Labor Market Concentration Heterogeneity of Minimum Wage Employment Effects

William Firmin

June 25, 2023

Abstract

Introductory Economics students learn that imposing a minimum wage decreases employment, but many studies find insignificant effects. The disconnect occurs when labor market concentration is not accounted for: in theory, employment decreases in perfect competition and increases in a monopsony. Controlling for this usually requires restricted data, so few studies have explored this source of heterogeneity. I construct a measure of labor market concentration using publicly available data and apply several approaches to estimating the employment effect of minimum wages across multiple data sets. The combined limitations of the data restricts my analysis to between 2000 and 2016. I take the methods from previous minimum wage literature and add my metric of concentration. The first two approaches regress employment on minimum wage, concentration, and other control variables, first at the sector and then individual level. The third uses a difference-in-differences approach in an event study across 13 treatment states. I find significant decreases in employment effects as competition increases, uncovering heterogeneity as theory would suggest. My findings provide an accessible measurement for labor market concentration and evidence for theory that corroborates recent literature.

1 Introduction

Almost every student who has taken an introductory economics class learns that imposing a minimum wage will reduce employment. The logic is simple: the cost of hiring workers rises, so firms cannot hire at the same levels as before. The logic is so simple that it's easily used years after taking the course. However, like in any subject, intro classes teach a simplified version of theory. Many nuances are ignored, albeit not without good reason. In addition, only a portion of these students study economics at a higher level, and even fewer take advanced courses in labor economics. In these classes they learn the impact of labor market concentration. The intro class focuses on perfect competition, where there are a number of equally powerful, competing employers in the job market. The advanced class introduces the idea of monopsony, where one powerful firm controls all hiring. General theory dictates that a well-chosen minimum wage can actually increase employment (Stigler, 1946), contrary to what intro students might expect. When employment does decrease under high concentration, it decreases less than under perfect competition (Bhaskar, Manning, and To, 2002) These two types of economies lie on opposite extremes of market concentration. This raises two important questions: what kind of economy do we live in, and how will a minimum wage affect it?

Numerous studies have contributed to minimum wage literature, and they generally find little to no effect on employment (Card and Krueger, 1994; Azar et al, 2019). Advocates of raising the minimum wage can use this to back their position, citing established economists and institutions. Some argue that these results come from the existence of substantial labor market concentration (Manning, 2011; Naidu, Posner, and Weyl, 2018),. The studies that find no effect typically aggregate data without differentiating by labor market concentration. While it provides estimates for the larger-scale economy as a whole, it averages out effects that may differ between smaller economies. For example, suppose half the country operates in a low-concentration job market that experiences a decrease in employment, while the other half has a high-concentration job market where jobs are created. An aggregate study might find no average change in jobs, giving a misleading conclusion that minimum wages don't affect employment.

Azar et al. (2019) provide empirical evidence for these differences in effects using online job posting data. Their findings support theory and highlight how aggregate approaches can mask heterogeneity across labor market concentration. Their labor market concentration data, however, comes from a private company, discouraging further study by others. Other microdata can be acquired through the US Census Bureau, but usage requires approval and research must be conducted in a secure Federal Statistical Research Data Center.

In this paper I present a measurement of labor market concentration using publicly available administration data from the US Census Bureau. I then use this to analyze the relation between minimum wage employment effects and labor market concentration, providing some supportive evidence for heterogeneity that aligns with theory. The presented metric decreases as concentration increases, so I refer to it as a ”competition” metric for clarity. My analysis consists of three approaches, each of which is adapted from previous minimum wage literature.

The first follows Azar et al. (2019), replacing their private data with my new metric. It regresses employment on minimum wage, competition, and other control variables, measuring how employment elasticity changes with market competition. I repeat the method for two groups that experience larger minimum wage bite: young workers (between 14 and 18 years old) and workers in the restaurant and retail sectors. Both show a significantly negative change in employment elasticity with respect to competition, where a 1 standard deviation increase in log competition is associated with a 0.022 and 0.014 decrease in elasticity respectively. While the direction supports theory, the magnitude is much lower than reported by Azar et al., who found a 0.2 decrease in the retail sector.

The second applies a similar approach to microdata from the Current Population Survey (CPS). It uses a fixed effects model (as does the first approach) without segmenting the data by industry or age. I estimate four total models with different combinations of 1) including competition or not and 2) including controls or not. The estimates show how effects can appear insignificant without accounting for competition. Both regressions without competition find insignificant results, whereas those with competition (both with and without controls) find significant negative interaction terms. Here, a 1 standard deviation increase in log competition leads to a 0.087 and 0.314 decrease in elasticity for with and without controls respectively. These directions also support theory, and the magnitudes are larger than in the first method. The estimate with controls is less than that found by Azar et al., whereas that found without controls is greater.

The final approach again uses the CPS data, but finds event-specific estimates. It compares the change in jobs just below and above a state’s new minimum wage, following Cengiz et al. (2019). Where Cengiz et al. regress these changes against the minimum-to-median wage ratio, I regress against competition. The model finds a significantly negative estimate, backing up both previous methods. A 1 standard deviation increase in log competition yields a 0.022 decrease in elasticity. This is consistent with the first method and backs up theory.

2 Data

2.1 Data Sources

Employment: I use two sources of employment data for my approaches. The first comes from the US Census Bureau’s records of Job to Job Flows (J2J). The panel data is indexed by Metro

Statistical Area (MSA), sector, age group, year, and quarter. It spans 433 metros, 20 sectors, 8 age groups, and the time range from Q3 2000 to Q3 2021. However, it is further limited for individual states. While the data for 23 states start in 2000, 13 start in 2001, 9 more start between 2003 and 2005, and 6 start in 2010. Later, I focus on smaller subsets for analysis. This data is also used in the next subsection for measuring concentration.

The primary employment variable (MainB) provides aggregated counts. It measures the number of main jobs in a quarter t. A worker is defined as having a main job from a firm in quarter t if they receive earnings from the in quarters t and $t-1$ that are greater than their earnings from any other firm during that time. In contrast, the NBER Merged Outgoing Rotation Group of the Current Population Survey (CPS) provides individual-level employment data for more focused investigation.

The CPS data begins at 1979, but I filter to Q3 2000 and after to match the J2J competition data. This results in just over 26 million observations up to 2016 (another limit imposed by minimum wage data). Using CPS is advantageous due to its additional information on hourly wages. Whereas the J2J counts are aggregated without respect to wage, I use the CPS data to examine employment effects at specific wage levels around the minimum wage. This provides a clearer picture since closer wages levels will experience a greater bite. I create a new employment variable in two steps. First, I use the employment status variable (EMPSTAT) to create an indicator variable for whether the individual is employed. I then multiply this by the survey weight (EARNWT), which estimates the number of people a surveyed individual represents. The resulting variable now gauges the employment count represented by each individual. For one of my approaches, I also aggregate the CPS data to create control variables such as population.

Minimum Wage: I utilize minimum wage panel data gathered by Vaghul and Zipperer (2016) at the state-quarter level. Unfortunately, this only covers May 1974 - July 2016, giving a final bound on usable data of Q3 2000 - Q2 2016.

Other Controls: In addition, I use variables from the Quarterly Census of Employment and Wages (QCEW) as controls for methods that do not use CPS. These include the log of total employment (across all sectors), log of total average wages, log of total quarterly establishments count, and metro size.

2.2 Concentration Measurement

Measuring labor market concentration is a difficult but key element of this paper. Previous studies use restricted data, limiting the ability of others to contribute. To get around this, I construct a more accessible measure of labor market competition from publicly available US Census Bureau data. I follow a theoretical construction by Manning (2011). The original idea is to use the ratio k of the arrival rate of job offers for an employed worker to the rate at which workers leave employment for non-employment. This captures competition among employers for workers and can be interpreted as the expected number of job offers a worker will receive in a spell of employment (Ridder and van den Berg, 2003). The US Census Bureau already provides the rate at which workers leave employment, but the rate of offers is more difficult to estimate. However, simpler search models yield a mapping between this and job-to-job transition rates, which are also retrieved from the US Census Bureau.

To derive the metric, first let λ denote the arrival rate of job offers and λ_e be the same but for employed workers. Then let δ denote the rate at which workers leave employment for non-employment, giving $k = \frac{\lambda_e}{\delta}$. As previously mentioned, δ is already tracked, but λ_e is not and must be replaced in some way. Let u be the unemployment rate and $G(f)$ be the fraction of workers at or below f in the wage distribution. Assuming that all workers move to higher-wage jobs when given the chance,

$$[\delta + \lambda_e(1-f)]G(f)(1-u) = f\lambda u \tag{1}$$

The left hand side describes the outflow of workers and is equated to the inflow on the right side, characterizing the steady-state. For the overall job market, the equivalent is

$$\delta(1-u) = \lambda u \tag{2}$$

This simply states that the amount of employed workers leaving for nonemployment (LHS) is equal to the number of unemployed workers finding jobs (RHS). Rearranging,

$$u = \frac{\delta}{\lambda + \delta} \tag{3}$$

which combined with (1) gives

$$G(f) = \frac{\delta f}{\delta + \lambda_e(1-f)} \tag{4}$$

Let ϕ be the transition rate to other jobs:

$$\begin{aligned} \phi = \lambda_e \int (1-f)g(f)df = \lambda_e \int G(f)df = \int \frac{\lambda_e \delta f}{\delta + \lambda_e(1-f)} df \\ = \delta \left[\frac{\delta + \lambda_e}{\lambda_e} \ln\left(\frac{\delta + \lambda_e}{\delta}\right) - 1 \right] \end{aligned} \tag{5}$$

Finally, dividing the transition transition rate to other jobs by the transition rate to unemployment and rewriting in terms of k gives

$$\frac{\phi}{\delta} = \frac{1+k}{k}\ln(1+k) - 1 \tag{6}$$

In addition, this measurement is monotonically increasing in k:

$$\frac{d}{dk}\left[\frac{\phi}{\delta}\right] = \ln\left(\frac{e^k}{1+k}\right)k^{-2} \tag{7}$$

which is positive for $k > 0$ and thus $\frac{\phi}{\delta} > 0$. Higher values indicate greater competition in the market, whereas lower values indicate greater concentration.

I estimate both rates with the J2J data, using variables EES and ENSep for ϕ and δ respectively. EES measures stable job-to-job flow with continuous employment. For this analysis, it is specified as flows originating from the area of interest and ending anywhere else. A worker is defined as having such a flow from firm a to firm b in quarter t if they have a main job (as defined before) with a in quarter t but transition to a main job with b by the end of the quarter. In addition, the worker must not receive earnings from a in $t+1$ or b in $t-1$. The other variable, ENSep, measures separations directly to nonemployment. A worker has such a separation if they have a main job at the beginning of quarter t but do not at the end of the quarter. The J2J data comes as specified for the employment data.

Using this data comes with several benefits over other sources. Azar et al. (2019) use data from online job postings to calculate the Herfindahl–Hirschman index (HHI) for individual markets. Their analysis focuses on groups that tend to be more exposed to the minimum wage, particularly retail workers. They note that while restaurant workers also experience a heavier bite, hiring often takes place offline in this sector, preventing analysis from the job postings data. In contrast, administrative data spans all sectors and allows for the study of any such group.

2.3 Summary Statistics

Table 1 displays summary statistics for key variables in the aggregate data. After cleaning and joining the data, the aggregate approach centered around young workers in the J2J data spans 11 years from 2005 to 2016 and 238 Metro Statistical Areas for a total of 78181 observations. It should be noted that not all variables represent only young workers. While key variables like employment are restricted in this way, most of the controls represent the entire MSA, regardless of age and industry. For example, "Avg Weekly Wage" is reported at the MSA-Industry level while "Total Avg Weekly Wage" is reported at the MSA level. The regression takes the log of most variables, but the raw numbers are reported for clarity.

Table 2 displays summary statistics for the individual-level data, but the variables regarding minimum wage are calculated at the state-level. The data spans 16 years and over 10 million observations from people aged 14-90 years old. Each record is estimated to represent on average 3,128 people. The competition metric is taken from the J2J data and merged with the survey data based on location, date, age, and industry. Location is first matched at the MSA level, but I increase this to the state level or ignore age/industry in the cases where there is a lack of data at that granularity. Changes to the minimum wage within the observed period range from -0.4% to 35%, directly affecting 4.3% of the working population on average.

While many papers analyze minimum wage at the state-level, I benefit from the MSA-level data through the broader range of labor market competition. Figure 1 displays this through a violin plot of the competition distributions. State-level data provides averaged-out competition measurements, compressing the distribution towards the center. In contrast, finer data at the MSA level captures more extreme values, offering insight into markets closer to monopsony and perfect competition.

3 Empirical Strategies

3.1 Method A (Aggregate)

My first approach follows directly from Azar et al. (2019), who use private job posting data to measure labor market concentration. I merge the J2J, QCEW, and minimum wage data and fit a fixed effects model to estimate the interaction between minimum wage employment effects and labor market concentration. Instead of a fixed effect for MSA, I take Allegretto, Dube, and Zipperer's (2017) suggestion of a lagged dependent variable. This accounts for unobserved heterogeneity where a two-way fixed effects strategy fails. In addition, I run two separate regressions for employment of young workers and employment in the restaurant and retail industries. These two groups have typically been used in literature to estimate the effects of minimum wage since they generally experience a greater bite. The model is as follows:

$$E_{mjt} = \beta_0 + \beta_1 MW_{mt} + \beta_2 C_{mjt} + \alpha MW_{mt} \times C_{mjt} + \beta_3 E'_{mjt} + \Lambda X_{mjt} + \mu_t + \lambda_j + \epsilon \qquad (8)$$

Where E is the log employment count, MW is the log active minimum wage, C is the log competition metric defined earlier, E' is the log employment count from the previous period, X contains several control variables, and μ and λ are fixed effects. Indices m, j, and t label metro area, industry, and year respectively.

Papers typically focus on β_1 to measure employment effects of minimum wage, but now the estimate of interest is α. This captures how effects change with respect to competition, the main goal of this paper.

3.2 Method B (Individual)

I aim to provide further support through another source of data: the CPS. This method uses a combination of the CPS, J2J, and minimum wage data sets. The dependent variable is the one constructed from the employment status and survey weight. Controls include the population of the state (extracted from CPS) and one-period lags of employment-related variables from J2J. The competition metric is also taken from the J2J data.

Going forward, this method resembles the previous, where I use a fixed effects model to regress employment against minimum wage and competition. For this I construct four total regressions. The first two do not include competition and serve to test whether its omittance results in insignificant estimates. This would verify the findings of previous papers that don't account for labor market concentration. The next two include competition. In each pair, the first model has only the main variables of interest while the second includes numerous controls. The models are in order as follows:

$$E_i = \beta_0 + \beta_1 MW_i + \mu_t + \delta_s + \lambda_j + \epsilon_i \tag{9}$$

$$E_i = \beta_0 + \beta_1 MW_i + \Lambda X_i + \mu_t + \delta_s + \lambda_j + \epsilon_i \tag{10}$$

$$E_i = \beta_0 + \beta_1 MW_i + \beta_2 C_i + \alpha MW_{st} \times C_i + \mu_t + \delta_s + \lambda_j + \epsilon_i \tag{11}$$

$$E_i = \beta_0 + \beta_1 MW_i + \beta_2 C_i + \alpha MW_{st} \times C_i + \Lambda X_i + \mu_t + \delta_s + \lambda_j + \epsilon_i \tag{12}$$

for individual i, state s, time t, and industry j. The model takes the log of employment, minimum wage, and competition as in Method A.

3.3 Method C (Event-Specific Estimates)

The final method aims to replicate the event-specific estimates of Cengiz et al. (2019) and uses an event study to examine missing and gained jobs across wage bins surrounding minimum wage increases. I start with the data from the previous method. The events are defined as in Vergara (2021): increases must be at least \$0.25 (2016 dollars), 2% of the working population must be affected, and there must be no other events within the 3 years prior and 4 years after. Each event uses a separate data set that consists of the 8 years surrounding the event for the target state and all clean states (those without minimum wage changes during this time). This specification, along with restrictions from competition data, yield 14 events across 13 unique states. Then the following model is estimated:

$$Y_{skth} = \sum_{\tau=-3}^{4} \alpha_{\tau kh} I^{\tau}_{sth} + \beta_h \theta_{sth} + \mu_{th} + \delta_{sh} + \rho_{kh} + u_{skth} \tag{13}$$

where s, k, t, and h indicate the state, k^{th} dollar bin relative to the minimum wage, year, and event respectively. Y represents the per-capita number of jobs in the specified group, and I^{τ} is a dummy variable indicating whether this observation is τ years from the event date. θ is the real minimum wage change for non-events. This includes minimum wage increases that are too small or do not have a large enough bind. μ, δ, and ρ are fixed effects.

The α coefficients are then used to calculate employment changes: excess jobs at or above minimum wage (Δa_{τ}) and missing jobs below (Δb_{τ}) are defined as

$$\Delta a_{\tau} = \frac{\sum_{k=0}^{4} \alpha_{\tau k} - \sum_{k=0}^{4} \alpha_{-1k}}{EPOP_{-1}} \tag{14}$$

$$\Delta b_{\tau} = \frac{\sum_{k=-4}^{-1} \alpha_{\tau k} - \sum_{k=-4}^{-1} \alpha_{-1k}}{EPOP_{-1}} \tag{15}$$

where $EPOP_{-1}$ is the sample average employment-to-population ratio just prior to the event (Cengiz et al., 2019). Theory would suggest that for events in more competitive markets $\Delta a_{\tau} + \Delta b_{\tau}$ is negative, while in more concentrated markets the sum is positive. I test this by regressing the estimated differences against the competition metric. The differences are averaged across the 4 years post-treatment, and the regression is weighted by population. A negative coefficient for competition would validate expectations.

4 Results

4.1 Method A (Aggregate)

The results of the regression are reported in Table 3. This method finds that elasticity decreases 0.024% among young workers and 0.047% within the restaurant and retail sectors with every 1% increase in the competition metric. This provides clear support for theoretical expectations: in both groups, increasing competition (towards perfect competition) decreases the effect of minimum wage on employment, whereas decreasing competition (towards monopsony) increases the effect.

I also refit the model for 7 other measurements of concentration, all obtained with other combinations of variables from the J2J data. They all stem from the earlier derivation, but the definitions of job transfers are slightly different. Of the 8 total concentration metrics, 7 yield significantly negative estimates for the interaction between minimum wage and competition in both cases. The

8th gives one insignificant and one significantly positive estimate.

In addition, I remove the main competition measurement from the model and use it to segment the data by decile of competition, estimating elasticity separately and displaying the heterogeneity visually. Figure 2 shows that the minimum wage elasticity of employment is significantly higher at the lowest levels of competition, representing the most monopsonic markets. It rules out insignificant effects that were found without accounting for competition. For young workers, we can see that the most competitive 50% of markets experience a significant decreasing effect, but the effects at high competition markets for restaurant and retail sectors are not as visible. Panel a shows a clear picture of the heterogeneity, but panel b is less conclusive. However, both agree that the most concentrated markets experience significantly positive elasticity near 0.6%.

4.2 Method B (Individual)

Table 4 displays the key results of the first regressions. Column 1 shows the results without including controls or competition. Column 2 then includes controls. Column 3 includes competition without controls, and column 4 includes both competition and controls. The results are consistent with both previous literature and the last method of this paper. Without accounting for competition, no significant effect is found regardless of controls. The most significant of the two is 0.010 with a standard error of 0.048 (no controls). This indicates that doubling the minimum wage would result in an expected 1% increase in employment.

The next two columns show that including competition reveals a significant relationship. Both models find that the employment elasticity with respect to minimum wage decreases with competition. Specifically, the model without controls estimates a 0.408% decrease in elasticity with each 1% change in the competition metric, and the model with controls estimates a smaller 0.113% decrease. In other words, more competitive markets experience more negative employment effects. This corroborates theory and the results from Part A, but these estimates are much larger.

4.3 Method C (Event-Specific Estimates)

Table 5 displays the estimates for the regressions of employment change against labor market competition. The columns represent dependent variables of total change, change in wage bins just above the minimum wage, and change in wage bins below the minimum wage respectively. Figure two displays the data visually: panel A shows total employment and panel B separates into jobs above and below minimum wage. As predicted by theory, the model finds a significantly negative coefficient of -0.146 for total employment change against competition. This supports both previous methods and yields an estimate between the two.

In addition, the estimate for jobs above minimum wage is larger in magnitude than that for jobs below. Logically, labor market concentration should have a lesser effect on missing jobs below the minimum wage since only certain jobs are allowed to remain under the legal level. In contrast, jobs above the minimum wage are affected by employer decisions and thus competition.

Figure 3 shows the event-specific estimates for each dependent variable, along with the regression through the points. The change in jobs below the minimum wage is consistently below the change in jobs just above, since jobs below are legally destroyed. All three variables show a clearly decreasing trend in the regression, but the points are spread out and less clear, giving R squared values around 0.45. It should be noted that population plays a key role in the estimates through the weights, but it is not displayed on the figure.

Averaging the effects at each year (weighted by population) produces Figure 4. The figure shows insignificant employment effects at each year, highlighting the importance of labor market concentration. This validates previous literature that found no effect without accounting for competition.

5 Conclusion

This paper studies the effect of minimum wages on employment and how it changes with labor market concentration. While theory predicts that changes to the minimum wage will affect employment, empirical studies tend to find little to no effect. Furthermore, attempting to study how these effects interact with labor market concentration requires non-publicly available data. The main contributions of this paper are the application of public data to measuring labor market concentration and using it to study minimum wage effects on employment. The application of Manning's concentration metric design to administrative data from the US Census Bureau allows easier studying of labor market concentration and provides another measurement for future comparison.

My analysis finds that while previous approaches yield no effect, accounting for market concentration reveals significant heterogeneity. These results are mostly consistent across multiple data sets and empirical methods, but the magnitude of the effects vary. Specifically, my methods find that one standard deviation increase in log competition results in decreases of 0.022, 0.014, 0.087, 0.314, and 0.022 in elasticity, whereas previous literature has found a decrease of 0.2. Only one estimate in this paper surpassed this, which decreases to 0.087 when controls are added. Despite the differences in magnitude, the estimates support the monopsony model and recent literature.

6 References

Allegretto, S., Dube, A., Reich, M., and Zipperer, B. (2013). Credible Research Designs for Minimum Wage Studies. *UC Berkeley: Institute for Research on Labor and Employment*. Retrieved from `https://escholarship.org/uc/item/3hk7s3fw`.

Azar, José, Emiliano Huet-Vaughn, Ioana Marinescu, Bledi Taska, and Till von Wachter. Minimum Wage Employment Effects and Labor Market Concentration. *NBER Working Paper Series*, no. w26101. Cambridge, Mass: National Bureau of Economic Research, 2019.

Bhaskar, Venkataraman, Alan Manning, and Ted To. 2002. "Oligopsony and monopsonistic competition in labor markets." *Journal of Economic Perspectives*, 16(2): 155–174.

Card, David, and Alan B. Krueger. 1994. "Minimum wages and employment: a case study of the fast-food industry in new jersey and pennsylvania." *American Economic Review*, 84(4): 772–793.

Doruk Cengiz, Arindrajit Dube, Attila Lindner, Ben Zipperer, The Effect of Minimum Wages on Low-Wage Jobs, *The Quarterly Journal of Economics*, Volume 134, Issue 3, August 2019, Pages 1405–1454, `https://doi.org/10.1093/qje/qjz014`.

Manning, Alan. "Chapter 11 - Imperfect Competition in the Labor Market." *In Handbook of Labor Economics*, edited by David Card and Orley Ashenfelter, Pages 973-1041. Elsevier, 2011. `https://doi.org/10.1016/S0169-7218(11)02409-9`.

Naidu, Suresh, Eric N. Posner, and E. Glen Weyl. 2018. "Antitrust Remedies for Labor Market Power." *Harvard Law Review*, 132(2).

Ridder, Geert and van den Berg, Gerard, (2003), Measuring Labor Market Frictions: A Cross-Country Comparison, No 814, IZA Discussion Papers, Institute of Labor Economics (IZA), `https://EconPapers.repec.org/RePEc:iza:izadps:dp814`.

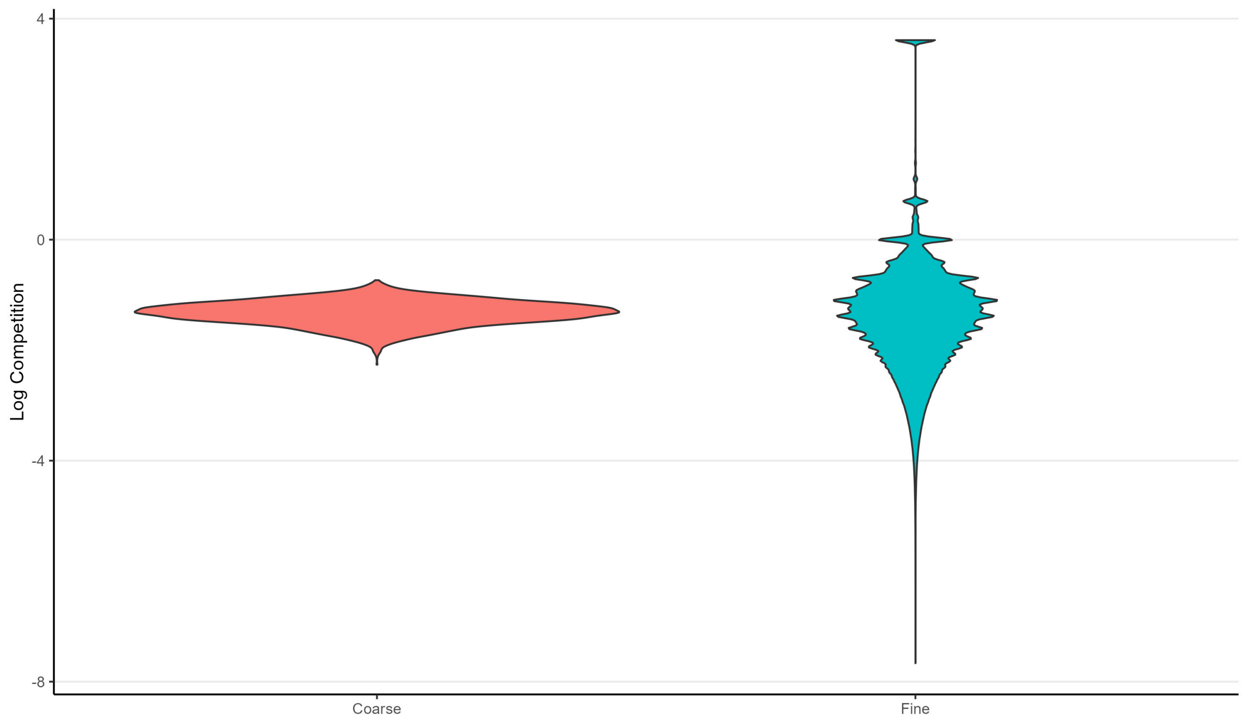
Stigler, George. 1946. "The economics of minimum wage legislation." *American Economic Review*, 36: 358–365.

Vaghul, K., Zipperer, B. (2016). Historical State and Sub-State Minimum Wage Data. *Washington Center for Equitable Growth*. `http://equitablegrowth.org/working-papers/historical-state-and-sub-state-minimum-wage-data`.

Vergara, D. (2021). Minimum Wages and Optimal Redistribution. `https://dvergarad.github.io/files/JMP_DV.pdf`.

Sarah Flood, Miriam King, Renae Rodgers, Steven Ruggles, J. Robert Warren and Michael Westberry. Integrated Public Use Microdata Series, Current Population Survey: Version 10.0 [dataset]. Minneapolis, MN: IPUMS, 2022. `https://doi.org/10.18128/D030.V10.0`

Figure 1: Distribution of Log Competition



Notes: This figure displays the distribution of the concentration metric for two different methods. Working with data on the state level averages out more extreme values of concentration in smaller markets. This is highlighted by the ”Coarse” distribution. In contrast, differentiating between MSA, industry, and age results in finer data that provides insight into a wider range of labor market concentration.

Table 1: Summary Statistics for Aggregate Data

Statistic	N	Mean	Median	St. Dev.
Avg Weekly Wage	78,181	736.665	669	408.014
Employment	78,181	602.109	149	1,602.895
Total Qtly Establishments	78,181	23,522	11,176	33,623
Total Employment Level	78,181	387,222	177,511	522,691
Total Qtly Wages	78,181	4,447,774,689	1,775,814,637	6,843,196,484
Total Avg Weekly Wage	78,181	787.355	770	133.871
Minimum Wage	78,181	6.939	7.250	1.015
Log Competition	78,181	−2.044	−2.057	0.902
Metro Size	78,181	2.365	2	1.291
Total Reference Wage	78,181	114.881	112.276	19.969
Avg Weekly Wage	16,154	391.301	415	114.049
Employment	16,154	28,541.900	13,444.5	44,036.460
Total Qtly Establishments	16,154	17,800	8,495	27,904
Total Employment Level	16,154	295,394	142,840	441,338
Total Qtly Wages	16,154	3,336,352,608	1,401,494,858	5,735,199,943
Total Avg Weekly Wage	16,154	776.187	761	128.734
Minimum Wage	16,154	7.011	7.250	0.989
Log Competition	16,154	−1.346	−1.334	0.296
Metro Size	16,154	2.069	2	1.192
Total Reference Wage	16,154	112.032	109.379	19.293

Notes: This table displays summary statistics for the aggregate data, which is a combination of the J2J, QCEW, and Minimum Wage data. The top pannel displays that for young workers, whereas the bottom shows that for the restaurant and retail sectors. The variable Employment Proportion is the one-quarter lag of the ratio of employment to employment of all ages. Total Qtly Establishments reports the number of establishments throughout all industries. Total Qtly Wages reports the sum of all wages across all industries. Total Avg Weekly Wage reports the average weekly wage across all industries. Metro Size is a factor variable for various ranges of population size. Total Reference Wage gives the Total Avg Weekly Wage divided by the Minimum Wage. These statistics come specifically from the data prepared for the analysis of young workers, which spans the years 2005-2016 across 238 Metro Statistical Areas. There are a total of 78,181 observations.

Table 2: Summary Statistics for Individual Data

Statistic	N	Mean	Median	St. Dev.
Age	1,745,336	47.517	49	22.648
Survey Weight	1,745,336	2,820.189	0.000	4,884.202
Employed	1,745,336	0.162	0	0.369
Employed (Weighted	1,745,336	1,253.445	0.000	3,546.106
Employment per Capita	1,745,336	0.0001	0.000	0.0003
Log Competition	1,745,336	−1.924	−1.915	0.771
Fed MW	1,745,336	6.642	7.250	0.868
State MW	1,745,336	7.211	7.250	1.045
Effective MW	1,745,336	7.178	7.250	1.060
Real MW	1,745,336	7.753	7.735	0.862
Real MW Change	1,745,336	0.082	0.000	0.261
MW Change Pct	1,745,336	0.011	0.000	0.037
Bind	1,745,336	0.040	0.034	0.022
Wage	1,745,336	2.523	0.000	6.837
Reference Wage	1,745,336	−5.506	−7.750	7.225
Wage Bin	1,745,336	−3.090	−5	5.122

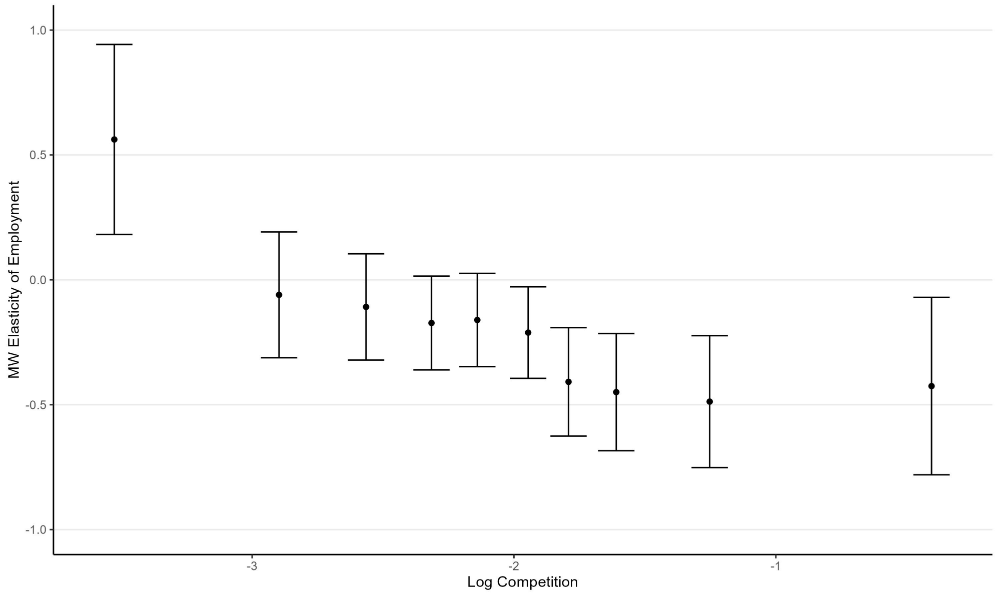
Notes: This table reports summary statistics for the cleaned CPS data. Employed indicates whether the individual is employed, not in the armed forces. The weighted employment variable is obtained through the product of Survey Weight and Employed. Employment per Capita is not the employment rate of the area but the weighted employment divided by population. The sum of this variable within an area would give the employment rate. Effective MW is the maximum of Fed MW and State MW, and it is used to calculate Real MW and its changes. Bind is calculated at the state-level to identify events and gives the portion of workers at or below the next minimum wage. Reference Wage gives the real difference between Wage and Minimum Wage, and Wage Bin assigns each record to a $1 bin with extreme values in -5 and 20. The data spans 2000-2016 and contains 10,589,279 records, but this is reduced to 4,236,941 due to the availability of wage data.

Table 3: Role of Competition in Aggregate Measurements

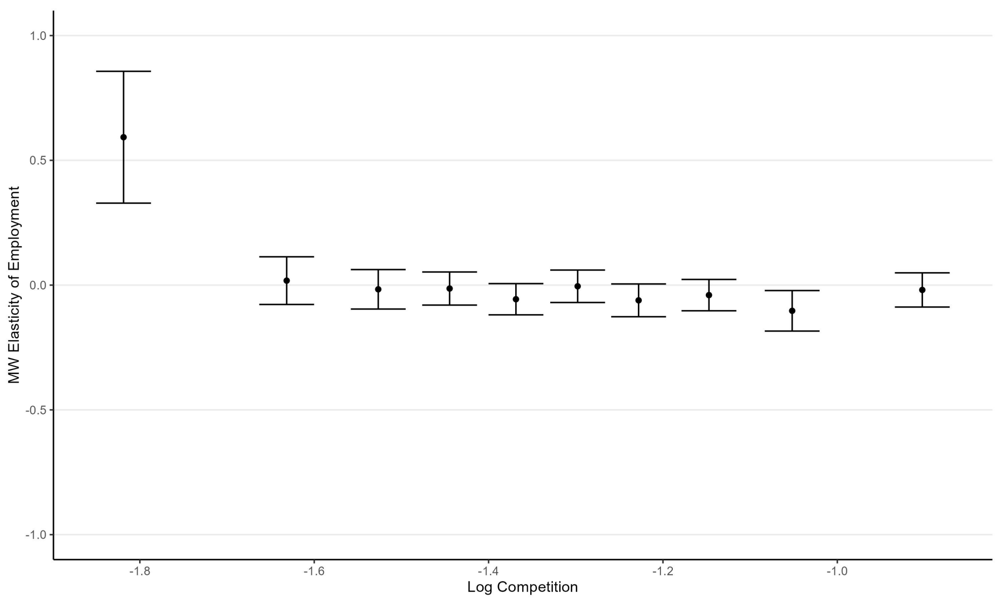
	Log Employment	
	Young Workers	Restaurant/Retail
	(1)	(2)
MW	-0.204^{***}	-0.039
	(0.042)	(0.022)
Competition	-0.070^{***}	0.011
	(0.012)	(0.017)
MW×Competition	-0.024^{***}	-0.047^{***}
	(0.006)	(0.009)

Notes: This table displays estimates for minimum wage employment effects with respect to labor market competition using the J2J aggregate data. Column 1 reports the estimates from data limited to young workers, whereas column 2 reports that from data limited to the Restaurant and Retail sectors. MW×Competition is the main estimate of interest, showing how the effects change with competition.

Figure 2: MW Elasticity of Employment by Competition



(a) Elasticity Among Young Workers



(b) Elasticity in the Restaurant and Retail Sectors

Notes: This figure displays how minimum wage employment effects change with respect to competition. Panel (a) reports that among young workers and panel (b) reports that within the restaurant and retail sectors. The estimates are obtained by filtering data to each competition decile and regressing employment on minimum wage (along with controls) without competition. Each point represents the estimate for one decile with 95% confidence intervals.

Table 4: Role of Competition in Individual-Level Measurements

	Log Employment			
	Basic		With Competition	
	(1)	(2)	(3)	(4)
MW	0.010	0.002	-0.510^{***}	-0.215^{***}
	(0.048)	(0.030)	(0.070)	(0.047)
Competition			2.147^{***}	0.194^{***}
			(0.057)	(0.038)
MW×Competition			-0.408^{***}	-0.113^{***}
			(0.028)	(0.019)
Controls	No	Yes	No	Yes

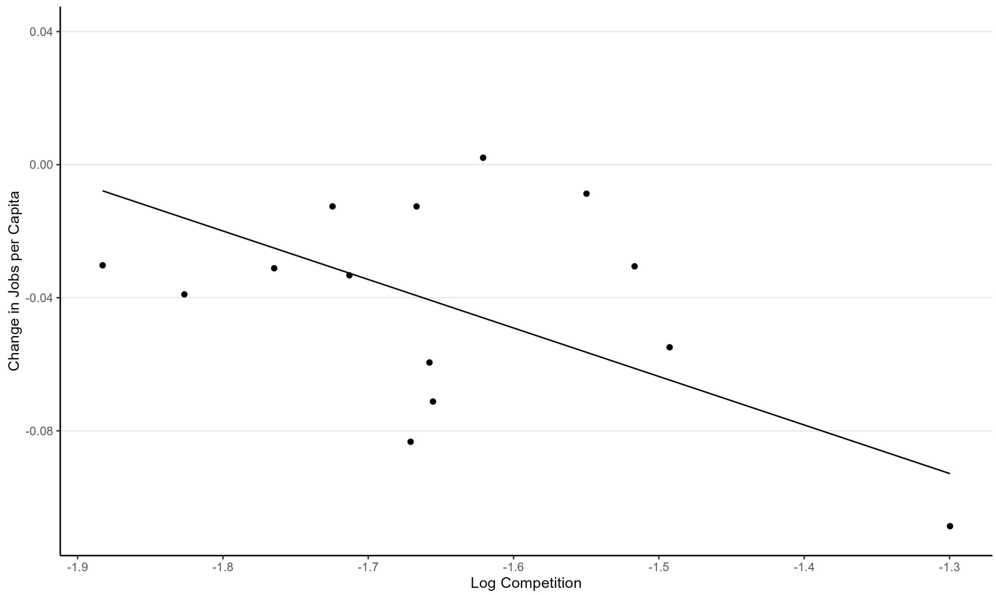
Notes: This table displays estimates for the role of competition using individual-level data. Column 1 reports effects without competition or controls. Column 2 reports effects without competition but with controls. Column 3 reports effects with competition but without controls. Column 4 reports effects with both competition and controls. For regressions with competition, MW×Competition is the main estimate of interest.

Table 5: Role of Competition in Event-Specific Estimates

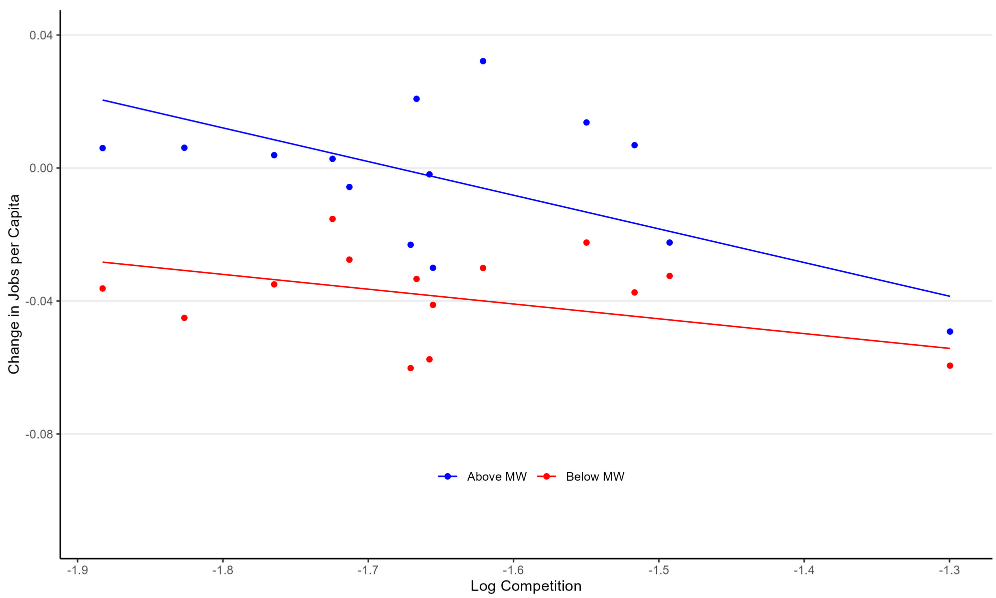
	Change in Employment		
	Total	Above MW	Below MW
	(1)	(2)	(3)
Log Competition	-0.146^{**}	-0.101^{**}	-0.045^{*}
	(0.047)	(0.031)	(0.019)

Notes: This table displays the effect of competition on event-specific employment changes. Changes in employment are calculated around minimum wage increases for both jobs just above and below the new minimum wage. The sum of both gives the total employment change. The effects of competition on these estimates are found through a simple linear regression. Column 1 reports the effect on total employment changes, column 2 reports the effect on employment change above the minimum wage, and column 3 reports the effect on employment change below the minimum wage.

Figure 3: Event-Specific Estimates



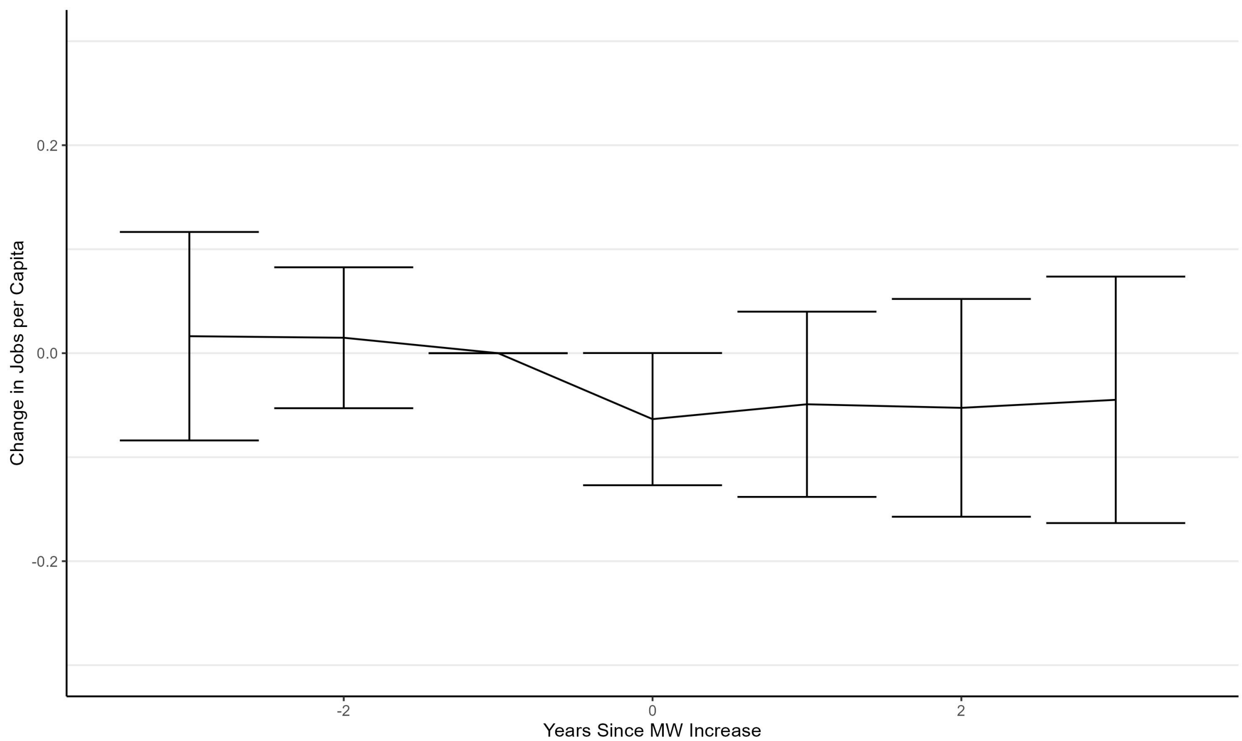
(a) Combined Change in Jobs



(b) Change in Jobs Above and Below MW

Notes: This figure displays the effect of competition on event-specific employment changes. Changes in employment are calculated around minimum wage increases for both jobs just above and below the new minimum wage. The sum of both gives the total employment change. The effects of competition on these estimates are found through a simple linear regression. Panel a shows the event-specific estimates and regression for change in total jobs. Panel b shows the event-specific estimates and regression for both jobs above and below the new minimum wage.

Figure 4: Effects by Year



Notes: this figure shows the average employment effect at each year relative to the year immediately before a significant minimum wage increase. The averages and variances are weighted by population of the treatment state at the time of the increase. The estimates are accompanied by 95% confidence intervals. This figure highlights the lack of significance found in employment effects without accounting for labor market concentration.