismatch between workers' abilities and the abilities required for different occupations. The results show that for the younger workers, the minimum wage is positively associated with mismatch.[3]

Even if higher minimum wages tend to keep workers in poorly matched occupations, if workers stay in high-skill occupations longer, the increase in mismatch might be offset by better skill development over time. Therefore, I investigate which types of occupational transitions are most affected by the minimum wage. I find that higher minimum wages are associated with a decrease in transitions from non-routine manual occupations (e.g., food preparation, building cleaning) to routine cognitive occupations (e.g., office and administrative support). This suggests that higher minimum wages are associated with less outflow from low-skill occupations rather than longer stays in high-skill occupations.[4]

To study the implication of the mismatch on aggregate output, I construct a stylized search-and-matching model with heterogeneous occupations and workers and a counterfactual \$15 minimum wage. I used the model to highlight two channels by which the minimum wage affects occupational mobility. The first channel is the wage compression channel, in which the minimum wage narrows the wage gap between mismatched occupations and better-matched occupations, reducing the gain of switching occupations, and thus decreasing workers' search incentives. The wage compression channel is more relevant for the low-ability workers than for the high-ability workers, because the minimum wage is more binding for the former. By reducing workers' incentive to switch to better-matched occupations than the ones they currently have, the wage compression channel

[3] I thank David Wiczer for kindly sharing the data in Guvenen et al. (2020).

[4] I follow Autor and Dorn (2013) in defining the non-routine manual occupations and other occupation categories.

keeps workers in mismatches longer.

The second channel is the employment effect channel, in which the minimum wage decreases firms' vacancy posting, and hence the job-finding rate. The decrease in vacancy posting reduces the occupational mobility of all workers, regardless of ability and mismatch.

Estimating the model using the generalized method of moments (GMM) shows that when the minimum wage increases from \$7.25 to \$15, the low-ability workers' occupational mobility decreases by 44%. The decrease in mobility arises from the wage compression channel and is non-linear. The reason for the non-linearity is that a small increase in the minimum wage only affects a small fraction of workers, whereas a large increase in the minimum wage rapidly raises the fraction of workers with a binding minimum wage.

The increase in the minimum wage in the model from \$7.25 to \$15 decreases the aggregate output by 0.4%, with the wage compression channel accounting for 80% of the decrease. The reduction in output is mostly due to the low-ability workers, whose aggregate output decreases by 1.3%. The reason for the large effect on aggregate output is that the fraction of workers affected by the large increase in the minimum wage is substantial, with around 40% of the labor force facing a binding minimum wage after the increase.[5]

Although several studies have shown that the minimum wage increases job tenure (e.g., Dube et al. (2007), Dube et al. (2016), Jardim et al. (2018)), different explanations for the result can lead to opposite implications. Dube et al. (2007) and Dube et al. (2016) interpret the positive correlation between the minimum wage and job tenure as a sign of an improvement in match quality. If that reasoning is true, there should be a negative correlation between the minimum wage and mismatch, or a tendency for workers to stay longer in occupations that have better growth opportunity. By contrast, if the positive correlation between the minimum wage and job tenure is a sign of reduced gain from

[5]The estimate comes from projecting wages into 2020 on a 2% annual growth rate then imposing a \$15 minimum wage, using CPS 2005 to 2016 data.

switching occupations, then the minimum wage should lead to slower labor market dynamism and more mismatch. The empirical evidence presented here supports the latter explanation. The positive correlation with higher mismatch does not seem to be associated with longer stays in higher-skill occupations. Instead, workers tend to stay longer in lower-skill non-routine manual occupations.

The search-and-matching model presented here extends the work-horse models of Moscarini (2005) and Flinn (2006) by incorporating heterogeneous occupations and workers. Similar to the models of Moscarini (2005) and Flinn (2006), search friction and match-specific productivity create rents, which workers do not fully extract, giving rise to firms' monopsony power. The minimum wage *ex post* changes the "effective" monopsony power of firms. By acting as a redistribution device, the minimum wage can have a minimal employment effect (see Neumark (2018a), Allegretto et al. (2017), Cengiz et al. (2019), Clemens and Wither (2019), Meer and West (2016), Harasztosi and Lindner (2019), Kreiner et al. (2020)). Introducing heterogeneous occupations allows me to study a new dimension of the effect of the minimum wage: efficiency loss as a result of less occupational switching. Gorry (2013) presents a search-and-matching model in which the minimum wage restricts flows of young individuals from unemployment to employment, which could have long-lasting effects as the minimum wage affects experience accumulation. The present study contributes to the literature by focusing on the flow from employment to employment, and shows that the minimum wage can decrease efficiency through the wage compression channel.

This study also contributes to the literature on price control and search behavior. I extend the static model of Fershtman and Fishman (1994) into a dynamic model with endogenous wage distributions. Fershtman and Fishman (1994) theoretically show that when search is costly, the minimum wage compresses the wage distribution, reducing the gain of searching and hence the search effort. My model links search effort to match-specific productivity and endogenous wage distributions. By compressing endogenous wage distributions, the minimum wage disconnects search effort from match-specific productivity, decreasing occupational switching that might otherwise result in better matches. Increases in the minimum wage therefore shift the wage distribution to the left, suppressing the reduction in wage inequality. These implications have empirical support from Clemens and Wither (2019) who show that wage growth is slower for low-skill workers in states where the federal minimum wage has deeper bite, and from Autor et al. (2016) who show that reductions in wage inequality achieved by the minimum wage are smaller than previously estimated.

The results have important policy implications. The wage compression effect suggests that an increase in the minimum wage can lead to a non-trivial decrease in aggregate output, even if employment does not decrease.

Outline The organization of the rest of the paper is: section 2 shows empirical evidence that the minimum wage decreases occupational mobility and is correlated with more mismatch and longer stays in non-routine manual occupations. Section 3 constructs the model and derives the stationary equilibrium. Section 4 shows that the minimum wage disincentivizes occupational switching through wage compression. In section 5 I estimate the model and quantitatively study the implications of the effect of the minimum wage on occupational mobility, mismatch, and aggregate output. Section 6 concludes. All proofs are in the appendix section B.

2 Empirical Evidence

2.1 Data

In 2005, the CPS started using the 4-digit Census code to define occupations. Prior to the date, the occupation code in the CPS is the 3-digit Census code. To obtain consistent measures of occupational mobility at a fine level, I choose 2005 to 2016 as the sample period.[6]

I merge two consecutive monthly files. Each interviewee in the CPS is interviewed for 4 months, leaves the sample for 8 months, and is interviewed again for 4 months. In the first and fifth months in the sample, the interviewees are asked to describe their usual job activities and duties, which are used to assign occupation codes. In each of the 2-4 and 6-8 months, the CPS uses a dependent coding system to identify workers who switch occupations (see Kambourov and Manovskii (2013)). In particular, the interviewees are asked the following questions:

1. Last month, it was reported that you worked for (employer's name). Do you still work for (employer's name) (at your main job)?

   Yes $\rightarrow$ Ask next question

   No $\rightarrow$ Skip to independent occupation questions

2. Have the usual activities and duties of your job changed since last month?

   No $\rightarrow$ Ask next question

   Yes $\rightarrow$ Skip to independent occupation questions

3. Last month you were reported as (a/an) (occupation) and your usual activities were (description). Is this an accurate description of your current job?

   Yes $\rightarrow$ Use dependent coding

   No $\rightarrow$ Ask independent occupation questions

There are two cases that identify a worker as an occupational switcher. In the first case, the worker answers "no" to the first question and has occupational code change. The case corresponds to workers who switch both employer and occupation. In the second case, the worker answers "yes" to the first question, "no" to the second question, and has occupational code change. This corresponds to workers who stay with the same employer but switch occupation.

[6] I end the sample at 2016 because city-level minimum wages were less common prior to 2016.

The occupation is still coded independently if the workers skip to the independent occupation questions. This means that the dependent coding system reduces only part of the measurement error. In the current context, the measurement error is more likely to attenuate the effect of the minimum wage than to pose an identification concern. For the measurement error to bias the result, the workers would need to respond to the minimum wage increase by systematically misreporting their usual job activities and duties, which is arguably unlikely.

The occupational switching measure does not include workers who transition to unemployment first and then start working in a new occupation. This is acceptable in the present analysis for two reasons. First, the CPS allows at most three consecutive observations for a single worker, which implies that it is only possible to look at occupational switching via short-term unemployment.[7] Second, occupational switching decisions of unemployed workers tend to be more affected by factors other than wages (see e.g. Carrillo-Tudela and Visschers (2020)), as their attachment to previous occupations varies with unemployment duration. These concerns are less relevant for employed workers. Further, if workers are unemployed after the minimum wage increase, it is ambiguous whether the displacement results from the firms' side or the workers' side. By looking only at employed workers' occupational switching, I abstract from the displacement effect and get a better measure of workers' occupational switching decisions.[8]

There are two cases that identify an occupational stayer. In the first case, the worker

[7] I look at the occupational mobility via E-U-E transition in the appendix section A.3. The results are insignificant, which could be because of poor data quality: less than 50% of the observations have positive monthly occupational mobility.

[8] A back-of-the-envelope calculation using the estimates in Topel and Ward (1992) shows that employment-employment transitions accounts for about half of all the occupational switches. Kambourov and Manovskii (2008) also find that a large fraction of occupational switching is within-firms switching.

answers "yes" to the third question. The coders would use last month's occupational code for the worker. This corresponds to workers who stay with the same employer and do not change occupation. In the second case, workers answers "no" to the first question but have no occupational code change. This corresponds to workers who switch employers but stay in the same occupation.

2.2 Empirical Methods

The baseline specification is the following two-way fixed-effect model:

$$\left(\frac{\text{Switcher}}{\text{Stayer+Switcher}}\right)_{st} = \alpha + \beta lnMW_{st} + \delta_t + \lambda_s + \Gamma X_{st} + \epsilon_{st} \tag{1}$$

where δ_t is the month-year fixed effect and λ_s is the state fixed effect. The log real minimum wages are obtained using the regional price index from the Bureau of Labor Statistics (BLS). Similar to the literature on the employment effect of minimum wages, I control for "supply factors" X_{st} of occupational switching. Specifically, I use the Quarterly Census of Employment and Wages (QCEW) to construct the share of manufacturing and retail employment for each state. If occupations in these industries have higher occupational mobility, and states with higher employment share in these industries are more likely to increase their minimum wages, then exclusion of such controls might bias the estimate of the effect of the minimum wage upwards.

I aggregate the outcome variable at the state level for subgroups of workers.[9] Specifically, I restrict the sample to the subgroup of workers and divide the number of occupational switchers by the sum of the occupational switchers and the occupational stayers, weighted by the sample weight. There are two reasons for the aggregation. First, aggregation can reduce measurement error at the individual level. Second, section 5 builds on

[9]The reason for the focus on subgroups of workers is that the bite of the minimum wage varies by worker characteristics.

the empirical evidence and uses a model to study counterfactuals. The empirical results for the aggregate level of occupational mobility serve as calibration targets.[10]

The identification challenges of the two-way fixed-effect regression are two-fold. The first is the fact that minimum wage policies are not randomly distributed across states. There are extensive discussions about the potential spatial confounds to the minimum wage (e.g., Dube et al. (2010); Allegretto et al. (2017); Neumark et al. (2014); Neumark (2018b,a)). The central issue lies in how to construct the controls. The advantage of the two-way fixed-effect regression is that it uses all the variation in the minimum wage policy (Neumark (2018b)). For each minimum wage increase in a given state, the control is all other states that do not increase the minimum wage concurrently, with equal weight given to each of the control states (Powell (2021)). Dube et al. (2010) take a different approach and construct controls using contiguous county pairs in which one county experiences a minimum wage increase and the other does not, essentially assigning all the weight to the neighboring counties when constructing the controls. The disadvantage of that approach is that it uses fewer variations in the minimum wage policy, which might otherwise be useful for identification (Neumark et al. (2014)). For example, if two neighboring counties both increase their minimum wages, they would be dropped from the sample.

To balance the weight assignments and the use of the available variations, I use the generalized synthetic control (GSC) method in Powell (2021) to construct controls, so that the controls' occupational mobility, in the absence of the minimum wage effect, has the highest correlation with the treatments' occupational mobility. The method utilizes all of the available variations, the same as in the two-way fixed-effect regression. I also mimic the placebo test in Dube et al. (2010) to see if there are potential spatial confounds.

The second identification challenge is the timing of the treatment, which is discussed

[10]The analysis is repeated at the individual level in the appendix section A.1. The results hold qualitatively but are smaller in magnitude, which is consistent with the concern for the measurement error.

by Meer and West (2016) and formalized by Goodman-Bacon (2021). If the minimum wage has long-run effects on occupational mobility, then a two-way fixed-effect regression will bias the estimate upward. I address this issue by including the state-specific time trends and showing that the results are robust. I also use a panel diff-in-diff regression (see Cengiz et al. (2019)) which estimates the dynamic effects of the minimum wage.[11]

2.3 Results

I first estimate the effect of the minimum wage on workers of different ages. I define younger workers as those 16 to 30 years of age and older workers as those 31 to 45 years of age. Table 1 presents the monthly occupational mobility of the workers. The average monthly occupational mobility rate is 2.9% for the younger workers and 1.5% for the older workers. Regression of the two panel data of the occupational mobility rate using equation (1) shows that increases in the minimum wage decrease the occupational of the younger workers but have no significant effect on that of the older workers. Specifically, a 10% minimum wage increase decreases younger workers' occupational mobility by 3%.[12] That is, if the minimum wage increases by 10% in a given month, 3 out of 100 employed younger workers who would have switched occupations in the absence of the minimum wage increase would choose to stay in their current occupation instead.

The elasticity of -0.3 is consistent with the findings of Dube et al. (2016) that a 10% increase in the minimum wage increases job tenure by 2%. The reason for the slightly larger estimate in the present work might be that occupational mobility includes occupational switching within employers.

The lack of effect on the older workers' occupational mobility is consistent with the

[11]Because the panel diff-in-diff regression does not calculate the elasticity, I use the two-way fixed-effect regression as the baseline. The elasticity is important for the quantitative exercise in section 5.

[12]It is calculated as $\log(1.1) \times (-0.01)/2.9\%$.

Table 1: The Effect of Minimum Wages on Occupational Mobility

	(1) Age 16-30	(2) Age 30-45	(3) High School	(4) College	(5) Age 16-30 × High School	(6) Age 16-30 × College	(7) GSC
				Two-Way Fixed Effect			
$lnMW_{st}$	-0.010**	0.001	-0.002	-0.002	-0.011*	-0.004	-0.011**
	(0.0040)	(0.0033)	(0.0036)	(0.0029)	(0.0058)	(0.0052)	p = 0.045
				With State-Specific Time Trends			
$lnMW_{st}$	-0.012***	0.001	-0.004	-0.002	-0.011*	-0.009	—
	(0.0040)	(0.0032)	(0.0036)	(0.0030)	(0.0057)	(0.0071)	
Mobility > 0	97%	94%	96%	99%	81%	67%	97%
Average Mobility	2.9%	1.5%	2.0%	1.8%	3.1%	2.2%	2.9%
N	7344	7344	7344	7344	7344	7344	7344
State FE	Y	Y	Y	Y	Y	Y	
Year Month FE	Y	Y	Y	Y	Y	Y	

Notes. The sample period is from 2005 to 2016. The columns present the results on the occupational mobility of corresponding sub-groups. The first row of regression uses state-level occupational mobility at the monthly frequency as the dependent variable. The second row of regression adds state-specific time trends. All regressions include the share of manufacture and retail trade employment as controls. The state-clustered standard error for the two-way fixed effect model is in parenthesis. *** means statistically different from zero at the 1% level, ** at the 5% level, * at 10% the level. The inference for the GSC uses a Wald statistic. For details, see Powell (2021).

notion that the minimum wage has more bite for the younger workers than for the older workers. It is also consistent with a learning model in which workers learn their best-matched occupations over time (see e.g. Gervais et al. (2016), Groes et al. (2015)). In such a model, the older workers are more likely to be well matched in their occupations than the younger workers, so the minimum wage has less effect on their switching incentives.

Next I study the effect of the minimum wage on the occupational mobility of workers with different levels of education. Workers with low levels of education are more likely to earn the minimum wage than workers with high levels of education (e.g., Neumark and Shirley (2021)). I construct the state-level monthly occupational mobility rate for two groups of workers: those with a high-school degree or less education and those with at least a college degree.

The results in table 1 suggest that the minimum wage has no significant effect on the occupational mobility of either group. The average monthly occupational mobility for both groups is around 2%, which is much lower than that for the younger workers (2.9%). This might mean that older workers' occupational choice is insensitive to the minimum wage, regardless of education level.

When I further restrict the sample to only include workers 30 years of age or younger and then divide these workers on the basis of education, the results in table 1 show that the minimum wage has a negative effect on the younger, less-educated workers' occupational mobility. Specifically, a 10% increase in the minimum wage decreases younger, less-educated workers' monthly occupational mobility by 3%, which is significant at the 10% level. The minimum wage does not have a significant effect on the occupational mobility of the younger, college-educated workers, although the point estimate is negative. These results suggest that the minimum wage decreases younger, less-educated workers' occupational mobility.

2.4 Robustness

2.4.1 Alternative Construction of Control Groups and the Placebo Test

I first address spatial confounds. As an alternative way to construct the control groups, I use the GSC method developed in Powell (2021). The GSC specification is:

$$\left(\frac{\text{Switcher}}{\text{Stayer+Switcher}}\right)_{st} = \alpha + \beta lnMW_{st} + \Gamma X_{st} + \boldsymbol{\delta_t \lambda_s} + \epsilon_{st} \tag{2}$$

where the controls X_{st} are the same as in equation (1). Compared with equation (1), the GSC replaces the state and time fixed effects with $\boldsymbol{\delta_t \lambda_s}$, which permits flexible, non-linear state-level trends and shocks that may be correlated with the minimum wage. For example, by letting

$$\boldsymbol{\delta_t} = \begin{bmatrix} 1 & t & t \end{bmatrix} \text{ and } \boldsymbol{\lambda_s} = \begin{bmatrix} s & 1 & s \end{bmatrix}$$

so that $\boldsymbol{\delta_t \lambda_s} = t + s + s * t$, the regression includes the state fixed effect, the time fixed effect, and the state-specific time trend.

The estimation procedure is summarized in the following equation:

$$(\hat{\beta}, \hat{\alpha}, \hat{\Gamma}, \hat{w}_1, ..., \hat{w}_N) =$$
$$\underset{a,b,\gamma,w_1,...,w_N}{\text{argmin}} \left\{ \sum_{s=1}^{N} \sum_{t=1}^{T} \left[Y_{st} - a - b * lnMW_{st} - \gamma X_{st} - \sum_{j \neq s} \left(w_s^j (Y_{jt} - a - b * lnMW_{st} - \gamma X_{st}) \right) \right]^2 \right\}$$

where Y_{st} is the occupational mobility in equation (2). To understand the equation, suppose California increases its minimum wage and that no other states increase the minimum wage. The GSC would guess coefficient values for the minimum wage and the controls X_{st}, and subtract their effects. It then obtains the subtracted occupational mobility for California and the other states. It assigns weights w_s^j to the other states by minimizing the squared difference between the subtracted occupational mobility of California and the weighted average of the other states' subtracted occupational mobility. The procedure produces a vector of weights that add up to one and specify how each state is weighted in the estimation. The GSC iterates the procedure on a grid of coefficients for the minimum wage and the controls until the overall sum of the squared difference is minimized.

In the current context, every state increased its minimum wage more than once. The GSC then produces a vector of weights for each state, specifying how the synthetic control for the state is constructed. Like the classic synthetic control, the GSC is a data-driven method. If the data suggests that the contiguous states are better controls in the sense that their occupational mobility is more similar to that of the treatment state, the GSC method would assign the highest weights to the contiguous states.

Using the GSC method, I estimate the effect of minimum wages on the younger workers' occupational mobility. The point estimate is -0.011 and significant at the 5% level, which is similar to the result in the baseline regression.[13] [14] The results suggest that the baseline regression is robust to the data-driven method of constructing controls.

Next, I test for the presence of spatial confounds by mimicking the placebo test in Dube et al. (2010). The idea of the placebo test is to assign the minimum wage policy of the treatment group (states with minimum wage increases) to the controls (states with no minimum wage changes), and perform a regression using only the controls. Because the controls do not receive the treatment, the counterfactual experiment should not produce significant results, unless there are potential confounds.

I adapt the placebo test by separating the states into two similarly sized subsets. The first subset is the infrequent changers: states that increase the minimum wage less often. The second subset is the frequent changers. The variation in the dependent variable should mainly come from the states that have frequent minimum wage increases. If there are no spatial confounds between the frequent changers and the infrequent changers, assigning the minimum wage policy of the former to the latter should not produce significant estimates.

I randomly assign the minimum wage policy of the frequent changers to the infrequent changers and perform the regression using equation (1) for only the infrequent changers.

[13]The inference is based on a Wald statistic. See Powell (2021) for details. The GSC results for the other subgroups of workers are in the appendix section A.

[14]To validate the GSC approach, I calculate the average correlation in the occupational mobility rates of each state and its generalized synthetic control after subtracting off the effect of the minimum wage. I find that the average correlation increases from 0.5 to 0.75 when switching from the two-way fixed-effect model to GSC, indicating that GSC produces better controls. I plot the occupational mobility rates for each state and its generalized synthetic control in the appendix section E.

For both the younger workers and the younger, less-educated workers, out of 500 permutations, less than 7% of the estimates are significant, suggesting that the infrequent changers are as valid controls in the context of minimum wages and occupational mobility.[15]

The results of the GSC regression and the placebo test provide little evidence of spatial confounds. Next, I address the identification challenge of the timing of the treatment.

2.4.2 State-Specific Time Trend and Panel Diff-in-Diff

In the context of the employment effect of the minimum wage, the two-way fixed-effect regression is often not robust to the inclusion of state-specific time trends (e.g., Meer and West (2016), Goodman-Bacon (2021)). If the minimum wage has dynamic effects on the outcome variable, the estimates in a two-way fixed-effect regression are a combination of short-run and long-run effects. The addition of state-specific time trends would capture long-run effects and thus change the estimates. Further, if there are underlying state-specific trends that are driving both the minimum wage and occupational mobility, the baseline regression is not robustness to adding state-specific time trends.

To address these issues, I use the following regression specification with state-specific time trends:

$$\left(\frac{\text{Switcher}}{\text{Stayer+Switcher}}\right)_{st} = \alpha + \beta lnMW_{st} + \delta_t + \lambda_s + t \times \lambda_s + \Gamma X_{st} + \epsilon_{st} \tag{3}$$

[15] I repeat the placebo test using two other division methods. In the first case, I separate the states into federal minimum wage states and higher-than-federal-minimum-wage states, based on the intuition that the federal minimum wage states are the controls in Dube et al. (2010). In the second case, I rank the states by the average percentage change in the minimum wage and separate the states into two similarly sized groups, based on the intuition that states with large minimum wage changes could drive the results. In both cases, less than 7% of the permutations produce significant results. The placebo tests suggest little evidence of spatial confounds in the context. The details of the placebo test algorithm are in the appendix section A.2.1.

The results in table 1 shows that the inclusion of state-specific time trends has little effect on the point estimate of the effect of the minimum wage on occupational mobility, although the estimate for changes from -0.1 to -0.012 for the younger workers, suggesting an even larger effect. Compared to the big changes in the estimates of the employment effect of the minimum wage with the inclusion of state-specific time trends, the results suggest that the effect of the minimum wage on occupational mobility is robust to the inclusion of state-specific time trends.

A more direct way to estimate the dynamic effects of the minimum wage is to use the panel diff-in-diff method in Cengiz et al. (2019), which allows the effect of the minimum wage to be examined both before and after an increase.

The empirical specification is

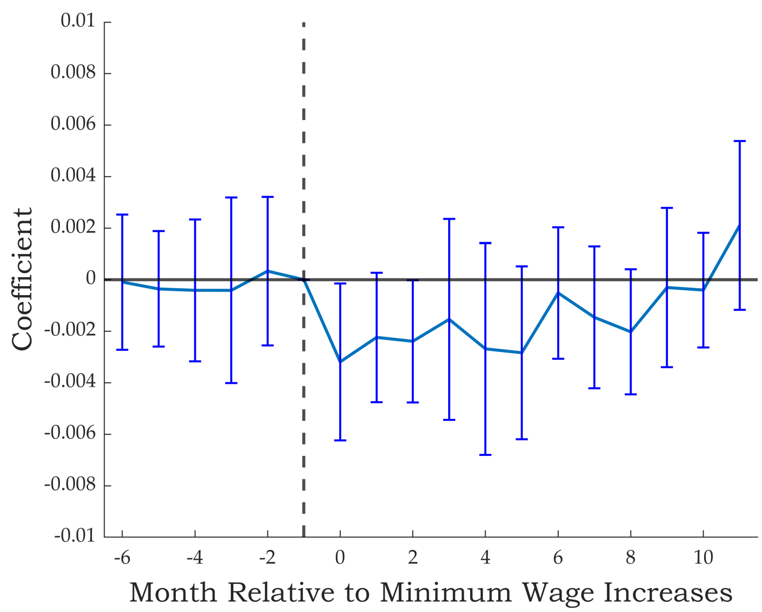
$$\left(\frac{\text{Switcher}}{\text{Stayer+Switcher}}\right)_{st} = \sum_{\tau=-6}^{11} \alpha_\tau \mathbb{I}_{st}^{\tau} + \delta_t + \lambda_s + \Omega_{st} + \Gamma X_{st} + \epsilon_{st} \tag{4}$$

The outcome variable is the occupational mobility of the younger workers. The treatment dummy $\mathbb{I}_{st}^{\tau}$ equals 1 if the minimum wage is raised τ months from date t in state s. Following Cengiz et al. (2019), I exclude federal minimum wage increases and only consider the state-level minimum wage increases that: 1. are more than \$0.25; 2. affect more than 2% of the workers in the state. Indicators for small and federal minimum wage increases are included in Ω_{st}. The "supply factor" controls X_{st} are the same as in equation (1). There are 95 qualifying minimum wage increases for the sample period from 2005 to 2016, with the average increase equal to \$0.6 or 9%.

Equation (4) examines 6 months before and 12 months after the minimum wage increase. The time horizon allows me to study the effects of the minimum wage in the short-run and see if there is evidence of longer persistence.

Figure 1 shows that there is no pre-trend before the minimum wage increase. In the first three months following the minimum wage increase, the effect is negative and significant at 5% level in the first month, with the coefficients significant at 10% level in the second and the third month. The point estimates remained negative until the 12th month after the minimum wage increase, indicating that the effects concentrate in the first year of the minimum wage increase. It is likely that labor market adjustments such as changing skill requirements, together with declines in real minimum wages and increases in per capita income cause the effects to disappear after a year.[16]

Figure 1: The Effect of the Minimum Wage on Occupational Mobility: Panel DiD



Notes. Figure 1 plots the estimates using equation (4). The blue line shows the evolution of the effects of the minimum wage on the younger workers' occupational mobility (relative to 1 month before the minimum wage increase). Specifically, the figure shows the effect three months before and 6 months after the minimum wage increase. The figure also shows the 95% confidence interval based on standard errors clustered at the state level.

These results show that there is little evidence of concurrent policies or underlying trends that might confound the estimates in the baseline regression given by equation (1). Further, the effect is significant at 10% for the first three months after the minimum wage

[16]In figure 3, I include periods that are 18 months after the minimum wage increase. The results are consistent, showing that one year after the minimum wage increase, the effects fluctuate around 0.

increase, corroborating the results in the baseline regression. The effects gradually reduce to 0 one year following the minimum wage increase.

2.5 Discussion of the Empirical Results

The decrease in occupational mobility associated with an increase in the minimum wage might be caused by factors related to the firm side or the worker side. On the firm side, if a minimum wage increase causes firms to post fewer vacancies (see Kudlyak et al. (2019)), then workers might find it more difficult to switch occupations. That is, the minimum wage might reduce occupational mobility by making it more difficult to find jobs.

On the worker side, a minimum wage increase might reduce workers' incentive to switch occupations in light of occupational switching costs. Cortes and Gallipoli (2018) show that there are large costs associated with occupational switching. Workers switch to occupations that better match their skills, provide better wages, or have a better career outlook, as long as the anticipated gain outweighs the switching cost. When the minimum wage increases, the potential wage gains from switching occupations are reduced, leading to a decline in occupational mobility.

Another worker-side explanation is that the minimum wage improves match quality, which induces workers to stay longer in their current jobs. This is suggested by Dube et al. (2016), who show that higher minimum wages increase job tenure.

The two worker-side explanations differ by their implications on match quality. If the first explanation is correct, the average match quality after an increase in the minimum wage is lower compared with the counterfactual without the minimum wage increase because workers switch to better-matched occupations at a slower rate. If the second explanation dominates, increases in the minimum wage lead to increased match quality.

To determine which explanation is more likely, I first assess the effect of the minimum wage on workers' job-finding rates and separation rates. I then study the effect of the minimum wage on match quality.

2.5.1 Implications on the Job-Finding Rate

I construct the job-finding rate using the CPS unemployment flows as in Shimer (2012). To the extent that the job-finding rate measures the difficulty of finding a job regardless of employment status, if a minimum wage increase does not affect the job-finding rate, a decrease in occupational mobility after the minimum wage increase is not likely to be driven by increased difficulty in finding jobs.

The empirical specification is

$$JFR_{st} = \alpha + \beta lnMW_{st} + \delta_t + \lambda_s + \Gamma X_{st} + \epsilon_{st} \tag{5}$$

where JFR_{st} are the job-finding rates for younger workers or younger, less-educated workers. The controls include state and month-year fixed effects. X_{st} includes manufacturing and retail employment shares as in the baseline regression.

Table 2 shows that the minimum wage has no significant effect on the job-finding rate, except for the regressions that use data from 2012 to 2016. The results are consistent for both the younger workers and the younger, less-educated workers. During the period 2005 to 2016, there is little evidence that the minimum wage affects the job-finding rates.

It is also useful to study whether the minimum wage leads to more displacement. While the occupational mobility provides information about employed workers, firms might displace the other workers into unemployment after a minimum wage increase. If that is the case, the employed workers are selected by the minimum wage increase and might not be representative.

To that end, I study the effect of the minimum wage on the separation rate using the following specification:

$$SPR_{st} = \alpha + \beta lnMW_{st} + \delta_t + \lambda_s + \Gamma X_{st} + \epsilon_{st} \tag{6}$$

Table 2: The Effect of Minimum Wages on Job Finding Rate and Separation Rate

	Job Finding Rate		Separation Rate	
	(1) Age 16-30	(2) Age 16-30 × High School	(3) Age 16-30	(4) Age 16-30 × High School
		2005 to 2016 (N = 7310)		
$lnMW_{st}$	-0.0447	-0.0552	-0.002	-0.003
	(0.0454)	(0.0531)	(0.005)	(0.009)
		2008 to 2016 (N = 5429)		
$lnMW_{st}$	-0.0856	-0.130	-0.005	-0.006
	(0.0687)	(0.0787)	(0.009)	(0.010)
		2010 to 2016 (N = 4205)		
$lnMW_{st}$	-0.1098	-0.171	-0.009	-0.011
	(0.0875)	(0.0966)	(0.011)	(0.012)
		2012 to 2016 (N = 2985)		
$lnMW_{st}$	-0.168*	-0.235**	-0.0131	-0.0147
	(0.0991)	(0.104)	(0.0121)	(0.0127)
State FE	Y	Y	Y	Y
Year Month FE	Y	Y	Y	Y

Notes. Table 2 constructs job finding rate and separation rate as in Shimer (2012). It shows the effect of the minimum wage on the job-finding rate and the separation rate using equation (5) and equation (6). The rows indicate the sample periods. I use state-clustered standard errors. *** means significant at 1% level, ** means significant at 5% level, * means significant at 10% level.

Equation (6) is identical to equation (5) except for the outcome variable. The separation rate construction follows Shimer (2005). Table 2 shows that there is no significant effect of the minimum wage on the separation rate. The null effect is consistent with the small or null estimates of the employment elasticity of the minimum wage. The null effects on the job-finding rates and separation rates suggest that the decrease in occupational mobility cannot be fully rationalized by firms' reactions to the minimum wage increase.

2.5.2 Implications on Match Quality

To determine the mechanism by which increases in the minimum wage reduce occupational mobility, I examine the relationship between the minimum wage and match quality.

I use the NLSY79 data and follow Guvenen et al. (2020) to construct a measure of match quality. The NLSY79 contains information about workers' skills based on the ASVAB test, which measures verbal, math, and social skills. Correspondingly, the O*NET characterizes occupations by skill requirements along verbal, math, and social dimensions.[17] I define mismatch as the distance between workers' skills according to the ASVAB test and occupations' skill requirements according to the O*NET. A low mismatch means that the match quality is likely to be high, and vice versa.

The empirical specification is

$$Mismatch_{ist} = \alpha + \beta lnMW_{st} + \Gamma X_{ist} + \delta_t + \lambda_s + \epsilon_{ist} \tag{7}$$

The observations are at the individual-state-year level. The state-level minimum wage is the same as in equation (1). The controls X_{ist} include age, gender, education, occupational tenure, a third degree polynomial for experience, and initial ability. There are state and year fixed effects. The sample is restricted to White younger workers 16 to 30 years of age who have two consecutive years of employment in the same state. The consecutive employment history is to filter out the workers that are marginally attached to the labor force, and the workers who move to other states but experience changes in both the minimum

[17] I thank David Wiczer for sharing their data.

wage and mismatch.[18] [19]

The results for the younger workers are shown in the first column of table 3. For these workers, a 10% increase in the minimum wage is associated with a 2% increase in mismatch, which suggests that a higher minimum wage is associated with lower average match quality.

For comparison, I examine the effect of the minimum wage on the older workers. The results are shown in the second column of table 3. For the older workers, there is no significant correlation between the minimum wage and mismatch.

I also estimate the effect of the minimum wage on mismatch separately for males and females using the following specification:

$$Mismatch_{ist} = \alpha + \beta lnMW_{st} \times Gender_i + X'_{ist}\gamma + \delta_t + \lambda_s + \epsilon_{ist} \tag{8}$$

The gender-specific results are shown in the last two columns of table 3. The estimates show that the effect is concentrated on the younger male workers. In particular, a 10% increase in the minimum wage is associated with 4% greater mismatch for the younger male workers, which is significant at the 5% level. By contrast, the minimum wage has no effect on mismatch among the younger female workers or the older workers.

The positive correlation between the minimum wage and mismatch suggests that the switching cost can explain the effect of the minimum wage on occupational mobility. In

[18]The white workers consist of 95% of the sample in Guvenen et al. (2020). When including the Hispanic and the Black workers, the results become insignificant. Given that the insignificance is driven by less than 5% of the sample, I include only the white workers as the main result.

[19]The NLSY79 starts from 1980 whereas the QCEW, necessary for constructing the manufacturing and retail employment shares, starts from 1990. Including the QCEW controls would significantly reduce the sample size. They also matter little in the baseline regression. I hence exclude the QCEW controls.

Table 3: Minimum Wage and Mismatch

	(1) Age 16-30	(2) Age 30-45	(3) Age 16-30	(4) Age 30-45
$lnMW_{st}$	0.307*	-0.272		
	(0.182)	(0.193)		
$lnMW_{st} \times Male$			0.446**	-0.092
			(0.186)	(0.376)
$lnMW_{st} \times Female$			0.111	-0.494
			(0.251)	(0.491)
Age	-0.005	0.006	-0.005	0.006
	(0.006)	(0.011)	(0.007)	(0.011)
$Education$	-0.068***	-0.046**	-0.068***	-0.046**
	(0.011)	(0.016)	(0.011)	(0.016)
$Female$	-0.017	-0.054		
	(0.030)	(0.044)		
$Occupation$	-0.029***	-0.015**	-0.029***	-0.015**
$Tenure$	(0.004)	(0.006)	(0.004)	(0.006)
Exp	0.016	0.014	0.016	0.016
	(0.024)	(0.052)	(0.024)	(0.053)
Exp^2	0.003	-0.067	0.004	-0.075
	(0.260)	(0.395)	(0.259)	(0.402)
Exp^3	-0.002	0.001	-0.002	0.002
	(0.007)	(0.009)	(0.007)	(0.009)
$Ability$	0.767***	0.107	0.767***	0.109
	(0.106)	(0.139)	(0.106)	(0.139)
Year FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
N	25833	15025	25833	15025

Notes. Table 3 shows the correlation between the state-level minimum wage and the workers' mismatch using NLSY79. The mismatch data is from Guvenen et al. (2020). The regression specification is equation (7). The standard error is clustered at the state level. ** means significant at 5% level, * means significant at 10% level.

other words, a higher minimum wage is likely to cause workers to stay longer in mismatched occupations.

It is important to consider which occupation transitions are most affected by the minimum wage. It is possible that a higher minimum wage is associated with higher mismatch but also causes workers to stay in high-skill occupations. For example, a worker's initial skills might be suited to food service, but a high minimum wage causes the worker to keep the job as an office clerk. The minimum wage promotes mismatch in the short run, but over time the worker might develop skills that allow her to climb the job ladder to higher-skill occupations such as management.

To learn if the minimum wage has differential effects on occupation transitions, I study the relation between the minimum wage and transition rates in four occupational categories following Autor et al. (2016): non-routine cognitive occupations (e.g., lawyer, engineer), non-routine manual occupations (e.g., food preparation, building cleaning), routine cognitive occupations (e.g., office and administrative support), and routine manual occupations (e.g., butcher, material moving).[20]

I first categorize workers as occupational switchers or stayers as in section 2.1. I then categorize the occupational switchers as switchers that stay within the same category (e.g., switch from one non-routine manual occupation to another non-routine manual occupation) or switchers that transit into other categories (e.g., switch from a non-routine manual occupation to a routine cognitive occupation). I calculate the transition rates by dividing the number of transitions by the total number of switchers and stayers, which yields 16 (=4×4) occupational transition rates. For each transition rate, I perform the following two-way fixed-effect regression:

$$\text{Transition Rate}_{st} = \alpha + \beta lnMW_{st} + \delta_t + \lambda_s + \Gamma X_{st} + \epsilon_{st} \tag{9}$$

[20]The aggregation is necessary due to data limitation. If the occupational flow is constructed at the 2-digit level, less than 50% of the observations are non-zero.

The regression is performed at the annual frequency because of data limitation.

The results shows that for the younger workers, a higher minimum wage is associated with lower transition rates from non-routine manual occupations to routine cognitive occupations.[21] If the routine cognitive occupations serve as job ladders to non-routine cognitive occupations, the results suggest that a higher minimum wage is associated with fewer transitions from manual occupations to these job ladders. During the sample period, the average transition rate from routine cognitive occupations to non-routine cognitive occupations is 1% per month, while the average transition rate from non-routine manual occupations to non-routine cognitive occupations is 0.4% per month. This means that workers in routine cognitive occupations are twice more likely as workers in non-routine manual occupations to transition into non-routine cognitive occupations.[22]

To summarize, the evidence is consistent with the switching-cost explanation for the negative effect of the minimum wage on occupational mobility. The association with higher mismatch and fewer transitions between certain types of occupations points to potential misallocation. In other words, without the minimum wage, workers might be more likely to switch to occupations that better match their skills or that lead to higher-skill occupations. In the remaining sections, I present a stylized model in order to 1) decompose the effect of the minimum wage on occupational mobility by incorporating the key components of the empirical analysis (i.e., the minimum wage, the switching cost, mismatch, and heterogeneous workers) and 2) study the impact on mismatch and aggregate productivity of a counterfactual increase in the minimum wage to $15.

[21] Table A.7 shows the results for all the occupational transition rates.

[22] From 2005 to 2016, the occupational transition matrix for the younger workers is shown in table A.8.

3 A Model with Heterogeneous Occupations and Workers

I construct a continuous-time search-and-matching model. The model defines occupations as in Guvenen et al. (2020): an occupation $j \in [0,1]$ is a summary index of skill requirements. A unit measure of workers differ ex ante in "ability", an index $a \in [0,1]$. The ability determines the rate at which workers learn the skill requirement. Another interpretation of ability is that it is related to the occupational specific human capitals (Kambourov and Manovskii (2008)). Mismatch is defined as the distance between the occupation index and the ability index $|a-j|$. The CDF of occupations is $H(j)$. The density of occupations is $h(j)$. The distribution of workers' ability is given by the CDF $G(a)$ with PDF $g(a)$.[23] [24]

Firms' only decision is how many vacancies they post, subject to a flow cost of vacancy κ. The distributions of occupations $H(j)$ and workers $G(a)$ are exogenous and determine the occupation of the vacancy and the type of workers the vacancy meets. Once a match forms, the vacancy's outside option is normalized to be 0.

An employed worker with ability a in an occupation with skill requirement j can produce a single good in a match. The productivity of a worker is match-specific and stochastic, because of factors such as learning-by-doing and match-specific human capital accumulation.

If worker a is in occupation j, her productivity evolves according to:

$$\frac{dX_t}{X_t} = \frac{a}{1+|a-j|}dt + \sigma dZ_t \tag{10}$$

where $\{Z_t\}_{t\geqslant 0}$ is a Brownian motion and σ governs the volatility. Equation (10) implies

[23] All results are retained if I have a joint CDF $N(a,j)$. I define $H(j)$ and $G(a)$ separately for ease of exposition.

[24] A job might include other features such as non-pecuniary components. One occupation, e.g. office clerk, could be two different jobs, if one is located in a nice office and the other is not.

that the worker's productivity grows at a rate $a/(1+|a-j|)$, but there are idiosyncratic shocks to the growth rate of productivity.[25]

The productivity specification captures several features that are consistent with empirical evidence. As will be shown later, higher-ability workers are more likely to have higher productivity and less likely to be affected by the minimum wage.[26] On the other hand, a mismatched worker is more likely to be affected by the minimum wage, leading to a correlation between the minimum wage and mismatch.[27]

For normalization, productivity is mapped one-to-one to output flow. I use productivity, current output, or simply output interchangeably, with the understanding that all three are flow values. I impose an upper-bound $\overline{x}$ on the match-specific productivity X_t so productivity cannot be arbitrarily large.[28]

---

[25] I micro-found the productivity process in a Ben-Porath economy in appendix section F, which shows that a model with endogenous human capital accumulation and idiosyncratic human capital shock leads to the productivity process equation (10).

[26] Deming and Kahn (2018) provide empirical support that skill requirements and match quality is positively correlated with higher wages.

[27] The mismatch measure is symmetric in the sense that, for a fixed j, a larger a and a smaller a could lead to the same mismatch. The interpretation is the following: if $a < j$, the mismatch comes from the worker's lack of skills for the occupation; If $a > j$, the mismatch comes from the worker's opportunity cost of staying in an occupation with a low skill requirement. In both cases, the mismatch gives the worker an incentive to switch occupations, which is the purpose of the model assumption. That is, the symmetric mismatch measure implies that workers that are "over-qualified" in the sense that $a > j$ have incentives to switch occupations. Any other specification that induces "over-qualified" workers to switch occupations would lead to the same qualitative results in the paper. Quantitatively, the model produces a good match to the empirical wage distribution.

[28] The upper bound is a technical assumption that guarantees the steady state existence.

Unemployed workers receive unemployment benefit b and search for jobs with the arrival rate λ determined in equilibrium. Upon job arrival, they are matched into an occupation with initial productivity x_p. Employed workers can also search on the job with efficiency given by α, so that their job arrival rate is $\alpha\lambda$.[29]

When workers switch occupations, they need to pay a one-time cost ϕ. The switching cost means that workers switch occupations only if the expected gain is sufficiently large. Workers are exogenously separated into unemployment at rate δ. Workers and firms are risk neutral and share a common discount parameter r.

Search friction and match-specific productivity create surplus for each realized match. Workers and firms split the surplus according to generalized Nash bargaining, in which workers have bargaining power β.[30] The Nash bargaining determines the workers' wages, subject to the minimum wage constraint as in Flinn (2006). If the Nash-bargained wage is lower than the minimum wage, the workers will earn the minimum wage. The minimum wage can then change the bargaining power ex-post.[31]

[29]Because workers reset their initial productivity, there is no task-specific human capital that can be transferred. This assumption is justified for the younger, less-educated workers: Weber (2008) show that less-educated workers have fast human capital depreciation; and Dinerstein et al. (2020) show that when task-specific human capital is not in use, it tends to depreciate. These results imply that only part of the task-specific human capital is transferred for low-ability workers, because the workers "forget" about the skills learned in the previous occupation.

[30]Moscarini (2005) has a detailed discussion of the micro foundation of Nash-bargaining wage setting with on-the-job search. The bargaining environment is more complex with on-the-job search because the employed workers can bargain with two potential employers simultaneously. I show in the appendix section B that an English first-price auction justifies the use of Nash bargaining.

[31]Any wage function that is decreasing in mismatch and increasing in ability (e.g., a predetermined wage function set by an intermediary) would preserve the results of the current anal-

Because a worker is risk neutral, her objective is to maximize expected discounted wages. Let w be the wage function that realizes the bargained outcome. A worker with ability a in occupation j maximizes:

$$V(x, a, j, m) = \mathbb{E}\left[\int_0^{\tau} e^{-rt} w(X_t, m) dt\right]$$

where x is the productivity at time 0, and m is the minimum wage.[32] The match dissolves at (stochastic) time τ, which depends on the worker's productivity $X_t(a, j)$ and the minimum wage. Hereafter, I abstract from the dependence on (a, j, m) and write $V(x)$ for simplicity unless confusion arises. Workers' only choices are whether to search on the job and whether to separate endogenously into unemployment.[33]

For an unemployed worker with ability a, the value function is

$$U(a, m) = b + \lambda \mathbb{E}[V(x, a, j, m)]$$

where the expectation is with respect to the output process and the occupation distribution. When there is no confusion, I write U in place of $U(a, m)$. For the rest of this section, I focus on the stationary equilibrium.[34]

ysis. I show in the appendix section G that the main implications of the model are also present in a directed search model with wage posting.

[32]This formulation is for ease of exposition. See equation (B.22) in appendix section B for the expanded formulation.

[33]Because search is costless, technically a worker can always search on the job. However, when her productivity is high, she would not switch even if she receives a job offer. The current formulation has the two advantages. First, it is robust to a small perturbation to search cost. Second, it non-trivially defines the measure of workers searching. The same argument is made in Moscarini (2005).

[34]Both the theoretical and quantitative convergence of the model is very fast with a half-life of

3.1 Wage Function

In a worker-occupation match (a, j), the worker receives instantaneous wage payment $w(x)$ and can search on the job with the arrival rate $\alpha\lambda$. The expected gain of switching is $\int_{\mathbb{T}^n} V(x_p, j)dH(j) - V(x)$, which depends on the worker's current value $V(x)$. The worker's value function $V(x)$ follows:

$$
\begin{aligned}
rV(x) =& w(x) + \tilde{a}xV'(x) + \frac{1}{2}\sigma^2 x^2 V''(x) - \delta[V(x) - U] \\
&+ \alpha\lambda \mathbb{I}_{\left\{\int_{\mathbb{T}^n} V(x_p,j)dH(j) - V(x) \geqslant \phi\right\}} \left[\int_{\mathbb{T}^n} V(x_p, j)dH(j) - V(x) - \phi\right]
\end{aligned} \tag{11}
$$

where $\mathbb{I}$ is the indicator function. If the worker's current value is low, possibly because of high mismatch or bad shocks, the worker would switch occupation and pay the switching cost ϕ. The worker also faces exogenous separation at the rate δ, upon which the worker becomes unemployed and receives the value of unemployment U. The first and second derivatives are because of the randomness in the productivity process and represent the continuation value of a match.

If a worker is unemployed, she receives unemployment benefit b and searches for jobs. Her value of unemployment is:

$$
rU = b + \lambda\left[\int_{\mathbb{T}^n} V(x_p, j)dH(j) - U\right] \tag{12}
$$

While on the job, a worker can endogenously quit to unemployment. The worker thus faces an optimal switching problem. Namely, the decision regarding occupational switching and endogenous separation depends on the worker's current productivity x and some cutoff points. Let $\underline{x} = inf\{x : V(x) > U\}$. The worker will quit to unemployment endogenously if her productivity x is less than $\underline{x}$. I refer to $\underline{x}$ as the endogenous separation cutoff.

about 2.7 months. This validates the focus on the steady state.

Similarly, I set

$$x_s = inf\left\{x : V(x) = \int_{\mathbb{T}^n} V(x_p, j)dH(j) - \phi\right\} \tag{13}$$

where x_s determines the worker's on-the-job search decision. I refer to x_s as the on-the-job search cutoff. When the worker's productivity x is between $\underline{x}$ and x_s, the expected payoff of staying in the current job is less than the expected payoff of switching occupations. The worker will then search on-the-job for other occupations. When the worker's productivity exceeds x_s, she will stay in her current occupation. Knowledge of x_s and $\underline{x}$ is thus equivalent to knowledge of the worker's decisions regarding occupational switching and endogenous separation.

The value function of the firm is:

$$\begin{aligned} rJ(x) = x - w(x) + \tilde{a}xJ'(x) + \frac{1}{2}\sigma^2 x^2 J''(x) - \delta J(x) \\ - \alpha\lambda \mathbb{I}_{\left\{\int_{\mathbb{T}^n} V(x_p,j)dH(j) - V(x) \geqslant \phi\right\}} J(x) \end{aligned} \tag{14}$$

The firm receives flow output x, pays the wage $w(x)$, and faces termination if the match separates exogenously at the rate δ or endogenously if the worker switches occupations. To simplify notation, I substitute $\mathbb{I}_{sw}$ for $\mathbb{I}_{\left\{\int_{\mathbb{T}^n} V(x_p,j)dH(j) - V(x) \geqslant \phi\right\}}$.

The associated distribution of output $f(x)$ has an infinitesimal generator that is the transpose of equation (14) (Gabaix et al. (2016)). The distribution satisfies

$$\frac{\sigma^2}{2}x^2 f''(x) + (2\sigma^2 - \tilde{a}^2)xf'(x) + (\sigma^2 - \tilde{a})f(x) - (\delta + \alpha\lambda\mathbb{I}_{sw})f(x) = 0 \tag{15}$$

The surplus of a match is split by generalized Nash bargaining. This implies that the worker's value function and the firm's value function are linearly related as follows:

$$\beta J(x) = (1 - \beta)[V(x) - U] \tag{16}$$

Taking the derivatives in equation (16) and plugging them into equation (11) and equation (14), the wage function is:

$$(17)\quad w(x) = \max\left\{\beta x + (1-\beta)b + \lambda(1-\beta)(1-\alpha\mathbb{I}_{sw})\left[\int_{\mathbb{T}^n} V(x_p, j)dH(j) - \phi - U\right], m\right\}$$

where m is the minimum wage.[35] The wage function in the absence of the minimum wage has three parts. The first and second parts suggest that the worker's wage is a convex combination of her current output and her unemployment flow benefit b. These two parts are standard in search models in which workers and firms share surplus linearly. The third part implies that the wage aggregates the worker's outside option given by $\lambda(1-\beta)\left[\int_{\mathbb{T}^n} V(x_p, j)dH(j) - \phi - U\right]$. The firm knows the worker's on-the-job search decision. Therefore, searching on the job incurs a wage cut of size $\lambda(1-\beta)\alpha\mathbb{I}_{sw}\left[\int_{\mathbb{T}^n} V(x_p, j)dH(j) - U - \phi\right]$.

3.2 Stationary Equilibrium

Let $f(x, a, j, m)$ be the stationary distribution of output associated with the pair (a, j) and the minimum wage m. Let s be the measure of job seekers. It is equal to the sum of unemployed workers and on-the-job searchers:

$$(18)\quad s = 1 - \int\int\int_{\underline{x}}^{\overline{x}} f(x, a, j, m)dxdG(a)dH(j) + \alpha\int\int\int_{\underline{x}}^{x_s} f(x, a, j, m)dxdG(a)dH(j)$$

Let v be the measure of vacancy. In equilibrium, I assume that the job arrival rate is determined by a constant return to scale matching function $M(s, v) = s^{\zeta}v^{1-\zeta}, \zeta \in (0, 1)$. The job arrive rate is $\lambda = M(s, v)/s = M(1, \theta) = \theta^{1-\zeta}$, in which θ is the market tightness. By the free entry condition, the cost of a vacancy κ must equal the expected gain for a firm:

$$(19)\quad \kappa = \int\int \lambda^{\frac{\zeta}{\zeta-1}} J(x_s, a, j, m)dG(a)dH(j)$$

[35] The details of the derivation of the wage function are in the appendix section B.

A stationary general equilibrium is a set of parameters $\{\lambda, \underline{x}, s, v, \theta\}$ and a list of functions $\{J, V, f\}_{a,j}$ that satisfy equations (11), (15), (18) and (19).[36] For the existence of an equilibrium, there needs to a λ such that equation (19) holds for some $\kappa \in (0, +\infty)$. Because $J(x, a, j, m)$ is uniformly bounded in the interval $[J(\underline{x}, 0, 1, m), J(\overline{x}, 1, 0, m)]$, the integrand on the right hand side of equation (19) decreases from $+\infty$ to 0 as λ increases from 0 to $+\infty$. Uniform boundedness of the function $J(x, a, j, m)$ also implies the continuity of the integral in λ. For any $\kappa \in (0, +\infty)$, there is at least one λ such that equation (19) holds, which guarantees the existence of a stationary general equilibrium:

Proposition 1. *There exists a stationary general equilibrium for any vacancy cost* $\kappa \in (0, +\infty)$.

3.3 Occupational Mobility

The occupational mobility in the stationary equilibrium is:

$$\mu = \alpha\lambda \int \int \int_{\underline{x}}^{x_s} f(x, a, j, m) dx dG(a) dH(j) \tag{20}$$

This is the integral of the stationary output distribution between $\underline{x}$ and x_s, weighted by the ability and occupation distribution.[37] This definition is consistent with the one in section 2 because both measure only on-the-job occupational switching.

For a fixed ability a, the occupational mobility is:

$$\mu_a = \alpha\lambda \int \int_{\underline{x}}^{x_s} f(x, a, j, m) dx dH(j) \tag{21}$$

[36]The derivations of the value functions and the output distribution are in the appendix section B.

[37]Kambourov and Manovskii (2009) notes that occupational mobility is correlated with wage inequality. This is also true in my model because both occupational mobility and wage inequality are determined by the same stationary distribution.

In the next section, I decompose how the occupational mobility responds to a minimum wage increase.

4 The Effect of Minimum Wages on Occupational Mobility

From equation (21), by taking the derivative with respect to the minimum wage, the response of the mobility is

$$\frac{\partial \mu_a}{\partial m} = \underbrace{\frac{\partial \lambda}{\partial m}\alpha \int \int_{\underline{x}}^{x_s} f(x,a,j,m)dxdH(j) + \alpha\lambda f(x,a,j,m)\frac{\partial \underline{x}}{\partial m}}_{\text{Employment Effect Channel}} \underbrace{- f(x,a,j,m)\frac{\partial x_s}{\partial m}}_{\text{Wage Compression Channel}} \tag{22}$$

From the derivative, the minimum wage affects occupational mobility by changing the on-the-job-search cutoff x_s. This is the wage compression channel. The employment-effect channel consists of two parts: the effect on the job-finding rate λ and the effect on the endogenous separation cutoff $\underline{x}$. In the next two subsections, I discuss the two channels in details.[38]

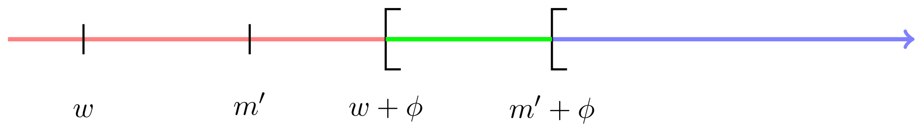
4.1 The Wage Compression Channel

The model shows that the minimum wage can decrease occupational mobility because of wage compression. The wage compression channel is shown in more detail in the appendix section B. Here I illustrate the intuition using the example in figure 2.

Suppose a worker's current wage is w, and there is a one-time switching cost ϕ. If the minimum wage m is less than the worker's current wage, the worker would switch to another occupation if the other occupation pays more than $w + \phi$. If the minimum wage increase from m to m', which exceeds the worker's current wage, the worker would only

[38] $\alpha\lambda \int_{\underline{x}}^{x_s} \frac{\partial f(x,a,j,m)}{\partial m} dxdH(j) = 0$ since the minimum wage only affects the productivity distribution by changing the cutoffs, i.e. $\partial f(x,a,j,m)/\partial m = 0$.

Figure 2: The Wage Compression Channel: An Example



Notes. Figure 2 illustrates the wage compression channel by a simple example. The worker's current wage is w, and there is a one-time switching cost ϕ if she switches occupations. If the minimum wage m is less than her current wage, she would switch to the other occupation if it pays more than $w + \phi$. If there is a minimum wage increase from m to m' which exceeds her current wage, she would switch to occupations that pay more than $m' + \phi$. She stops switching to occupations that pay between $(w + \phi, m' + \phi)$, leading to a decrease in occupational mobility.

switch to occupations that pay more than $m' + \phi$. As a result, the worker stops switching to occupations that pay between $(w + \phi, m' + \phi)$, leading to a decrease in occupational mobility.

The example shows that the key ingredients for the wage compression channel are the switching cost, the positive correlation between wage and productivity, and that there is no one-for-one spillover of the minimum wage to higher wage levels.[39] The occupational switching cost is consistent with Cortes and Gallipoli (2018) and the empirical evidence. The assumption of no spillover is likely to hold in the short run.[40]

In the model, the wage compression channel has larger effects on lower-ability and mismatched workers' occupational mobility, because the minimum wage is more binding for

[39]The wage compression channel exists in a directed search model as well. I show in the appendix section G that in a directed search model with wage posting in which the output is decreasing in mismatch also implies that the minimum wage leads to a decrease in occupational mobility and more mismatch.

[40]Neumark et al. (2004) shows that there is spillover to the wages near the minimum wage at the annul frequency. The spillover is much less than one-for-one. As shown in figure 1, the minimum wage's effect on occupational mobility is concentrated in the first year of the minimum wage increase. These suggest that the assumption of no spillover is valid.

them. Hence, lower-ability and mismatched workers will stay in a mismatched occupation longer, implying that a higher minimum wage leads to more mismatch, which is consistent with the positive association between the minimum wage and mismatch described in section 2.5.2.

4.2 The Employment Effect Channel

The minimum wage could have a displacement effect by which a higher minimum wage decreases the value of a match to firms, increasing the probability of endogenous separation. An increasing rate of separation decreases occupational mobility, because workers who would have remained on the job and search for another occupation become displaced.[41] The size of the displacement effect depends not only on the magnitude of the minimum wage change, but also on the probability that productivity drifts in low values. My model hence features differential displacement effects based on ability and mismatch.[42]

The minimum wage could also reduce firms' vacancy posting. In equation (19), firms adjust their vacancy postings in the new equilibrium when the minimum wage increases. The value function of firms decreases, so firms reduce their vacancy posting. The reduction in vacancy posting results in a lower job arrival rate, which decreases occupational mobility. Importantly, the reduction in vacancy posting affects all workers' occupational mobility regardless of ability and mismatch.[43]

[41] Mathematically, it means that the output at which J is zero would be higher than before after a minimum wage increase. This would cause the endogenous separation cutoff $\underline{x}$ to increase.

[42] Clemens et al. (2020) show that employers are more likely to expect education credentials after a minimum wage increase. In the present context, this is reflected by a higher displacement probability for the low-ability workers.

[43] Kudlyak et al. (2019) shows that the elasticity of the vacancy posting for at-risk occupations with respect to the minimum wage is -0.24. The present model abstracts from the potential het-

In the next section, I quantitatively evaluate the effect of the minimum wage.[44] The quantitative analysis is useful, because the minimum wage increases in the data are small, averaging around 6%, or $0.39. To study the effect of a large minimum wage increase, a linear extrapolation of the empirical results might not be appropriate if the effects are non-linear. Furthermore, I seek to quantify the impacts on mismatch, aggregate productivity, and welfare. The natural approach is to use the model.

5 Model Estimation and Quantitative Analysis

I estimate the model parameters in the steady state using the CPS data from 2005 to 2016 and the empirical results from section 2. Following Shimer (2005), I calculate a baseline job finding rate λ of 0.36 and a separation rate δ of 0.02. I set the minimum wage at $7.25 per hour, equal to the federal minimum wage. I use states that had a minimum wage equal to $7.25 at the end of 2016 to construct the moment targets.[45]

The ability parameter a corresponds to education and the occupation skill requirement j corresponds to occupation skill intensity, as in Autor and Dorn (2013).

erogeneous impact of the minimum wage on vacancy posting because of the focus on the wage compression channel. The model captures the small employment effect in reduced form, without taking a stand on the potential distributional change in the occupation vacancy posting. An extension of the model to incorporate differential job-finding rates as a function of the minimum wage, workers' ability, and occupations' skill requirements is beyond the scope of the present work and left for future research.

[44] There is literature that emphasizes the effect of minimum wages on increasing the search effort of unemployed workers (e.g. Acemoglu (2001), Flinn (2006), Ahn et al. (2011)) and inducing labor force participation (e.g. Flinn (2006)). The model can extend to allow for such responses. See the appendix section C for details.

[45] A list of the federal minimum wage states is in table A.9.

I discretize the intervals of ability and occupation skill intensity each into ten grid points, so that each ability grid point has one point in the occupation grid that corresponds to its optimal occupation. The distribution $Beta(\kappa_1, \kappa_2)$ determines the measure of workers at each ability grid point.

I calibrate (κ_1, κ_2) to match the distribution of workers' education levels in the CPS. Specifically, I divide the workers into three groups by educational achievement: 1) high-school degree or less, 2) some college or associate degree, 3) college degree. In the sample, 28.3% of the workers had a college degree, 28.5% of the workers had an associate degree or vocational training, and 43.2% of the workers had no education beyond high school. I categorize grids 1 and 4 to be low-ability workers, 5 to 7 to be medium-ability workers, and 8 to 10 to be high-ability workers. The parameters of the Beta distribution are calibrated to match the empirical composition of workers by education. The resulting distribution is $Beta(0.8877, 0.9415)$.

The accuracy of finding a good match affects workers' occupational mobility because workers are less likely to switch occupations if they are in good matches. In the model, the probability that a worker matches with the optimal occupation is governed by the distribution of occupations $G(j)$. Instead of specifying the distribution, I introduce a parameter ρ that governs the probability that workers end up in their optimal occupation when searching on the job or transiting from unemployment to employment. A worker has probability ρ of finding her optimal occupation and equal probability of finding any of the other occupations, given by $(1-\rho)/9$. A ρ of 0.1 means that the worker is not targeting any particular occupation.

ρ also affects the gain from switching. If $\rho > 0.1$ and there is no switching cost, occupational switching is good because workers have a higher probability of moving to their optimal occupations. To calibrate the parameter ρ, I target the average percentage wage gain after switching occupations. In the model, the wage change comes from changes in mismatch because productivity is match-specific. I use the estimates in Guvenen et al. (2020)

in which a back-of-the-envelope calculation shows that on average workers experience 1% wage growth attributed to a reduction in mismatch when they switch occupations.[46]

Another key determinant of occupational mobility is the on-the-job-search threshold x_s, which is a function of workers' ability a and the minimum wage. The function expands as

$$x_s(a, m) = s_0 + s_1 a + s_2 \mathbb{I}_{(a<qm)} m \tag{23}$$

The indicator function allows a single parameter q to compactly capture the differential effect of the minimum wage according to workers' ability. The constant s_0 absorbs the cost of switching.

The endogenous separation cutoff relates directly to the *employment* effect of the minimum wage. I use the following linear Taylor expansion to estimate the endogenous separation cutoff:

$$\underline{x}(a, m) = p_0 + p_1 a + p_2 m \tag{24}$$

I use λ' to denote the job-finding rate after the minimum wage increase.

I discretize the output process by the following Euler-Maruyama approximation:

$$X_{t+1} = X_t + \frac{a}{1 + |a - j|} X_t \Delta_t + \sigma X_t \mathbb{N} \sqrt{\Delta_t}$$

where $\mathbb{N}$ is a standard normal random variable. The choice of time step $\Delta_t = 0.01$ allows the approximation to track the exact solution of the output process closely.

The other moment targets include the occupational mobility rates by education, the wage distribution statistics, and the effect of the minimum wage on occupational mobil-

[46]The addition of the parameter ρ does not change any of the result in section 3 and section 4. The implied joint CDF $N(a, j)$ would have more weight along the trace if $\rho > 0.1$.

ity. In the sample, the monthly average occupational mobility rate is 2.0% for high-school workers, 1.8% for associate-degree workers, and 1.8% for college workers. I set these mobility rates as targets for the low-ability, medium-ability, and high-ability workers respectively. Similarly, the unemployment rate target is 7.5% for the low-ability workers, 6.2% for the medium-ability workers, and 3.6% for the high-ability workers.

In section 2, a 10% minimum wage decreases younger, less-educated workers' occupational mobility by 3%. Therefore, I set the occupational mobility elasticity of the minimum wage to be 3% for the low-ability workers in the model. I set the elasticity at 0 for medium-ability and high-ability workers.

The model also targets the employment elasticity of the minimum wage. Despite various findings in the literature, it is arguably the case that the employment effect on workers with at least an associate degree is small. I therefore set the targets to be 0 for medium-ability and high-ability workers. For low-ability workers, I set the elasticity at -0.1, which is on the smaller end of the spectrum in the literature that finds a negative employment effect of minimum wages.

Other targets include the P50/P10, P40/P10, P30/P10, and P20/P10 ratios, in which P10 stands for the 10th percentile in the wage distribution. I also include a set of moments that relate to the extent to which the minimum wage binds. Using the CPS data, I find that 5.1% of workers earn a binding minimum wage during the sample period, and 40% of workers face a binding minimum wage if the minimum wage is increased to $15 in 2020. These estimates are consistent with a report by the National Employment Law Project.[47] I also include the mean-to-variance ratio of the wage distribution as a target because it relates to σ in equation (10).

Together there are 10 parameters and 20 moments. I use the GMM method to estimate

[47]Source: https://www.nelp.org/publication/growing-movement-15/. I project 2% annual wage growth into 2020 and impose a $15 minimum wage to calculate the fraction of workers facing a binding minimum wage.

the parameters following Lise and Robin (2017).[48]

Table 4 shows that eight out of ten parameters are significant at the 5% level and table 5 shows that the model matches the moment targets. The change in vacancy posting, or equivalently the change in job arrival rate λ', is small: a 10% increase in minimum wage only decreases the job arrival rate by 1.4%. This is because the job arrival rate affects the occupational mobility and employment of all workers equally, regardless of ability. Therefore, it needs to be small, so that there is no effect of minimum wages on occupational mobility and employment for the medium-ability and high-ability workers.

Table 4: Parameter Estimation Results

Parameters									
ρ	0.498**	σ	0.72**	λ'	0.355**	q	0.027**	p_0	0.65
	(0.236)		(0.262)		(0.006)		(0.001)		(1.351)
p_1	-0.55	p_2	0.008**	s_0	1.05**	s_1	-0.17**	s_2	-0.009**
	(0.363)		(0.001)		(0.031)		(0.040)		(0.001)

Notes. ** means statistically significant at the 5% level. ρ is the targeted search parameter. $\{s\}_{(0,1,2)}$ and $\{p\}_{(0,1,2)}$ are the Taylor expansion coefficients. λ' is the job arrival rate after a 10% increase in the minimum wage. σ is the productivity volatility. q captures the non-linearity in the on-the-job search cutoff.

Note that after a 10% minimum wage increase, the occupational mobility of low-skill workers drops by 3% in the new steady state, whereas in the data the effects dissipate after a year. The discrepancy could result from the short-run nature of the model, because there is no aggregate productivity growth or inflation to erode the effects of the minimum wage. Nevertheless, the occupational mobility transition path in the model remains within the 95% confidence interval of the empirical estimates for most periods within in the first 18

[48]The details of the numerical algorithm are given in the appendix section D. After specifying the ability and occupation distribution, the only state variable is the productivity. Because the value functions and the wage distribution have closed form solutions, the economy is easy to solve numerically.

months of the minimum wage increase, shown in figure 3.[49]

Table 5: Moment Targets and Model Estimates

Targets	Data	Model Estimates
Wage gain	1%	1.6%
Separation rate, low ability workers	7.5%	5.3%
Separation rate, mid ability workers	6.2%	5%
Separation rate, high ability workers	3.6%	3.6%
Fraction of workers earning less than $7.25	5%	4.6%
Fraction of workers earning less than $15	40%	41%
Occupational mobility, low ability workers	2.0%	3.3%
Occupational mobility, mid ability workers	1.8%	1.9%
Occupational mobility, high ability workers	1.8%	1.1%
Elasticity of occupational mobility, low ability workers	-0.3	-0.3
Elasticity of occupational mobility, mid ability workers	0	-0.1
Elasticity of occupational mobility, high ability workers	0	0
Elasticity of employment, low ability workers	-0.1	-0.1
Elasticity of employment, mid ability workers	0	0
Elasticity of employment, high ability workers	0	0
P20/P10	1.21	1.24
P30/P10	1.46	1.47
P40/P10	1.75	1.73
P50/P10	2.06	2.02
Variance to mean ratio	13	13

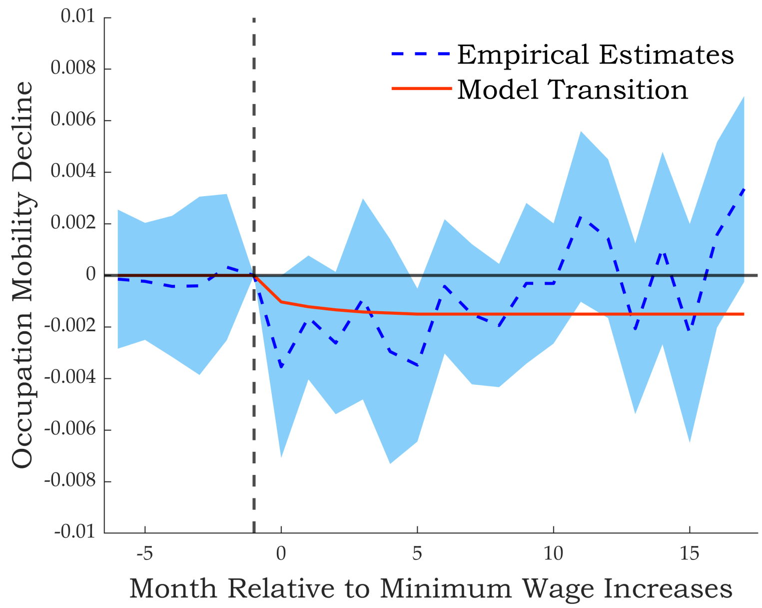
Notes. Table 5 shows the moment targets and the model results. The 1% wage gain from occupational switching is from Guvenen et al. (2020). The low ability workers correspond to the high-school workers, the mid ability some college workers, and the high ability Bachelors degree workers. The elasticity is with respect to the minimum wage.

The model transition path suggests that the occupational mobility of low-ability workers drops immediately following a 10% minimum wage increase, reflecting the change in

[49]The empirical estimates are the average decline in the occupational mobility of younger workers for the valid minimum wage policies. These estimates are partly comparable to the model transition path because the average minimum wage increase in the data is 9%, similar to the 10% increase in the model. The difference is that the empirical estimates could be driven by large minimum wage changes (see e.g. Clemens and Strain (2021)) whereas model transition path comes from targeting the average elasticity of occupational mobility with respect to the minimum wage.

their search incentives. After the initial decline, the occupational mobility converges to the level in the new steady state, reflecting the adjustment in the job-finding rate to satisfy the equilibrium condition.

Figure 3: Occupational Mobility Following a Minimum Wage Increase: Model Transition and Empirical Estimates



Notes. Figure 3 plots the model transition path of occupational mobility decline for low-ability workers and empirical estimates from equation (4). The 95% confidence interval uses standard errors clustered at the state level. The model converges to the new steady state in 5 periods. The transition path is within the 95% confidence interval of empirical estimates for most periods in the 18 months after minimum wage increases.

5.1 The Effect of the Minimum Wage on Occupational Mobility

I increase the minimum wage by about 100% from $7.25 to $15 in the model. I perform 1000 simulation with the model and calculate the average decrease in occupational mobility.[50] To focus on the wage compression channel, and because there is little empirical evidence

[50] A $15 nation-wide minimum wage was part of the Democratic party's platform in the 2016 election. It is also currently under discussion. See, for example, Clemens (2019).

on how a large change in the minimum wage might affect the job-finding rate, I restrict the job-finding rate to be λ'. The effect of the \$15 minimum wage on the endogenous separation cutoff is not restricted. [51]

The increase dis-incentivizes occupational switching by the lower-ability workers the most, reducing their occupational mobility by as much as 44%. By contrast, the medium-ability and high-ability workers do not show any significant decrease in occupational mobility. Overall, occupational mobility falls by 30% after the 100% increase in the minimum wage.

When I restrict the model to have only the wage compression channel by setting $\lambda' = 0.36$ and $p_2 = 0$, the model estimate matches the linear extrapolation of the empirical results, as shown in figure 4 (a). Adding the employment effect channel further decreases occupational mobility. However, the effect is small compared with that of the wage compression channel, which accounts for 90% of the decrease in occupational mobility.

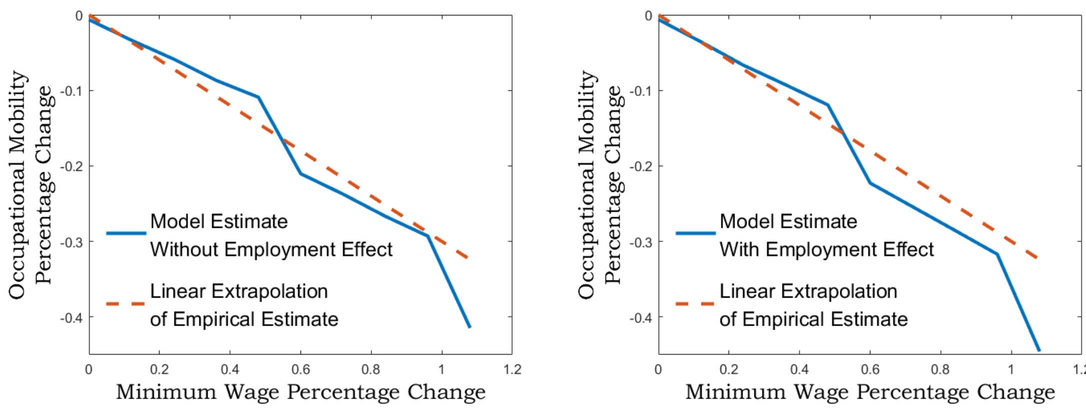
When the percentage increase in the minimum wage becomes large, the slope of the model estimate becomes steeper. The non-linearity comes from the shape of the empirical wage distribution. When the minimum wage is \$7.25, the part of the wage distribution affected by a small increase in the minimum wage is flat. Therefore, a small increase in the minimum wage only affects a small fraction of workers. Further increases in the minimum wage cut into the part of the wage distribution where the slope rises steeply, and the fraction of workers facing a binding minimum wage increases non-linearly.

Figure 5 (a) illustrates the fraction of workers that face a binding minimum wage across occupations. Two features stand out. First, the fraction of workers facing a binding minimum wage differs significantly across occupations, decreasing as average wages increase. Second, when the minimum wage increases to \$15, the fraction of workers facing a binding

[51]The large increase in the minimum wage affects workers' occupational mobility by both the wage compression channel and the employment effect channel. However, for the employment effect channel, the change in the job-finding rate is as if the minimum wage increases by only 10%.

Figure 4: The Effect of Minimum Wages on Occupational Mobility

(a) No Employment Effect (b) With Employment Effect



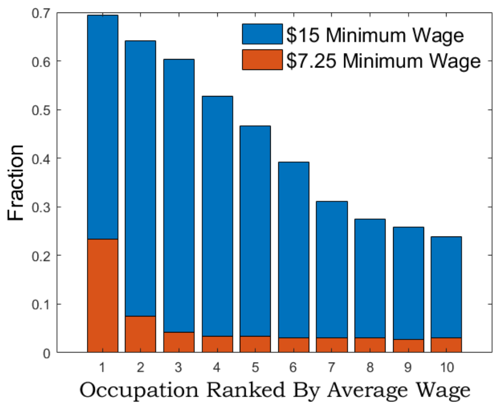
Notes. Figure 4 plots the percentage decrease in occupational mobility as a function of the percentage increase in the minimum wage. In figure (a) I shut down the employment effect channel by holding the job arrive rate constant and making the disemployment effect to be 0. The dash line is the percentage decline in occupational mobility based on the linear extrapolation of the empirical estimate in section 2. In figure (b) I plot the overall change in occupational mobility, which looks similar to (a). The comparison suggests that the wage compression channel accounts for a large fraction of the decrease.

minimum wage more than triples for some occupations.

Figure 6 shows the empirical counterpart of figure 5 (a). It plots the fraction of workers with a binding minimum wage across 2-digit occupations, ranked by average wage using CPS Merged Outgoing Rotation Groups (MORG). I project the wages into 2020 at a 2% annual growth rate and impose a \$15 minimum wage. A comparison of figure 5 and figure 6 suggests that the \$15 minimum wage would significantly increase the fraction of workers with a binding minimum wage. Notably, even with the current minimum wage, there are non-trivial fractions of minimum wage workers in high-wage occupations (e.g., lawyer, computer engineer). This reflects potential occupational mismatch, which is consistent with the model results. In particular, under the current minimum wage, the fraction of minimum wage workers in the highest-wage occupation (0.4%) is almost identical between the model and the data. Because the model does not target the fraction, the

Figure 5: Model Fraction of Workers with a Binding Minimum Wage

(a) Fraction of Workers with a Binding Minimum Wage by Occupations



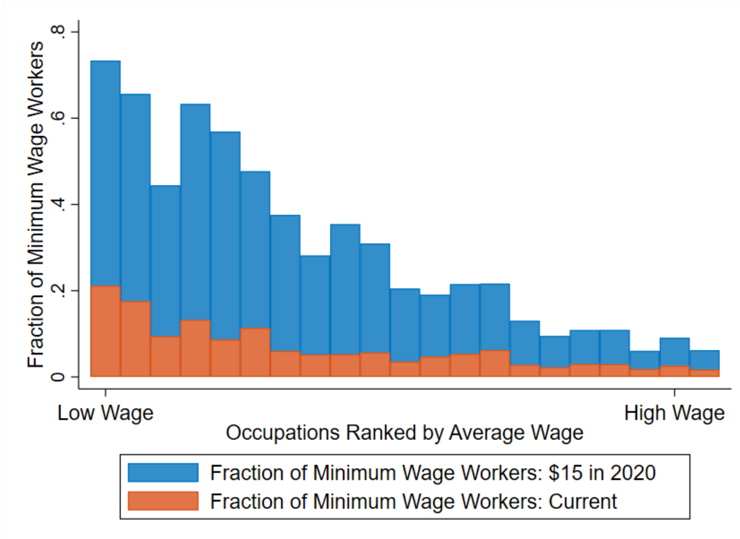
(b) Fraction of Workers with a Binding Minimum Wage by Ability

Notes. Figure 5 plots the fraction of workers with a binding minimum wage by occupation ranked by average wage in (a) and by workers' ability in (b). Figure (a) is similar to figure 6, indicating the model matches the data well. When the minimum wage is $7.25, few workers earn the minimum wage in high-wage occupations. When the minimum wage increases to $15, the fraction of workers with a binding minimum wage increases substantially in all occupations. In figure (b), it shows that a large fraction of medium ability workers earn the $15 minimum wage, while only low ability workers earn the $7.25 minimum wage. The comparison demonstrates the non-linear effect of the minimum wage on the fraction of minimum wage workers.

similarity suggests that the model matches the data well.

Figure 5 (b) shows the fraction of workers with a binding minimum wage across ability grid points. With a minimum wage of $7.25, only the low-ability workers earn the minimum wage. When the minimum wage increases to $15, some medium ability workers start to earn the binding minimum wage. This is because the $15 minimum wage cuts into a much larger fraction of the wage distribution and affects workers with higher levels of skills.

Figure 6: Fraction of Minimum Wage Workers by Occupations



Notes. Figure 6 plots the fraction of workers with binding minimum wages across occupations. The estimates is from CPS merged outgoing rotation groups from 2005 to 2016. Occupation code uses 2-digit 2002 Census code. There are 22 occupations. I rank them by average wage and plot them on the x-axis. The red bar plot shows the fraction of workers with binding minimum wages under current minimum wages. I project the wages to grow at 2% a year into 2020 to calculate the estimated fraction of workers with a binding minimum wage assuming a $15 minimum wage in 2020.

5.2 Occupational Mobility Response and Aggregate Output

Both the wage compression channel and the employment effect channel contribute to the negative mobility response to increases in the minimum wage. Less employment dampens aggregate output. In addition, for workers who remain employed, a drop in mobility further decreases aggregate output, because the workers stay in mismatches longer. In other words, a higher minimum wage slows down occupational switching towards better matches, which leads to an increase in aggregate mismatch and hence a decrease in output.

To understand the extent to which the minimum wage increases aggregate mismatch, I compare mismatch before and after a minimum wage increase. I increase the minimum wage to $15 and perform 1000 simulations. For an employed worker with ability a, I calculate $\mathbb{I}_{(|a-j|>0)}$ which is the probability that the worker is not in her optimal occupation.

I then average the probability across all workers and all periods. The result captures the average time spent in non-optimal occupations. The \$15 minimum wage makes the low-ability workers 2% more likely to be in non-optimal occupations. For the medium-ability and high-ability workers, there is no significant change in the probability of being in a non-optimal occupation.

The increase in mismatch translates to a decrease in aggregate output. On average, the low-ability workers' output decreases significantly by 1.3%. The output of the medium-ability and high-ability workers are not affected. Overall, the \$15 minimum wage decreases aggregate output by as much as 0.4%. The large reduction is because 40% of all workers are influenced by the \$15 minimum wage. Of the 0.4% decrease in aggregate output, the wage compression channel accounts for 80%, or 0.0032 percentage points.[52]

Since the decline in the occupational mobility is most significant in the year of the minimum wage increase, the decrease in aggregate output should be viewed as a short-run effect. Nevertheless, effects of large minimum wage increases might last longer than smaller increases (Clemens and Strain (2021)). In the longer horizon, the interaction between large minimum wage increases and other factors such as career outlook, skill development, and occupation skill composition changes could further complicate the analysis. A comprehensive analysis of those factors is beyond the scope of the present work, so I leave the question to future research.

6 Conclusion

I estimate that the elasticity of occupational mobility with respect to the minimum wage is -0.3 for the younger workers. The decline in occupational mobility is associated with an increase in mismatch and longer stays in non-routine manual occupations.

I construct a search-and-matching model and highlight two channels by which the min-

[52]Details of the decomposition can be found in the appendix section D.

imum wage decreases occupational mobility. The first channel is the wage compression channel, in which the minimum wage reduces the gain acquired by workers for switching to occupations that better match their skills. The reduction in occupational mobility after a minimum wage increase leads to more mismatch. The second channel is the employment effect channel, in which the minimum wage displaces workers and decreases firms' vacancy posting and hence the job arrival rate.

In the model, the introduction of a $15 minimum wage decreases low-ability workers' occupational mobility by 44%, leading to an increase in mismatch that is concentrated among low-ability workers. Because mismatch reduces output, the negative mobility response to the higher minimum wage shifts the weight of the output distribution towards the left tail, resulting in a 0.4% decrease in output, 80% of which is accounted for by the wage compression channel. The results have important policy implications. Even if employment does not decrease, a large minimum wage increase can lead to a non-trivial decrease in aggregate output via the wage compression channel which leads to slower labor market dynamism and more mismatch.

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