Cross-State Differences in the Minimum Wage and Out-of-state Commuting by Low-Wage Workers*

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Abstract

The 2009 federal minimum wage increase, which compressed cross-state differences in the minimum wage, is used to investigate the claim that low-wage workers are attracted to commute out of state to neighboring states that have higher minimum wages. The analysis focuses on Public Use Microdata Areas (PUMAs) that experience commuting flows with one or more neighboring state. A difference-in-differences-in-differences model compares PUMAs that experienced a sizeable increase or decrease in their cross-border minimum wage differential to those that experience smaller change in the cross-border differential . Out-of-state commuting of low wage workers (less than 10 dollars an hour) is then compared to that of moderate wage workers (10-13 dollars an hour). The results suggest that an increase in own state's minimum wage, relative to neighbor's, increases the frequency with which low-wage workers commute out of the state. The analysis is replicated on the subset of PUMAs that experience commuting flows with more than one neighboring state, so that the estimates are identified entirely within PUMA. As a whole, the results suggest that low-wage workers tend to commute away from minimum wage increases rather than towards them.

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I. Introduction

A February 15, 2014 *New York Times* articles titled "Crossing Borders and Changing Lives, Lured by Higher State Minimum Wages" profiles workers commuting across state borders in response to cross-state differentials in the minimum wage. The article states:

> "Ms. Lynch is one of the many minimum-wage migrants who travel from homes in Idaho, where the rate is $7.25, to work in Oregon, where it is the second highest in the country, $9.10. Similar migrations unfold every day in other parts of Idaho — at the border with Washington, which has the highest state minimum, $9.32, and into Nevada, where the minimum rate tops out at $8.25.
>
> Their experiences underscore what many proponents of raising the wage assert: that even seemingly small increases in pay can galvanize people's lives, allowing workers to quit second jobs, buy cars or take vacations."

Are low-wage workers attracted to commute across state lines in response to a higher minimum wage in a neighboring state? Evidence that a higher minimum wage in a neighboring state induces cross-border commuting would suggest that the disemployment effects of a minimum wage increase are small relative to the wage effects. Alternatively, if cross-border commuting is induced by a higher minimum wage in own state, relative to the neighboring state, this would be consistent with sizeable disemployment effects.

The effect of the minimum wage hikes on cross-border commuting also has methodological implications for other minimum wage studies. Neumark (2014) points out that if workers affected by the minimum wage find jobs in a nearby state, this increase in employment in the neighboring state can increase the size of disemployment effects estimated using a cross-border comparison strategy. But this is only true if workers are fully migrating across state lines, or if the employment outcome is based on place of work. In much of the literature, employment is measured based on residential location. Under these circumstances, out-of-state commuting in response to a minimum wage increase would dampen the estimated disemployment effects.

This paper tests for empirical evidence that differences across states in the minimum wage attract workers to commute out of state. Between 2007 and 2009, the federal minimum wage increased from $5.15 to $7.25, compressing cross-border minimum wage differentials. American Community Survey (ACS) data from 2005-2011 are used to analyze changes in out-of-state commuting by low-wage workers under 30 in response to this federal minimum wage increase.

The analysis focuses on the set of Public Use Microdata Areas (PUMAs) that prior to the policy change experienced cross-state commuting flows of low-education workers. A difference-in-differences-in-differences model compares the change in out-of-state commuting for low wage workers (less than 10 dollars an hour) to moderate wage (10-13 dollars a hour) workers, and compares PUMAs that experience either a sizeable increase or decrease in their cross-border minimum wage differential to PUMAs that experience smaller changes in the cross-border differential.[1] All specifications control for PUMA*Year fixed-effects, which control for any PUMA-level time-varying unobservables that equally affect workers with wages less than 10 dollars per hour and those with wages 10-13 dollars per hour.

Additional estimates are generated using exclusively the set of PUMAs that experience commuting flows with more than one neighbor state, and for whom the federal minimum wage increase has a differential effect on the cross-border minimum wage gaps with the two different neighbors. In this case, the estimates are identified entirely within PUMA. This approach tests whether cross-border commuting rates from the same PUMA to the two different neighboring states respond to the relative changes in the cross-border minimum wage differentials.

[1]Results from Clemens and Withers (2014) and Neumark et al. (2004) suggest that the effects of the federal minimum wage hike on worker wages should be confined low enough in the wage distribution that there is little concern that the federal increase shifts workers from the low-wage to the moderate-wage comparison group. This concern is discussed in more detail in Section II.C.

None of the estimates from the difference-in-differences-in-differences analysis or from the analysis of PUMAs with multiple neighbor states are consistent with low-wage workers commuting across state lines towards a higher minimum wage in the neighboring state. In the period prior to the federal minimum wage increase, when cross-border differentials were larger, there is no evidence that low-wage workers commuted at higher rates (relative to moderate-wage workers) to neighbors with a higher minimum wage. None of the estimates indicate that the federal minimum wage hike, which compressed cross-border differentials, led to a decrease in out-of-state commuting from states that previously had low minimum wages relative to a neighboring state. In fact, many of the estimates are statistically significant and consistent with disemployment effects of the minimum wage hike increasing out-of-state commuting by low-wage workers from states most affected by the federal minimum wage increase. Overall, the results suggest that low-wage workers tend to commute away from minimum wage increases rather than towards them.

Previous work by Kuehn (2016) finds, in contrast to our results, that workers commute towards higher minimum wages using aggregate county-level commuting flow data for all workers for 2009-2013. But his cross-sectional estimates are not generated using any variation over time in minimum wages, nor are they generated using a subsample of workers likely to be affected by the minimum wage or compared to workers less likely to be affected. As a result, Kuehn explicitly states that his estimates should not be interpreted as causal.[2] A recent study of a minimum wage increase in Seattle to 11 dollars an hour compared Seattle to surrounding areas using a differences-in-differences analysis. The findings indicated that workers who, in the period prior to the increase, worked in Seattle and earned less than 11 dollars an hour, were 2.8

[2] Kuehn's only interest is in establishing the correlation between the minimum wage differential and commuting flows, which he points out will bias estimates of minimum wage employment effects using cross-border comparisons regardless of whether or not the commuting effect is causal.

percentage points more likely be working outside of Seattle as a result of the minimum wage increase (The Seattle Minimum Wage Study Team, 2016). Because they do not observe place of residence, the study authors are not able to decompose this effect into residential migration and commuting responses. In related work, Cadena (2014) and Orrenius and Zavodny (2008) find that immigrant workers are less likely to locate in states that raise their minimum wages, though Boffy-Ramirez (2013) finds that higher minimum wages attract immigrant workers.

There is also a wider literature on the effect of cross-border differences in state policies (e.g. Holmes, 1998; McKinnish, 2005; Coomes and Hoyt, 2008; Jofre-Monseny, 2014), which has largely focused on residential, rather than work, location decisions. Argawal and Hoyt (2016) analyze the effect of cross-border income tax differentials on commuting behavior in Metropolitan Statistical Areas (MSAs) that cross state borders. They find that an increase in the state income tax differential increases average commute time, but they do not explicitly measure cross-border commuting.

As detailed in Neumark and Washer (2008), there is a long literature on minimum wage effects, much of it debating the size and existence of disemployment effects. For example, Brochu and Green (2013) find that the minimum wage affects both the hiring rate and the layoff rate for older workers, but that these two effects cancel out so that overall employment rates are relatively unaffected. Sabia (2008) finds disemployment effects for less-educated single mothers and Sabia, Burkhauser and Hansen (2012) find disemployment effects of a minimum wage hike for workers ages 16-29, with the largest effects for workers ages 16-24.

This paper is most similar in methodology to Clemens and Withers (2014) and Thompson (2009). Clemens and Withers (2014) estimate the effect of the federal minimum wage increase on low-wage workers in states with previously low minimum wages compared to states with previously high minimum wages. They find negative effects of the federal minimum wage increase on the employment and income growth of low-wage workers. A key feature of their analysis using longitudinal data from the Survey of Income and Program Participation (SIPP) is that they can focus on the sample of workers who earned less than $7.50 an hour prior to the federal increase, and also use a comparison group who made $8.50-$10 per hour in the baseline period. Thompson (2009), who finds that minimum wage increases decrease teen employment in counties with previously low average teen wages relative to those with previously high average teen wages, also uses a within-state comparison to difference out unobserved state-specific changes or trends that might otherwise bias estimates of the minimum wage effect. Allegretto et al (2009) analyze minimum wage effects on teen employment using 74 commuting zones that cross state boundaries, but they do not study commuting as an outcome. Within-commute zone differences in the state minimum wage allow them to control for commute-zone*year fixed-effects, but they are unable to control for state*year fixed-effects because they do not use a within-state comparison group.

Allegretto et al. (2011) and Dube et al. (2010) argue that previous studies finding disemployment effects are biased due to geographically correlated unobserved changes in economic conditions. Both papers find that when estimates are generated using comparisons of geographically proximate areas or by controlling for state-level unobserved trends, estimates no longer support disemployment effects. Addison et al. (2009) report similar findings when estimates are generated controlling for geographic area-specific trends. In contrast, Neumark et al. (2014) demonstrate that similar, and in some cases even more flexible, estimation strategies still produce evidence of disemployment effects. Meer and West (2016) provide evidence that minimum wage increases change the trajectory of job growth rather than generating a discreet drop in employment. As such, specifications that include state-time trends will understate the negative effect of a minimum wage increase on employment.

The estimation strategies in this paper also designed to avoid bias due to unobserved changes in local economic conditions. First, out-of-state commuting by definition is an outcome that is generated by the comparison of local economic conditions in own state to conditions close by in neighboring states. This is the same premise that led Allegretto et al. (2009) to analyze commuting zones in their study of teen employment effects, though they do not consider commuting behavior. Second, a comparison of changes in out-of-state commuting by low wage and moderate wage workers nets out changes in local economic conditions that affect both types of workers. This within-PUMA comparison allows for the inclusion of PUMA*Year fixed-effects in the regression specifications. Third, some estimates are produced using only variation within-PUMA in commuting to two different neighboring states. This is a benefit to studying cross-border commuting rather than employment outcomes. It is not possible to analyze employment effects leveraging the fact that a single PUMA has more than one neighboring state, but it is possible to do so for out-of-state commuting by comparing flows from the same PUMA to two different destination states. Finally, a falsification test of the differences-in-differences-in-differences model is estimated to rule our prior trends, using only observations from the period before the federal minimum wage increase. In this case, the difference-in-differences-in-differences estimates are small, statistically insignificant, and of opposite sign from the estimates obtained using the full sample.

II. Methodology

The federal minimum wage increased to $5.15 in 1997 and remained there until 2007 legislation set a schedule for the federal minimum wage to rise to $7.25 by July of 2009 (first to

$5.85 in July 2007, and $6.55 in July 2008). In January 2007, 21 of the 49 states in the continental U.S. still had minimum wages at the federal minimum of $5.15, 21 had minimum wages above $5.15 but less than $7.25, and 7 had minimum wages above $7.25.

A. Identifying Analysis Sample of PUMAs

The 2005-2011 ACS data identify place of work and place of residence using consistently defined Public Use Microdata Areas (PUMAs), which are geographic areas of no less than 100,000 residents that do not cross state lines. The ACS samples are not sufficiently large to calculate annual PUMA-to-PUMA commuting flows for subgroups affected by the minimum wage. Instead, individual-level analysis will be conducted using as the dependent variable whether a worker in a given PUMA commutes to a different state for work. Additionally, aggregate-level analysis will be performed at the PUMA-neighbor state level using as the dependent variable the fraction of workers in the PUMA who commute to a particular neighboring state.

It is necessary to first determine the set of PUMAs that have sufficiently low cost of commuting into another state that a minimum wage increase might affect cross-state commuting behavior. The ACS data are used to identify those PUMAs that already experience a flow of commuting workers to or from another state prior to the federal minimum wage hike. These PUMAs are then included in the analysis sample.

The preexisting commuting flows are used to indicate which PUMAs have a sufficiently low cost of out-of-state commuting to be affected by the minimum wage policy change, rather than using measures such as geographic distance to determine the set of PUMAs for analysis. This approach has several benefits. First, the fact that noticeable commuting flows already exist in at least one direction across this border indicates that there is a common labor market which crosses the state boundary. This is exactly the set of local labor markets we wish to include in our analysis sample. Second, this approach avoids diluting the analysis sample with boundary PUMAs for which a change in the minimum wage differential cannot generate a commuting response because cross-border commuting costs are too high. Finally, it is important to note that the federal minimum wage increase acted to compress cross-border differentials in the minimum wage. Therefore, if the low-wage workers were previously commuting across state borders towards higher minimum wages, the federal increase should act to reduce out-of-state commuting in the places where these flows already existed. Therefore, it seems reasonable to start with the set of PUMAs that previously experienced such flows. It is theoretically possible that a large disemployment effect of the federal minimum wage increase could generate new out-of-state commuting flows in places where commuting did not previously occur, but this seems unlikely, and moreover, only biases us against finding results consistent with disemployment effects.

This same principle is used to identify the "neighboring" state or states of a particular PUMA. If a PUMA experiences a preexisting flow of commuters from or to another state, that state is considered sufficiently "close" to the PUMA to be labeled a neighbor state.

To be specific regarding the construction of the analysis sample, first the sample of workers who are ages 18 and over with less than 1 year of college and who report a place of residence and a place of work within the continental U.S. is used to calculate the cross-border commuting rates. The fraction of those workers residing in the PUMA in 2005-2008 who work in another state measures the outflow of commuters in the baseline period (*PrePercOut*). The fraction of those workers working in the PUMA in 2005-2008 who reside in another state measures the inflow of commuters in the baseline period (*PrePercIn*). PUMAs that have an average outflow (*PrePercOut*) or inflow (*PrePercIn*) in 2005-2008 of at least one percent with at least one other state are included in the analysis sample.[3] Using this criteria, there are 534 PUMAs in the analysis sample. The state with which the PUMA experiences a commuting flow of at least one percent is considered the PUMA's neighboring state. In cases where the PUMA experiences flows of at least one percent with more than one other state, that PUMA will have more than one neighboring state. A robustness check below will vary the commuting flow cutoff used to determine the analysis sample from one percent to three percent.

B. Minimum Wage Policy Variable

Past minimum wage studies have raised the concern that state-level increases in the minimum wage could be endogenous to changes in state-level macroeconomic conditions. To minimize this concern, this paper uses the federal minimum wage increase as an exogenous shock to the cross-border minimum wage differential for a given PUMA, and takes as the key policy variable how much the federal increase is predicted to change the cross-border differential given the minimum wages for the PUMA and the neighboring state in 2007. This is similar to the approached used by Clemens and Withers (2014), who designate states as either "bound" or "unbound" by the federal increase based on their prior minimum wage.

For each PUMA in the sample, the following calculation is used to measure how the federal minimum wage hike is predicted to change the minimum wage differential between own state and the neighboring state:

$$\begin{aligned} MinWageChange = {} & [MinWage2007\_Neighbor - MinWage2007\_OwnState] \\ & -[MinWageFloor2010\_Neighbor - MinWageFloor2010\_OwnState] \end{aligned}$$

Where:

[3] PUMAs are only included in the analysis sample if there are at least 500 total observations across 2005-2008 of workers ages 18 and older with less than 1 year of college with which to calculate the flow rates.

$$MinWageFloor2010 = \begin{cases} 7.25 & \text{if } MinWage2007 < 7.25 \\ MinWage2007 & \text{otherwise} \end{cases}$$

Therefore, if a PUMA has a *MinWageChange* of 1, the federal minimum wage increase is expected to increase own state's minimum wage by one dollar relative to the neighboring state. A *MinWageChange* of -1 indicates that the federal minimum wage increase is expected to increase neighbor state's minimum wage by one dollar relative to own state.[4] If a PUMA has more than one neighboring state, *MinWageChange* is calculated for each neighboring state.

Table 1 reports the distribution of *MinWageChange* for the sample of 534 PUMAs in the analysis sample. If the PUMA has more than one neighboring state, the *MinWageChange* value used in Table 1 is the one that is greatest in absolute value. For 193 of the 534 PUMAs, the federal policy change does not affect the minimum wage differential with the neighboring state. This is either because the two states are both above the new federal minimum wage of $7.25, or they had the same minimum wage in 2007. For another 104 PUMAs, the minimum wage differential is affected by less than a dollar. The analysis in this paper will particularly focus on 91 "treatment" PUMAs (from 23 states) for which *MinWageChange* is at least 1.5 in absolute value.[5] A "positive treatment" group of 48 PUMAs with *MinWageChange* of at least 1.5 and a "negative treatment" group of 43 PUMAs with *MinWageChange* of -1.5 or less will each be compared to the 443 comparison PUMAs with smaller minimum wage changes. Figure 1 maps the 543 PUMAs in the analysis sample, with separate designations for the positive treatment group, negative treatment group and the comparison group. As a robustness check below,

[4]MinWage2007 is the state minimum wage on January 1, 2007.

[5] PUMAs are included in a treatment group as long as *MinWageChange* is greater than or equal to 1.5 in absolute value for at least one neighbor with which they have a prior commuting inflow or outflow rate of at least one percent.

additional analysis will be conducted defining the treatment PUMAs as those with a *MinWageChange* at least 1 in absolute value or at least 2 in absolute value.

C. Comparison across Wage Groups

It is possible to estimate a difference-in-differences specification comparing changes in out-of-state commuting for the treatment groups of PUMAs that experience a sizable increase or decrease in the minimum wage differential to the comparison group of PUMAs that experience smaller changes. There will be the concern, however, that there are other factors changing in the state or PUMA that also affect cross-border commuting. It would be preferable to estimate this double-differences analysis for a group of workers affected by the minimum wage and to compare it to estimates from a group of similar workers not affected by the minimum wage. One possible approach is to compare workers with very low levels of education to moderately-educated workers. Table 2, which reports wage distribution information by education level, demonstrates that splitting the sample based on education is unlikely to be productive.

Table 2 again uses the analysis sample of 534 PUMAs. The first two rows report the 10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} percentiles of hourly wages for workers ages 18-60 for two different education groups: those with less than a high school education, and those with at least a high school degree (or GED) but less than one year of college. It is clear that only the lower tail of either educational category will be affected by a minimum wage increase to $7.25. Most importantly for the purpose of this analysis, while it is true that a larger fraction of high school dropouts will be affected by the minimum wage increase than the high school graduates, the degree of overlap between the two distributions suggests that differences-in-differences-in-differences estimates comparing these two groups will not produce particularly informative estimates.

The remaining two rows of Table 2 restricts the sample only to workers younger than 30. While a larger fraction of the sample will now be affected by the minimum wage increase to $7.25/hour, the degree of overlap in the distributions of the two education groups has only increased. Table 2 suggests that in order to generate a reasonable comparison group for this analysis, the sample will need to be split based on wage, rather than on education. Therefore, the difference-in-differences-in-differences analysis will compare workers with an hourly wage less than $10 to workers with an hourly wage of $10-$13. Because low-wage workers tend to be young and to have low educational attainment, the analysis sample will be restricted to workers under 30 with less than 1 year of college so that the two wage groups are more homogenous in age and education.

Table 3, using the same sample as Table 2, reports the out-of-state commuting rates for different groups of workers based on education, wage and age. The out-of-state commuting rate for workers ages 18-29 with less than one year of college and wages less than 10 dollars an hour (5.7%) is lower than the rate for workers ages 18-29 with less than one year of college and wages 10-13 dollars and hour (7.2%), but both are less than the overall out-of-state commuting rate for workers ages 18-29 with less than a high school degree (7.9%). It is important to remember that these commuting rates are calculated using only the set of PUMAs with elevated cross-border flows.

The low-wage group is constructed to include workers who make above the minimum wage, up to 10 dollars an hour. This wider interval is used to avoid the concern that the federal minimum wage increase could be shifting some workers from the low-wage group to the moderate-wage comparison group. Clemens and Wither's (2014) analysis of the effect of the effect of the 2007-2009 federal minimum wage increase on "bound" and "unbound" states found no evidence of effects on worker wages for workers who had been making $8.50-$10 an hour prior to the minimum wage hike. Because pre-hike wages are not observed for workers in post-hike years, the conservative approach is to use an upper bound above $8.50 an hour, making $10 a reasonable choice for the upper bound.[6]

It should be noted that the analysis sample only contains workers who live in the PUMA. If some workers become unemployed or migrate out of the PUMA in response to a minimum wage increase, they will exit the sample for that PUMA. The effect on the commute rate depends on whether those who exit the sample previously had higher or lower than average commute rates. To the extent that those who exit had previously had a higher than average commute rate, this analysis will understate a commute rate response to a disemployment effect. To the extent that those who exit had previously had a lower than average commute rate, this analysis will overstate the commute rate response. But, to be clear, in this latter case, the estimates are overstated due to other margins of disemployment effects. This issue does not bias the analysis towards finding disemployment effects where there are none.

There is an additional concern that some workers may change groups by commuting across state lines. If a worker who makes less than $10/hour in his home state commutes across state lines to earn more than $10/hour, that workers will be used to calculate the commute rate for the $10-13/hour group when he should be used to calculate the commute rate for the less than $10/hour group. Empirically we know that commute rates increase with wage. In this case, commute rates for a given wage group will be understated, because the number of people commuting "out" of the wage group to receive wages above the upper threshold will be more

[6] This choice of upper bound is also consistent with the results of Neumark et al. (2004), who find that the effects of a minimum wage increase on worker wages are small above 130% of the minimum wage.

than the number of people commute "into" the wage group from a lower or non-working wage group.

Appendix A shows that under the conditions most relevant for this analysis, that commute rates are not very high, estimated *changes* in commute rates will also be attenuated towards zero and this will attenuate the differences-in-differences estimates in this paper. Therefore, the calculations in Appendix A indicate that, given that average commute rates and changes in commute rates are relatively small, the bias generated by the use of wage categories will also be small and, furthermore, that the differences-in-differences estimates will likely be attenuated towards zero.

D. Regression Sample and Specification

The individual sample used for the regression analysis consists of workers ages 18-29 with less than one year of college and a calculated hourly wage between 2 and 13 dollars an hour who reside in one of the 534 PUMAs in the analysis sample. Within this sample of workers, those with calculated hourly wages of 10-13 dollars an hour are used as a comparison group of moderate-wage workers who should not be affected by the cross-border minimum wage differential, while low-wage workers with hourly wages of less than 10 dollars an hour are potentially responsive to the cross-border minimum wage differential. The years of analysis are 2005-2008, for the period before the federal policy change, and 2010-2011, for the period after the policy change.[7] 2009 is excluded from the analysis as a transitional year.[8]

[7] The analysis is restricted to years prior to 2012 because PUMA boundaries change in 2012. PUMA-level geography is not reported in the 2001-2004 ACS data.

[8] 2008 is retained in the before period because the federal minimum wage had only increased to $5.85 at the start of the year, and increases to $6.55 at the end of July 2008. Given that sampling for the ACS occurs uniformly across the year, and that there is likely a time lag for commuting patterns to respond, it seems appropriate to include 2008 in the before period. Excluding 2008 does not change the findings, but there is a loss of precision from the reduction in sample size.

The primary analysis uses a differences-in-differences-in-differences specification. For the first difference, the "positive treatment" PUMAs (*MinWageChange*≥1.5) and the "negative treatment" PUMAs (MinWageChange≤-1.5) are compared to the comparison PUMAs (-1.5<*MinWageChange*<1.5).[9] For the second difference, the period before the federal minimum wage increase is compared to the period after. For the third difference, low-wage workers with hourly wages less than 10 dollars per hour are compared to moderate-wage workers with slightly higher wages of10-13 dollars per hour. The regression specification is:

$$\begin{aligned} DiffPOW_{ipt} = {} & \beta_0 + \beta_1 PosTreat_p * After_t * LowWage_i + \beta_2 NegTreat_p * After_t * LowWage_i \\ & + \beta_3 PosTreat_p * LowWage_i + \beta_4 NegTreat_p * LowWage_i + \beta_5 LowWage_i * After_t \\ & + \beta_5 LowWage_i + X_i \beta_6 + \gamma_{pt} + \varepsilon_{ipt} \end{aligned} \tag{1}$$

where for individual *i* living in PUMA *p* in year *t*, *DiffPOW* is an indicator that equals one if the state of work differs from the state of residence. *PosTreat* is an indicator that equals 1 if *MinWageChange* for PUMA p is at least 1.5 and *NegTreat* is an indicator that equals 1 if *MinWageChange* for PUMA p is -1.5 or less. *After* is an indicator that equals 1 for years 2010-2011 (compared to 2005-2008). *Low Wage* is an indicator that equals 1 if the hourly wage is less than 10 dollars per hour (compared to 10-13 dollars per hour).

If low-wage workers were previously attracted to commute across state lines in order to receive a higher minimum wage, then we would expect the rise in own state's minimum wage, relative to that of the neighbor's, to reduce the rate of out-of-state commuting. We would expect this reduction in out-of-state commuting to be experienced primarily by workers making less than 10 dollars an hour. If so, our estimate of β_1 should be negative. If, on the other hand, the rise in own state's minimum wage generates a disemployment effect, which might increase

[9] As was the case in Table 1, if a PUMA has more than one neighboring state, the *MinWageChange* value that is greatest in absolute value is used to determine treatment status.

cross-border commuting for very low-wage workers relative to moderate-wage workers, then β_1 would be positive. For similar reasons, we would expect β_2 to be positive if workers were previously attracted to commute across state lines in response to a higher minimum wage, while a negative β_2 would be consistent with disemployment effects of a minimum wage increase.

X is a vector of control variables that includes age, age-squared, and indicators for female, less than a high school degree, high school or GED degree, black, Hispanic, immigrant, and married. PUMA*Year fixed-effects are included in the model, which control for any PUMA-level time-varying unobservables that equally affect workers with wages less than 10 dollars per hour and those with wages 10-13 dollars per hour.[10] The estimates are therefore identified by the within-PUMA comparison of low wage and moderate wage workers.

Because it is important in DinDinD analysis to rule out the possibility of prior trends, a version of equation (1) will be estimated in which the sample is restricted to the years 2005-2008. For this specification, the *After* indicator equals one for the years 2007-2008. In order to validate the assumptions of the DinDinD model, the DinDinD coefficient estimate from this specification should be close to zero and statistically insignificant.

E. PUMAs with two neighbors

An additional source of variation to be exploited is that some PUMAs have more than one neighbor state with which they experience cross-border commuting flows. In order to leverage this source of variation, it is necessary to first aggregate the data up from individual workers to annual out-of-state commuting rates calculated at the PUMA-neighbor state-wage group level. The specification analogous to (1) using aggregated data is:

[10] *NegTreat*After* and *PosTreat*After* are not included in the regression specification because they are collinear with the PUMA*Year fixed-effects.

(2)

$$\begin{aligned} FrCommute_{wpnt} = \beta_0 + \beta_1 PosTreat_{pn} * After_t * LowWage_w + \beta_2 NegTreat_{pn} * After_t * LowWage_w \\ + \beta_3 PosTreat_{pn} * LowWage_w + \beta_4 NegTreat_{pn} * LowWage_w + \beta_5 LowWage_w * After_t \\ + \beta_5 LowWage_w + \gamma_{pn*t} + \varepsilon_{ipt} \end{aligned}$$

FrCommute is the fraction of workers in wage group *w* residing in PUMA *p* that commute to work in state *n* in year *t*. *PosTreat* is an indicator that equals one if *MinWageChange* for PUMA *p* relative to neighbor state *n* is greater than or equal to 1.5. *NegTreat* is an indicator that equals one if the *MinWageChange* for PUMA *p* relative to neighbor state *n* is less than or equal to -1.5. The regression includes PUMA-NeighborState*Year fixed-effects. This controls for any time-varying unobservables that equally affect the commuting flows of low-wage and moderate-wage workers between PUMA *p* and neighbor state *n*. An alternative version of equation (2) is estimated using the net commuting rate as the dependent variable. In this case, the number of in-commuters to PUMA *p* from neighbor state *n* is differenced out of the numerator of *FrCommute*.

A two-neighbor-state sample is then generated by first restricting the original analysis sample of 534 PUMAs to the 160 PUMAs that have commuting flows in the baseline period of at least one percent with two different neighbor states. For the majority of these 160 PUMAs, however, the minimum wage hike has a very similar effect on both neighbor states. A within-PUMA comparison of flows to the two different neighbor states is only useful if the minimum wage hike has a differential impact on the two different neighbors. Therefore, following the findings in Table 5, the sample is restricted to the 27 PUMAs with two neighbors where the federal minimum wage hike has a differential effect on the two neighbor states of at least 1.5 dollars.

Within each PUMA in this sample, the PUMA-NeighborState pair that has the most positive value of *MinWageChange* is designated as the “treatment” PUMA-NeighborState for that PUMA. In this sample, a difference-in-differences-in-differences experiment occurs within each PUMA. For example, PUMA 12100 in Alabama experiences cross-border commuting into both Florida and Mississippi. The *MinWageChange* for PUMA 12100 with Florida is 1.5 and with Mississippi is 0. The 12100-Florida PUMA-neighbor state pair is therefore the treatment and 12100-Missippi is the comparison. The question of interest is whether the out-of-state commutes of low-wage workers (relative to moderate-wage workers) from Alabama to Florida decrease relative to the commutes into Mississippi when the federal minimum wage increase is imposed.

The specification used for the two-neighbor-state sample is:

$$\begin{aligned} FrCommute_{wpnt} &= \beta_0 + \beta_1 Treat_{pn} * After_t * LowWage_w + \beta_2 Treat_{pn} * LowWage_w \\ &\quad + \gamma_{pn*t} + \delta_{p*lw} + \phi_{p*lw*after} + \varepsilon_{wpnt} \end{aligned} \tag{3}$$

Not only does equation (3) include controls for PUMA-neighbor state*Year fixed-effects, as was the case in equation (2), but the within PUMA variation across neighbor states allows PUMA*low wage fixed-effects and PUMA*low wage*after fixed-effects to be included as well. This allows each PUMA to have time-varying unobservables that differentially affect low-wage workers compared to moderate-wage workers, and identifies the parameters of interest based on the differential change within PUMA in the relative commute rates with the two different neighbor states.

Because the treatment PUMA-neighbor state pairs are those within each PUMA that have the most positive *MinWageChange* value, a positive β_1 is consistent with disemployment effects of a minimum wage increase and a negative β_1 is consistent with workers commuting across state lines to receive a higher minimum wages in the neighboring state. Equation (3), like equation (2), is also additionally estimated using the net commuting rate as the dependent variable.

III. Results

A. Individual-level analysis

Table 4 reports results from the individual-level analysis of out-of-state commuting using equation (1). Columns 1-3 include controls for PUMA fixed-effects and year fixed-effects, while columns 4-6 control for PUMA*year fixed-effects.

Columns 1 and 2 of Table 4 first report separate differences-in-differences estimates for low-wage and moderate-wage workers, while column 3 reports the combined DinDinD results for the full sample. Focusing first on positive treatment effect estimate, the estimate of 0.010 in column 1 indicates that among workers with wages below 10 dollars per hour, the increase in own state's minimum wage generates a small, positive, statistically significant increase in the probability of commuting out of state. It could be, however, that out-of-state commuting is responding to something other than the minimum wage increase. For example, it could be that economic conditions in states that previously had lower minimum wages are declining relative to states with previously higher minimum wages.

Column 2 therefore estimates the same difference-in-differences model for workers with wages between 10 and 13 dollars an hour. Among these workers, there is a statistically significant *decrease* of -0.024 in out-of-state commuting in response to the federally-mandated minimum wage increase. This suggests that unobserved changes in economic conditions are making it less attractive for moderate-wage workers to commute out of states that previously had low minimum wages (and were the most affected by the federal increase) into states that previously had higher minimum wages (and were the least affected by the federal increase). This is consistent with analysis of Clements and Wither (2014), who find that states that had the highest minimum wages prior to 2008, and therefore were the least effected by the federal increase, were more severely affected by the Great Recession. It is therefore surprising that the low-wage workers actually show a modest increase in commuting into these states. This relative increase in commuting by low-wage workers is consistent with a disemployment effect of the minimum wage hike in their own state.[11] To the extent that employers respond to the minimum wage increase by substituting slightly higher skilled workers for the low-wage workers, this would also be consistent with moderate-wage workers decreasing out-of-state commuting at the same time low-wage workers increase out-of-state commuting.

The DinDinD result for the positive treatment group reported in column 3 is consistent with the estimates reported in columns 1 and 2. The estimate of 0.035 for the positive treatment PUMAs indicates that low wage workers in the positive treatment PUMAs experience a statistically significant *increase* in out-of-state commuting in response to the minimum wage increase.

The results in columns 1-3 for the Negative Treatment group, however, suggest a smaller treatment effect. The positive estimate of 0.008 for the moderate-wage workers indicates that moderate-wage workers very modestly increased out-of-state commuting from negative treatment PUMAs. This positive estimate is consistent with the discussion above that the negative treatment PUMAs (which had higher minimum wages in the baseline period) experienced a larger economic shock from the Great Recession, but the magnitude is small and the estimate is statistically insignificant. The fact that the low-wage workers increase out-of-

[11] An alternative explanation for the fact we do not obtain a negative coefficient estimate for the low-wage workers as we do for the moderate-wage workers is that the low-wage workers had much lower out-of-state commuting rates to begin with, leaving little potential for a response. But, as indicated by the commute rates reported in Table 3 as well as the coefficient on *Low Wage* in column 3 of Table 4, the difference in out-of-state commuting rates between the low-wage and moderate-wage workers is not large enough to support this explanation.

state commuting less than the moderate wage workers, only 0.001 compared to 0.008, is also consistent with the fact that they are somewhat repelled by the increase in the minimum wage in the neighboring state, but the difference in magnitudes is much smaller than that observed for the positive treatment PUMAs. The DinDinD estimate reported in column 3 for the negative treatment group is therefore a small and statistically insignificant -0.008.

The comparison of the DinDinD estimates in column 3 for the positive and negative treatment groups therefore suggest an asymmetric effect, where the positive treatment effect is larger in magnitude than the negative treatment effect. Additional sensitivity analysis found that these results are largely robust to the exclusion of any particular state or border in the data set with one exception. The negative treatment effect estimate is quite sensitive to the exclusion of the six Ohio PUMAs on the Indiana border which are in the negative treatment group.[12] Column 4 replicates the DinDinD analysis on a restricted sample that excludes these six PUMAs. The positive treatment estimate is unaffected, but the negative treatment estimate increases in magnitude from -0.008 to a statistically significant -0.023. In column 4, we cannot reject the null hypothesis of a symmetric effect (i.e., we cannot reject $H_o : \beta_{postreat*a*lw} = -\beta_{negtreat*a*lw}$).

Because the negative treatment effect estimate is sensitive to the inclusion of these 6 PUMAs, the results in the remaining Tables 5-7 are reported for both the restricted sample and the full sample. The final two columns of Table 4 only report results from the restricted sample, but the results using the full sample are also noted in the text below.

Column 5 adds PUMA*year fixed-effects to the model in column 4. To the extent that the DinDinD comparison of low wage and moderate wage workers already differences out the effect of omitted time-varying local characteristics, such as the unemployment rate, the results

[12] Examination of the raw data confirms that, unlike the other PUMAs in the negative treatment group, that there is a sizable increase in out-of-state commuting by low-wage workers relative to high-wage workers in this set of Ohio PUMAs.

should not be sensitive to the addition of these fixed-effects. As expected, the DinDinD estimate is relatively insensitive to the richer set of fixed-effects.[13]

The final column of Table 4 tests for evidence of differential trends prior to the federal minimum wage increase. In column 6, the sample is restricted to the years 2005-2008. The *After* indication in equation (1) is now replaced with an indicator that equals one for the years 2007-2008. The results in column 6 show no statistically significant evidence of prior trends. Additionally, the signs of the DinDinD estimates in this column are both of opposite sign compared to the estimates in column 5. This suggests that any prior trends that do exist work against the findings in column 5.[14]

It is also worth noting the coefficients on *PositiveTreatment*LowWage* and *NegativeTreatment*LowWage* in columns 3-5. These estimates indicate whether, prior to the federal increase, low-wage workers disproportionately commuted across state borders towards higher minimum wages. The negative coefficient on *PositiveTreatment*LowWage* is negative (though insignificant), suggests that the low-wage workers were slightly less likely, relative to moderate-wage workers, to commute out-of-state if the neighbor had a higher minimum wage. Similarly, the small positive coefficient on *NegativeTreatment*LowWage* indicates that low-wage workers were slightly more like to commute out-of-state if the neighbor had a lower minimum wage. Neither coefficient estimate indicates that low-wage workers were commuting to states with higher minimum wages prior to the federal minimum wage hike.

Table 5 considers the sensitivity of the results to the definition of the treatment group. Panel A reports estimates using the restricted sample and Panel B reports estimates using the full

[13] The estimates obtained estimating the specification from Table 4 column 5 on the full sample are reported below in Table 5 panel B column 1.

[14] When the prior trends model in column 6 is estimated on the full sample, the coefficient on *postreat*after*lw* is unaffected, while the coefficient on *negtreat*after*lw* changes from -0.14 to -0.11 and remains statistically insignificant.

sample. All models in the table control for PUMA*year fixed-effects as well as the individual controls used in Table 4. Column 1 replicates the results from column 5 of Table 4 for both the restricted and full samples. In column 2, the definition of *Positive Treatment* is changed to *MinWageChange*≥1 and *Negative Treatment* to *MinWageChange*≤-1.

Column 2 shows that the treatment effects become smaller and statistically insignificant when the definition of treatment is broadened in this way. A comparison of results in columns 1 and 2 suggests that the effect of a change the cross-border minimum wage differential on cross-border commuting is non-linear, with small changes in the minimum wage differential having very little effect on commuting, but changes as large as 1.5 dollars having a noticeable effect.[15] This is consistent with the presence of out-of-state commuting costs which limit the commuting response to smaller changes in the cross-border minimum wage differential.

In column 3, the definition of *Positive Treatment* is changed to *MinWageChange*≥2 and *Negative Treatment* to *MinWageChange*≤-2. As shown in Table 1, under this definition, there are only 10 Positive Treatment PUMAs and 13 Negative Treatment PUMAs.[16] The signs and magnitudes of the treatment effects are similar to those in column 1, but the standard errors are considerable larger due to the smaller size of the treatment groups, and the estimates are therefore statistically insignificant.

It should be noted, however, that while the positive and negative treatment effect estimates in columns 2 and 3 of Table 4 are not statistically different from zero, they are statistically different from each other. The test of equality of the two DinDinD estimates ($H_o : \beta_{postreat*a*lw} = \beta_{negtreat*a*lw}$) in column 2 has a p-value of 0.034 in the restricted sample and

[15] Estimates using 1.25 and 1.75 as the treatment group cut-off are consistent with the pattern of results in Table 5.

[16] The estimates in column 3 are identified using only a few key state borders with large minimum wage differentials, specifically: Idaho's borders with the much higher minimum wage states of Washington and Oregon, and New Hampshire's borders with the much higher minimum wage states of Massachusetts and Vermont.

0.089 in the full sample. In column 3, the p-value is 0.057 in both samples. There is therefore, in both columns 2 and 3, a statistically significant difference in commuting effects between positive treatment PUMAs and negative treatment PUMAs that is consistent with disemployment effects of the minimum wage.

Column 4 returns to the treatment definitions used in column 1, but restricts the sample to PUMAs which previously experienced a higher rate of cross-border commuting. Only those PUMAs for which *PrePercIn* or *PrePercOut* is at least three percent in the before period are included in the sample. As would be expected, both DinDinD estimates are larger in magnitude than those in column 1 and remain statistically significant.

B. PUMA-level analysis and PUMAs with two neighbors

Before focusing on the subset of PUMAs with two neighbors, Table 6 first reports estimates of equation (2) to confirm that the results are not sensitive to analyzing aggregate commuting flows, rather than individual workers. The analysis in Table 6 uses the treatment group cutoffs (1.5 and -1.5) used in Table 4. Unlike the individual-level analysis in Tables 4 and 5, in Table 6 the unit of observation is a PUMA-neighbor state-wage group. The dependent variable is the fraction of workers living in the PUMA who commute to work in the neighbor state. Performing the analysis on aggregated data results in the omission of the individual-level controls from the regression.

Columns 1 and 2 report analysis using the restricted sample and columns 3 and 4 use the full sample. Columns 1 and 3 report estimates from equation (2). These estimates are similar to those in column 1 of Table 5, indicating that that aggregating the analysis to the PUMA-neighbor state-wage group level, and eliminating the additional individual-level controls, had a relatively small effect on the results.

Columns 2 and 4 of Table 6 use the net commuting rate as the dependent variable, so that the number of workers commuting into the PUMA from the neighboring state is differenced out of the numerator of the commuting rate used in columns 1 and 3. The DinDinD estimates for the positive treatment group become even larger in magnitude, but the DinDinD estimates for the negative treatment group are largely unaffected.

The results for the restricted sample reported in Table 6 display a greater degree of asymmetry between positive and negative treatment effects compared to Tables 4 and 5. A test for asymmetric effects ($H_o : \beta_{postreat*a*lw} = -\beta_{negtreat*a*lw}$), however, still fails to reject the null hypothesis that the magnitude of the effects is the same.

Finally, it is worth noting that the negative coefficient estimates on *PosTreat*LowWage* and the negative coefficient estimates on *NegTreat*LowWage*, while in most cases statistically insignificant, indicate that low-wage workers did not commute across state lines towards higher minimum wages in the period before the federal minimum wage hike.

Table 7 restricts the sample from Table 6 to the 27 PUMAs that meet two criteria: 1) they experience commuting flows in the baseline period of at least one percent with more than one state, and 2) the federal minimum wage hike has a differential effect on the two neighbor states of at least 1.5 dollars.

Table 7 reports estimates from equation (3), which includes controls for PUMA-NeighborState*Year fixed-effect, PUMA*low wage fixed-effects and PUMA*low wage*after period fixed-effects. In this case, the treatment group contains the PUMA-neighbor state pair within each PUMA for which *MinWageChange* is the most positive. There is no separate estimation of positive and negative treatment group effects in Table 7. Column 1 reports the analysis of the out-of-state commuting rate for the restricted sample. The positive and statistically significant DinDinD estimate is consistent with an increase in out-of-state commuting for the PUMA-neighbor state pair that experiences the largest increase in own minimum wage relative to the neighbor state minimum wage. In other words, as was the case in Tables 4-5, the results indicate that low-wage workers are commuting away from minimum wage increases, rather than towards minimum wage increases. The DinDinD estimate for the net commuting rate in column 2 is also positive, but smaller and statistically insignificant. There results for the full sample reported in columns 3 and 4 are similar.[17]

The negative coefficient estimates on *treatment*lowwage* in Table 7 indicate that prior to the federal minimum wage hike, low-wage workers (relative to moderate wage workers) were less likely to commute to the neighbor state with the highest minimum wage than to neighbor states with lower minimum wages.

IV. Conclusions

This paper tests for empirical evidence that low-wage workers are attracted to commute across state lines by a higher minimum wage in the neighboring state. None of the empirical results are consistent with a cross-border attraction of minimum wages. In the period prior to the federal minimum wage increase, when cross-border differentials were larger, there is no evidence that low-wage workers commuted at higher rates (relative to moderate-wage workers) to neighbors with a higher minimum wage. In response to the federal minimum wage increase which compressed cross-border minimum wage differentials, low-wage workers modestly increased out-of-state commuting out of states most affected by the federal minimum wage increase. In comparison, moderate-wage workers reduced the rate at which they commuted out of states most affected by the federal increase. If moderate-wage workers offer an appropriate

[17] Only one of the PUMAs excluded from the restricted sample is in the two-state sample, therefore difference between the restricted and full samples in Table 7 is even smaller than in previous tables.

counterfactual for low-wage workers, these results are consistent with a disemployment effect of a minimum wage increase.

This paper reinforces the fact that there is more than one margin on which effects of a minimum wage hike could be felt. Furthermore, the findings also indicate that cross-border studies of minimum wage effects on employment may be biased by spillovers created by cross-border commuting, with the direction of the bias depends on whether employment is measured based on residential location or work location. When employment is measured based on residential location, cross-border studies will tend to understate disemployment effects.

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Appendix A

The analysis in this paper compares the out-of-state commute rates of workers making less than \$10/hr to those making \$10-\$13/hr. This raises the measurement concern that there are some individuals whose market wage in their home state is less than \$10/hr, but commute across state lines to receive a market wage that is above \$10. This places them in the wrong observed wage category for the purpose of calculating the commute rate. Similarly, there could be workers who would not work in the home state (and therefore would not be in the sample), but commute across state lines in order to obtain a wage above their reservation wage.

This appendix presents simple calculations that show that this threshold effect will cause estimates of the commute rates to be attenuated towards zero when commute rates are larger for workers with higher wages. The basic intuition is that the number of commuters who exit the wage category by commuting into a higher wage category will exceed the number of commuters who enter the wage category by commuting out of a lower wage (or non-work) category. Additionally, estimated changes in the commute rates will also be attenuated towards zero as long as the commute rates are not very large.

Let ϕ_j be the commute rage in wage category j, ϕ_{j-1} be the commute rate in the wage category j-1, and $x = \phi_j - \phi_{j-1}$. Consistent with the data, we expect commute rates to increase across wage categories so that $x > 0$

Let α be the fraction of commuters who would have been categorized in j-1 in the home state, but work in category j in the neighbor state. For simplicity, α is constant across the wage categories, but similar results would hold if α varied by wage category.

Estimating ϕ_j by dividing the number of commuter in category j by the sum of the number of non-commuters in category j plus the number of commuters in category j:

$$E(\hat{\phi}_j) = \frac{\phi_j - \alpha x}{1 - \alpha x}$$

So $\hat{\phi}_j$ is attenuated towards zero.

For a change in the commute rate in category j, $\Delta\phi_j = \beta$, where α and ϕ_{j-1} remain the same,

$$E(\Delta\hat{\phi}_j) = \beta \frac{(1-\alpha) + \alpha(\phi_j - x)}{[1-\alpha(x+\beta)](1-\alpha x)}.$$

This will also be attenuated towards zero when $\phi_j + (1-\alpha x)(x+\beta) < 1$.

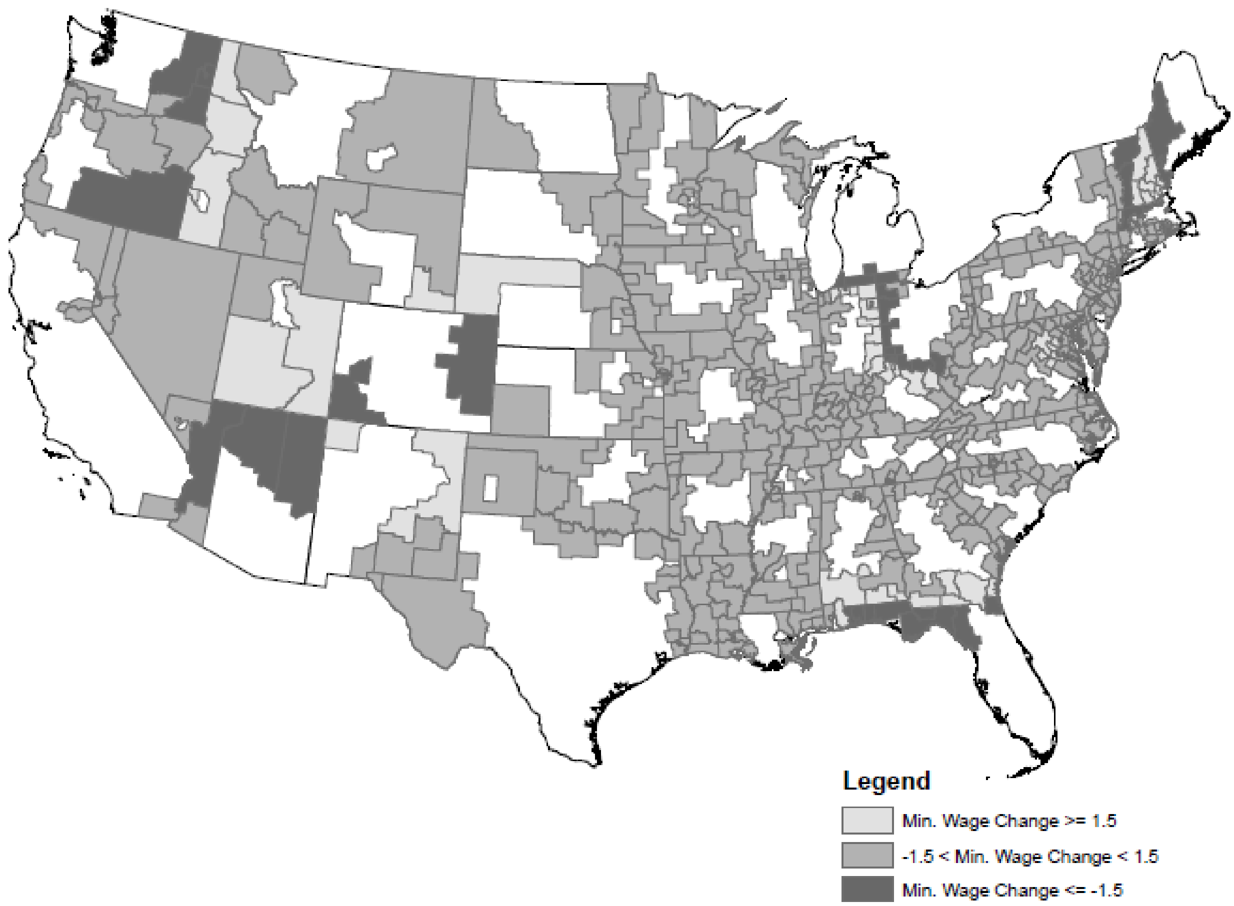

Figure 1: Analysis Sample of PUMAs by Treatment Group

Table 1: Distribution of federal policy induced change in minimum wage relative to neighbor, Sample of PUMAs with cross-state-border commuting flows

	# of PUMAs
Relative Minimum Wage Change≥2	10
1.5≤ Relative Mininum Wage Change<2	38
1≤Relative Minimum Wage Change<1.5	66
0<Relative Minimum Wage Change<1	49
Relative Minimum Wage Change=0	193
-1<Relative Minimum Wage Change<0	55
-1.5<Relative Minimum Wage Change≤-1	80
-2<Relative Minimum Wage Change≤-1.5	30
Relative Minimum Wage Change≤-2	13
N	534

Notes: Sample is the set of PUMAs with cross-border commuting flows of at least 1 percent in the baseline period. The relative minimum wage change is the change in the state minimum wage, relative to the neighbor state, induced by the federal minimum wage increase. Change is calculated based on the 2007 minimum wage difference between the two states.

Table 2: Distribution of hourly wage by education and age group

	Hourly Wage				
	10th percentile	25th percentile	50th percentile	75th percentile	90th Percentile
Ages 18-60					
Less than HS degree	5.69	7.71	11.09	15.91	22.44
HS graduates w/ less than 1 year of college	6.94	9.64	14.27	19.77	27.48
Ages 18-29					
Less than HS degree	4.82	6.75	9.31	12.54	17.36
HS graduates w/ less than 1 year college	5.53	7.71	10.61	14.46	19.29

Notes: ACS 2005-2008. Sample is workers ages 18 and older with less than one year of college residing in one of the 534 PUMAs used in Table 1.

Table 3: Out-of-State Commuting Rates

	% Working in a Different State	
	Ages 18-60	Ages 18-29
Less than HS degree	7.6%	7.9%
Less than 1 year college & Wage<10	5.5%	5.7%
Less than 1 year college & 10≤Wage<13	6.5%	7.2%

Notes: Sample is as described in the notes of Table 2. Table reports percent of workers whose state of work differs from state of residence.

Table 4: Difference-in-differences-in-differences estimates, minimum wage increases and out-of-state commuting by low-wage workers

	Low Wage=1	Low Wage=0	Full Sample	Restricted Sample	Restricted Sample	Prior Trends 2005-2008
Positive Treatment *After*Low Wage			0.035***	0.035***	0.037***	-0.011
			(0.010)	(0.010)	(0.010)	(0.017)
Negative Treatment *After*Low Wage			-0.008	-0.023*	-0.022*	0.014
			(0.012)	(0.013)	(0.013)	(0.013)
Positive Treatment *After	0.010*	-0.024**	-0.025*	-0.025*		
	(0.006)	(0.010)	(0.010)	(0.007)		
Negative Treatment *After	0.001	0.008	0.009	0.015		
	(0.006)	(0.010)	(0.012)	(0.012)		
Positive Treatment *Low Wage			-0.008	-0.008	-0.009	-0.003
			(0.009)	(0.009)	(0.008)	(0.011)
Negative Treatment *Low Wage			0.004	0.008	0.010	0.003
			(0.007)	(0.008)	(0.008)	(0.011)
Low Wage*After			0.001	0.001	0.000	0.003
			(0.003)	(0.003)	(0.003)	(0.004)
Low Wage			-0.010***	-0.010***	-0.010***	-0.011***
			(0.002)	(0.002)	(0.002)	(0.003)
PUMA FEs	Y	Y	Y	Y	-	-
Year FEs	Y	Y	Y	Y	-	-
PUMA*Year FEs	N	N	N	N	Y	Y
N	79,831	35,077	114,908	113,299	113,299	77,236

Notes: Sample in columns 1-3 is sample of workers ages 18-29 described in the notes of Table 2, restricted to workers with hourly wages below 13 dollars. Restricted sample in columns 4-6 further eliminates the 6 Ohio PUMAs on the Indiana border. Table reports results from equation (1): *Positive Treatment* is an indicator for a positive federally-induced minimum wage change, relative to neighbor, of 1.5 or more, *Negative Treatment* is an indicator for a negative federally-induced minimum wage change, relative to neighbor, of -1.5 or more, and *Low Wage* is an indicator for hourly wage below 10. In columns 1-5, *After* is an indicator for post-2009. In column 6, the sample is restricted to years 2005-2008 and *After* is an indicator for 2007-8. All regressions control for age, age-squared and indicators for female, white, black, Hispanic, immigrant, less than high school, high school. Standard errors are clustered at the PUMA. *p-value<0.1, **p-value<0.05, ***p-value<0.01

Table 5: Difference-in-differences-in-differences estimates, sensitivity to treatment definition and sample restriction

	Treatment= (Change>1.5)	Treatment= (Change>1)	Treatment= (Change>2)	Treatment= (Change>1.5) Higher Flow Sample
Panel A: Restricted Sample				
Positive Treatment *After*Low Wage	0.037***	0.009	0.034	0.048***
	(0.010)	(0.008)	(0.026)	(0.013)
Negative Treatment *After*Low Wage	-0.022*	-0.012	-0.040	-0.038*
	(0.013)	(0.008)	(0.029)	(0.023)
Test equality of positive and negative DinDinD estimates: p-value	0.000	0.034	0.057	0.001
N	113,299	113,299	113,299	77,733
Panel B: Full Sample				
Positive Treatment *After*Low Wage	0.038***	0.009	0.033	0.048***
	(0.010)	(0.008)	(0.026)	(0.013)
Negative Treatment *After*Low Wage	-0.007	-0.008	-0.041	-0.007
	(0.013)	(0.008)	(0.029)	(0.020)
Test equality of positive and negative DinDinD estimates: p-value	0.004	0.089	0.057	0.017
N	114,908	114,908	114,908	79,342

Notes: Table 5 replicates the analysis in Table 4, varying the definition of the treatment groups. All regressions include PUMA*Year fixed effects and the individual controls listed in the notes of Table 4. Column 1 uses the same samples and treatment groups used in Table 4. In Column 2 treatment PUMAs have a relative minimum wage change of 1 or more in absolute value. Column 3 treatment PUMAs have a relative minimum wage change of 2 or more in absolute value. Column 4 further restricts the sample to PUMAs with a cross-border flow of at least 3 percent before the federal policy change, retaining the treatment group definitions used in column 1. Standard errors are clustered at the PUMA. *p-value<0.1, **p-value<0.05, ***p-value<0.01

Table 6: Aggregate PUMA-Neighbor state cross-border commuting rates

	Restricted Sample		Full Sample	
	Out Commuting Rate	Net Commuting Rate	Out Commuting Rate	Net Commuting Rate
Positive Treatment *After*Low Wage	0.033**	0.070**	0.033***	0.070**
	(0.12)	(0.028)	(0.012)	(0.028)
Negative Treatment *After*Low Wage	-0.015	-0.012	-0.003	-0.009
	(0.013)	(0.024)	(0.012)	(0.021)
Positive Treatment *Low Wage	-0.004	-.018	-0.004	-0.018
	(0.009)	(0.005)	(0.009)	(0.015)
Negative Treatment *Low Wage	0.014*	0.019	0.008	0.018
	(0.008)	(0.014)	(0.07)	(0.012)
Low Wage*After	0.005	-0.003	0.005	0.003
	(0.003)	(0.006)	(0.003)	(0.006)
Low Wage	-0.012***	-0.023***	-0.012***	-0.023***
	(0.002)	(0.005)	(0.002)	(0.005)
N	8496	8496	8616	8616

Notes: Table 6 uses the samples from Table 4, aggregated to the PUMA-neighbor state-year-wage group level and reports estimates from equation (2). Dependent variable in columns 1 and 3 is out commuting rate from PUMA to neighboring state. Dependent variable in columns 2 and 4 is net commuting rate (differencing out number of commuters into the PUMA from neighboring state). All regressions control for PUMA-neighborstate*year fixed-effects. Standard errors clustered at the PUMA. *p-value<0.1, **p-value<0.05, ***p-value<0.01

Table 7: PUMAs with Two Neighbor States

	Restricted Sample		Full Sample	
	Out Commuters	Net Commuters	Out Commuters	Net Commuters
Treatment*After *Low Wage	0.040*	0.025	0.035	0.022
	(0.024)	(0.034)	(0.024)	(0.033)
Treatment*Low Wage	-0.015	-0.027*	-0.012	-0.023
	(0.015)	(0.015)	(0.015)	(0.016)
N	732	732	756	756

Notes: Table 7 uses the sample from Table 6, restricted to the 27 PUMAS that have commuting flows with two neighbor states, and a difference in the MinWageChange between the two neighbor states of 1.5 or greater. The dependent variables are described in the notes of Table 6. Table reports results from equation (3). *Treat* is an indicator variable that equals one for the PUMA-neighbor state pair in each PUMA with the most positive value of *MinWageChange*. All regressions control for PUMA-neighborstate*year fixed-effects, PUMA*lowwage fixed-effects and PUMA*lowwage*after fixed-effects. Standard errors clustered at the PUMA. *p-value<0.1, **p-value<0.05, ***p-value<0.01