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OWN-WAGE ELASTICITY:
QUANTIFYING THE IMPACT OF MINIMUM WAGES ON EMPLOYMENT

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ABSTRACT

The own-wage elasticity (OWE) of employment estimated using minimum wage increases provides an economically meaningful measure of the policy on jobs. We discuss how to interpret the magnitude of the OWE, including in terms of welfare and under alternative models of the labor market. We present a comprehensive set of OWE estimates from 88 studies and introduce an regularly updated repository of the estimates---https://economic.github.io/owe---an up-to-date snapshot of the existing literature for scholars and policymakers. We find that most studies to date suggest a fairly modest impact of minimum wages on jobs: the median OWE estimate of 72 studies published in academic journals is -0.13, which suggests that only around 13 percent of the potential earnings gains from minimum wage increases are offset due to associated job losses. Estimates published since 2010 tend to be closer to zero.

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A minimum wage own-wage elasticity repository is available at https://economic.github.io/owe/

1 Introduction

A large body of research measures the effects of minimum wages on employment. However, when the groups of workers being studied differ significantly, commonly used measures such as the elasticity of employment with respect to the minimum wage are not directly comparable across studies. An elasticity of -0.05 is relatively small for a group like teenagers, where around forty percent of workers are earning the minimum wage, but it represents a large effect for all workers with a college degree, only a small share of whom are minimum wage workers (Cengiz et al., 2019). Therefore, existing attempts at aggregating studies using this metric (Doucouliagos and Stanley 2009, Wolfson and Belman 2019, Neumark and Shirley 2022) do not provide a very clear guide to understanding the quantitative implications of current research. At best, these aggregations allow us to determine the sign of the effect, but they ultimately fail to convey whether the employment effects of the policy are "small" or "large" in a meaningful way.

In this paper, we aggregate studies using a measure that scales the employment effect by the policy's effect on the average wage, what we refer to as the own-wage elasticity (OWE) of employment from minimum wage changes. We explain why this is an economically meaningful measure and how it is useful for understanding the welfare effects of the policy. We also introduce the Minimum Wage OWE Repository, a regularly updated collection of OWE estimates that serves as a quantitative gauge for the state of the literature: `https://economic.github.io/owe/`.

Version 1.0.0 of the OWE repository contains 88 minimum wage studies issued since 1992 covering minimum wage increases in the United States, United Kingdom, Canada, and several European Union countries (Czech Republic, Hungary, Germany, Netherlands, Portugal, and Slovakia). Of the 72 studies published in academic journals, the median OWE is -0.13 and the mean OWE is -0.25. When focusing on the 21 published studies that examine broad groups of low-wage workers, rather than narrow subsets like teens or restaurant workers, the median OWE is 0.02.

While this paper does not attempt to adjudicate among studies that arrive at different conclusions, the magnitudes of these estimates suggest that, when considering the research literature as a whole, the estimated employment effects of the minimum wage are small. As we explain in the paper, the median OWE of -0.13 implies that the total increase in earnings for workers (with or without jobs) is about 87 percent as large as it would be in the absence of job losses due to the minimum wage. Additionally, 71% of published studies have OWE estimates more positive than -0.4, indicating that the total wage bill still rises by at least 60 percent of how much earnings would have increased without employment reductions.

The rest of the paper is structured as follows. In Section 2, we describe the conceptual and measurement issues surrounding the OWE. In Section 3, we explain our selection of studies for the OWE repository, as well as our choice of estimates and inferential procedures. Section 4 reports our key findings, and Section 5 concludes.

2 Concept and Measurement

2.1 Defining the OWE

Typical reviews of the literature focus on the elasticity of employment with respect to the minimum wage, sometimes called the minimum wage elasticity of employment ϵ^E, defined as the percent change in employment for a given percent change in the minimum wage:

$$\epsilon^E = \frac{\%\Delta\text{Employment}}{\%\Delta\text{Minimum Wage}}.$$

Reviews of the literature that compile and aggregate ϵ^E include Doucouliagos and Stanley (2009), Wolfson and Belman (2019), and Brown et al. (1982).[1] The focus on adolescents in Brown et al. (1982) improved the internal consistency of the review, but came at the cost of generalizability. More recently, Neumark and Shirley (2022) use a mix of elasticities from different studies, some of which are minimum wage elasticities, and others which are OWEs. This makes the magnitudes

[1]See also the review of employment elasticities in Neumark and Wascher (2007) and Brown and Hamermesh (2019), and the review of employment and distributional effects in Brown (1999).

less interpretable.[2]

Although the use of the minimum wage elasticity (ϵ^E) is common in reviews, there are a number of problems with this approach. First, ϵ^E is not a useful way of summarizing the employment effects of the minimum wage when comparing across groups and minimum wage policy experiments that have different "bites" in terms of how much they affect the underlying wage distribution. For example, consider the two hypothetical minimum wage increases of 50% in Table 1, drawing on Dube (2019): in Case A, the minimum wage increase is binding for 10% of all workers, 15% of those in retail, and 50% of those in restaurants; and in Case B, it is binding for 5% overall, 10% in retail, and 30% of those in restaurants.

One study might use Case A and estimate the minimum wage elasticity of employment $\epsilon^E = -0.10$ for restaurants, while another study might focus on retail in Case B and estimate the elasticity $\epsilon^E = -0.02$. Even though Case A's estimated elasticity is five times larger than Case B's, the difference between these estimates is simply due to differences in the bite of the policy. Case study A involves a more generally binding minimum wage increase and focuses on a lower-wage group. Indeed, when calculating the elasticity of average wages for each group with respect to the minimum wage

$$\epsilon^W = \frac{\%\Delta\text{Average wage}}{\%\Delta\text{MinimumWage}}$$

we see in Table 1 that the policy in Case study A raises restaurant worker wages much more than the policy in Case study B raises retail worker wages. A larger estimate of the elasticity of the average wage ϵ^W with respect to the policy results from a more binding minimum wage increase and a tighter focus on a subgroup for whom the minimum wage is more impactful.

A more useful measure that accounts for differences in the bite of the policy is the own-wage elasticity (OWE) of employment, which describes how employment for a specific group responds

[2]For example, Figure 3 of Neumark and Shirley (2022) reports an OWE of -0.14 (a small effect) from Bailey et al. (2021), but a minimum wage elasticity of employment of -0.07 for the entire workforce from Meer and West (2016). While Meer and West (2016) does not report a wage effect or an OWE (and hence is not included in our database), a minimum wage elasticity of employment of -0.07 for the entire workforce suggests very large job losses. However, comparing these two elasticities could lead a reader to mistakenly conclude that Bailey et al. (2021) find much larger job losses than Meer and West (2016).

to an increase in the average wage of that group induced by the minimum wage change. In practice, the OWE is often estimated by dividing the elasticity of employment with respect to the minimum wage (ϵ^E) by the elasticity of the group's average wage with respect to the minimum wage (ϵ^W):

$$\text{OWE} = \frac{\left(\frac{\%\Delta\text{Employment}}{\%\Delta\text{MinimumWage}}\right)}{\left(\frac{\%\Delta\text{Average Wage}}{\%\Delta\text{MinimumWage}}\right)} = \frac{\epsilon^E}{\epsilon^W}.$$

The corresponding OWE estimate for restaurant workers in Case A is -0.20, exactly the same as the OWE estimate for retail workers in Case B. Although the employment elasticities with respect to the minimum wage (ϵ^E) are very different, in these hypothetical cases there is no heterogeneity in how responsive employment is to wage changes after accounting for variation in the "bite" of the policy. The calculation of the OWE produces a more apples-to-apples comparison by scaling ϵ^E by the group's wage increase. In this case, when focusing on the employment elasticity ϵ^E one could arrive at a mistaken conclusion that the employment responses to wage changes in restaurants are more pronounced for a larger minimum wage increase (Case A), when in reality the difference in ϵ^E simply reflects that the minimum wage is more binding in Case A than in Case B. Furthermore, in the case of retail, while the OWE is slightly larger in magnitude in Case A, comparing ϵ^E would lead to the opposite conclusion and mistakenly suggest the employment effects in retail were more pronounced in Case A.

A second, related drawback of studies focused on the employment elasticity ϵ^E is that policy-makers cannot reliably use ϵ^E to extrapolate or predict employment effects of future minimum wage increases. Multiplying the future policy's minimum wage change by the employment elasticity ϵ^E from a given study would be inappropriate because there may be large differences between the "bites" of the future minimum wage increase and the policies examined by the study, as underlying wage distributions vary across time, geographies, industries, and demographic groups. Using the OWE provides a solution to this problem: multiplying an OWE estimate by an estimate of the average wage change induced by the future policy will provide a more valid estimate of the future policy's employment effects.[3] For example, were one to use the median OWE of -0.13 for published studies in this review, a minimum wage increase that raised the average wage bill of restaurant worker wages by 10 percent would result in total reduction of restaurant jobs by 1.3 percent.

A third limitation of aggregations of the employment elasticity ϵ^E is that some papers estimating ϵ^E fail to provide evidence that the policies they study actually change wages. In such cases, it becomes harder to attribute any observed employment changes to the causal effects of the minimum wage. As we explain below using an instrumental variables framework, failing to estimate the wage effects of the policy ϵ^W is akin to not reporting a first stage. However, focus on the OWE addresses this issue by limiting attention to studies that report both employment and wage effects, thereby filtering the evidence base to include only those studies that establish a stronger causal link between the policy and employment changes.

2.2 IV and structural interpretations of the OWE

The OWE has a natural instrumental variables (IV) interpretation as an "indirect least squares" estimate: ϵ^E is the reduced form coefficient, while ϵ^W is the first stage coefficient (this is discussed in greater detail in Dube and Lindner 2024). In this context, the minimum wage change serves as an instrument for wages in the structural equation regression of employment on wages. When minimum wage policy events are used as a (binary) instrument, the OWE represents the Wald IV estimate of the local average treatment effect (LATE). If only a subset of the individuals in the treated group are compliers—those whose wages increase due to the minimum wage hike—then the OWE measures the average change in employment from an minimum wage-induced increase in wages for the complier population. Another attractive implication of the LATE interpretation is that if we expand our sample by adding "never takers" (individuals completely unaffected by the policy), the OWE remains a valid LATE estimate, provided the first stage is sufficiently strong. This is not true for the minimum wage elasticity, ϵ^E, which is diluted by the inclusion of "never

[3] For example, Congressional Budget Office (2019) writes of employment elasticities ϵ^E that "elasticities in the literature are typically scaled to the increase in the statutory minimum wage, but that approach can yield misleading estimates of employment changes."

takers."

If the labor market were perfectly competitive, with employment under the minimum wage policy being purely demand-determined, the same IV would identify the labor demand elasticity. In a regression context, the endogenous variable would be the log of the market wage, the dependent variable would be an indicator of employment, and the minimum wage increase event would serve as a binary instrument. The resulting regression estimate would yield a semi-elasticity, and dividing this estimate by the sample mean employment of the relevant population would translate it into the labor demand elasticity. However, even in this case, the OWE does not correspond to an average of labor demand elasticities from raising an individual firm's wage, because there are market-wide responses (like output price adjustment). Rather, it is the derived demand elasticity, in the sense of Hicks and Marshall (see Dube and Lindner (2024) for more).

However, when the labor market is imperfectly competitive, the compliers' employment probability is no longer solely determined by labor demand, because it is also determined by labor supply. If the equilibrium is purely monopsonistic, where all firms are labor supply constrained both before and after the policy, the OWE would measure how compliers' labor supply responds to an increase in the firm-level wage, along with a similar increase in wages at other firms in the labor market. (This is why the OWE would not be an average of pure firm-level labor supply elasticities, as the minimum wage change is not just a firm-specific experiment.) In an intermediate case—where some firms employing compliers are labor supply constrained, while others are demand constrained—the OWE reflects a mixture of labor demand and labor supply factors. This discussion also highlights why the OWE is likely to be less negative or even positive in magnitude when the labor market is more monopsonistic: only among a relatively smaller share of compliers do employment changes reflect pure labor demand considerations, which tend to be unambiguously negative in sign. However, even when a structural interpretation is unavailable, the OWE tells us the net impact on employment probabilities from the policy that raises wages by a certain amount, one of the primary welfare considerations for workers and policymakers.

The IV interpretation of the OWE also provides us with a useful understanding of what happens without a strong first-stage effect of the policy on the group's average wage. In that case, the OWE estimate has a weak instrument bias towards the OLS estimate. In other words, an OWE estimate without a strong first-stage wage effect would yield an estimate close to simply regressing log employment on log wages along with any additional controls (such as unit and time effects).

2.3 Welfare relevance of the OWE

For welfare analysis of minimum wages, a key ingredient is the elasticity of total pre-tax earnings of all low-wage workers (including those without a job) with respect to the policy, ϵ^Y. In most welfare analyses of minimum wages, a positively signed ϵ^Y is a necessary condition for the policy's desirability. Intuitively, if low-wage workers as a whole had lower earnings after a minimum wage increase, it would be difficult to justify the policy regardless of how much weight we put on other workers, business owners, or procedural concerns. Conversely, if the minimum wage raises pre-tax earnings of low-wage workers sufficiently (aided by a lack of major disemployment effect), it would allow the social planner to reduce transfers to low-wage workers which are costly to fund using taxes.[4] The larger is ϵ^Y, then, *ceteris paribus*, the more likely it is for the policy to represent an improvement in social welfare, especially when the welfare weights skew towards low-wage workers and their beneficiaries.

There is a close relationship between ϵ^Y and the OWE. To the extent hours effects are already incorporated into earnings or employment estimates–or to the extent the hours elasticities are small, as they are found in many studies that do separately estimate them–we can write the elasticity of pre-tax earnings as the sum of the employment and wage elasticities:

$$\epsilon^Y = \epsilon^W + \epsilon^E = \epsilon^W \times (1 + \text{OWE}) .$$

As long as the wage effect is positive, i.e., $\epsilon^W > 0$, the sign of ϵ^Y is positive if and only if OWE > -1. Moreover, the smaller is the magnitude of the OWE, the closer will be the elasticity of total earnings,

[4]For example, see Vergara (2023) for a formal analysis along this direction.

$\epsilon^Y > 0$, to the wage elasticity, $\epsilon^W > 0$. In other words, when the OWE is -0.1, it means that around 10 percent of the potential increase in earnings are forfeited due to job losses. Conversely, when the OWE is -0.9, it indicates a loss of 90 percent of that potential earnings increase.

Armed with our understanding of how the OWE relates to the effect of minimum wages on the total earnings of low-wage workers, we can place the size of the estimates in a more meaningful context. In this paper we provide a general assessment following the rubric used in Dube (2019). An OWE that is less negative than -0.4 can be considered as having, at most, a small negative effect on jobs, whereas an OWE falling between -0.4 and -0.8 can be characterized as having a medium impact. In contrast, an OWE more negative than -0.8 signifies a large negative impact on jobs, as it erases more than 80 percent of the potential earnings gains. Of course, categorizations like this inherently involve some degree of subjectivity, and others may choose to classify the estimates differently. This is one of the benefits of assembling the OWE repository and making it publicly available, as it allows researchers to categorize and present the estimates the way they see fit.

3 Selection of studies and estimates for the OWE repository

Due to the central importance of the OWE in understanding the magnitude of employment effects across studies, a comprehensive and up-to-date set of estimates is needed. We created the Minimum Wage OWE Repository at `https://economic.github.io/owe/` to be a regularly updated data set of all minimum wage studies that provide enough information to estimate the OWE.

Other authors have recognized the utility of compilations of OWE estimates from minimum wage studies, both as reviews of existing research and also as tools with which to compare their own estimates. For example, OWE estimates were constructed for 24 studies by Harasztosi and Lindner (2019) and for 55 studies by Dube (2019). These articles, and also papers like Azar et al. (2023), Bailey et al. (2021), and Derenoncourt and Montialoux (2021), graphically compare their own estimates with the distribution of OWE estimates from rest of the literature. Papers like Godøy et al. (2024), Giupponi et al. (2024), and Hampton and Totty (2023) also specifically discuss how their OWE estimates compare to set of estimates provided by Dube (2019). Finally, to evaluate prospective minimum wage increases, Congressional Budget Office (2019) used a weighted average of OWE estimates derived from existing research. The Minimum Wage OWE Repository makes these comparisons easier for researchers and policymakers.

3.1 Study selection for the OWE repository

To construct the existing set of estimates, we started with the lists compiled by Harasztosi and Lindner (2019), Dube (2019), Neumark and Shirley (2022), and Brown and Hamermesh (2019) and then added other (especially more recent) publications that provide the necessary information.

There are five requirements for a study to be included in the OWE repository:

Requirement 1. *The study must evaluate the employment effects of changes in the statutory minimum wage.*

This requirement excludes studies of collectively bargained wages (e.g., Kreiner et al. 2020) or corporate wage policies.

Requirement 2. *The study must estimate a statistically significant, positive wage effect of the minimum wage, in addition to estimating the employment effect, for the same group of workers using a similar research design.* [5]

As we discuss above, both wage and employment effects are required to calculate the OWE, and a statistically significant, positive wage effect is the necessary information that the minimum wage increases are indeed binding.

Requirement 3. *The study must be published after 1992 and include "quasi-experimental" or "experimental" variation.*

Due to the lack of policy variation and available data, studies prior to the 1990s mostly used aggregate time-series variation. We intentionally restrict the OWE repository to subsequent studies

[5] Some papers not meeting this requirement simply do not analyze wages (e.g., Meer and West 2016). Other papers provide evidence on the wage distribution, but not an estimate of the effect on average wages for the group studied needed to scale the employment effects (e.g., Clemens and Wither 2019).

that use variation in actual minimum wage policies based on quasi-experimental empirical methods, like difference-in-differences. This "new minimum wage research" began with the October 1992 issue of the *ILR Review*, which published articles that "have taken seriously Richard Freeman's advice that labor economists should search for natural experiments and use these to evaluate hypotheses" (Ehrenberg 1992).

Requirement 4. *Studies older than 10 years must have been published in an academic journal.*
The OWE repository only includes studies that are intended to be published in an academic journal. To balance the inclusion of the most recent research with the long timelines in academic publishing, we accept unpublished working papers and government research reports, provided they have been updated in the last 10 years; older papers are excluded. The OWE repository data includes an indicator for publication status, and in Section 4 we describe the results of all papers in the OWE repository, as well as those that are published.

Requirement 5. *The study must focus on the United States, the United Kingdom, countries in the European Union, or Canada.*
Version 1.0.0 of the OWE repository only includes studies from these countries simply because this is the research with which we are most familiar. We will relax this requirement in future versions of the OWE repository.

After imposing these requirements, there are 88 studies in Version 1.0.0 of the OWE repository, 72 of which have been published in a peer-reviewed journal. The earliest papers are from the October 1992 ILR Review (Card 1992a, Card 1992b, and Katz and Krueger 1992). Figure 1 shows that 49 published studies, or 68%, were published in 2010 or later. The Figure also shows that it has recently become more common for studies to report an OWE estimate directly, as opposed only reporting separate employment and wage elasticity estimates. Since 2020, a majority of studies have directly reported OWE estimates.

Most studies in the repository examine minimum wage policies in the United States. Table 2 shows that 56 of the published studies cover the United States and 16 are from other countries. There are currently 8 published studies on UK minimum wages and 3 studies on German minimum wages, and there is one study each for Canada, Czech and Slovak Republics, Hungary, Netherlands, and Portugal.

The current repository contains publications from 30 economics journals. The journals with at least 4 published studies are the *ILR Review* (13), *Journal of Labor Economics* (8), *Industrial Relations* (6), *Journal of Human Resources* (5), *Labour Economics* (5), and *The Review of Economics and Statistics* (4). Of the "top five" journals in economics, only *Econometrica* failed to publish minimum wage studies with the required information.

3.2 Choice of estimates, aggregation, and inference in the OWE repository

To simplify the OWE repository and to give each study equal weight, we used only a single OWE estimate from each study. In general, we attempted to use the authors' most preferred empirical specification; when this was unclear, we reached out to the authors for guidance on model or sample selection. When there were estimates for a range of groups, we chose the estimate for the broadest group of low-wage workers presented in the paper (with the requirement that, as described above, the study estimated a statistically significant, positive wage effect). We used an average of multiple estimates in 20 studies overall, or in 15 published studies). This was the case when multiple estimates of low-wage groups were reported by the paper and the preferred specification was unclear, or when the authors indicated a preference to average multiple estimates in our direct communication with them. When averaging across groups, we have typically used group sizes to weight the estimates. In general, we first calculated the averages of the wage and employment elasticities and then took the ratio to obtain the OWE; an exception is when the OWE is already calculated by groups, in which case we took the averages of those (e.g., Hampton and Totty, 2023; Azar et al., 2023; Clemens and Strain, 2021). The Appendix (and the repository) describe the calculations behind each estimate.

We preferred using OWE estimates and their standard errors when they were directly reported by the authors, as was the case in 34 studies overall, or in 29 published studies. When the authors did not report an OWE, we calculated it by dividing the employment and wage effects as described above. In those cases, we followed Harasztosi and Lindner (2019) and Dube (2019) for inference and constructed confidence intervals for the OWE using the delta method and assuming independence of the employment and wage elasticities.[6] When we averaged multiple point estimates, we calculated the standard error of the averaged estimate as the square root of the average of the variances. There was not enough information to construct a standard error for the OWE estimate in 10 studies overall, or in 6 published studies, but in these cases we still report the OWE estimates.

In 16 studies, we converted semi-elasticities to elasticities by dividing by sample means. 3 studies used regression specifications that include both the headline minimum wage and subminimum wage for tipped workers in the US; for these papers we added the headline and tipped minimum wage estimates to simulate the effect of changing both policies, since it is rare in the US for the tipped minimum wage to change without an accompanying increase in the headline minimum wage.

Figure 2 shows all of the studies and estimates in Version 1.0.0 of the OWE repository. Both this dataset, available at `https://economic.github.io/owe`, and also the Appendix to this paper, list the source of the underlying OWE or employment and wage estimates in the original papers, as well as additional assumptions or other information and communication used to arrive at the estimates. We view the OWE repository as a living document and welcome any feedback from authors in terms of selecting the most preferred estimates. We also encourage authors to contact us with new studies that should be included in the repository. Researchers can email the authors, or they can publicly submit estimates and suggestions by filing an "issue" in the underlying GitHub repository.[7]

3.3 Comparison to meta-analysis

Some past work has used meta-analysis to summarize estimates for minimum wage studies (e.g., Wolfson and Belman, 2019; Doucouliagos and Stanley, 2009). Similar to meta-analysis, our goal

[6]See Seltman (no date) for a derivation of the first-order approximation of the variance of the ratio of two random variables. When there is zero covariance, $\text{var}\left(\frac{X}{Y}\right) \approx \frac{1}{\overline{Y}^2}\text{var}(X) + \frac{\overline{X}^2}{\overline{Y}^4}\text{var}(Y)$.

[7]Emails can be sent to benzipperer@gmail.com and Github issues can be filed at `https://github.com/Economic/owe/issues`.

here is to provide a summary of estimates from a particular literature. However, there are important differences. Most importantly, we are reporting the distribution of OWE estimates without assuming they all are different statistical estimates of the same underlying estimand. The true OWE may vary depending on the context, or the group. For example, the OWE using minimum wage variation by age group may reflect greater labor-labor substitution. Similarly, the OWE may be more negative in a tradable sector where it is more difficult to pass through costs as prices. Or, it may be more positive in a more monopsonistic labor market. Moreover, we do not consider the reported precision of the estimate to be a reliable indicator of its accuracy. More credible designs may use less minimum wage variation, resulting in lower precision, but they may also have less bias. Finally, we make no effort to correct for "publication bias" (there is some evidence of such bias in the minimum wage literature, e.g., Andrews and Kasy 2019).

Instead, our goal is to report the distribution of estimates in a transparent way, which makes it easier to assess the literature and look for differences in estimates by groups or over time. In this way, our approach to summarizing the literature is similar in spirit to Neumark and Shirley (2022), who also discuss how their approach differs from meta-analysis. Different from them, however, our use of the OWE (instead of a mixture of "elasticities" as they do) makes the estimand more comparable across studies, groups, and time.

4 Findings

4.1 Estimates for all low-wage groups

Taking into account all the OWE estimates in the repository, Table 3 shows that the median estimate is -0.14. When we focus on the 72 published studies, the median OWE estimate is -0.13. The mean OWE elasticity is -0.22 for all studies, and -0.25 for published ones. The 56 published studies from the US are similar, with median and mean OWEs of -0.11 and -0.22, respectively.

Overall, these estimates suggest a fairly modest impact of minimum wages on jobs. The median published elasticity of -0.13 indicates that the total earnings of low-wage workers increase by 87%

of the expected amount following a minimum wage hike, assuming no job losses from the policy. In other words, the employment reductions offset only about 13% of the potential gains in earnings. The mean published OWE suggests an offset of 25%.

Next, we categorize the entire range of estimates by size according to our criteria: those more negative than -0.8 are labeled as "large negative," those between -0.4 and -0.8 are termed "medium negative," and those more positive than -0.4 are called "small negative or positive." Figure 3 depicts the distribution for the 72 published studies, which we emphasize throughout this review. Of these published studies, 51 (or 71%) exhibit small negative or positive OWE estimates, whereas only 12 (or 17%) demonstrate OWE estimates that qualify as large negative. Collectively, these findings from the body of studies suggest that, thus far, minimum wage policies have significantly increased the wages of low-income groups more than they have adversely impacted employment, if at all, thereby effectively boosting total earnings for low-wage workers (excluding hours adjustments, which only some studies take into account).

4.2 Results for broad groups of low-wage workers

A limitation of examining all estimates is that the majority (51 out of 72 published studies) focus on specific subgroups. These subgroups include teens, restaurant workers, nurses, and grocery workers, among others. However, results from these subgroups might not fully represent the broader effects of minimum wage policies, especially if these commonly studied groups omit other low-wage workers who are harder to categorize narrowly. For instance, a significant portion of the research concentrates on teens because detecting wage effects is generally more straightforward for teens compared to other groups, such as all workers without a college degree. This trend is particularly evident in times when the minimum wage's impact has been minimal, affecting only a small portion of the workforce. Nonetheless, the generalizability of teen-based estimates is questionable, especially as teens make up a decreasing fraction of the low-wage workforce.[8]

For this reason, we have categorized papers that provide estimates for broad groups of low-

[8]For example, Congressional Budget Office (2019) utilizes different wage elasticity estimates for teens and adults in evaluating potential minimum wage hikes.

wage workers that more accurately reflect the overall impact of the policy. We describe an OWE estimate as pertaining to a "broad" or "overall" group of low-wage workers if the studied group likely encompasses the majority of workers directly affected by the policy. This includes works like Cengiz et al. (2019), which estimates the effects of US minimum wages on the total number of low-wage jobs by employing a bunching approach and cross-state minimum wage variations to analyze changes in the frequency distribution of wages. Similarly, Jardim et al. (2022) evaluates the change in jobs paying $19 or less in Seattle in comparison to other areas in Washington state. Giupponi et al. (2024) also adopts a similar method, applied to a national-level UK policy by examining how the policy impacts different sections of the frequency distributions across various regions in the UK. Other studies include Derenoncourt and Montialoux (2021), which examines all adults aged 25 to 55, and Bailey et al. (2021), which examines men, aged 16-64. For US studies, we also regard as broad those OWE estimates that focus on all workers with at most a high school education, such as Monras (2019), or utilize demographic predictors to capture the majority of workers, such as Cengiz et al. (2022). Lastly, studies that provide broad estimates include those that track incumbent workers who were earning near the minimum wage before the policy change (e.g., Currie and Fallick, 1996; Neumark et al., 2004; Hampton and Totty, 2023).[9]

In many cases, papers provide estimates for various subgroups of the population, but we have preferred using the estimate from the broadest group of workers affected by the policy, as we described in Section 3.2. For example, from Cengiz et al. (2022), we use the OWE estimate for the "high-recall" group of predicted low-wage individuals, which they estimate to capture three quarters of minimum wage workers. Hampton and Totty (2023) provide an OWE estimate for all low-wage individuals that is a weighted average of OWE estimates for specific age groups.

In summary, we classify 21 studies, roughly one third of all published studies, as "broad." Figure 4 shows the distribution of OWE estimates from these studies compared to the remaining 51 studies that focus on more specific groups of workers. The median OWE estimate for studies of the broad or overall low-wage workforce is 0.02. Large or medium negative OWE estimates are

[9]A detailed discussion of different methodologies used to estimate such "broad" effects is available in Dube and Lindner 2024.

uncommon: in 19 or 90% of these studies, there are only small negative or positive effects.

Estimates for OWE based on narrower groups are more negative but still align with minor employment impacts. The median OWE value for these 51 analyzed studies stands at -0.17. Part of the discrepancy between broad and narrow OWE estimates may indicate labor-labor substitution, or for certain industries, a reallocation of workers between sectors (for more, see Dube and Lindner (2024)). Another key distinction is that estimates involving broader groups tend to derive from newer studies: 62 percent of broad OWE estimates originate from papers published in the past five years, in contrast to 27 percent of narrow OWE estimates. As noted in Section 4.4, newer research tends to find a more positive OWE. Among studies published since 2010, the median OWE for 30 narrow group studies was -0.08, whereas the median for the 18 broad group studies was 0.02: recent research shows less difference in OWE estimates between narrow and broad groups.

4.3 Results for specific narrower groups

The most frequent "narrow group" studies focus on particular low-wage sectors or demographic groups with a high number of low-wage workers. Figure 5 shows the estimates for the key groups—workers in low-wage sectors, and teens. Of the 51 published narrow group studies, 21 are concentrated in the restaurant or retail sectors. The studies report a median OWE of -0.09 and an average of -0.17; 6 out of 20, or 28%, of the studies showed a medium or large negative OWE. Generally, studies in low-wage sectors indicate a minor effect of minimum wage policies on employment, closely matching the overall evidence.

Teens are another important group, accounting for 15 of the 50 narrower studies. In this case, the OWE estimates appear slightly more negative, with a median of -0.17 and a mean of -0.25. However, it is important to note that these magnitudes are still modest; approximately 67% of the estimates indicate positive or only small negative effects.

4.4 Heterogeneity over time

Finally, we show how this evidence base has evolved over time. Figure 6 plots the mean and median published estimates of OWE by decade, along with the (bootstrapped) 95% confidence interval, as well as a scatter plot of the underlying estimates. We find a substantial amount of heterogeneity over time, though with some interesting nuances.

First, there are only 6 OWE estimates from the 1990s, but these tended to to more positive. At the same time, as the number of studies grew during the aughts (the first decade of the 21st century), the OWE estimates tended to be more negative. The 17 estimates from that decade had a median of -0.45 and mean of -0.52. However, both the number of studies and their positivity grew over the next two decades. The 27 papers from the current decade have a median of 0.00, and a mean of -0.15. Both the mean and the median are more negative than from the aughts, and the differences are statistically significant at the 5% level.[10]

It has become less common for studies to estimate sizable negative employment effects in the past decade and half than it used to be before. As Figure 7 shows, the share of large or medium negative published studies has fallen by more than half since 2010: from 48 percent before 2010 to 20 percent since 2010.[11] About 45 percent of studies published since 2010 contain positive OWE estimates. Since econometric methodology has improved over time, as researchers have paid more attention to identification strategies and methods of inference, it may be reasonable to place more weight on more recent studies, which generally tend to suggest OWE estimates closer to zero.

4.5 Comparisons to other reviews

Elasticities in Neumark and Shirley (2022)

In some limited ways, it is possible to compare these estimates to a recent review of employment elasticities by Neumark and Shirley (2022), who consider studies from the US published in an

[10] A one-tailed t-test rejects the hypothesis that the mean (or median) OWE in 2020-2024 is less than or equal to its value in 2000-2009 using OLS (or quantile regression) robust standard errors.

[11] A t-test rejects the null that the shares are the same at the 5 percent significance level.

academic journal by 2021. For comparability, in this section, we focus solely on published studies from the US. The magnitudes from the two reviews are difficult to compare since Neumark and Shirley (NS) use a mix of elasticities, while we only consider the OWE. However, we can consider the sign of effects, since this is determined only by the sign of the reduced-form elasticity ϵ^E. We first compare the sign distributions between our two reviews, and shed light on any differences. Subsequently, we discuss the the correspondence between the sign of the effect and the magnitudes of the OWE.

First, 28% (19/69) of the studies in the Neumark and Shirley (2022) replication data are positive, according to the sign of the median estimate (some studies have multiple estimates).[12] In our OWE repository, 41% (23/56) of published US studies have a positive OWE. In other words, the OWE repository is somewhat more likely to find a positive elasticity than NS. This could be for three distinct reasons. First, it is possible that we were more likely to classify a paper's elasticity as being positive than NS. Second, it could be that the papers excluded from the NS database have a more positive estimate. Third, it could be that the papers excluded from the OWE repository (but present in NS) are more likely to be negative. Here, we quantify the role of each of these three possibilities.

Table 4 tabulates the set of 89 papers that form the superset of study estimates from our two sets of reviews. Of these, both reviews provide estimates for 36 studies (the "overlap sample"). There are 20 studies in the OWE repository that are not in the NS database (the "NS missing" sample), and there are 33 studies that are in the NS database but not in the OWE repository ("DZ missing" sample).

We begin with the overlap sample of 36 studies. We find that the two datasets classified the sign of study's employment effect similarly in 33/36 times; in 2 cases we classified a study as negative when NS classified as positive, while in 1 case NS classified a study as negative when we classified as positive. It is encouraging that the classification by both teams was very similar, so it was unlikely to reflect any subjective assessment about the qualitative nature of the study's findings.

Because the reviews essentially agree on sign classification in the overlap sample, the difference

[12]The replication data for Neumark and Shirley (2022) is available at `https://sites.socsci.uci.edu/~dneumark/MW_IR.zip`.

in the positive shares between our two reviews is entirely due to which studies are missing from which review. First, there are 20 published studies on the US that should or would be included in the NS data, but are not; 12 of them were published in 2021 or later, which is perhaps why they are missing, while 8 of them were published prior to 2021. 50% (10/20) of these missing-NS studies had a positive signed estimate, considerably larger than the 28% share of all studies in the NS data. Simply augmenting the the NS data to include these studies increases the positive share to 33%. This closes 37% of the sign gap between the two reviews.

The remainder of the gap comes from the 33 studies missing from the OWE repository. Of these 33 studies, almost all (31) were excluded because they did not have a usable wage estimate.[13] These 33 studies were much less likely to be positive (5/33 or 15%). In other words, studies without a reported first-stage wage effect were more likely to find a negative effect.

Of course, the sign distribution of estimates is not very informative about the size of the effects. To shed light on this, we restrict our sample to the 36 overlapping studies: among the overlap sample, we categorize 36% as having a positively signed employment effect, which is about halfway between the positively signed shares of the full DZ and NS samples, and not very different from either. This overlap sample has a median OWE of -0.20, still implying a "small negative" effect (while somewhat more negative than our median OWE for published US studies of -0.11). In other words, roughly 2/3 of the estimates being negative still yields a magnitude of the OWE that is quite small in size, and implies only a 20% offset in earnings from employment changes. This underscores the importance of using the OWE as opposed to relying on signs to draw inference about the quantitative impact of the policy.

4.5.1 Labor demand elasticities

How do our estimates compare to existing reviews of the elasticity of labor demand? Hamermesh (1993) find a range for the own-wage labor demand elasticity of -0.15 to -0.75; Lichter et al. (2015) reports a median own-wage elasticity of labor demand of -0.42. Our estimates fall towards the

[13] Two were excluded because they did not follow a standard quasi-experimental design.

low end of these ranges. However, there are several ways in which our estimates measure different objects in comparison to these reviews. First, the OWE from minimum wage increases is a market-level phenomenon: it can reflect both firm-level adjustments as well as cross-firm reallocation and price adjustment. Similarly, if the labor market is imperfectly competitive, the OWE can reflect both labor supply and labor demand. Finally, our OWE estimates are concentrated in low-wage sectors of the economy, which are predominantly non-tradable.

5 Discussion and conclusion

The OWE is an important measure for quantifying the employment effect of minimum wages. It is also easy to compute as long as the authors report the impact of the policy on wages in addition to the impact on employment. Most minimum wage studies conducted in the past five years do so, and many recent studies report the OWE estimates in the paper. This is a very positive development. In fact, a growing number of papers additionally benchmark their OWE estimate to compilations of estimates from the literature, which shows that researchers recognize the usefulness of the OWE as the go-to measure for understanding employment effects of minimum wages. At the same time, the lists used in these papers are often *ad hoc*, limited in scope, and not systematically compiled—which underscores the importance of the exercise undertaken in this paper.

For both scholars as well as policymakers, it is vital to have up-to-date estimates of the OWE. For example, the Congressional Budget Office has in 2019 and 2021 constructed OWE estimates.[14] Moreover, sometimes authors may be interested in comparing their estimates to only a subset of existing ones. For these reasons, it is important to have an easily accessible set of estimates from the literature that is updated in real time. In addition, the online repository model also allows authors to submit new estimates, revise previous ones from working papers if these change over the course of the publication process, or if they disagree with our current estimates. Moreover, all changes to the estimates are themselves publicly available through GitHub's version control features. We

[14] They collected or constructed "employment elasticities for directly affected workers with respect to the change in their own wage." https://www.cbo.gov/system/files/2019-07/CBO-55410-MinimumWage2019.pdf

think this is a model that is applicable more generally to other topics as a way to provide transparent and timely summaries of the literature.

In the future, we plan to expand the repository to include estimates from other countries, especially developing economies.

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Table 1: Hypothetical elasticities for two minimum wage increases

	Affected share	ϵ^E	ϵ^W	OWE
Case A				
All workers	0.10	0.01	0.03	0.33
Retail	0.15	−0.03	0.20	–0.15
Restaurants	0.50	−0.10	0.50	–0.20
Case B				
All workers	0.05	0.00	0.00	—
Retail	0.10	−0.02	0.10	–0.20
Restaurants	0.30	−0.05	0.25	–0.20

Notes: Affected share is the share of the workforce bound or directly affected by the hypothetical minimum wage increase. ϵ^E is the elasticity of employment with respect to the minimum wage and ϵ^W is the elasticity of the average wage with respect to the minimum wage. OWE is the own-wage elasticity of employment due to the minimum wage.

Table 2: Frequency of OWE studies, by country

	All studies	Published studies
United States	70	56
United Kingdom	10	8
Germany	3	3
Canada	1	1
Czech and Slovak Republics	1	1
Hungary	1	1
Netherlands	1	1
Portugal	1	1

Notes: The table reports the number of studies by country from the Minimum Wage Own-Wage Elasticity Repository, Version 1.0.0, https://economic.github.io/owe.

Table 3: Summary of OWE estimates, by publication status and study characteristics

	Number of studies	Median OWE	Mean OWE
All studies	88	–0.14	–0.22
All published studies	72	–0.13	–0.25
United States-only	56	–0.11	–0.22
Other countries	16	–0.19	–0.35
Overall / broad group	21	0.02	–0.10
Narrow group	51	–0.17	–0.30
Restaurants or retail	21	–0.09	–0.17
Teenagers	15	–0.17	–0.25
Published before 2010	23	–0.40	–0.31
Published since 2010	49	–0.04	–0.21
Authors reported OWE	29	0.00	–0.09
Precision-weighted	66	0.00	–0.09

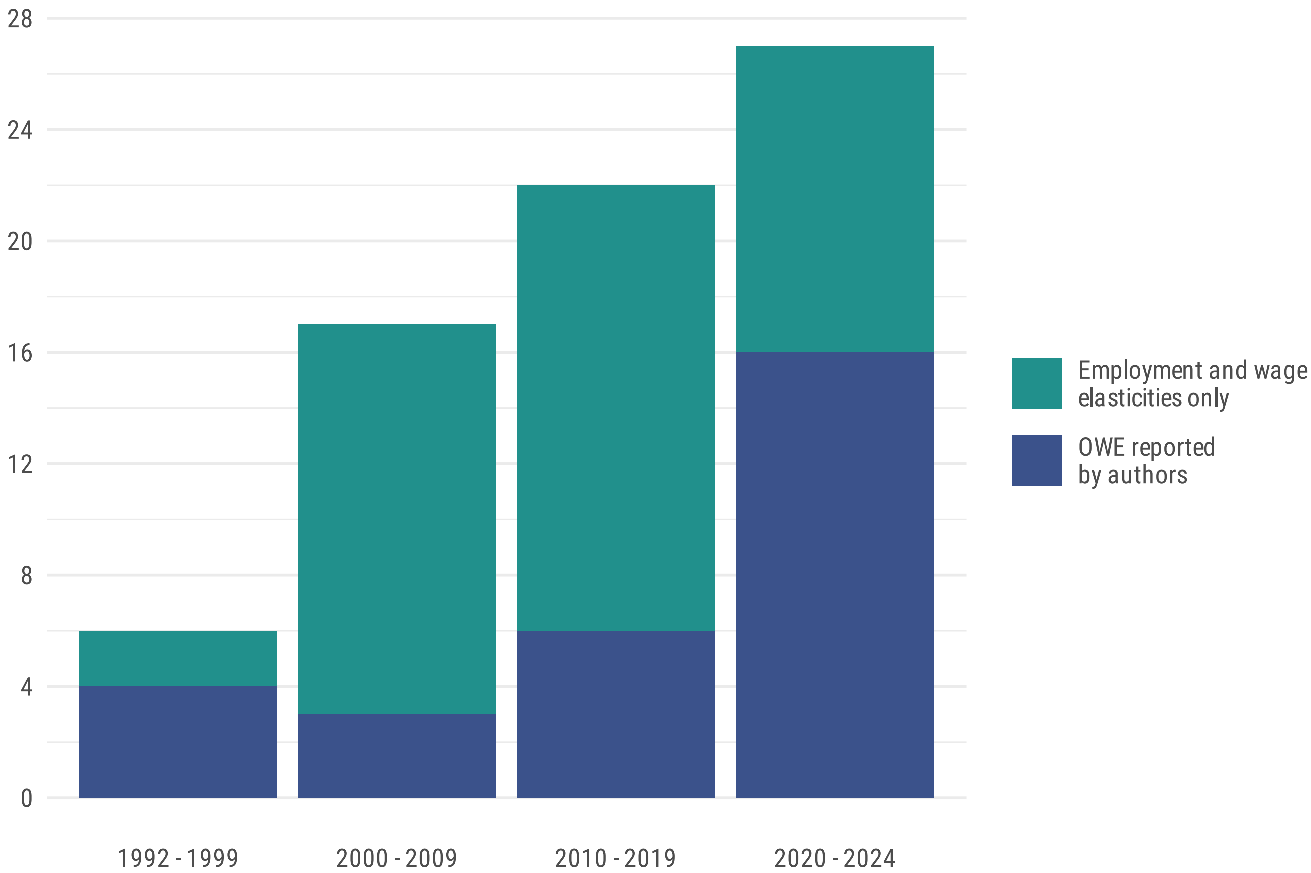
Notes: The table reports summary statistics from the Minimum Wage Own-Wage Elasticity Repository, Version 1.0.0, https://economic.github.io/owe. Precision-weighted estimates are restricted to studies with an estimated standard error and are weighted by the inverse of the variance.

Table 4: Number of published US studies by sign of the employment effect in this review and Neumark and Shirley (2022)

	NS missing	NS negative	NS positive	**DZ status total**
DZ missing		28	5	**33**
DZ negative	10	21	2	**33**
DZ positive	10	1	12	**23**
NS status total	**20**	**50**	**19**	**89**

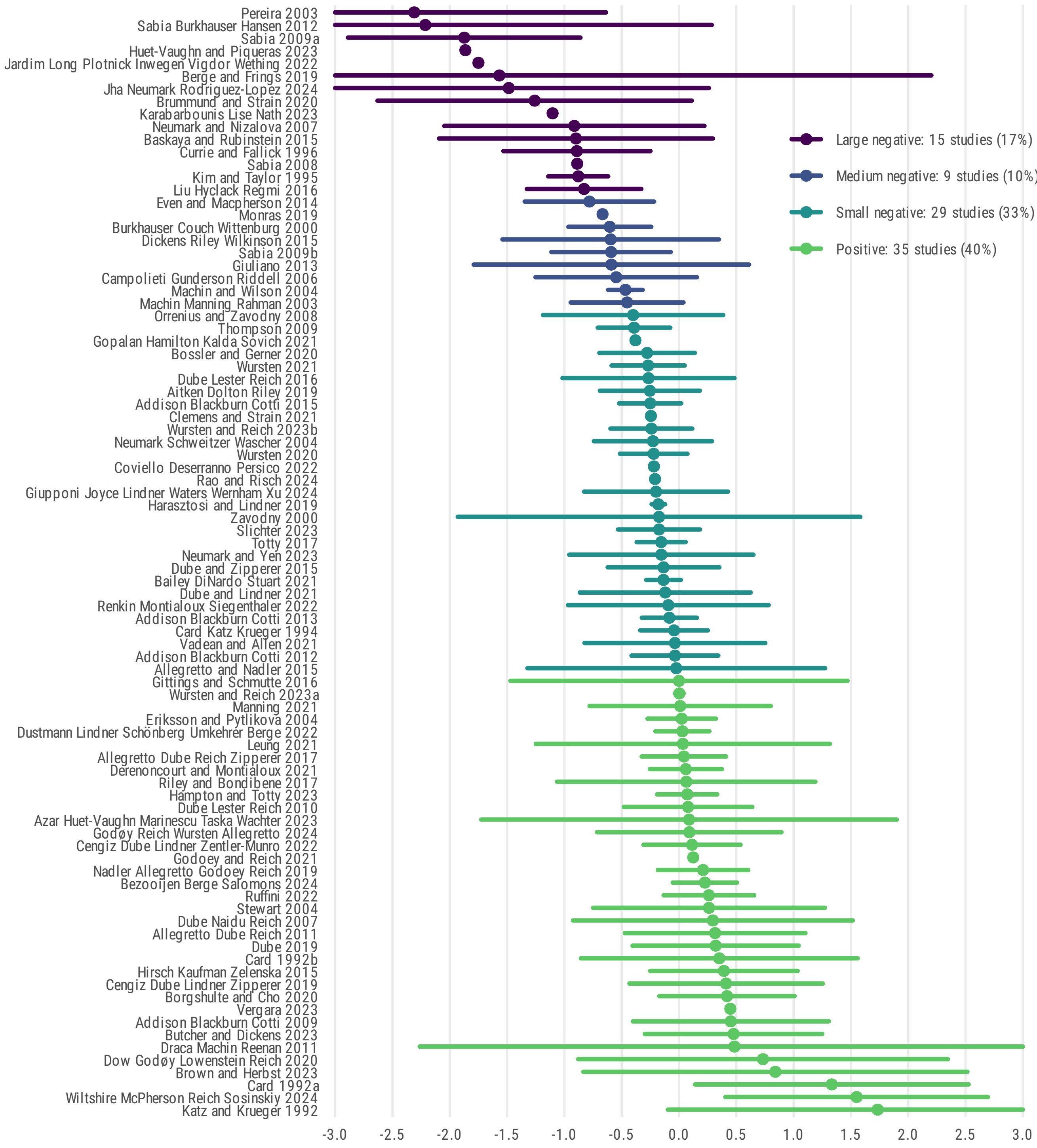
Notes: The table reports the number of published US studies in the Minimum Wage Own-Wage Elasticity Repository, Version 1.0.0, `https://economic.github.io/owe` (DZ) and in Neumark and Shirley (2022) (NS), by sign of the employment effect used in each review.

Figure 1: Number of published studies in the OWE repository, by OWE estimate reporting status and time period



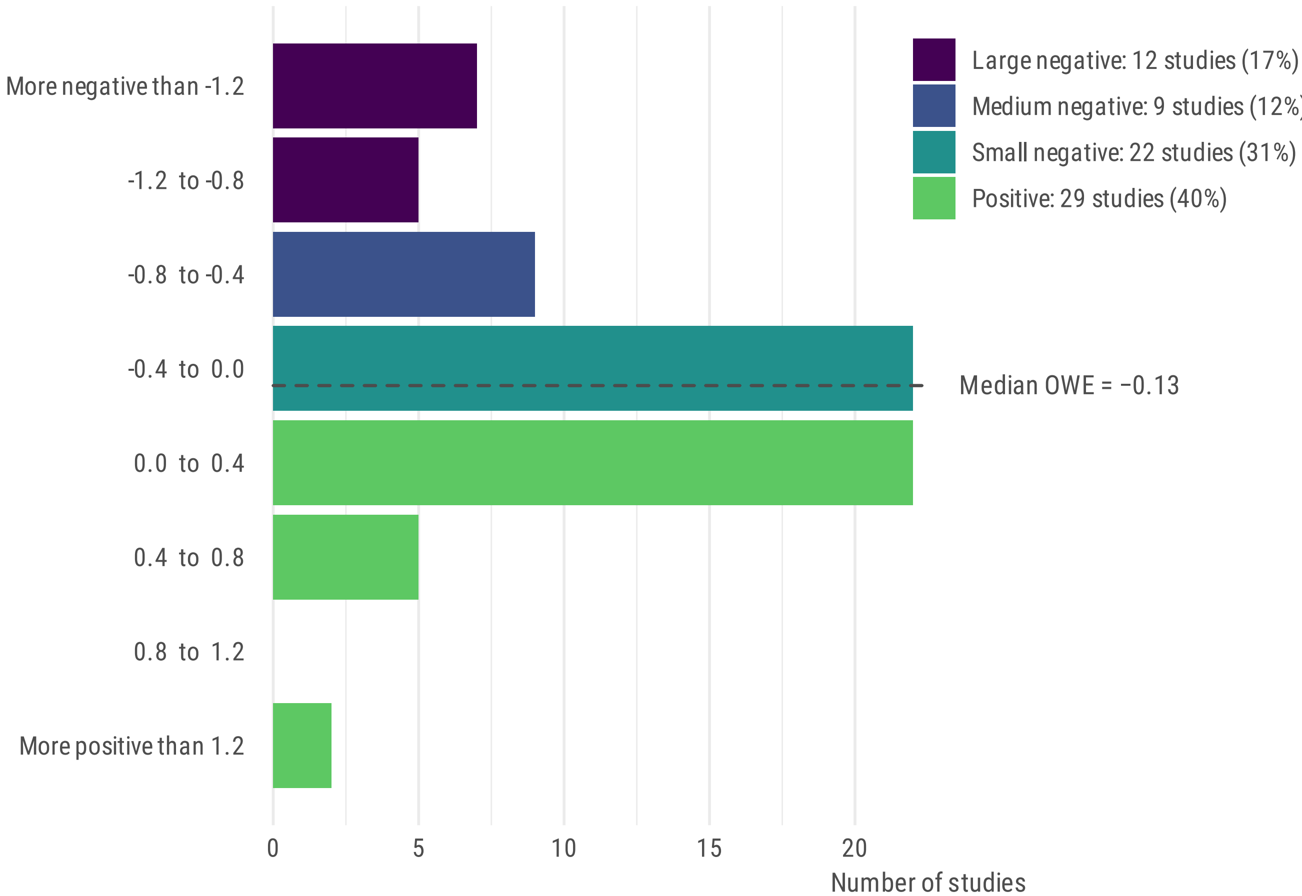
Notes: The figure shows the number of published studies that directly report an OWE estimate and those that just report employment and wage effects in Minimum Wage Own-Wage Elasticity Repository, Version 1.0.0, https://economic.github.io/owe.

Figure 2: Distribution of own-wage elasticity estimates and confidence intervals



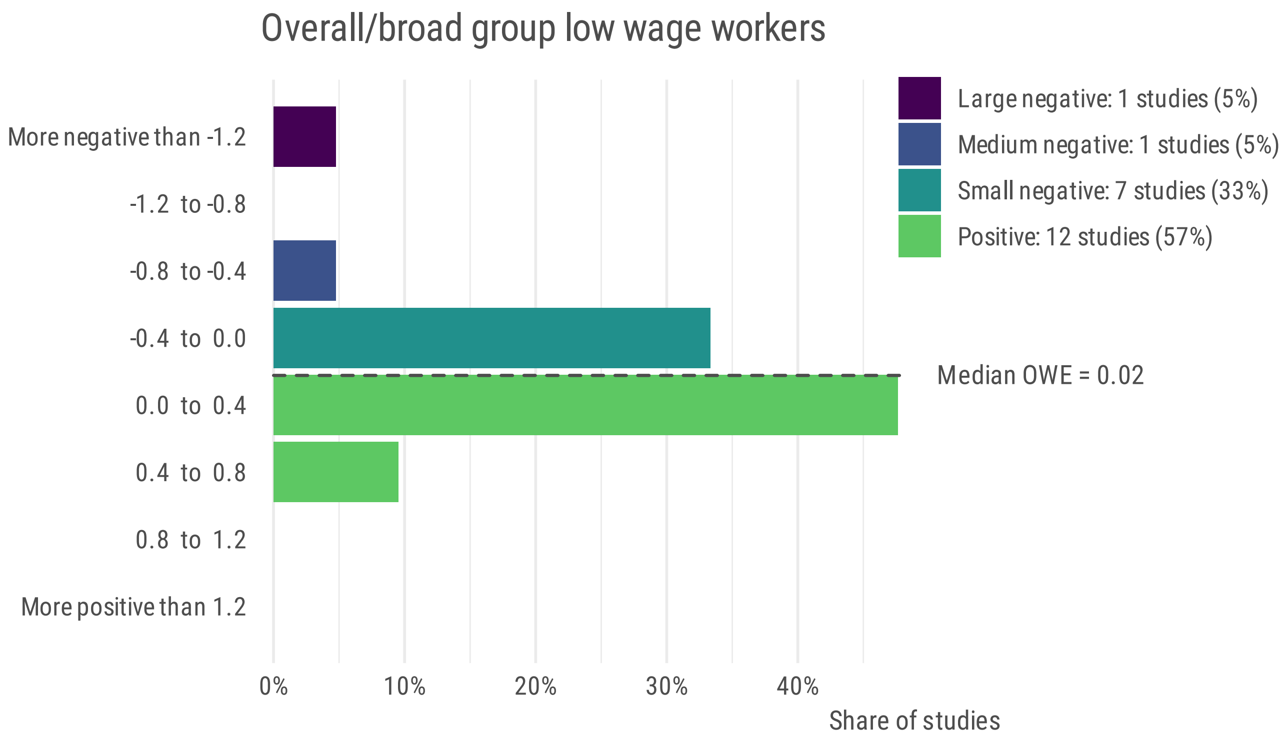
Notes: The figure shows own-wage elasticity estimates and, when available, their 95% confidence intervals, for all published and unpublished studies in the Minimum Wage Own-Wage Elasticity Repository, Version 1.0.0, https://economic.github.io/owe. Confidence intervals are winsorized at [-3, 3]. The OWE estimate ranges are "large negative" (less than -0.8), "medium negative" (greater than or equal to -0.8 but less than -0.4), "small negative" (greater than or equal to -0.4 but less than 0.0), and "positive" (greater than or equal to 0.0).

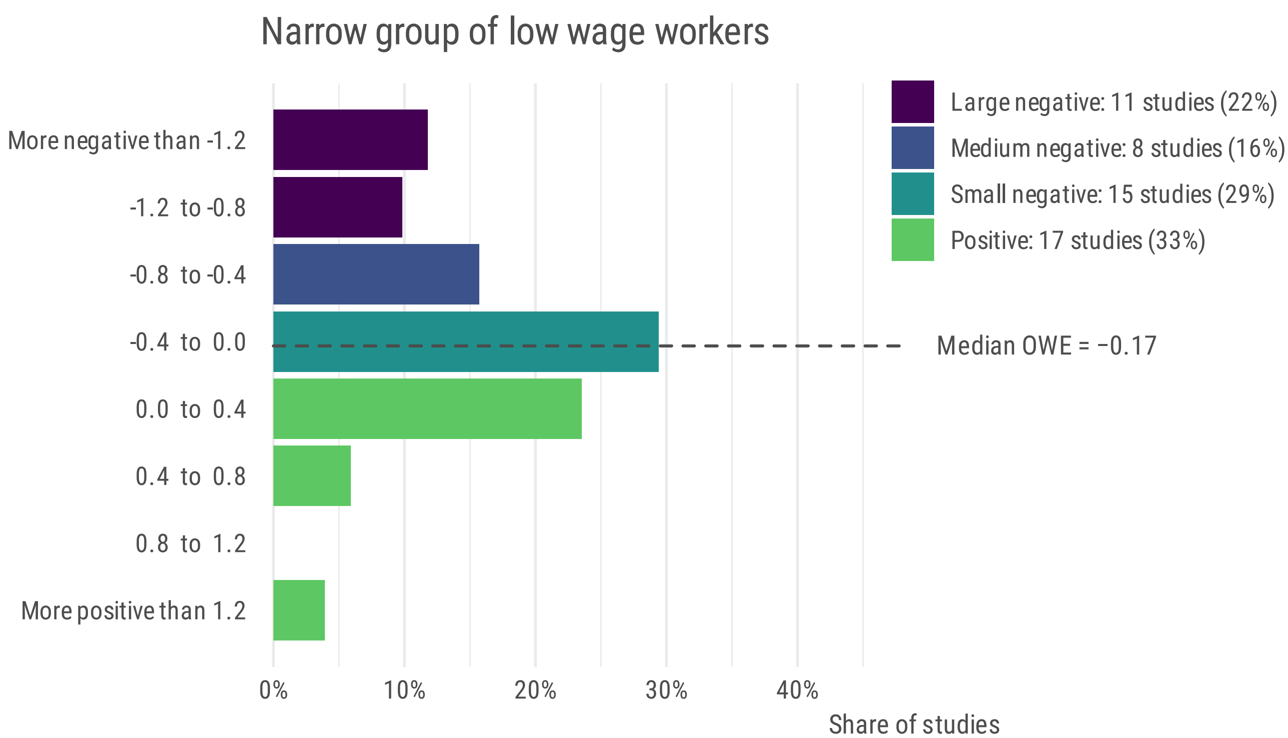
Figure 3: Distribution of published studies, by own-wage elasticity estimate range



Notes: The figure shows the number of published studies in each own-wage elasticity interval from the Minimum Wage Own-Wage Elasticity Repository, Version 1.0.0, https://economic.github.io/owe. The OWE estimate ranges are "large negative" (less than -0.8), "medium negative" (greater than or equal to -0.8 but less than -0.4), "small negative" (greater than or equal to -0.4 but less than 0.0), and "positive" (greater than or equal to 0.0).

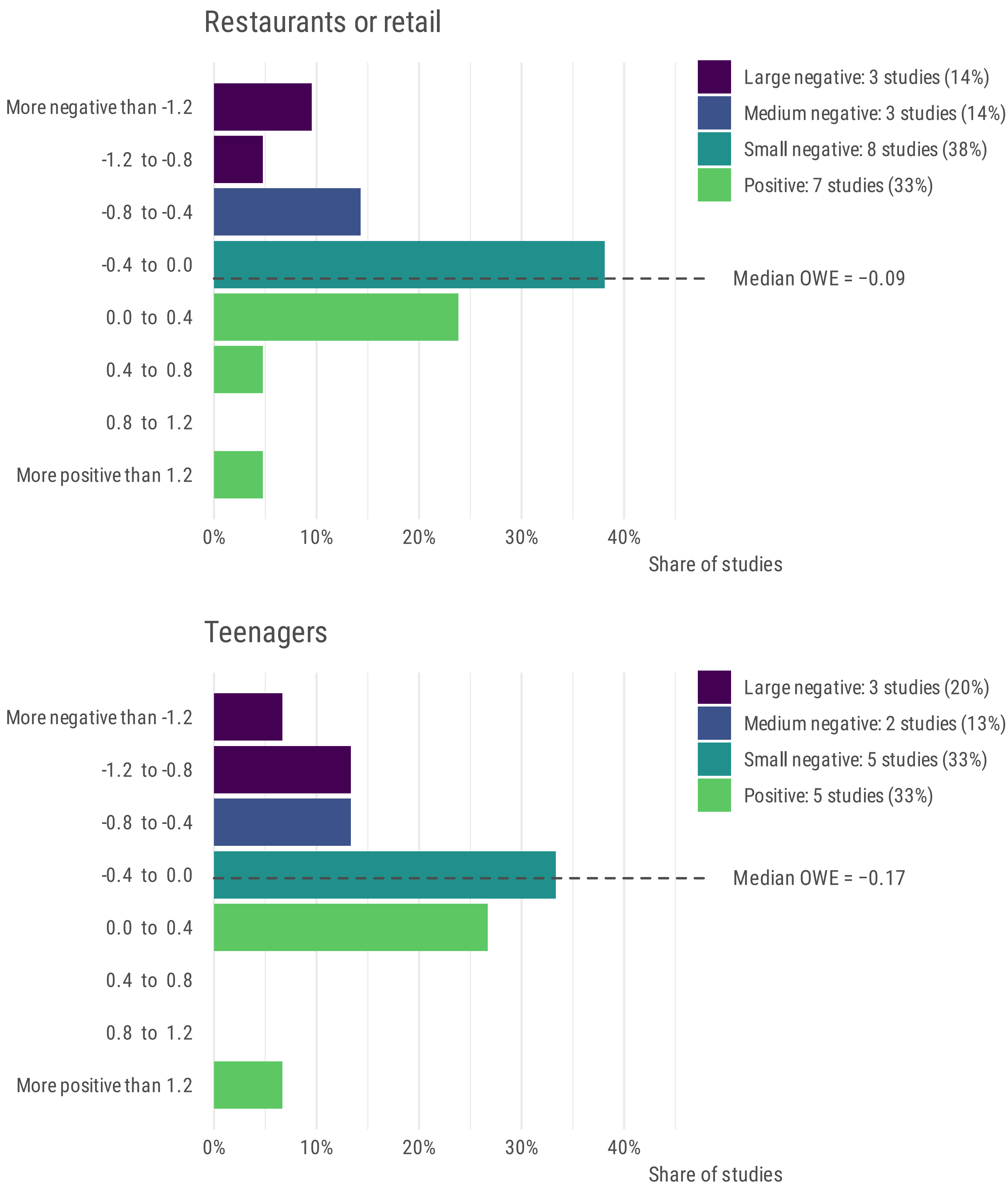
Figure 4: Distribution of published studies, overall/broad and narrow subgroups





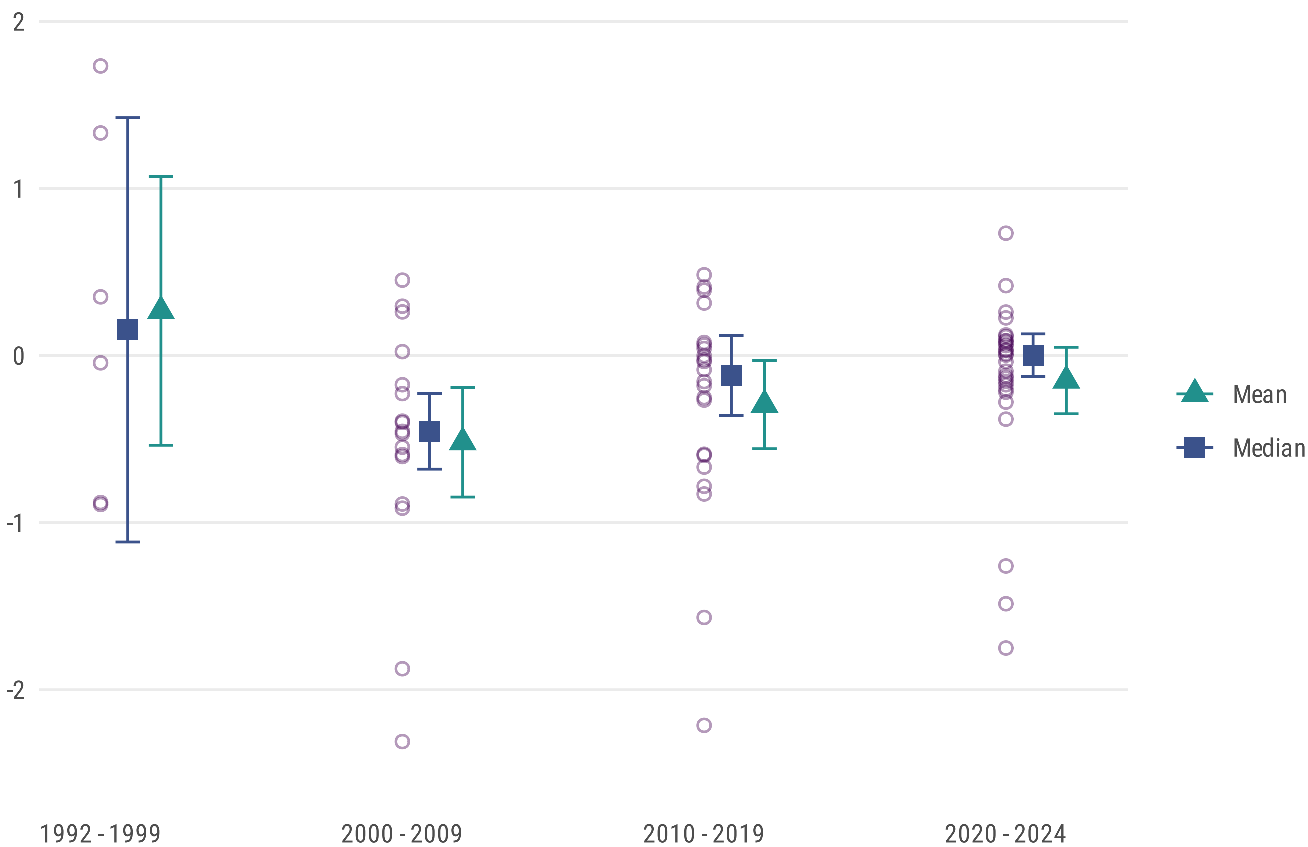
Notes: The figure shows the number of published studies in each own-wage elasticity interval from the Minimum Wage Own-Wage Elasticity Repository, Version 1.0.0, https://economic.github.io/owe. The OWE estimate ranges are "large negative" (less than -0.8), "medium negative" (greater than or equal to -0.8 but less than -0.4), "small negative" (greater than or equal to -0.4 but less than 0.0), and "positive" (greater than or equal to 0.0).

Figure 5: Distribution of published studies, restaurants or retail and teenagers



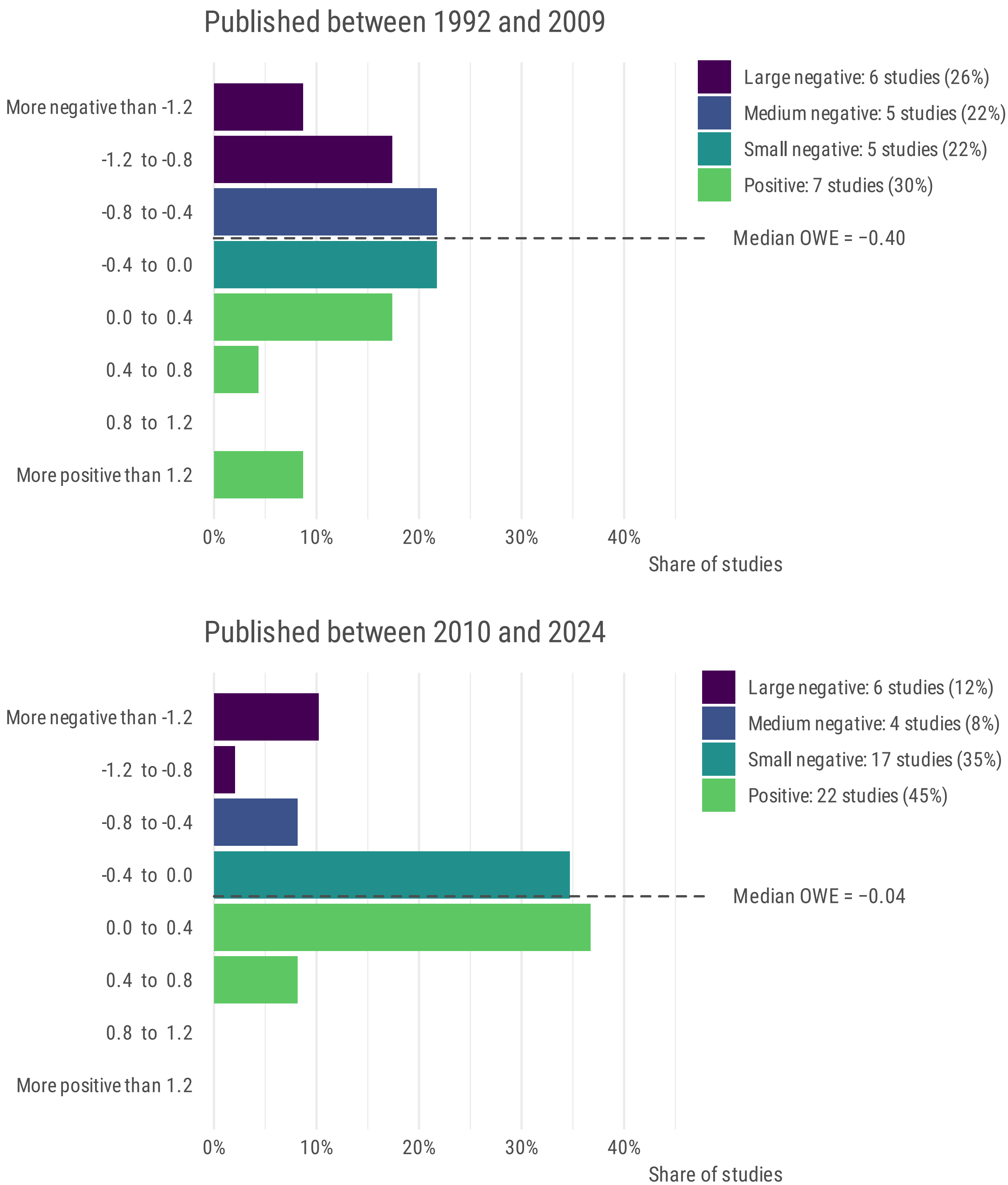
Notes: The figure shows the number of published studies in each own-wage elasticity interval from the Minimum Wage Own-Wage Elasticity Repository, Version 1.0.0, https://economic.github.io/owe. The OWE estimate ranges are "large negative" (less than -0.8), "medium negative" (greater than or equal to -0.8 but less than -0.4), "small negative" (greater than or equal to -0.4 but less than 0.0), and "positive" (greater than or equal to 0.0).

Figure 6: Mean and median OWE estimates by publication decade



Notes: The figure shows, by publication decade, the distribution, mean, and median of published OWE estimates from the Minimum Wage Own-Wage Elasticity Repository, Version 1.0.0, https://economic.github.io/owe. 95% confidence intervals for the mean and median each decade are from the standard errors of 1 million bootstrap replications.

Figure 7: Distribution of published studies, before and after 2010



Notes: The figure shows the number of published studies in each own-wage elasticity interval from the Minimum Wage Own-Wage Elasticity Repository, Version 1.0.0, https://economic.github.io/owe. The OWE estimate ranges are "large negative" (less than -0.8), "medium negative" (greater than or equal to -0.8 but less than -0.4), "small negative" (greater than or equal to -0.4 but less than 0.0), and "positive" (greater than or equal to 0.0).

Appendix: Papers and sources for all OWE estimates

Addison Blackburn Cotti 2009

John T. Addison, McKinley L. Blackburn and Chad D. Cotti. “Do Minimum Wages Raise Employment? Evidence from the U.S. Retail-trade Sector”, Labour Economics.

Own-wage elasticity estimate: 0.452 (0.436)

Source of estimate: Weighted average of wage and employment elasticities for three sectors with statistically positive wage effects: convenience stores; specialty food stores; beer, wine, and liquor stores. Elasticities from Table 4 (estimates with county-level trends). Weights are mean employment counts from Table 1.

Addison Blackburn Cotti 2012

John T. Addison, McKinley L. Blackburn and Chad D. Cotti. “The Effect of Minimum Wages on Labour Market Outcomes: County-Level Estimates from the Restaurant-and-Bar Sector”, British Journal of Industrial Relations.

Own-wage elasticity estimate: -0.035 (0.193)

Source of estimate: Wage and employment elasticities from Table 3 (estimates with county-level trends). Authors write that ”specifications with trends are to be preferred” (p.426).

Addison Blackburn Cotti 2013

John T. Addison, McKinley L. Blackburn and Chad D. Cotti. “Minimum Wage Increases in a Recessionary Environment”, Labour Economics.

Own-wage elasticity estimate: -0.084 (0.122)

Source of estimate: Earnings and employment elasticities from Table 2, row 1 (food and drinking places), ”county trends” specifications. Authors prefer this specification over ”basic” and ”border county”: ”our preference is to direclty model county-specific trends, and with this approach the estimates are quite precise” (p.35). No reported wage effects for analysis using CPS or ACS, or for unemployment heterogeneity analysis.

Addison Blackburn Cotti 2015

John T. Addison, McKinley L. Blackburn and Chad D. Cotti. “On the Robustness of Minimum Wage Effects: Geographically-Disparate Trends and Job Growth Equations”, IZA Journal of Labor

Economics.

Own-wage elasticity estimate: -0.251 (0.138)

Source of estimate: Employment and earnings elasticities for restaurant and bar sector using county-specific linear trends, because the authors select that specification as their ”preferred model” on page 7, for the 1990-2014 period, which is the longest period in their sample. Employment elasticity from the top panel of Table 3, column ”1st”. Earnings elasticity from the top panel of Table 6, column ”1st”.

Aitken Dolton Riley 2019

Andrew Aitken, Peter Dolton and Rebecca Riley. “The Impact of the Introduction of the National Living Wage on Employment, Hours, and Wages”, NIESR Discussion Paper.

Own-wage elasticity estimate: -0.254 (0.223)

Source of estimate: Percent wage change from Table 5, row 1, specification 1. To calculate the percent employment change, we take the percentage point employment change from Table 7, row 1, specification 1 and divide it by the 0.67 treated group mean in 2015. These are the ”2015 as treatment year” estimates, estimating the effect of the 2016 increase, as opposed to the ”2016 as treatment year” estimates, which focus on the 2017 uprating.

Allegretto Dube Reich 2011

Sylvia Allegretto, Arindrajit Dube and Michael Reich. “Do Minimum Wages Really Reduce Teen Employment? Accounting for Heterogeneity and Selectivity in State Panel Data”, Industrial Relations.

Own-wage elasticity estimate: 0.315 (0.402)

Source of estimate: Wage and employment elasticities from Table 3, specification 4, row ”All teens”. Employment elasticity standard error calculated by scaling standard error of semi-elasticity by ratio of elasticity to semi-elasticity.

Allegretto Dube Reich Zipperer 2017

Sylvia Allegretto, Arindrajit Dube, Michael Reich and Ben Zipperer. “Credible Research Designs for Minimum Wage Studies”, ILR Review.

Own-wage elasticity estimate: 0.043 (0.188)

Source of estimate: Teen wage and employment elasticities from Table 1, specification 2 (linear trends), row "Division-period FE".

Allegretto and Nadler 2015

Sylvia Allegretto and Carl Nadler. "Tipped Wage Effects on Earnings and Employment in Full-Service Restaurants", Industrial Relations.

Own-wage elasticity estimate: -0.024 (0.662)

Source of estimate: Sum of the headline and tipped wage and employment elasticities to approximate the effect of a marginal increase in both the headline and tipped minimum wage. Wage and employment elasticities from Table 2, Panel A (Full service Restaurants), specification 4 (Division-period effects and state-specific time trends), adding the tipped and headline minimum effects together. Standard errors assume no covariance between the tipped and headline minimum wage effect estimates.

Azar Huet-Vaughn Marinescu Taska Wachter 2023

José Azar, Emiliano Huet-Vaughn, Ioana Elena Marinescu, Bledi Taska and Till Von Wachter. "Minimum Wage Employment Effects and Labor Market Concentration", The Review of Economic Studies.

Own-wage elasticity estimate: 0.088 (0.925)

Source of estimate: Weighted average of elasticities and their variances for the three mid-HHI occupation OWEs presented in Figure 7 (Stock Clerks, Retail Sales, and Cashiers), where the weights are the sample sizes from Table 3. Authors emailed the three OWEs coefficients and standard errors used in Figure 7.

Bailey DiNardo Stuart 2021

Martha J. Bailey, John DiNardo and Bryan A. Stuart. "The Economic Impact of a High National Minimum Wage: Evidence from the 1966 Fair Labor Standards Act", Journal of Labor Economics.

Own-wage elasticity estimate: -0.135 (0.077)

Source of estimate: Own-wage elasticity reported in Table 3, panel A (Employed during year), specification 3. Selected this particular estimate with authors over email.

Baskaya and Rubinstein 2015

Yusuf Soner Baskaya and Yona Rubinstein. "Using Federal Minimum Wages to Identify the Impact of Minimum Wages on Employment and Earnings across the U.S. States", Working Paper.

Own-wage elasticity estimate: -0.899 (0.609)

Source of estimate: Employment elasiticity is the average of estimates from Table 10a, Panel A, row 1, specifications 5 and 8, where the estimates are divided by the sample mean employment rate in Appendix Table A2, column 1, last row. Wage elasticity is the average of estimates from Table 10b, Panel A, row 1, specifications 5 and 8.

Berge and Frings 2019

Philipp vom Berge and Hanna Frings. "High-impact minimum wages and heterogeneous regions", Empirical Economics.

Own-wage elasticity estimate: -1.567 (1.923)

Source of estimate: Wage and employment effects are the average across three specifications. Wage growth effects from Table 1, row "Treatment effect (East)", specifications 3 through 5. Employment growth effects from Table 3, row "Treatment effect (East)", specifications 3 through 5.

Bezooijen Berge Salomons 2024

Emiel van Bezooijen, Wiljan van den Berge and Anna Salomons. "The Young Bunch: Youth Minimum Wages and Labor Market Outcomes", ILR Review.

Own-wage elasticity estimate: 0.226 (0.143)

Source of estimate: Own-wage elasticity from Table 4, Jobs specification

Borgshulte and Cho 2020

Mark Borgshulte and Heepyung Cho. "Minimum Wages and Retirement", ILR Review.

Own-wage elasticity estimate: 0.419 (0.301)

Source of estimate: The statistically significant earnings elasticity estimate is from Table 3, specification 5, Panel E. The analogous employment elasticity estimate is Table 3, specification 5, panel A.

Bossler and Gerner 2020

Mario Bossler and Hans-Dieter Gerner. "Employment Effects of the new German Minimum Wage: Evidence from Establishment-level Microdata", ILR Review.

Own-wage elasticity estimate: -0.278 (0.212)

Source of estimate: Own-wage elasticity reported in Table 2, specification 3 (Derived labor demand elasticity), Panel B (Intensive treatment definition). Authors emailed to select this specification.

Brown and Herbst 2023

Jessica H. Brown and Chris M. Herbst. "Minimum Wage, Worker Quality, and Consumer Well-Being: Evidence from the Child Care Market", IZA Discussion Paper.

Own-wage elasticity estimate: 0.841 (0.855)

Source of estimate: Earnings and employment elasticities reported in specification 1 (All) of Table 1.

Brummund and Strain 2020

Peter Brummund and Michael R. Strain. "Does Employment Respond Differently to Minimum Wage Increases in the Presence of Inflation Indexing?", Journal of Human Resources.

Own-wage elasticity estimate: -1.259 (0.699)

Source of estimate: Employment and earnings elasticities from an equally weighted average of the three specifications Table 5. The earnings and employment elasticities for each column are the sum of the ln(Minimum Wage) and Indexed X ln(Min wage) coefficients. The standard errors for the sum of these coefficients is the square root of the sum of the variances. The final pooled employment and earnings elasticities are the equally weighted averages across columns.

Burkhauser Couch Wittenburg 2000

Richard V. Burkhauser, Kenneth A. Couch and David C. Wittenburg. "A Reassessment of the New Economics of the Minimum Wage Literature with Monthly Data from the Current Population Survey", Journal of Labor Economics.

Own-wage elasticity estimate: -0.604 (0.184)

Source of estimate: Wage elasticity from Table 2, specification 1 (1979-1992, seasonal, state, and year effects). Employment elasticity from the "controls for state-level autocorrelation and heteroskedasticity correction" elasticity reported in Table 7, specification Table 3 (4) (1979-1992, seasonal, state, and year effects), where the semi-elasticity standard error is scaled by the ratio of the elasticity to semi-elasticity. Authors prefer models without year effects but our review is restricted to DD-style estimators as opposed to repeated time series, so we chose the year fixed effect estimate in paper that had statistically significant wage effects and a similar employment effect specification that seem to be preferred by author.

Butcher and Dickens 2023

Tim Butcher and Richard Dickens. "Impact of the National Living Wage using Geographic, Age and Gender Wage Variation", Low Pay Commission.

Own-wage elasticity estimate: 0.476 (0.395)

Source of estimate: Wage percent change from Table 3, column 4. Employment percent change is the percentage point change in employment from Table 4, column 4, divided by the overall employment rate of 0.65 (see footnote 65).

Campolieti Gunderson Riddell 2006

Michele Campolieti, Morley Gunderson and Chris Riddell. "Minimum Wage Impacts from a Prespecified Research Design: Canada 1981-1997", Industrial Relations.

Own-wage elasticity estimate: -0.548 (0.359)

Source of estimate: Own-wage elasticity reported in Table 4, panel "Including prime-age skilled employment rate", specification "Youths 16-24 combined".

Card 1992a

David Card. "Do Minimum Wages Reduce Employment? A Case Study of California, 1987-89", ILR Review.

Own-wage elasticity estimate: 1.333 (0.609)

Source of estimate: Estimates from "Difference in Differences" column of Table 4. Wage elasticity from row "Mean Log Wage". Employment semi-elasticity and standard error from row "Employment rate (

Card 1992b

David Card. "Using Regional Variation in Wages to Measure the Effects of the Federal Minimum Wage", ILR Review.

Own-wage elasticity estimate: 0.352 (0.616)

Source of estimate: Own-wage semi-elasticity reported in Table 4, specification 5, scaled by the mean of teen employment rates in 1989 across all groups (0.455).

Card Katz Krueger 1994

David Card, Lawrence F. Katz and Alan B. Krueger. "Comment on David Neumark and William Wascher, "Employment Effects of Minimum and Subminimum Wages: Panel Data on State Minimum Wage Laws"", ILR Review.

Own-wage elasticity estimate: -0.043 (0.15)

Source of estimate: Own-wage semi-elasticity reported in Table 2, row 5, specification 2, divided by unweighted teen epop mean in footnote b (0.466).

Cengiz Dube Lindner Zentler-Munro 2022

Doruk Cengiz, Arindrajit Dube, Attila Lindner and David Zentler-Munro. "Seeing beyond the Trees: Using Machine Learning to Estimate the Impact of Minimum Wages on Labor Market Outcomes", Journal of Labor Economics.

Own-wage elasticity estimate: 0.114 (0.216)

Source of estimate: Own-wage elasticity reported in Table 2, specification 3 , row "Employment elasticity with respect to wage" (High recall, Boosted tree)

Cengiz Dube Lindner Zipperer 2019

Doruk Cengiz, Arindrajit Dube, Attila Lindner and Ben Zipperer. "The Effect of Minimum Wages on Low-Wage Jobs", Quarterly Journal of Economics.

Own-wage elasticity estimate: 0.411 (0.43)

Source of estimate: Own-wage elasticity reported in Table 1, specification 1, row "Emp. elasticity w.r.t affected wage"

Clemens and Strain 2021

Jeffrey Clemens and Michael R. Strain. "The Heterogeneous Effects of Large and Small Minimum Wage Changes: Evidence over the Short and Medium Run Using a Pre-Analysis Plan", NBER Working Paper.

Own-wage elasticity estimate: -0.245 (NA)

Source of estimate: Authors suggested simple average of own-wage elasticities reported in Table 10, specifications 1 (Low-Skill, All Changers) and 5 (Young, All Changers).

Coviello Deserranno Persico 2022

Decio Coviello, Erika Deserranno and Nicola Persico. "Minimum Wage and Individual Worker Productivity: Evidence from a Large US Retailer", Journal of Political Economy.

Own-wage elasticity estimate: -0.219 (NA)

Source of estimate: Own-wage elasticity reported on p. 2352 and footnote 43.

Currie and Fallick 1996

Janet Currie and Bruce C. Fallick. "The Minimum Wage and the Employment of Youth Evidence from the NLSY", Journal of Human Resources.

Own-wage elasticity estimate: -0.891 (0.327)

Source of estimate: Employment elasticity uses semi-elasticity from table 2, specification 4 (Fixed Effects), divided by 0.97, the proportion employed in next year, 1987, from Table 1. Wage elasticity from Table 4, Panel B, specification 2 (Fixed Effects).

Derenoncourt and Montialoux 2021

Ellora Derenoncourt and Claire Montialoux. "Minimum Wages and Racial Inequality", Quarterly Journal of Economics.

Own-wage elasticity estimate: 0.06 (0.16)

Source of estimate: Own-wage elasticity reported in Table 6, first column (All) of "Baseline cross-state design" specification, row "Emp. vs (unemp/nilf) elast.". This row is referred to in authors' comparison of own-wage elasticities across specifications in Section V.A.5.

Dickens Riley Wilkinson 2015

Richard Dickens, Rebecca Riley and David Wilkinson. "A Re-examination of the Impact of the UK National Minimum Wage on Employmen", Economica.

Own-wage elasticity estimate: -0.596 (0.482)

Source of estimate: Weighted average of wage and employment elasticities across three groups: female full-time, female part-time, and male full-time. Weights from Table 2 pre-treatment observation counts. Wage elasticities from Table 3, line 1998. Employment semi-elasticity from Table 5, line 1998, scaled by pre-period treatment group-specific employment inferred from Figure 2.

Dow Godøy Lowenstein Reich 2020

William H. Dow, Anna Godøy, Christopher A. Lowenstein and Michael Reich. "Can Economic Policies Reduce Deaths of Despair?", Journal of Health Economics.

Own-wage elasticity estimate: 0.733 (0.823)

Source of estimate: Wage elasticity reported in Table A1, Panel B, specification 1. Employment semi-elasticity reported in Table A1, Panel B, specification 2, divided by mean employment of the regression sample, 0.565, calculated using a modified version of the authors' replication package file wage_ag051120.do, available here: https://gist.github.com/benzipperer/7860f1055036b95d9e04a212e2b61bed

Draca Machin Reenan 2011

Mirko Draca, Stephen Machin and John Van Reenan. "Minimum Wages and Firm Profitability", American Economic Journal: Applied Economics.

Own-wage elasticity estimate: 0.484 (1.401)

Source of estimate: Simple average from Table 5 of the high-market power and low-market power wage (panel A) and employment elasticities (panel C).

Dube 2019

Arindrajit Dube. "Impacts of minimum wages: review of the international evidence", Her Majesty's Treasury.

Own-wage elasticity estimate: 0.32 (0.37)

Source of estimate: Own-wage elasticity reported in text at top of page 33.

Dube Lester Reich 2010

Arindrajit Dube, T. William Lester and Michael Reich. "Minimum Wage Effects Across State Borders: Estimates Using Contiguous Counties", The Review of Economics and Statistics.

Own-wage elasticity estimate: 0.079 (0.286)

Source of estimate: Own-wage elasticity reported in Table 2, specification 6, row "Labor demand elasticity".

Dube Lester Reich 2016

Arindrajit Dube, T. William Lester and Michael Reich. "Minimum Wage Shocks, Employment Flows, and Labor Market Frictions", Journal of Labor Economics.

Own-wage elasticity estimate: -0.266 (0.383)

Source of estimate: Wage and employment elasticities from Table 3, specification 2. Authors communicated that teens is the preferred group.

Dube Naidu Reich 2007

Arindrajit Dube, Suresh Naidu and Michael Reich. "The Economic Effects of a Citywide Minimum Wage", ILR Review.

Own-wage elasticity estimate: 0.296 (0.622)

Source of estimate: Employment log change from Table 7, panel "Ln(employment)", specification 1 ("Full sample"). Wage effect from Table 2, specification 1 ("Full sample"), divided by 10.22, the Table 1, Wave 1, Treatment Group, Average Wage.

Dube and Lindner 2021

Arindrajit Dube and Attila Lindner. "City Limits: What Do Local-Area Minimum Wages Do?", Journal of Economic Perspectives.

Own-wage elasticity estimate: -0.12 (0.38)

Source of estimate: Own-wage elasticity reported in Figure 3, Panel B.

Dube and Zipperer 2015

Arindrajit Dube and Ben Zipperer. "Pooling Multiple Case Studies Using Synthetic Controls: An Application to Minimum Wage Policies", IZA Discussion Paper.

Own-wage elasticity estimate: -0.135 (0.249)

Source of estimate: Employment and wage elasticities from Table 6, Hodges-Lehmann estimate, with standard errors interpolated from the confidence interval.

Dustmann Lindner Schönberg Umkehrer Berge 2022

Christian Dustmann, Attila Lindner, Uta Schönberg, Matthias Umkehrer and Philipp vom Berge. "Reallocation Effects of the Minimum Wage", Quarterly Journal of Economics.

Own-wage elasticity estimate: 0.03 (0.12)

Source of estimate: Own-wage elasticity reported in footnote 27 on page 316.

Eriksson and Pytlikova 2004

Tor Eriksson and Mariola Pytlikova. "Firm-level Consequences of Large Minimum-wage Increases in the Czech and Slovak Republics", LABOUR.

Own-wage elasticity estimate: 0.024 (0.152)

Source of estimate: Weighted average of the reported own-wage elasticities in Tables 6 and 7. Czec OWE is the simple average of four OWE estimates in columns three and four of Table 6, Panel 1 (two-thirds) Total and Panel 2 (wage gap). Slovak OWE is the simple average of four OWE estimates in columns three and four of Table 7, Panel 1 (two-thirds) Total and Panel 2 (wage gap). We then report a weighted average of these two country-specific OWEs, where the weights are the total 1998 employment sizes reported in Table 4 (Czech) and Table 5 (Slovak).

Even and Macpherson 2014

William E. Even and David A. Macpherson. "The Effect of the Tipped Minimum Wage on Employees in the U.S. Restaurant Industry", Southern Economic Journal.

Own-wage elasticity estimate: -0.782 (0.288)

Source of estimate: Sum of the headline and tipped wage and employment elasticities to approximate the effect of a marginal increase in both the headline and tipped minimum wage. Wage elasticities from Table 1 and employment elasticities from Table 2, using specification 1 (Full service, 1990:1 to 2011:4, no state-specific time trends), rows "Log of Tipped Minimum Wage" and "Log of Minimum Wage". Standard errors assume no covariance between the tipped and headline minimum wage effect estimates. Standard errors calculated from t-statistics assuming normal distribution.

Gittings and Schmutte 2016

R. Kaj Gittings and Ian M. Schmutte. "Getting Handcuffs on an Octopus: Minimum Wages, Employment, and Turnover", ILR Review.

Own-wage elasticity estimate: 0 (0.75)

Source of estimate: Earnings elasticity from Table 4, Panel A, specification "Log (earnings)". Employment semi-elasticity from Table 4, Panel A, specification "Employment / Population", divided by 0.28, the mean QWI Teen end-of-quarter EPOP from Table 1.

Giuliano 2013

Laura Giuliano. "Minimum Wage Effects on Employment, Substitution, and the Teenage Labor Supply: Evidence from Personnel Data", Journal of Labor Economics.

Own-wage elasticity estimate: -0.59 (0.613)

Source of estimate: Own-wage elasticity reported in Table 4, column 6. To calculate the standard error, we use the reported employment and wage elasticities and their standard errors. Wage elasticity from Table 4, column 6, row 1. Employment semi elasticity from Table 4, row 2, column 6 divided by the Table 1, All Stores FTE mean of 14.7.

Giupponi Joyce Lindner Waters Wernham Xu 2024

Giulia Giupponi, Robert Joyce, Attila Lindner, Tom Waters, Thomas Wernham and Xiaowei Xu. "The Employment and Distributional Impacts of Nationwide Minimum Wage Changes", Journal of Labor Economics.

Own-wage elasticity estimate: -0.2 (0.32)

Source of estimate: Own-wage elasticity reported in Table 2, Panel A.

Godoey and Reich 2021

Anna Godoey and Michael Reich. "Are Minimum Wage Effects Greater in Low-Wage Areas?", Industrial Relations.

Own-wage elasticity estimate: 0.124 (NA)

Source of estimate: Own-wage elasticity reported in Table A2, sample: High school or less, specification 1 (All).

Godøy Reich Wursten Allegretto 2024

Anna Godøy, Michael Reich, Jesse Wursten and Sylvia Allegretto. "Parental Labor Supply: Evidence from Minimum Wage Changes", Journal of Human Resources.

Own-wage elasticity estimate: 0.09 (0.41)

Source of estimate: Own-wage elasticity reported in Table 2, column "Any, Any".

Gopalan Hamilton Kalda Sovich 2021

Radhakrishnan Gopalan, Barton H. Hamilton, Ankit Kalda and David Sovich. "State Minimum Wages, Employment, and Wage Spillovers: Evidence from Administrative Payroll Data", Journal of Labor Economics.

Own-wage elasticity estimate: -0.38 (NA)

Source of estimate: Own-wage elasticity reported on page 696 for total employment ("implied total labor demand elasticity"). Other own-wage elasticities are reported but this seems to be the broadest.

Hampton and Totty 2023

Matt Hampton and Evan Totty. "Minimum wages, retirement timing, and labor supply", Journal of Public Economics.

Own-wage elasticity estimate: 0.072 (0.134)

Source of estimate: Weighted average of the own-wage elasticities reported in Table 7, where the weights are the sample sizes in Panel A. Standard errors for each group are calculated from the confidence interval span divided by 2 times 1.96.

Harasztosi and Lindner 2019

Peter Harasztosi and Attila Lindner. "Who Pays for the Minimum Wage", American Economic Review.

Own-wage elasticity estimate: -0.18 (0.03)

Source of estimate: Own-wage elasticity reported by authors on page 2695.

Hirsch Kaufman Zelenska 2015

Barry T. Hirsch, Bruce E. Kaufman and Tetyana Zelenska. "Minimum Wage Channels of Adjustment", Industrial Relations.

Own-wage elasticity estimate: 0.392 (0.328)

Source of estimate: Own-wage elasticity reported in Table 5, specification 7 (IV, Store FE), which authors refer to as their "preferred employment elasticity" on page 218.

Huet-Vaughn and Piqueras 2023

Emiliano Huet-Vaughn and Jon Piqueras. “The Asymmetric Effect of Wage Floors: A Natural Experiment with a Rising and Falling Minimum Wage”, IZA Discussion Paper.

Own-wage elasticity estimate: -1.864 (NA)

Source of estimate: Wage change from Figure 2 inset and employment change from Figure 3 inset.

Jardim Long Plotnick Inwegen Vigdor Wething 2022

Ekaterina Jardim, Mark C. Long, Robert Plotnick, Emma van Inwegen, Jacob Vigdor and Hilary Wething. “Minimum-Wage Increases and Low-Wage Employment: Evidence from Seattle”, American Economic Journal: Economic Policy.

Own-wage elasticity estimate: -1.75 (NA)

Source of estimate: Wage elasticity from Table 6a, specification ”SC levels”, row ”2016:III”. Employment elasticity from Table 6c, specification ”SC levels”, row ”2016:III”. Communication with authors suggests synthetic control ”levels” specification.

Jha Neumark Rodriguez-Lopez 2024

Priyaranjan Jha, David Neumark and Antonio Rodriguez-Lopez. “What’s across the Border? Re-Evaluating the Cross-Border Evidence on Minimum Wage Effects”, Journal of Political Economy Microeconomics.

Own-wage elasticity estimate: -1.485 (0.89)

Source of estimate: Wage and employment elasticities from Table 3, specification 1.

Karabarbounis Lise Nath 2023

Loukas Karabarbounis, Jeremy Lise and Anusha Nath. “Minimum Wages and Labor Markets in the Twin Cities”, NBER Working Paper.

Own-wage elasticity estimate: -1.103 (NA)

Source of estimate: Simple average of Minneapolis and St. Paul elasticities from Table 2, Baseline panel, 2021 values. Wage elasticities from ”Wage” columns and employment elasticities from ”Jobs” columns. Authors refer to Table 2 estimates in a discussion of own-wage elasticities in Section 5.3.

Katz and Krueger 1992

Lawrence F. Katz and Alan B. Krueger. “The Effect of Minimum Wages on the Fast-Food Industry”, ILR Review.

Own-wage elasticity estimate: 1.734 (0.934)

Source of estimate: Own-wage elasticity reported in Table 5, specification 2.

Kim and Taylor 1995

Taeil Kim and Lowell J. Taylor. “The Employment Effect in Retail Trade of California’s 1988 Minimum Wage Increase”, Journal of Business and Economic Statistics.

Own-wage elasticity estimate: -0.879 (0.133)

Source of estimate: Own-wage elasticity reported in Table 4, specification 8 (IV).

Leung 2021

Justin H. Leung. “Minimum Wage and Real Wage Inequality: Evidence from Pass-Through to Retail Prices”, The Review of Economics and Statistics.

Own-wage elasticity estimate: 0.034 (0.654)

Source of estimate: Earnings and employment elasticities from Table 4, specification 2 (Grocery). Paper includes results for other sectors, but the main focus appears to be grocery stores where price effects are clear.

Liu Hyclack Regmi 2016

Shanshan Liu, Thomas J. Hyclack and Krishna Regmi. “Impact of the Minimum Wage on Youth Labor Markets”, LABOUR.

Own-wage elasticity estimate: -0.828 (0.254)

Source of estimate: Employment and wage elasticities from Table 2, specifications ”14-18”, Panel B.

Machin Manning Rahman 2003

Stephen Machin, Alan Manning and Lupin Rahman. “Where the Minimum Wage Bites Hard: Introduction of Minimum Wages to a Low Wage Sector”, Journal of the European Economic Association.

Own-wage elasticity estimate: -0.453 (0.251)

Source of estimate: Simple average of own-wage elasticities reported in Table 6, specifications 7 and 8, panel ”Change in log number employed”.

Machin and Wilson 2004

Stephen Machin and Joan Wilson. “Minimum Wages in a Low-Wage Labour Market: Care Homes in the UK”, The Economic Journal.

Own-wage elasticity estimate: -0.467 (0.077)

Source of estimate: CONFIRM SOURCE TK

Manning 2021

Alan Manning. “The Elusive Employment Effect of the Minimum Wage”, Journal of Economic Perspectives.

Own-wage elasticity estimate: 0.011 (0.404)

Source of estimate: Wage and employment elasticities are the hours-weighted average of unweighted average elasticities (across seven specifications) for ages 16-19 and ages 20-24. Group Age 16-19 receives a weight of about 29

Monras 2019

Joan Monras. “Minimum Wages and Spatial Equilibrium: Theory and Evidence”, Journal of Labor Economics.

Own-wage elasticity estimate: -0.667 (NA)

Source of estimate: Own-wage elasticity reported in Table 3, specification ”Model 4”, row ”Implied local labor demand elasticity, FTE”. Specification confirmed with author by email.

Nadler Allegretto Godoey Reich 2019

Carl Nadler, Sylvia Allegretto, Anna Godoey and Michael Reich. “Are Local Minimum Wages Too High and How Could We Even Know?”, IRLE Working Paper.

Own-wage elasticity estimate: 0.21 (0.201)

Source of estimate: Earnings elasticity from Table 3, specification 2, panel B. Employment elasticity from Table 3, specification 4, panel B.

Neumark Schweitzer Wascher 2004

David Neumark, Mark Schweitzer and William Wascher. “Minimum Wage Effects throughout the Distribution”, Journal of Human Resources.

Own-wage elasticity estimate: -0.227 (0.263)

Source of estimate: Weighted average

Neumark and Nizalova 2007

David Neumark and Olena Nizalova. “Minimum Wage Effects in the Longer Run”, Journal of Human Resources.

Own-wage elasticity estimate: -0.913 (0.579)

Source of estimate: Wage elasticity from Table 2, specification 1, panel ”16-19”. Employment semi-elasticity from Table 2, specification 2, panel ”16-19”, divided by 46.45, the mean employment from Table 1, specification ”16-19-year olds”, ”Whole sample”.

Neumark and Yen 2023

David Neumark and Maysen Yen. “The employment and redistributive effects of reducing or eliminating minimum wage tip credits”, Journal of Policy Analysis and Management.

Own-wage elasticity estimate: -0.154 (0.41)

Source of estimate: Sum of the headline and tipped wage and employment elasticities to approximate the effect of a marginal increase in both the headline and tipped minimum wage. Wage and employment elasticities from Table 2, Panel A (1990-2019), for full-service restaurants (the sum of headline and tipped minimum wage coefficients for either limited service and full-limited specifications are not positive and statistically significant). Wage elasticity from specification 1 and employment elasticity from specification 4. adding the tipped and headline minimum effects together. Standard errors assume no covariance between the tipped and headline minimum wage effect estimates.

Orrenius and Zavodny 2008

Pia M. Orrenius and Madeline Zavodny. “The Effect of Minimum Wages on Immigrants’ Employment and Earnings”, ILR Review.

Own-wage elasticity estimate: -0.4 (0.401)

Source of estimate: Wage elasticity from Table 3, row ”Less-Educated Immigrants”, specification 2. Employment elasticity from Table 4, panel A (”Real Minimum Wage”), row ”Less-Educated Immigrants”, specification 2.

Pereira 2003

Sonia C. Pereira. “The impact of minimum wages on youth employment in Portugal”, European Economic Review.

Own-wage elasticity estimate: -2.31 (0.854)

Source of estimate: Employment effect from Table 2, column 2 (1986-1988), row 2 (ages 30-35), divided by mean employment of 0.785 referenced in footnote 16. Wage effect from Table 1, column 2 (1986 and 1988), row 2 (ages 30-35). Specifications chosen because of the reference to them on p. 236.

Rao and Risch 2024

Nirupama Rao and Max Risch. “Who’s Afraid of the Minimum Wage? Measuring the Impacts on Independent Businesses Using Matched U.S. Tax Returns”, Working Paper.

Own-wage elasticity estimate: -0.209 (0.011)

Source of estimate: Own-wage elasticity and standard error reported on p. 14.

Renkin Montialoux Siegenthaler 2022

Tobias Renkin, Claire Montialoux and Michael Siegenthaler. “The Pass-Through of Minimum Wages into U.S. Retail Prices: Evidence from Supermarket Scanner Data”, The Review of Economics and Statistics.

Own-wage elasticity estimate: -0.093 (0.446)

Source of estimate: Wage and employment elasticities from Table 4, specification Grocery Stores, specification 1 (”Baseline”): wage elasticity from Panel A and employment elasticity from Panel B. The table also presents results for retail and restaurants but the focus of the paper is groceries.

Riley and Bondibene 2017

Rebecca Riley and Chiara Rosazza Bondibene. “Raising the standard: Minimum wages and firm productivity”, Labour Economics.

Own-wage elasticity estimate: 0.064 (0.575)

Source of estimate: Wage and employment effects from Table 2, specification ”OLS regression” and ”£12,000” cutoff. Log change in wages from row ”Labour costs”, and log change in employment from row ”Employment”. The ”£12,000” cutoff version is used because this is the version shown in the paper's figures.

Ruffini 2022

Krista Ruffini. “Worker Earnings, Service Quality, and Firm Profitability: Evidence from Nursing Homes and Minimum Wage Reforms”, The Review of Economics and Statistics.

Own-wage elasticity estimate: 0.261 (0.202)

Source of estimate: Wage elasticity from Table 2, specification 3. Employment elasticity from Table 3, specification 5. Author communicated these preferred elasticities by email.

Sabia 2008

Joseph J. Sabia. “Minimum Wages and the Economic Well-Being of Single Mothers”, Journal of Policy Analysis and Management.

Own-wage elasticity estimate: -0.888 (NA)

Source of estimate: Wage elasticity from Table 4, row ”Single mothers with ¡ high school education”, column ”Estimated Elasticity”. Employment elasticity from Table 5, Panel II (”¡ HS Education”), row ”Min. wage elasticity”, specification 1 (Employment).

Sabia 2009a

Joseph J. Sabia. “Identifying Minimum Wage Effects: New Evidence from Monthly CPS Data”, Industrial Relations.

Own-wage elasticity estimate: -1.874 (0.517)

Source of estimate: Wage elasticity from Table 3, row ”MINWAGE”, specification 6 (1979-2004, Year effects). Employment elasticity from Table 4, row ”Min wage elasticity”, specification 6 (1979-2004, Year effects), with standard error from semi-elasticity scaled by the ratio of the elastiticy to semi-elasticity.

Sabia 2009b

Joseph J. Sabia. “The Effects of Minimum Wage Increases on Retail Employment and Hours: New Evidence from Monthly CPS Data”, Journal of Labor Research.

Own-wage elasticity estimate: -0.592 (0.266)

Source of estimate: Wage elasticity from Table 2, specfication 1, row ”Min wage elasticity”. Employment elasticity from Table 3, specification 1, row ”Min wage elasticity”. Standard errors are calculated from multiplying the elasticity estimate by the the ratio of the semielasticity standard error to semielasticity point estimate.

Sabia Burkhauser Hansen 2012

Joseph J. Sabia, Richard V. Burkhauser and Benjamin Hansen. “Are the Effects of Minimum Wage Increases Always Small? New Evidence from a Case Study of New York State”, ILR Review.

Own-wage elasticity estimate: -2.213 (1.275)

Source of estimate: wage: Table 2 column 5; emp: Table 3 column 5

Slichter 2023

David Slichter. “The employment effects of the minimum wage: A selection ratio approach to measuring treatment effects”, Journal of Applied Econometrics.

Own-wage elasticity estimate: -0.174 (0.182)

Source of estimate: Simple average of earnings and employment changes across five time period specifications, ”t” through ”t+4”. Earnings effects from Appendix Table 6 and employment effects from Panel A of Table 2.

Stewart 2004

Mark B. Stewart. “The Impact of the Introduction of the U.K. Minimum Wage on the Employment Probabilities of Low-Wage Workers”, Journal of the European Economic Association.

Own-wage elasticity estimate: 0.262 (0.516)

Source of estimate: Wage elasticity from Table 1, LFS actual hours, Full set of time dummies added. Employment elasticity from dividing the retentation rate percentage point change by an estimate of the average retention rate. Percentage point change in the retention rate is the simple average of Adult men and Adult women Table 2 raw linear difference-in-difference estimates, wage based on actual hours. Average retention rate of 81.4

Thompson 2009

Jeffrey P. Thompson. “Using Local Labor Market Data to Re-examine the Employment Effects of the Minimum Wage”, ILR Review.

Own-wage elasticity estimate: -0.392 (0.161)

Source of estimate: Wage: Table 6, column 1 row 1; Emp: Table 5, column 1 row 1

Totty 2017

Evan Totty. “The Effect of Minimum Wages on Employment: A Factor Model Approach”, Economic Inquiry.

Own-wage elasticity estimate: -0.155 (0.109)

Source of estimate: Wage: Table 9, IFE; Emp: Table 3, IFE

Vadean and Allen 2021

Florin Vadean and Stephen Allen. “The Effects of Minimum Wage Policy on the Long-Term Care Sector in England”, British Journal of Industrial Relations.

Own-wage elasticity estimate: -0.036 (0.402)

Source of estimate: Weighted average of the employment and earnings elasticities for residential care (Table 3) and domiciliary care (Table 4). Weights are employment shares from p.311. Wage effects from column 1, row 1, and employment effects from column 3, row 1 of each table.

Vergara 2023

Damián Vergara. “Minimum Wages and Optimal Redistribution”, Working Paper.

Own-wage elasticity estimate: 0.448 (NA)

Source of estimate: Elasticities from row ”Second stage (elasticity)” of Table A.3 using the year X Census division specification because that is used in the simulations. Wage elasticity from column 3 and employment elasticity from column 6.

Wiltshire McPherson Reich Sosinskiy 2024

Justin C. Wiltshire, Carl McPherson, Michael Reich and Denis Sosinskiy. “Minimum Wage Effects and Monopsony Explanations”, IRLE Working Paper.

Own-wage elasticity estimate: 1.55 (0.584)

Source of estimate: Own-wage elasticity reported in Table 4, Panel B, which is the authors' preferred estimate via email correspondence.

Wursten 2020

Jesse Wursten. "Is Politics the Missing Piece of the Minimum Wage Puzzle?", Working Paper.

Own-wage elasticity estimate: -0.221 (0.15)

Source of estimate: wage = Table 5, panel A, column 5; emp = table 2, panel B, column 1

Wursten 2021

Jesse Wursten. "Estimating the earnings and employment effects of the minimum wage through differences in exposure across US counties", Working Paper.

Own-wage elasticity estimate: -0.269 (0.163)

Source of estimate: Simple average of the elasticities for low and high vulnerability counties on p.12. Elasticity estimates (standard errors) for earnings are 0.06 (0.02) and 0.20 (0.03) and for employment are -0.02 (0.02) and -0.05 (0.02). Estimates and standard errors provided from author by email.

Wursten and Reich 2023a

Jesse Wursten and Michael Reich. "Racial inequality in frictional labor markets: Evidence from minimum wages", Labour Economics.

Own-wage elasticity estimate: 0.003 (0.019)

Source of estimate: Weighted average of HSOL ¡ $20 OWEs in Table E4 using shares in Table 2. OWE estimates (and standard errors) are Black 0.04 (0.04); White 0.00 (0.01); and Hispanic -0.01 (0.03). Sample shares are Black 0.11, White 0.71, and Hispanic 0.12.

Wursten and Reich 2023b

Jesse Wursten and Michael Reich. "Small Business and the Minimum Wage", IRLE Working Paper.

Own-wage elasticity estimate: -0.241 (0.182)

Source of estimate: Weighted average of three wage and employment elasticities for restaurants, teens, and young adults, where the weights are the ”Group size in 2019Q4”: Restaurants, Table 3, Firm size All; Teens 14-18, Table 5, Firm size All; Young adults 19-21, Table 6, Firm Size All.

Zavodny 2000

Madeline Zavodny. “The Effect of the Minimum Wage on Employment and Hours”, Labour Economics.

Own-wage elasticity estimate: -0.174 (0.896)

Source of estimate: Employment elasticity from Table 1, specification 1, row ”Log of real minimum wage”. Hourly wage semi-elasticity estimate and standard error from Table 1, specification 7, row ”Log of real minimum wage”, divided by 5.68, reported in Table 2 for the Total sample as the ”Average real hourly wage in the first year”.