

# The Effect of Maryland's 2022 Minimum Wage Increase on Employment in the Fast-Food Industry\*

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## Abstract

Economic theory suggests that increasing minimum wage could lead to a decrease in employment, especially for industries most sensitive to minimum wage laws. Using Pennsylvania as a control group, we study the labor implications of Maryland's increase in minimum wage in 2022 using a difference-in-differences approach. Although OLS regressions infer that the minimum wage hike had no effect on employment in the fast-food industry, our more rigorous fixed effects regressions indicate that the minimum wage law had a negative and statistically significant impact on employment, implying that higher minimum wage caused an increase in unemployment among fast-food workers.

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# 1 Introduction

According to conventional economic theory, a rise in a state's minimum wage should result in an increase in the unemployment level, all other factors remaining constant, due to the increased costs of production when such laws go into effect. However, Card & Krueger (1994) provides a seminal study on the effect of the 1992 New Jersey minimum wage increase and found that there is no statistically significant effect of raising minimum wages on employment in the fast-food industry, which provides an ideal market to analyze due to the tendency of these restaurants to employ a large number of minimum wage workers.

Card and Krueger (1994) survey a number of fast-food chain restaurants in New Jersey and Pennsylvania to collect information on the percentage of part-time and full-time employees each restaurant employed, the number of hours they worked, the prices of meals, and the wages paid before and after the minimum wage law went into effect. In a follow-up paper, Card and Krueger (2000) respond to critiques by Berman (1995) and Neumark and Wascher (2000) by appending their original survey data with the ES-202 program, which is published by the Bureau of Labor Statistics and provides quarterly employment statistics by county and industry.<sup>1</sup>

In order to revisit the topic, we empirically analyze the fast-food industry in Maryland and Pennsylvania before and after the minimum wage increase in Maryland on January 1, 2022, thirty years after the New Jersey law in Card & Krueger (1994). On this date, Maryland's minimum wage increased from \$11.75 per hour to \$12.50 per hour, whereas Pennsylvania's minimum wage had not changed since it was set at \$7.25 per hour in 2010.<sup>2</sup> Given that its minimum wage has remained constant, Pennsylvania serves as an appropriate control group to determine the potential correlation between the 2022 Maryland wage law and employment in the fast-food industry.

Using a difference-in-differences approach, we study the effect of the increase in Maryland's minimum wage in 2022 on the employment level in the fast-food restaurant industry. When we estimate our regression specification using the ordinary least squares (OLS) method, the results

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<sup>1</sup><https://www.bls.gov/respondents/mwr/electronic-data-interchange/home.htm>

<sup>2</sup><https://www.dol.gov/agencies/whd/state/minimum-wage/history>

suggest that the minimum wage hike had no effect on employment in the fast-food industry. However, we find that the minimum wage law had a negative and statistically significant impact on employment when we implement a more rigorous fixed effects regression model. We conclude that the higher minimum wage in Maryland caused unemployment among fast-food workers to increase relative to the employment trend in Pennsylvania.

## 2 Empirical Analysis

As with Card and Krueger (2000), the Quarterly Census of Employment and Wages (or ES-202 program) serves as the main data set used in the paper and is publicly available from the Bureau of Labor Statistics (BLS). Notable variables from this program are quarterly employment level, the number of limited-service restaurants each quarter, and total quarterly wages. We collect data for each county in Maryland and Pennsylvania in 2021 and 2022, which serves as our before and after time periods related to the effective date of the Maryland minimum wage law. We append the ES-202 program with county-level population data, which is published annually by the Population Division of the US Census Bureau.

Table 1: Summary Statistics

Variable	Definition	Mean (Std. Dev.)
$emplvl_{it}$	Employment level of fast-food workers in county $i$ in time $t$	2,196.77 (3,004.41)
$estabs_{it}$	Number of fast-food establishments in county $i$ in time $t$	162.73 (244.82)
$wages_{it}$	Total wages (in millions) for fast-food workers in county $i$ in time $t$	11.05 (16.52)
$pop_{it}$	Population (in thousands) of county $i$ in time $t$	210.58 (286.65)
N	Number of observations	728

Table 1 reports the summary statistics for our data. Given that an observation in our data set is at the county-year-quarter level, each variable is indexed by county  $i$  in year-quarter  $t$ . Two

things to note is that both the *wages* and *pop* variables have been scaled in millions and thousands, respectively. As such, the average total wages for fast-food workers for a specific county in a particular year-quarter is \$11,048,876.29, whereas the average county-level population is 210,575.4 people.

Table 2: Difference-in-Differences in Employment for Counties in Maryland vs. Pennsylvania

	2021 (y22 = 0)	2022 (y22 = 1)	Difference between time periods
Maryland ( $MD = 1$ )	3,089.87	3,125.50	35.63
Pennsylvania ( $MD = 0$ )	1,821.23	1,919.71	98.48
Difference between groups	1,268.64	1,205.79	-62.85

Table 2 presents the mean values for *emplvl*, the employment level for fast-food workers, for counties in Maryland (our treatment group) vs. counties in Pennsylvania (our control group) in 2021 (before time period) and 2022 (after time period). For example, 3,089.87 fast-food workers were employed in Maryland counties in 2021, on average. Although fast-food establishments in Maryland counties increased employment by an average of 35.63 workers, fast-food establishments in Pennsylvania counties increased employment by a larger amount, 98.48 workers, on average. Assuming that fast-food establishments in Maryland would have responded like those in Pennsylvania had the minimum wage law not taken effect, we calculate that the gap between the average level of employment that Maryland should have experienced is  $35.63 - 98.48 = -62.85$  workers. In other words, the difference-in-differences (DID) in employment for counties in Maryland vs. Pennsylvania is negative, implying that Maryland's minimum wage law caused employment to decrease (or conversely, a rise in unemployment).

In order to ascertain whether the DID statistic in Table 2 is truly negative or actually zero, we estimate the following OLS regression equation:

$$y_{it} = \beta_0 + \beta_1 y22_t + \beta_2 MD_i + \beta_3 y22_t \cdot MD_i + \epsilon_{it}, \quad (1)$$

where the dependent variable is *emplvl*, the employment level of fast-food workers in county  $i$

in time  $t$ . The three control variables include  $y22$ , a dummy variable indicating the after time period ( $y22 = 1$ ) or the before time period ( $y22 = 0$ );  $MD$ , a dummy variable indicating whether the county is located in Maryland ( $MD = 1$ ) or Pennsylvania ( $MD = 0$ ); and the interaction term of  $y22$  and  $MD$ . In order to determine the statistical significance for the DID estimator in Table 2, we focus our attention on the sign and significance of  $\beta_3$ .

Table 3: Difference-in-Differences Regression Results

	Dep. Var.: <i>emplvl</i>
$y22$	98.48 (232.83)
$MD$	1,268.64*** (400.00)
$y22 \cdot MD$	-62.85 (569.18)
N	728

Note: The dependent variable is *emplvl*, the employment level in a specific county in a particular year-quarter. Robust standard errors are reported in parentheses. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 3 reports the regression results for Equation (1) with robust standard errors. Note that the estimated coefficient for each of the control variables is directly tied to a numerical value in Table 2. For instance, the estimated coefficient for  $y22$  is 98.48, which is precisely the difference in the before and after time periods for our Pennsylvania control group:  $1,919.71 - 1,821.23 = 98.48$ . Moreover, the estimated coefficient for  $MD$  is 1,268.64, which is the difference between our Maryland treatment group and our Pennsylvania control group in the before time period:  $3,089.87 - 1,821.23 = 1,268.64$ . Finally, the estimated coefficient for the  $y22 \cdot MD$  interaction term provides our DID estimate of -62.85. However, the regression results suggest that this parameter is statistically insignificant with a robust standard error of 569.18, implying that the minimum wage law in Maryland had no impact on employment in the fast-food sector.

Of course, there are other factors that can influence employment other than the minimum wage law. Equation (2) expands on Equation (1) by including additional control variables:

$$y_{it} = \beta_0 + \beta_1 y22_t + \beta_2 MD_i + \beta_3 y22_t \cdot MD_i + \beta_4 X_{it} + \varepsilon_{it}. \quad (2)$$

Four variables are contained in  $X_{it}$ . First, *estabs* is the number of fast-food establishments in county  $i$  in time  $t$ . Second, *wages* is the total wages (in millions) for fast-food workers for a specific county in a particular year-quarter. Third, *pop* is the population (in thousands) of county  $i$  in time  $t$ . Finally, we include seven time dummies for each of our time periods (2021:Q2 - 2022:Q4), excluding the dummy variable for 2021:Q1 to serve as our base time period and avoid perfect collinearity issues. As with Equation (1), we estimate Equation (2) with robust standard errors.

Table 4: Ordinary Least Squares Regression Results

	Dep. Var.: <i>emplvl</i>		Dep. Var.: $\ln(\textit{emplvl})$	
	(1)	(2)	(3)	(4)
<i>y22</i>	153.74 (441.88)	-198.18*** (55.02)	0.132 (0.192)	0.078 (0.110)
<i>MD</i>	1,268.64*** (401.59)	-17.34 (44.59)	0.582*** (0.147)	0.360*** (0.095)
<i>y22 · MD</i>	-62.85 (571.47)	-69.68 (63.24)	-0.083 (0.210)	-0.097 (0.120)
<i>estabs</i>		-1.61* (0.92)		-0.005*** (0.001)
<i>wages</i>		128.28*** (8.53)		0.016* (0.009)
<i>pop</i>		4.49*** (0.59)		0.007*** (0.001)
N	728	728	674	674

Note: The dependent variable in Columns (1) and (2) is *emplvl*, the employment level in a specific county in a particular year-quarter, whereas  $\ln(\textit{emplvl})$ , the log transformation of *emplvl*, is the dependent variable in Columns (3) and (4). Estimated coefficients for time trend dummies are suppressed. Robust standard errors are reported in parentheses. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 4 presents the regression results for Equation (2) in four columns. Columns (1) and (2) report the level-level regression results using *emplvl* as the dependent variable without and with additional control variables, respectively. Meanwhile, Columns (3) and (4) report the log-level regression results using  $\ln(\textit{emplvl})$  as the dependent variable without and with additional control variables, respectively. To be sure, Column (1) in Table 4 is constructed to replicate the regression results in Table 3. We can then compare the DID estimator by examining the sign and significance of the *y22 · MD* interaction term in Column (2). Even when including additional control variables

into our level-level regression analysis, the DID estimator in Column (2) remains negative, yet statistically insignificant. Again, this suggests that Maryland’s minimum wage law has no effect on employment in the fast-food industry.

Given the differing sizes of counties in Maryland compared to Pennsylvania, it also makes sense to take a look at employment changes as a percent change rather than a nominal change. Since we implement a log-level specification in Columns (3) and (4), we can interpret the estimated coefficient for the  $y22 \cdot MD$  interaction term as the minimum wage law in Maryland causing employment to decrease by approximately 8.3% and 9.7%, respectively. However, the large standard errors suggest that these effects are statistically insignificant.

Table 1 reports that there are 728 observations in our data set so there is no surprise that there are 728 observations used in the regression results for Columns (1) and (2). However, the number of observations for Columns (3) and (4) is reduced to 674 since there are 54 observations in which counties did not report employment data for that year-quarter. Since  $emplvl = 0$  in those 54 observations, we could not take the log transformation for  $\ln(emplvl)$  and are left with 674 observations for our log-level regressions.

Admittedly, our OLS regression model may be subject to omitted variable bias so we proceed with a more rigorous fixed effects regression specification:

$$y_{it} = \alpha + \beta_1 y22_t + \beta_2 y22_t \cdot MD_i + \beta_3 X_{it} + \delta_i + v_t + \varepsilon_{it}, \quad (3)$$

where  $\delta_i$  and  $v_t$  are fixed effects for county  $i$  and year-quarter  $t$ , respectively. We cluster standard errors by county to account for heteroskedasticity and serial correlation, as well as weight the regression results by 2021 county population given the variation in county size and prominence in the state economy. Otherwise, the variables included in Equation (3) follow the specification in Equation (2). To be sure, the  $MD$  dummy variable is time-invariant and gets absorbed by the  $\delta_i$  county fixed effects.

Table 5: Weighted Fixed Effects Regression Results

	Dep. Var.: <i>emplvl</i>		Dep. Var.: <i>ln(emplvl)</i>	
	(1)	(2)	(3)	(4)
<i>y22</i>	622.79*** (188.31)	-87.12** (33.88)	0.086*** (0.012)	0.038*** (0.007)
<i>y22 · MD</i>	-322.80** (126.39)	-183.00*** (39.45)	-0.042*** (0.014)	-0.029** (0.013)
<i>estabs</i>		2.33 (1.69)		0.001*** (0.000)
<i>wages</i>		67.91*** (6.30)		0.004*** (0.001)
<i>pop</i>		-10.51*** (2.33)		0.000 (0.000)
N	728	728	674	674

Note: The dependent variable in Columns (1) and (2) is *emplvl*, the employment level in a specific county in a particular year-quarter, whereas *ln(emplvl)*, the log transformation of *emplvl*, is the dependent variable in Columns (3) and (4). Regression results are weighted by 2021 population values. County fixed effects and year-quarter fixed effects are suppressed. Standard errors are clustered by county and reported in parentheses. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 5 presents the weighted fixed effects regression results. As with our discussion of previous regression results, our attention is focused on the sign and significance of the *y22 · MD* interaction term. In contrast to our analysis of Table 4, the estimated coefficients for the DID estimator are negative and statistically significant. Columns (1) and (2) suggest that employment levels for fast-food workers in Maryland counties fell by 322.80 workers and 183.00 workers, respectively, compared to changes in employment levels in Pennsylvania. Moreover, the log-level results in Columns (3) and (4) infer a 4.2% and 2.9% reduction in employment for fast-food workers in Maryland. Thus, the 2022 minimum wage law had a negative and statistically significant effect on employment in Maryland, implying that higher minimum wage caused an increase in unemployment among fast-food workers.

As with Table 4, there is a discrepancy in the number of observations in our level-level specifications in Columns (1) and (2) compared to our log-level specifications in Columns (3) and (4) in Table 5. There are 54 observations where *emplvl* = 0 since counties did not report data for those time periods. As such, there are 54 less observations that could be used in our log-level specifications. Naturally, there could be a concern that the missing data could be driving our results



in Table 5. In some cases, a county only missed reporting employment data in one time period, whereas other counties chronically provided missing data. As a robustness check, we eliminate all observations pertaining to counties that fail to report data in at least one year-quarter, bringing the number of observations down to 648. In other words, 81 of the 91 counties in both Maryland and Pennsylvania provide data for all 8 quarters in our sample time period.

Table 6: Weighted Fixed Effects Regression Results (Robustness Check)

	Dep. Var.: <i>emplvl</i>		Dep. Var.: <i>ln(emplvl)</i>	
	(1)	(2)	(3)	(4)
<i>y22</i>	631.14*** (189.89)	-87.99** (34.86)	0.086*** (0.012)	0.037*** (0.007)
<i>y22 · MD</i>	-325.35** (127.61)	-184.53*** (39.88)	-0.042*** (0.014)	-0.029** (0.013)
<i>estabs</i>		2.33 (1.69)		0.001*** (0.000)
<i>wages</i>		67.98*** (6.35)		0.005*** (0.001)
<i>pop</i>		-10.49*** (2.34)		0.000 (0.000)
N	648	648	648	648

Note: The dependent variable in Columns (1) and (2) is *emplvl*, the employment level in a specific county in a particular year-quarter, whereas *ln(emplvl)*, the log transformation of *emplvl*, is the dependent variable in Columns (3) and (4). Regression results are weighted by 2021 population values. County fixed effects and year-quarter fixed effects are suppressed. Standard errors are clustered by county and reported in parentheses. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 6 reports the regression results for Equation (3) using our subsample of counties that provide employment data for each and every time period in our sample. Despite the reduction in the number of observations, the statistical inference is qualitatively similar to the key takeaways from Table 5. Namely, the estimated coefficients for the *y22 · MD* interaction term remain negative and statistically significant in Columns (1) - (4). As such, we conclude that our results in Table 5 are not sensitive to the data limitations inherent in the BLS ES-202 data set. The upshot is that Maryland's 2022 minimum wage law significantly reduced employment above and beyond what was expected based on employment data from the fast-food sector in Pennsylvania.

### 3 Conclusion

Determining an appropriate living wage is essential for policymaking in the future, specifically for state lawmakers considering raising the minimum wage. An adverse effect on a state's levels of employment could cause policymakers to be much more hesitant to push through increases. Consistent with the findings in Card and Krueger (1994), our OLS regressions suggest that Maryland's minimum wage hike in 2022 had no statistically significant effect on overall employment levels. However, our fixed effects models suggest a negative and statistically significant effect on employment, implying that higher minimum wage increased unemployment in Maryland, all else equal. There is much at stake here; the jobs and lives of millions of Americans could be affected by new state laws such as this one, especially in an age of minimum wage hikes.

There are a few caveats to our study. Unlike with Card and Krueger (2000), we are unable to individually survey fast-food restaurants across Maryland and Pennsylvania to gather data. Nevertheless, we utilize the same ES-202 program from the Bureau of Labor Statistics just as they did, and yet our findings contrast with theirs. One possible reason for the discrepancy is the different treatment states: New Jersey vs. Maryland. Another possible issue is the timing of our data sets. Indeed, the overall economic climate has evolved from 1992 to 2022.

Nonetheless, our paper sheds more light on the ongoing discussion on the labor implications of minimum wage laws. Perhaps there is a certain threshold when it comes to minimum wage hikes, in which there is no significant effect on employment below a certain amount, whereas there is a negative effect if the minimum wage is raised too much. Alas, we leave the determination of how much is too much for future research.

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