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The distributional effects of minimum wages: Evidence from linked survey and administrative data

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Abstract

States and localities are increasingly experimenting with higher minimum wages in response to rising income inequality and stagnant economic mobility, but commonly used public datasets offer limited opportunities to evaluate the extent to which such changes affect earnings growth. We use administrative earnings data from the Social Security Administration linked to the Current Population Survey to overcome important limitations of public data and estimate effects of the minimum wage on growth incidence curves and income mobility profiles, providing insight into how cross-sectional effects of the minimum wage on earnings persist over time. Under both approaches, we find that raising the minimum wage increases earnings growth at the bottom of the distribution, and those effects persist and indeed grow in magnitude over several years. This finding is robust to a variety of specifications, including alternatives commonly used in the literature on employment effects of the minimum wage. Instrumental variables and subsample analyses indicate that geographic mobility likely contributes to the effects we identify. Extrapolating from our estimates suggests that a minimum wage increase comparable in magnitude to the increase experienced in Seattle between 2013 and 2016 would have blunted some, but not nearly all of the worst income losses suffered at the bottom of the income distribution during the Great Recession.

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1 Introduction

Income inequality has increased dramatically in the United States over the last three decades (Piketty and Saez, 2003). Perhaps as a consequence, citizens and policymakers alike have become increasingly concerned about economic mobility, especially over the last decade (Chetty et al., 2014, 2017). At the same time, states have taken steps to increase their minimum wages above the federal minimum, motivated in part by these concerns and supported by research showing that the decline in the real value of the minimum wage in recent decades is associated with increased bottom-tail inequality (DiNardo et al., 1996; Lee, 1999; Lemieux, 2008; Autor et al., 2016). In 2016, 30 states had binding minimum wages above the federal minimum wage, up from 22 in 2006 and 12 in 1996, as illustrated in Figure 1.

Considering the relationship between the minimum wage and aggregate measures of income inequality or mobility in the cross-section is certainly an important line of inquiry, but such analysis provides an incomplete picture of how particular workers' earnings are affected by changes in minimum wage policy. Measures based only on the distribution of observed income may be distorted if truncation of the wage distribution at the minimum wage leads to unemployment (Lee, 1999). Moreover, income volatility is high in the region of the distribution likely to be affected by the minimum wage, so changes in the dollar values associated with low percentiles of the income distribution over time likely reflect the experiences of different people, each with potentially limited direct exposure to employment at or near the minimum wage. In order to understand how changes in the minimum wage affect the long run earnings trajectories of affected workers, one would want to track the minimum wage exposure and earnings of particular workers over time and see if the earnings of those exposed to higher minimum wages grow at a different rate than the earnings of those exposed to lower minimum wages. We aim to provide such evidence here.

Whether raising the minimum wage increases earnings at the bottom of the distribution in the short run depends on the change in wages among employed workers and the change in the probability of being employed. It is clear that workers directly affected by an increase in the minimum wage who remain employed see their wages increase mechanically to at least the new minimum wage. Several studies indicate that some workers whose wages were above the old minimum but near the new minimum before it was established may also see their wages rise due to spillover effects of minimum wage increases (DiNardo et al., 1996; Lee, 1999; Neumark et al., 2004; Lemieux, 2008; Brochu et al., 2015; Autor et al., 2016; Cengiz et al., 2017; Phelan, 2018), with recent estimates indicating that these effects extend up to \$2–\$4 dollars per hour above the new minimum wage and may account for as much as 40 percent of the earnings increase associated with raising the minimum wage.

There is less agreement on the extent to which increasing the minimum wage affects the probability of being employed among affected workers.[1] One strand of the modern literature, originating with Card and Krueger (1994) and exemplified in recent works by Dube et al. (2010); Allegretto et al. (2011); Dube and Zipperer (2015); Totty (2017); and Cengiz et al. (2017), finds minimal change in employment due to increases in the minimum wage. The combination of increased wages and no change in the probability of employment leads increases in the minimum wage to raise incomes at the bottom of the distribution in this context (Dube, 2017).

Another strand of research, distinguished from the first in part by the nature of the controls for local employment trends its models include, finds that raising the minimum wage does reduce employment, at least among certain groups of workers. Neumark and Wascher (1992, 2002) provide canonical examples here, but other researchers have also found reductions in employment or hours due to minimum wage increases (e.g. Neumark et al. 2004; Sabia 2009a,b; Sabia et al. 2009; Even and Macpherson 2014; Meer and West 2016; Jardim et al. 2017). Where employment effects are potentially negative, short-run earnings effects are theoretically ambiguous and in practice can be negative (Neumark et al., 2004).

For questions about medium- to long-run earnings effects of changes in the minimum wage on individual workers, prior research is less informative, because, with a few exceptions, data limitations permit only cross-sectional analysis of individual-level data or panel analysis of aggregate data. Though estimates from some such studies indicate that the immediate effect of minimum wage increases is to raise incomes at the bottom of the distribution, other studies have identified dynamic considerations that could lead an individual's longer-term experience to differ from the earnings change realized immediately after the minimum wage is increased.

Meer and West (2016) find that minimum wage increases may reduce the growth rate of employment rather than the stock of jobs in existence at the time it is increased. If this is the case, the probability of an affected worker being employed could decline over time rather than immediately, potentially leading to a long-run reduction in earnings even if earnings rise in the short run. Similarly, interruptions in employment induced by minimum wage changes, even if they are not permanent, can influence subsequent earnings through their effects on job tenure and experience, as suggested by Neumark and Nizalova (2007). Alternatively, Dube et al. (2016) find that increasing the minimum wage reduces turnover, especially among low-tenure workers. If a higher minimum wage keeps a worker attached to employment, opportunities to move up the job ladder within her firm could lead the long-run change in earnings to exceed that observed

[1] For an excellent review of the literature on employment effects of the minimum wage, as well as reviews of literatures on effects on several other outcomes, see Belman and Wolfson (2014).

in the short run.

There is little empirical evidence on this question, largely due to data constraints. Public datasets commonly used in analyses of minimum wages, including the Current Population Survey (CPS) and Quarterly Workforce Indicators (QWI) data, are not well suited to analyzing income growth because they provide little to no ability to track specific individuals' income over time. Clemens and Wither (2016) provide a notable exception by using the 2008 panel of the Survey of Income and Program Participation (SIPP), finding that binding minimum wage increases slowed income growth. However, it may be difficult to generalize from this setting, as the minimum wage increases and wage growth in question took place during the Great Recession. Phelan (2018) avoids complications due to the recession by using an earlier SIPP panel but focuses on wage growth rather than earnings growth. In addition to the difficulty of tracking individuals' income over time, there is evidence of systematic mismeasurement of income in surveys. Survey questions about income suffer from differential non-response and measurement error that can be especially severe at the bottom of the income distribution (Abowd and Stinson, 2013; Bollinger et al., 2015; Chenevert et al., 2016; O'Hara et al., 2016; Brummet et al., 2018). This measurement error could complicate evaluation of how that region of the income distribution responds to changes in minimum wages.

We address previously binding data constraints by linking responses to the CPS to administrative data on earnings from the Social Security Administration (SSA)'s Detailed Earnings Record (DER). This allows us to consider the importance of measurement error in evaluating distributional effects of minimum wages and to analyze individual-based measures of income growth. Taking the recentered influence function approach of Dube (2017) as our starting point, we begin by replicating his analysis of the effects of minimum wages on the cross-sectional distribution of income using survey data and then substituting administrative measures of earnings where possible. We find that using administrative earnings data does little to change the original result–increasing the minimum wage raises family incomes at the bottom of the distribution. However, administrative and survey data do yield meaningfully different results when we consider the effect of minimum wages on growth incidence curves. Using administrative data, we find that increases in the minimum wage lead to faster growth at low percentiles of the income distribution, with the magnitude of this effect declining to zero around the 15th percentile. Survey data yield noisier estimates that do not follow a discernible pattern.

That growth incidence curve ordinates respond to changes in the minimum wage does not necessarily imply that any particular individual's earnings trajectory will be affected. We thus turn our attention to how minimum wages affect individual mobility profiles constructed using the panel nature of our administrative data. Estimates using a local linear regression technique show that increasing the minimum wage leads to faster income growth at the bottom of the distribution over the following one to five years. Indeed, the effects we identify are larger in magnitude when considering earnings growth over a five-year horizon than over a one-year horizon, indicating that the higher minimum wages that produce the initial increases in earnings at the bottom of the distribution estimated cross-sectionally in prior studies likely do not on average have dynamic or subsequent negative effects that mitigate or reverse those gains. The pattern of point estimates is similar under both our baseline specification, which is based on Dube (2017), and a more parsimonious specification similar to that discussed in Neumark et al. (2014b). The pattern of point estimates is also robust to the inclusion or exclusion of individuals reporting zero earnings. Instrumental variables regressions and subsample analyses splitting the sample into movers and stayers indicate that some of the positive income growth we find at the bottom of the distribution may be attributable to geographic mobility.

The rest of this paper is organized as follows: Section 2 discusses our data in detail, Section 3 lays out our empirical strategies, Section 4 discusses our results, and Section 5 concludes.

2 Data

Consistent with Dube (2017), our analysis begins with the Annual Social and Economic Supplement (ASEC) to the CPS. Conducted in March of each year, the ASEC contains the same set of detailed demographic and labor market variables collected in each month's basic survey, as well as detailed information on income from various sources during the preceding calendar year. We use data from survey years 1991, 1994, and 1996 through 2013.[2] Where we analyze survey-reported income measures directly, we match the approach employed in Dube (2017) as closely as possible. Throughout our analysis, we focus on individuals between the ages of 16 and 64.

As discussed above, cross-sectional data cannot provide insight into how the earnings trajectories of particular workers respond to changes in the minimum wage, and even the one-year panel that is constructible from the CPS has limited capacity to address this question. In order to overcome this limitation, we link CPS respondents to their annual earnings histories obtained from the Social Security Administration's Detailed Earnings Record. The DER contains all earnings reported on a W-2 form, as well as self-employment income that is subject to taxation under the Self-Employment Contributions Act, for each individual in each year.[3] The extract available to us through the Center for Administrative Records Research and Applications

[2] CPS ASEC surveys collected in 1992, 1993 and 1995 have not been processed through the system that assigns unique individual identifiers to each respondent.

[3] Because self-employment losses are not subject to taxation under SECA, the data report only positive self-employment earnings. We include these self-employment earnings in our baseline analysis. Estimates produced using an income measure

(CARRA) at the U.S. Census Bureau contains annual W-2 earnings summed across all jobs for each calendar year from 1979 through 2012 for all individuals who responded to the CPS ASEC between 1991 and 2013. If an individual has no W-2 or self-employment earnings in a year, that person-year is omitted from the DER. We impute zero earnings to individuals who lack a DER record in a given year if they appear in the data with positive earnings in at least one year both before and after the year in question.

The linkage between the CPS ASEC data and the DER data is performed using Protected Identification Keys (PIKs), unique individual identifiers assigned by CARRA's Person Identification Validation System (PVS). This system assigns PIKs to both survey and administrative records based on personally identifiable information like social security numbers, date of birth, place of birth, name, and address. Demographic information that is generally fixed (race, sex, education when observed for adults 25 and older) or progresses deterministically (age) is linked to all years of DER income data. Where we use survey-based income and location information, we match it with DER data from the calendar year to which the CPS ASEC refers.

We use data on the binding minimum wage in each state and year from Vaghul and Zipperer (2016). In order to assign binding minimum wages to each person-year observation, we need data on state of residence. The CPS collects this information, but only while individuals are in sample, i.e. not for the vast majority of person-years covered by the DER earnings history data. In order to assign state of residence to as many person-years as possible, we turn to data from IRS form 1040, as well as data from certain information returns, which we use as our primary source of location information for the sake of consistency. Both 1040s and information returns contain address information, including state of residence. Form 1040 is available to us beginning with the 1998 tax year, and information returns are available beginning in 2005. We again link address information from tax returns to our DER/CPS ASEC panel using PIKs.

Where state of residence from Form 1040 and an information return conflict, we use the data from the 1040. Where no Form 1040 is available and address data from multiple information returns conflict, we use the modal state of residence if possible; if not, we select a state of residence at random from those listed on available information returns.[4] Where no address information is available from tax returns for a year in which an individual responded to the CPS ASEC, we use the state of residence reported in the survey. For person-years in which we observe no state of residence information, we impute state of residence if valid observations of residence in the same state are available both before and after the observation in question. Otherwise, the observation is omitted from our analysis.

that excludes self-employment earnings are similar.

[4]Because we are analyzing state-level changes in minimum wages, we need only identify each individual's state of residence. The share of people for whom address information available from tax forms is conflicted as to state of residence is negligible.

3 Empirical Strategy

We employ three different estimation techniques to analyze how the minimum wage affects the distribution of income, growth in the dollar values associated with each percentile, and the earnings trajectories of individuals who begin at each percentile.

3.1 Cross Sectional Distributional Effects

We begin by analyzing the effect of the effective minimum wage on the cross-sectional distribution of income (and wages). To do this, we use the same recentered influence function (RIF) regression methodology used in Dube (2017). RIF regressions are a tractable way to estimate distributional effects of policies (such as the minimum wage). The influence function $IF(y, \nu)$ is commonly used in robust statistics, and, as the name suggests, captures the influence of a single observation y on a distributional statistic ν. The recentered influence function is constructed by adding back the value of the distributional statistic so that $RIF(y, \nu) = IF(y, \nu) + \nu$. The recentered influence function has the useful property that

$$\nu = E(RIF(y, \nu)) = E[E(RIF(y, \nu)|X)\} \tag{1}$$

The RIF for the pth quantile point v_p is defined as

$$RIF(y, v_p) = \begin{cases} v_p + \frac{p}{f(v_p)} & \text{if } y > v_p \\ v_p - \frac{1-p}{f(v_p)} & \text{if } y < v_p \end{cases}$$

Due to the property in equation 1, a regression estimated with this RIF as the dependent variable, and policy and demographic variables of interest can be used to assess how a policy (such as the minimum wage) affects specific quantiles of the income distribution. The parameters of an RIF regression have a non-intuitive interpretation (the effect of a small location change in variable X on the functional of interest, in this case the quantile). So, to ease interpretability, we present our estimates as elasticities by dividing through by the quantile (since as noted, $E(RIF(y, v_p)) = v_p$).

To estimate the effects of the minimum wage on the distribution of family incomes, we estimate regressions of the form:

$$RIF(y_{ist}, v_p) = \alpha_{d(s),t} + \alpha_s + \alpha_t + \gamma_s t + \gamma_s Recession_t + \sum_{j=-1}^{3} \beta_j log(MW_{s,t-j}) + \Gamma X_i + \theta X_{st} + e_{ist}$$

This corresponds to the most saturated specification from Dube (2017) and includes three lags and one lead of the minimum wage in addition to a contemporaneous measure ($log(MW_{s,t-j})$), Census division-by-year ($\alpha_{d(s),t}$), state (α_s) and year (α_t) fixed effects, state-specific linear trends ($\gamma_s t$), and state-by-recession-year ($\gamma_s Recession_t$) fixed effects; individual demographic characteristics (X_i); and state-level time varying aggregate confounders (X_{st}) including the unemployment rate and output per capita.[5] Standard errors are clustered at the state level.

Individually, the β_j coefficients represent the effect of the minimum j years from the base year on the pth percentile of the earnings distribution in the base year. Lagged measures of the minimum wage are included to allow for the possibility that such effects may not be realized immediately (e.g. if changes in the minimum wage lead to changes in employment or earnings with a two year lag, the minimum wage from year $t-2$ may have an effect on the pth percentile of the earnings distribution in year t). The lead measure serves as a control for possible differential trends across states that may not be captured by the included fixed effects and state-specific linear trends. Here we focus on the sum of the β coefficients from the lagged and contemporaneous minimum wage measures, which Dube terms the minimum wage long-run (i.e. incorporating both lagged and contemporaneous effects) semi-elasticity for the unconditional quantile partial effect at the pth percentile of family income.

3.2 Growth Incidence Curves

In addition to studying the cross-sectional distributional effects of minimum wages, a topic which has been well-studied, we also extend the distributional analysis to study how minimum wages affect absolute earnings mobility (or earnings growth), a topic largely absent from the minimum wage literature. We consider the effects of minimum wages on earnings mobility in two ways: first, we consider the effect of minimum wages on the earnings growth at percentiles of the wage distribution, and second, we consider how minimum wages affect individual earnings growth. These two concepts correspond to growth incidence curves and income mobility profiles, respectively.

A growth incidence curve between two years describes the income growth rate at each percentile of the initial income distribution. Figure 2 provides an example that depicts growth between 2005 and 2010 across the distribution. Formally, let γ be the overall income growth rate between the two years. The pth growth

[5] Dube's estimating equations indicate that his specifications include one lag and three leads of the minimum wage in addition to a contemporaneous measure ($log(MW_{s,t-j})$). However, his descriptions of his estimates indicate that his specifications instead include three lags and one lead. Consistent with those descriptions and our own judgment, we include three lags and one lead.

incidence curve ordinate is

$$GIC(p) = \gamma q(v_p)$$

Where $q(x)$ is the growth pattern – the proportion of average growth accruing the xth percentile of the initial income distribution. Growth incidence curve ordinates can be analyzed using a similar recentered influence function regression methodology to the quantile results above. The recentered influence function for the pth GIC ordinate is given by (via Essama-Nssah and Lambert 2012):

$$RIF(y, GIC_p) = \begin{cases} \gamma\{(\frac{y}{\mu_F} + 1)q(v_p) + \frac{pq'(v_p)}{f(v_p)}\} & \text{if } y > v_p \\ \gamma\{(\frac{y}{\mu_F} + 1)q(v_p) + \frac{(1-p)q'(v_p)}{f(v_p)}\} & \text{if } y < v_p \end{cases}$$

Since there are multiple pairs of years in the repeated cross-section sample, we calculate this RIF for all overlapping pairs of years, indexing by the base year. So for example, In our analysis of the one-year GIC RIF, we stack the 1998-1999 GIC with the 1999-2000, 2000-2001, etc. GIC RIF, and assign time-varying state variables and minimum wage changes according to the base year. We once again estimate a fully saturated dynamic model of the form

$$RIF(y_{ist}, GIC_p) = \alpha_{d(s),t} + \alpha_s + \alpha_t + \gamma_s t + \gamma_s Recession_t + \sum_{j=-n}^{3} \beta_j log(MW_{s,t-j}) + \Gamma X_i + \theta X_{st} + e_{ist}$$

where t now indexes the base year of a growth incidence curve and n is the number of years between the base year and the year used to measure earnings growth. Standard errors are clustered at the state level. We estimate these models for one- and five-year GICs using the internal CPS cross-sectional data. In this setting, we focus our discussion on the sum of all β_j coefficients, thus including more slowly developing effects of changes in the minimum wage prior to the base year as well as effects of changes that occur during years between the base year and the year used to measure wage growth. We calculate GICs using individual earnings, again contrasting survey-only wage data with wage data from the SSA DER.

3.3 Income Mobility Profiles

Growth incidence curves are anonymous, in that the identities of individuals in two years are irrelevant for calculating an index – only their normalized rank is relevant. However, if there is any re-ranking over time, then the income growth summarized by the growth incidence curve will not necessarily reflect the actual individual income growth experienced by any given individual. An alternate, non-anonymous method of measuring individual income growth is to examine instead "income mobility profiles" (van Kerm, 2009), which may more closely align with the earnings trajectories experienced by individuals.

Intuitively, income mobility profiles summarize the average individual income growth experienced by individuals who start out at a given percentile of the earnings distribution. More formally, following van Kerm (2009), let X denote earnings in the base year and Y denote final year earnings so that $F_{Y|X=x}$ is the conditional distribution of earnings in the final year conditional on a given level of base year earnings. Then let the pth ordinate of the income mobility profile be defined as

$$m(p) = \int_{z_-}^{z_+} \delta(x(p), y) dF_{Y|X=x(p)}(y)$$

where $\delta(.)$ is a measure of individual earnings growth between the base year and final year, and $x(p) = F_X^{-1}(p)$. Graphing this income mobility profile $m(p)$ against the percentiles of the base year distribution p provides a visualization of how individual earnings growth varies across the initial earnings distribution. Figure 3 provides an example that depicts income mobility profiles between 2005 and 2010 across the distribution. Note that the change in wage and salary earnings between 2005 and 2010 for individuals who began at low percentiles of the distribution differs substantially from the change in the amount of wage and salary earnings associated with those percentiles (depicted in Figure 2 over that same period). Changes in earnings throughout the distribution affect the dollar values associated with each percentile, while changes in earnings among those who start at low percentiles are more likely to be large in percentage terms (relative to lower base levels of earnings) and positive (e.g. due to mean reversion among workers with temporarily low earnings).

Our approach to estimating the effect of the minimum wage on individual earnings growth captured by an income mobility profile concept differs from the RIF approach for GICs above in two ways. Estimating the effect of minimum wages on income mobility profiles requires that individuals can be linked over time, whereas, because GICs are anonymous, no data linkage is strictly necessary to estimate the RIF regressions in 3.2. More importantly, however, because income mobility profiles summarize the joint distribution of base year and final year earnings, the RIF approach is no longer feasible.

To capture the effect of minimum wages on individual income growth we instead adopt a local linear regression approach, estimating the effect of minimum wages on income growth for a narrow bin around a given percentile of the base year distribution. Specifically, we estimate local linear regressions with a rectangular kernel of the form

$$\delta(x,y) = \alpha_{d(s),t} + \alpha_s + \alpha_t + \gamma_s t + \gamma_s Recession_t + \sum_{j=-n}^{3} \beta_j log(MW_{s,t-j}) + \Gamma X_i + \theta X_{st} + e_{ist} \quad (2)$$

where $x \in [x(p-0.025), x(p+0.025)]$, for each $p \in 1, 2, ..., 99$, and n is the number of years between the base and final years.[6] Then the sum of the lags and leads of the minimum wage coefficients $\sum_{j=-n}^{3} \beta_j$ as the total effect of minimum wages on n-year ahead earnings growth. Standard errors are clustered at the state level.

We define the distance function $\delta(x, y)$ as either $log(y) - log(x)$ or $asinh(y) - asinh(x)$. In both cases, we can interpret the total effect as a partial elasticity – the effect of a 1 percent increase in the nominal minimum wage on n-year ahead income growth rate (measured in percentage points). As in the GIC, we focus our discussion on the sum of all the β_j coefficients. The two $\delta(x, y)$ functions allow us to investigate the effect of minimum wages on a transition to or from full-year unemployment – since $log(y) - log(x)$ is undefined if earnings are zero in either the base year or final year, and so regressions using this distance function summarize the intensive margin effects on individuals who have positive earnings in both years. However, since the inverse hyperbolic sine function is well-defined for zero earnings, regressions using $asinh(y) - asinh(x)$ as a distance function summarize both the intensive margin effects and potential extensive margin effects for individuals with positive earnings in the base year but zero earnings in the final year.

4 Results

Using the strategies described in the previous section, we investigate how changes in the minimum wage affect the distribution of income. Although the details of the estimates differ, we consistently find that raising the minimum wage increases incomes at the bottom of the distribution and that this increase persists for several years.

[6] In principle, it is possible to add individual fixed effects to this estimating equation. We calculate n-year ahead earnings growth using each pair of years for which the calculation is feasible given our data, so individuals could appear in a given regression multiple times. However, with individual fixed effects included, the coefficient of interest is identified only by within-person variation in minimum wage exposure. Because of the way we estimate effects on income mobility profiles, this amounts to requiring that individuals appear in the same relatively narrow income range more than once in order to be included in the sample (an individual whose earnings were near the fifth percentile in only one year, for example, would only appear in our fifth percentile sample as a single observation, and an individual fixed effect would effectively remove that person from the sample). Since the outcome being analyzed is earnings growth, limiting the sample to individuals whose earnings are repeatedly in the same region of the distribution is conceptually unappealing and would likely bias our estimates toward zero. As such, we do not include individual fixed effects in any of our income mobility profile analyses.

4.1 Cross Sectional Distributional Effects

We begin by producing cross-sectional estimates of the effects of the minimum wage on the distribution of income using the strategy described in Section 3.1 that mimics the one employed in Dube (2017).[7] In addition to producing estimates that rely exclusively on self-reported measures of income from the CPS ASEC, we also produce estimates that incorporate administrative earnings data. In addition to replicating the Dube result as closely as possible as a starting point for subsequent analyses, we also investigate whether those estimates are sensitive to the source of income data used to produce them. The fact that non-response rates in the CPS ASEC vary across the distribution of income and are higher in the tails is well documented, and variation in measurement error across the income distribution has been identified in multiple surveys (Abowd and Stinson 2013; Bollinger et al. 2015; Chenevert et al. 2016; O'Hara et al. 2016; Brummet et al. 2018), estimates based on administrative earnings data could differ from those based on survey data.

Figure 4 presents these cross-sectional estimates. The solid line represents the sum of the lagged and contemporaneous β_j coefficients from the estimating equation in Section 3.1, while the shaded area represents the 95 percent confidence interval associated with that sum. The first panel, on the left, is based exclusively on self-reported family income from the CPS. The middle panel is based exclusively on administrative earnings data from the DER, aggregated to the family level.[8] The third panel, on the right, is based on a hybrid measure of family income that is constructed by replacing the self-reported wage and salary component of family income with the administrative measure of wage and salary income wherever possible.

All three panels show a pattern of estimates that is qualitatively similar to the one presented in Dube (2017): the elasticity of family income with respect to the minimum wage tops out at about 0.5 near the fifth percentile and then gradually declines in magnitude moving up the distribution. The estimates based on CPS ASEC and hybrid income measures are statistically significant between roughly the fifth and 15th percentiles. Estimates based on the DER income measure are generally not statistically significant, though this appears to be due to lower precision in these estimates, as the pattern of point estimates is very similar to the CPS ASEC and hybrid cases. This similarity leads us to conclude that the effects of the minimum wage on the distribution of family income reported in Dube (2017) and approximately replicated here does not merely arise from changes in measurement error but are rather driven by changes in actual earnings.

[7] The estimates presented here align most closely with those presented in Figure 5 of Dube (2017). Dube refers to these estimates as "long-run elasticities," as opposed to "medium-run elasticities" based on fewer lagged minimum wage measures. As we do not consider such distinctions here, we will refer to our estimates simply as elasticities.

[8] Note that this measure differs conceptually from the CPS income measure, as the DER includes only wage and salary earnings and SECA-taxable self-employment earnings, while the CPS measure includes income from all sources, including, for example, businesses, dividends, social security, or child support, among many others.

4.2 Growth Incidence Curves

Next, we consider the effects of the minimum wage on growth incidence curves, using the methodology described in Section 3.2. For this analysis and the subsequent analysis of income mobility profiles, we work at the individual level and use wage and salary income rather than family income. Because growth incidence curves are anonymous and estimation does not require repeat observations of specific individuals, we produce estimates based on both CPS ASEC and DER measures of wage and salary income.

Figure 5 shows estimates of the effects of the minimum wage on one-year-ahead growth incidence curves. Figure 6 shows five-years-ahead estimates. Here, the solid line represents the sum of all the β_j coefficients from the estimating equation in Section 3.2, and the shaded area is the associated 95 percent confidence interval. The left panel depicts estimates based on the CPS ASEC measure of wage and salary earnings, while the right panel is based on the DER wage and salary measure.

Unlike the cross-sectional estimates, the growth incidence curve estimates do differ significantly across income measures. In both Figures 5 and 6, the point estimates based on the CPS ASEC income measure are noisier across the distribution than those based on the DER income measure, and they do not suggest that the effects of the minimum wage are concentrated at the bottom of the distribution, as one might expect based on the results from the previous section. In contrast, the point estimates based on the DER income measure change relatively smoothly over the income distribution, and the pattern that emerges is similar to the one depicted in Figure 4. It is worth highlighting that while it would have been technically feasible to estimate effects of the minimum wage without access to data from the DER, doing so would have produced inconsistent and imprecise results, as illustrated by these figures. The improvements in the stability and in some cases precision of these estimates associated with using the administrative earnings measure serve as another demonstration of the potential benefits of using such data. While we do not provide any evidence as to why the relationship between the minimum wage and earnings growth at the bottom of the distribution is smoother and more stable with administrative data than with survey data, if survey data from low-income workers are differentially affected by non-response and misreporting that obscures the nature of that relationship, replacing those data with more accurate administrative records could change these estimates in the way we observe.

Comparing the DER panels of Figures 5 and 6 indicates that the growth at low percentiles of the earnings distribution persists for several years. Looking one year ahead in Figure 5, point estimates of the earnings elasticity with respect to the minimum wage are largest near the bottom of the distribution, reaching about 0.4 and then declining to approximately zero around the 15th percentile. However, only the estimate for the eighth percentile is statistically significant. Looking five years ahead in Figure 6, the pattern of estimates is similar, but the magnitudes of the estimates at the bottom of the distribution are larger. At the fifth percentile, for example, the five-years-ahead elasticity is about 0.75, while the one-year-ahead elasticity is about 0.25. Moreover, the five-years-ahead estimates are statistically significant between the third and eighth percentiles. The five-years-ahead estimates still decline to approximately zero around the 15th percentile. Comparing these estimates suggests that the effects of the minimum wage on the bottom of the earnings distribution may grow in magnitude over time, but that growth is concentrated in the region of the distribution that was immediately affected; the influence of the minimum wage does not appear to move further up the distribution over time.

4.3 Income Mobility Profiles

Finally, we examine how changes in the minimum wage affect the earnings trajectories of workers with initial earnings at different points in the distribution, estimating these effects as described in Section 3.3. As the dependent variable here is the percent change in earnings between the base year and some year in the future, and the measures of the minimum wage on the right-hand side remain in logs, the estimates produced in this section are semi-elasticities rather than elasticities. Figure 7 depicts the effects of the minimum wage on earnings growth after one year, while Figure 8 presents analogous estimates looking five years ahead. As with our growth incidence curve analysis, the solid line represents the sum of all the β_j coefficients, and the shaded area is the associated 95 percent confidence interval.[9]

Again, the minimum wage has its largest effects on earnings growth at the bottom of the distribution. After one year, point estimates of the semi-elasticity of earnings with respect to the minimum wage top out around 0.7 at the third percentile before declining to approximately zero temporarily around the 15th percentile and permanently around the 25th percentile. These estimates are only statistically significant at a few percentiles. After five years, estimates have grown in magnitude at the bottom of the distribution, reaching approximately 1.9 at the second percentile. The decline in the magnitude of the semi-elasticity estimates over the distribution is more gradual five years out, as they reach zero around the 30th percentile. Estimates at several additional percentiles are statistically significant in this setting, including a few around the 20th percentile.[10]

[9] We allow the scale of the y-axis to vary across our main figures in order to facilitate assessment of variation in our estimates across the earnings distribution. However, if our figures are considered at a glance, varying scales may obscure differences in the magnitudes of our estimates across specifications. We present fixed-scale versions of our main income mobility profile figures in Appendix A to enable easy cross-specification comparisons.

[10] Throughout the main text of this paper, we analyze the effects of changes in the nominal minimum wage. However, our results are robust to instead using the real value of the minimum wage. See Appendix B for reproductions of select figures

While we do not directly investigate specific pathways by which raising the minimum wage increases earnings growth, the fact that we find effects that appear to grow in magnitude and move up the distribution over time may provide suggestive evidence regarding some possible mechanisms. For example, one way in which a higher minimum wage might increase average wage growth could be by raising the floor below workers who experience involuntary separations from better-paying jobs but manage subsequently to find minimum wage employment (i.e. replacing a $12 per hour job with a $9 per hour job leads to earnings growth that is less negative, conditional on hours, than replacing it with an $8 per hour job would). But while this mechanism may be operative to some extent, it is not clear why this effect would grow in magnitude or move up the distribution over time. On the other hand, if higher minimum wages reduce turnover and keep workers on job ladders within their firms, opportunities for promotion over several years could lead to earnings growth effects that are larger after five years than after one. Similarly, while existing evidence points to spillover effects that raise the wages of workers who earned more than the minimum wage prior to a given increase, those spillovers do not reach all the way up the pay scale, leading to some degree of compression. If firms gradually decompress their pay scales over time, e.g. in order to reestablish distinctions between or hierarchies among workers, the effects of increasing the minimum wage on earnings growth could extend further up the distribution after five years than after one. Of course, other possibilities remain, and investigating them further would be a fruitful avenue for future research.

The semi-elasticity estimates we produce at the bottom of the distribution may seem large in isolation, but when placed in context, their magnitudes appear more reasonable. The estimates we present are played out over the course of several years (up to nine in the case of our five-years-ahead estimates). As semi-elasticities, each coefficient included in the sum we present corresponds to a 100 percent increase in the minimum wage. Interpreted directly, the estimates we present correspond to the change in earnings growth that would be realized if the minimum wage were doubled. Rescaled to a more reasonable change in the minimum wage (a ten percent increase, say), our estimates indicate that wage growth at the second percentile five years later would be about 19 percentage points higher. That may still seem like a large effect, but this represents the effects of a ten percent increase in the minimum wage as it plays out over the course of the nine-year window covered by the lags and leads included in these regressions. Moreover, average five-year earnings growth among workers beginning at the second percentile is very large in percentage terms. For example, Figure 3 shows that between 2005 and 2010, the average worker whose earnings were in the second percentile in 2005 had earnings that were over 250 percent higher in 2010, despite the intervening Great

portraying the effects of the minimum wage on income mobility profiles based on regressions that use lags and leads of the real minimum wage as independent variables.

Recession. In this context, a 19 percentage point increase in earnings among workers starting at the second percentile due to a ten percent increase in the minimum wage represents an increase in earnings growth on the order of seven to eight percent relative to the mean.

4.3.1 Alternative Controls for Regional Time-Varying Heterogeneity

Our baseline specification for estimating the effects of minimum wages on individual income growth controls for regional time-varying heterogeneity through the inclusion of state-specific linear trends, state-specific recession-year controls, and region-by-year fixed effects, in addition to the standard two-way (state and year) fixed effects that are consistent across almost all state-variation based papers in the minimum wage literature. This literature has a long history of arguments about whether this saturated specification is the proper way to estimate the effects of minimum wages. One strain of literature (e.g. (Allegretto et al., 2011)) has advocated for a maximalist strategy of controlling for as much time-varying heterogeneity as possible, which we have adopted in our baseline specification. We take this approach in part because Totty (2017) finds that the unobserved heterogeneity captured by factor model estimators when estimating minimum wage employment elasticities resembles the type of time-varying regional heterogeneity one might expect to capture using state-specific time trends. However, another strain of literature (e.g. (Neumark et al., 2004, 2014b,a)) has argued that these saturated specifications either throw out good variation with the bad or may be "bad controls." They suggest using more parsimonious specifications without state-specific trends or recession controls.

It is noteworthy that these arguments are not (purely) methodological, as using these two sets of specifications to study the effects of minimum wages on employment tend to result is substantially different effects, with the parsimonious specification tending to find larger, more negative effects on employment, while the saturated specification tends to result in statistically insignificant and occasionally positive effects on employment. Studies of the effect of minimum wages on wage levels, however, tend to be more consistent across specifications. To assess whether our baseline results are driven by our choice of a saturated specification, we thus estimate similar local linear regression models as above, but using a more parsimonious specification including state and year fixed effects and excluding controls for time-varying heterogeneity across regions.[11]

Figure 9 summarizes the results of local linear regression models of the total dynamic effect of minimum wages on income growth with a parsimonious, two-way fixed effects specification for a one-year ahead income

[11] We also estimate specifications that include state, year, and census division by year fixed effects but do not include state-specific linear trends. We see these specifications as representing an intermediate degree of saturation, between the parsimonious two-way fixed effects model and our baseline specification. These estimates are presented in Appendix C and generally fall between the baseline estimates and the estimates from the parsimonious specification discussed below.

growth definition, and Figure 10 looks five years ahead. Although the effect sizes are somewhat attenuated in this specification relative to the baseline analysis, and the pattern of point estimates that is evident in the baseline analysis is less discernible across the base year earnings distribution looking one year ahead, the pattern of (relative) effect sizes does re-emerge when considering earnings five years ahead. The five-year estimates are also generally larger in magnitude than the one-year estimates over the most affected region of the base year earnings distribution (up to roughly the 20th percentile), a phenomenon that is also clearly observed in estimates derived from our baseline specification. Thus, point estimates from both the saturated and parsimonious specifications indicate that the effects of the minimum wage on earnings growth are largest at the bottom of the distribution and larger after five years than after one year, though they differ somewhat on the magnitude of these effects.

4.3.2 Incorporating Non-Employment

Modern minimum wage research has long recognized that potential disemployment effects complicate analyses of how the distribution of wages responds to minimum wage increases (Lee, 1999). If the truncation of the wage distribution associated with the minimum wage affects who is employed, the change in the density of the observed wage distribution will not reflect wages lost by newly non-employed workers. Recent work has addressed this complication by splitting the wage distribution into bins and analyzing hazard functions or frequency distributions (Brochu et al., 2015; Cengiz et al., 2017). These issues are less severe when analyzing earnings rather than wages because the minimum wage does not directly truncate the earnings distribution. However, employment effects remain an important consideration.

Our baseline specification partially incorporates employment effects because earnings are measured on an annual basis. A minimum wage increase could lead to a net reduction in annual earnings despite mechanically increasing an individual's hourly wage if it also reduces the fraction of the year that individual is employed. When we measure earnings growth by taking the difference in log earnings between the base year and some year in the future, this potential response would be reflected in our measure as long as an individual has positive earnings in both years. However, some individuals do go entire years without any wage or salary earnings, and to the extent that they do so because of changes in the minimum wage, we would want our estimates to incorporate that response as well. Because the natural logarithm is not defined at zero, our baseline specification excludes individuals who have zero earnings in either the base year or the year we use to measure earnings growth and do not capture earnings changes due to full-year non-employment induced by changes in the minimum wage.

In order to capture earnings changes arising from full years of non-employment, we re-estimate our baseline specification with the change in earnings calculated using the inverse hyperbolic sine transformation instead of the log transformation. The percent difference approximation associated with differences in logged values also holds for the inverse hyperbolic sine, but the inverse hyperbolic sine has the additional benefit of being defined at zero.

Figures 11 and 12 show our estimates of the effects of the minimum wage on one- and five-year-ahead income mobility profiles, respectively. Both show patterns of point estimates that are similar to and not statistically distinguishable from those presented in our baseline analysis, though estimates at the bottom of the distribution are less precise and change somewhat less smoothly across percentiles. No percentile sees statistically significant changes in one-year earnings growth due to the minimum wage in this specification, and only a few see statistically significant effects looking five years ahead.

We also consider how increases in the minimum wage might differentially affect the probability of having no wage and salary earnings in the years we use to assess earnings growth for people with base year earnings at different points in the distribution. Figure 13 shows changes in the probability of having zero wage and salary earnings one year ahead, while Figure 14 reports analogous estimates looking five years ahead. Most of these estimates are not statistically significant, especially five years ahead, and they are relatively small in magnitude once contextualized as in Section 4.3, but the point estimates align with the baseline and inverse hyperbolic sine estimates in intuitive ways. Regions of the distribution in which the inverse hyperbolic sine estimates (which incorporate observations with zero earnings for the full year) are more negative/less positive than the baseline estimates (which do not) also tend to have higher probabilities of having no wage and salary earnings, and vice versa.

In general, our semi-elasticity estimates for the most affected part of the base-year income distribution are more positive when we consider earnings growth over five years than over one year. This pattern holds even when earnings growth is measured using the inverse hyperbolic sine formulation, which incorporates complete non-employment in the measurement year into the estimates, and when regressions do not include controls for time-varying heterogeneity across place, a specification that tends to produce more negative estimates of the effects on the minimum wage on employment. The fact that our estimates become more positive over longer horizons rather than reverting to zero or becoming negative suggests that earnings gains at the bottom of the distribution are on average preserved and reinforced rather than mitigated by dynamic or more slowly developing effects of minimum wage increases.

4.3.3 The Role of Geographic Mobility

Our analysis of the effects of minimum wages on income mobility has thus far been agnostic as to how this income mobility in fact occurs. This has been largely due to the fact that interrogating mechanisms requires more data than we have–we do not observe hours worked or hourly wages, for instance. We do, however, observe individual's locations over time, so we can investigate the degree to which geographic mobility may act as a mediating force for the baseline results in, for example, Figure 7. We investigate the implications of geographic mobility for our results in three ways: we stratify results by geographic mobility, instrument for minimum wages by the minimum wage in the base year state, and directly examining the effect of minimum wages on mobility.

We first directly examine whether minimum wages induce individuals to move across state lines – any such effect would be expected to be concentrated at the bottom of the income distribution. To do this, we estimate regressions of the form in Equation 2 with an indicator for whether an individual lived in a different state in the final year relative to the base year. Figure 15 summarizes the results of these local linear regressions for a one-year-ahead mobility window. The results across the income distribution uniformly point to a null (albeit imprecisely estimated) effect of minimum wages on mobility. Results are essentially identical for a five-year-ahead mobility window, which again suggests there are no direct effects of minimum wages on mobility.

Even if minimum wages have no effect on mobility properly, it may nonetheless be the case that there are heterogeneous effects of minimum wages on income mobility for individuals who move versus individuals who stay in the same state. We examine this potential heterogeneity by re-estimating the baseline income mobility regressions, now stratifying the sample into "movers" and "non-movers." We define movers as individuals who moved to a different state in any year after the base year within the income growth window. We estimate one- and five-year window versions of these stratified regressions, which are summarized in Figures 16 and 17. In both income growth windows, there is evidence that minimum wages increase income growth at the bottom of the income distribution for movers, but little to no evidence of any statistically significant effects for non-movers.

Although we find no direct evidence that minimum wages directly induce interstate mobility, the heterogeneous effects across movers and non-movers may be an indication of a potentially endogenous sorting process. To assess whether this sorting may be biasing our baseline results, we consider a final set of instrumental variables models. In these models, we instrument for the leading log minimum wage terms using minimum wages from each individual's base-year state of residence (so, for example, an individual who moved from Michigan to California would have Michigan's minimum wage in the final year as instruments for California's minimum wage in the final year). Figures 18 and 19 report estimates of these IV regressions for one-year-ahead and five-year-ahead income growth windows. In both cases, we see broadly similar patterns of effect sizes across the income distribution, with larger effects at the bottom of the distribution, and small, insignificant effects past the 15th percentile. Particularly in the five-year-ahead case, the effects are less precisely estimated than the OLS effects (although this is expected in IV estimation). The qualitative similarity in effects across the income distribution for the IV results and the baseline OLS results suggests that geographic mobility, while important for the story, and the source of heterogeneous impacts, is likely not an endogenous driver of the minimum wage-income mobility effect, bolstering the case that the effects of minimum wages on income growth estimated here are in fact causal.

5 Conclusion

Understanding how minimum wage increases affect earnings growth is critical, particularly as states and localities experiment with higher minimum wages in response to rising income inequality and stagnant economic mobility. Previous cross-sectional work has found that increasing the minimum wage raises family incomes at the bottom of the distribution, but if minimum wages also change labor market dynamics, individuals who have higher earnings at a point in time due to an increase in the minimum wage may see those gains reversed, or intensified, over time.

Most public datasets commonly used in the minimum wage literature have limited ability to address how earnings growth responds to minimum wage increases because they are either composed of repeated cross-sections or have panel dimensions that cover relatively limited periods of time. Moreover, since error in survey measurement of income may vary across the distribution, using survey data to analyze the earnings response to minimum wage changes among workers at the bottom of the distribution could potentially produce misleading results if, for example, actual and reported earnings are differentially responsive to changes in policy.

In this paper, we take advantage of administrative earnings data from SSA linked to the CPS ASEC first to assess the importance of measurement error in cross-sectional estimates of the earnings effects of minimum wage increases. We find that cross-sectional estimates of the effects of the minimum wage on earnings at a point in time are little affected by computing family income using administrative measures of wage and salary earnings in combination with survey-based measures of income from other sources rather than using strictly survey-based income measures. However, when we focus specifically on wage and salary earnings and estimate growth incidence curves cross-sectionally, we do find meaningful differences between estimates produced using survey and administrative data. Survey-based estimates are generally noisy and not statistically significant, indicating no particular pattern of response to changes in the minimum wage across the distribution. Estimates of effects on growth incidence curves based on administrative data resemble the point-in-time estimates, with higher growth in the value of low percentiles of the earnings distribution.

In light of current efforts to raise state and local minimum wages to historically high levels, we consider how the distribution of earnings might have evolved differently if the minimum wage had been substantially higher during recent periods of economic expansion and contraction. Specifically, we consider what our growth incidence curve results (from the right panel of Figure 6) imply about how a 37 percent increase in the binding minimum wage (comparable in magnitude to the well-publicized recent increase in the minimum wage in Seattle, WA from $9.47 to $13 per hour) would affect income growth across the income distribution from two baselines: the 1994–1999 five-year ahead growth incidence curve and the 2005-2010 growth incidence curve. These two baselines characterize income growth during the largest expansion and recession in recent history, respectively. Figures 20 and 21 summarize these thought experiments. The results are striking: during an expansion, these thought experiments suggest that large increases in minimum wages substantially increase the progressivity of growth. On the other hand, while a large increase in minimum wages would blunt the worst of the income losses during the Great Recession, even a very large increase is not sufficient to reduce these income losses to zero.

We then use the administrative earnings data to conduct longitudinal analyses of how the earnings of workers who begin at different percentiles of the distribution respond to changes in the minimum wage by estimating effects on income mobility profiles. Again, the pattern of effects we find resembles that exhibited by the point-in-time and growth incidence curve estimates. Raising the minimum wage increases earnings growth for workers with base-year earnings near the bottom of the distribution. Our estimates suggest that a persistent ten percent increase in the minimum wage would increase earnings growth over five years by about seven to eight percent relative to the mean for workers beginning at the lowest percentiles of the distribution. The magnitude of our estimates generally declines to approximately zero by the 15th to 30th percentile, depending on the specification. This effect persists when measuring earnings growth up to five years ahead, and it is robust to a variety of alternative specifications. Our instrumental variables and subsample analyses suggest that geographic mobility contributes to the increase in earnings growth we find, although geographic mobility itself is not directly caused by minimum wages. These results suggest that individuals who are able to move across state lines capture the bulk of the income growth benefits of minimum wage increases.

Perhaps the most consistent through-line in our results is that raising the minimum wage increases earnings at the bottom of the distribution whether we estimate these effects using cross-sectional or longitudinal data, and our estimates of effects on earnings growth, both using the growth incidence curve and income mobility profile approaches, resemble the cross-sectional estimates from Dube (2017). Without taking any particular position on whether or to what extent they may be occurring, our income mobility profile analysis is equipped to capture potentially adverse earnings effects associated with increases in the minimum wage, such as any that might arise from changes in labor market dynamics, reduced hours, or decreased probability of employment over several years. The fact that our estimates remain positive at the bottom of the distribution despite being net of such possible negative effects suggests that higher wages outweigh those factors that would tend to reduce earnings among workers who are arguably most likely to experience them. Moreover, the fact that our estimates for the most affected region are more positive over longer horizons suggests that this balance is likely not reversed or mitigated over time on average. Indeed, our baseline estimates are sufficiently precise to rule out five-year earnings growth semi-elasticities more negative than about -0.3 throughout the distribution, and we can rule out substantially negative earnings growth effects over five years within the bottom quartile of the distribution, where one might expect workers to be most directly affected by changes in the minimum wage.

Further investigating the contributions to earnings growth of these various possible responses to changes in the minimum wage remains a fruitful avenue for future research. Specifically, the relationships between the minimum wage, earnings growth, changes in the probability of employment, job turnover, duration of employment, and job and employer characteristics deserve particular attention. Additionally, the connection between minimum wages, income growth and the business cycle is an important future avenue of research, given the thought experiment in Figure 21. Administrative data on employment and earnings, especially higher frequency data linked to information on employers such as the Longitudinal Employer-Household Dynamics (LEHD) database, will be especially useful in studying these questions.

References

Abowd, J. and Stinson, M. (2013). Estimating measurement error in annual job earnings: A comparison of survey and administrative data. *Review of Economics and Statistics*, 95(5).

Allegretto, S., Dube, A., and Reich, M. (2011). Do minimum wages really reduce teen employment? Accounting for heterogeneity and selectivity in state panel data. *Industrial Relations*, 50(2):205–240.

Autor, D. H., Manning, A., and Smith, C. L. (2016). The contribution of the minimum wage to US wage inequality over three decades: A reassessment. *American Economic Journal: Applied Economics*, 8(1):58–99.

Belman, D. and Wolfson, P. J. (2014). *What Does the Minimum Wage Do?* W.E. Upjohn Institute for Employment Research, Kalamazoo, MI.

Bollinger, C. R., Hirsch, B. T., Hokayem, C. M., and Ziliak, J. P. (2015). Trouble in the tails? Earnings nonresponse and response bias across the distribution. Working paper.

Brochu, P., Green, D. A., Lemieux, T., and Townsend, J. (2015). The minimum wage, turnover, and the shape of the wage distribution. Working paper.

Brummet, Q., Flanagan-Doyle, D., Mitchell, J., Voorheis, J., Erhard, L., and McBride, B. (2018). Investigating the use of administrative records in the consumer expenditure survey. CARRA Working Paper Series, Working Paper 2018-01.

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

Cengiz, D., Dube, A., Lindner, A., and Zipperer, B. (2017). The effect of minimum wages on low-wage jobs: Evidence from the United States using a bunching estimator. Working paper.

Chenevert, R. L., Klee, M. A., and Wilkin, K. R. (2016). Do imputed earnings earn their keep? evaluating SIPP earnings and nonresponse with administrative records. U.S. Census Bureau Working Paper, SEHSD-WP2016-18, SIPP-WP-275.

Chetty, R., Grusky, D., Hell, M., Hendren, N., Manduca, R., and Narang, J. (2017). The fading American dream: Trends in absolute income mobility since 1940. *Science*, 356(6336):398–406.

Chetty, R., Hendren, N., Kline, P., and Saez, E. (2014). Where is the land of opportunity? The geography of intergenerational mobility in the United States. *Quarterly Journal of Economics*, 129(4):1553–1623.

Clemens, J. and Wither, M. (2016). The minimum wage and the Great Recession: Evidence of effects on the employment and income trajectories of low-skilled workers. Working paper.

DiNardo, J., Fortin, N. M., and Lemieux, T. (1996). Labor market institutions and the distribution of wages, 1973-1992: A semiparametric approach. *Econometrica*, 64(5):1001–1044.

Dube, A. (2017). Minimum wages and the distribution of family incomes. IZA Discussion Paper No. 10572.

Dube, A., Lester, T. W., and Reich, M. (2010). Minimum wage effects across state borders: Estimates using contiguous counties. *Review of Economics and Statistics*, 92(4):945–964.

Dube, A., Lester, T. W., and Reich, M. (2016). Minimum wage shocks, employment flows, and labor market frictions. *Journal of Labor Economics*, 34(3):663–704.

Dube, A. and Zipperer, B. (2015). Pooling multiple case studies using synthetic controls: An application to minimum wage policies. IZA Discussion Paper No. 8944.

Essama-Nssah, B. and Lambert, P. J. (2012). *Chapter 6: Influence Functions for Policy Impact Analysis*, pages 135–159.

Even, W. E. and Macpherson, D. A. (2014). The effect of the tipped minimum wage on employees in the U.S. restaurant industry. *Southern Economic Journal*, 80(3):633–655.

Jardim, E., Long, M. C., Plotnick, R., van Inwegen, E., Vigdor, J., and Wething, H. (2017). Minimum wage increases, wages, and low-wage employment: Evidence from Seattle. NBER Working Paper No. 23532.

Lee, D. S. (1999). Wage inequality in the United States during the 1980s: Rising dispersion or falling minimum wage? *Quarterly Journal of Economics*, 114(3):977–1023.

Lemieux, T. (2008). The changing nature of wage inequality. *Journal of Population Economics*, 21:21–48.

Meer, J. and West, J. (2016). Effects of the minimum wage on employment dynamics. *Journal of Human Resources*, 51(2):500–522.

Neumark, D. and Nizalova, O. (2007). Minimum wage effects in the longer run. *Journal of Human Resources*, 42(2):435–452.

Neumark, D., Salas, J. M. I., and Wascher, W. (2014a). More on recent evidence on the effects of minimum wages in the united states. *IZA Journal of Labor Policy*, 3(1):1–26.

Neumark, D., Salas, J. M. I., and Wascher, W. (2014b). Revisiting the minimum wage-employment debate: Throwing out the baby with the bathwater? *Industrial and Labor Relations Review*, 67(Supplement):608–648.

Neumark, D., Schweitzer, M., and Wascher, W. (2004). Minimum wage effects throughout the wage distribution. *Journal of Human Resources*, 39(2):425–450.

Neumark, D. and Wascher, W. (1992). Employment effects of minimum and subminimum wages: Panel data on state minimum wage laws. *Industrial and Labor Relations Review*, 46(1):55–81.

Neumark, D. and Wascher, W. (2002). State-level estimates of minimum wage effects: New evidence and interpretations from disequilibrium methods. *Journal of Human Resources*, 37(1):35–62.

O'Hara, A., Bee, A., and Mitchell, J. (2016). Preliminary research for replacing or supplementing the income question on the american community survey with administrative records. Census Bureau Working paper.

Phelan, B. J. (2018). Reexamining the ripple effect of minimum wages. Working paper.

Piketty, T. and Saez, E. (2003). Income inequality in the United States, 1913–1998. *Quarterly Journal of Economics*, 118(1):1–41.

Sabia, J. J. (2009a). The effects of minimum wage increases on retail employment and hours: New evidence from monthly CPS data. *Journal of Labor Research*, 30(1):75–97.

Sabia, J. J. (2009b). Identifying minimum wage effects: New evidence from monthly CPS data. *Industrial Relations*, 48(2):311–328.

Sabia, J. J., Burkhauser, R. V., and Hansen, B. (2009). Are the effects of minimum wage increases always small? new evidence from a case study of New York state. *Industrial and Labor Relations Review*, 65(2):350–376.

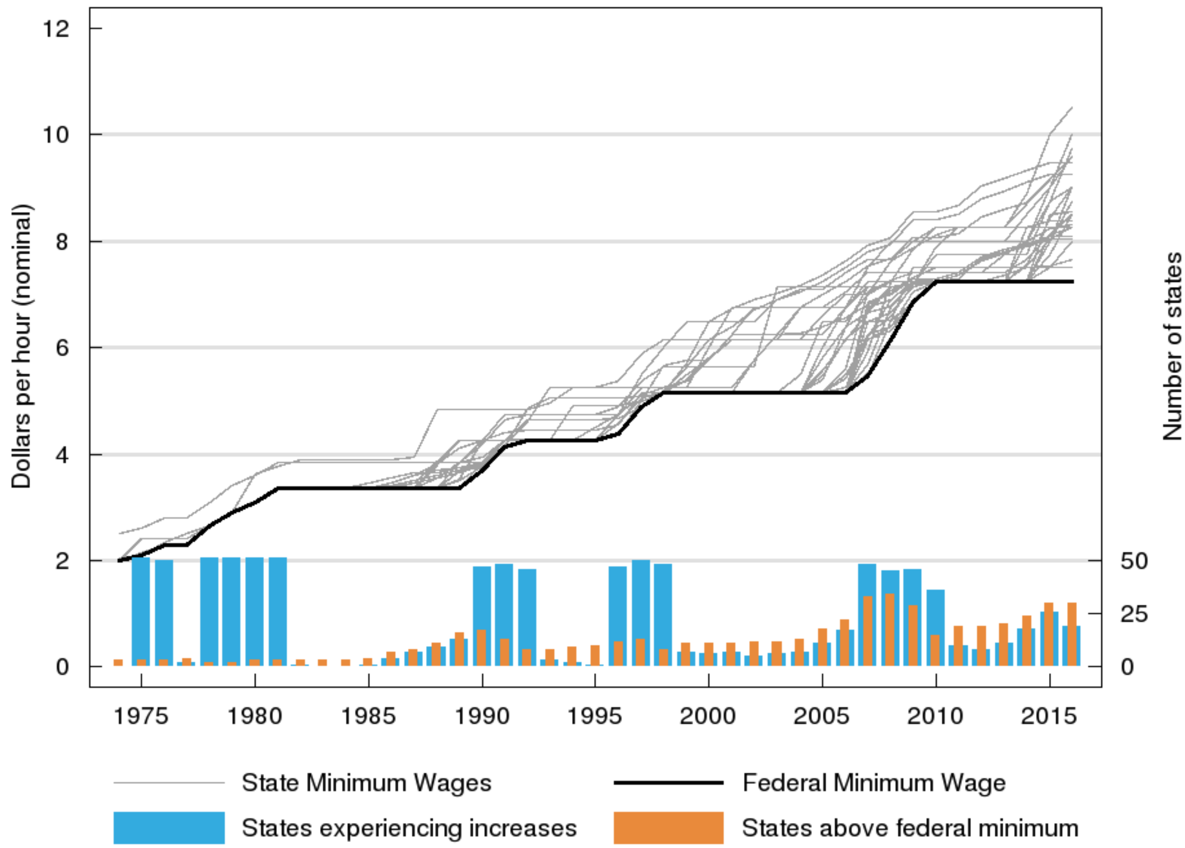
Totty, E. (2017). The effect of minimum wages on employment: A factor model approach. *Economic Inquiry*, 55(4):1712–1735.

Vaghul, K. and Zipperer, B. (2016). Historical state and sub-state minimum wage data. Washington Center for Equitable Growth working paper.

van Kerm, P. (2009). Income mobility profiles. *Economics Letters*, 102.

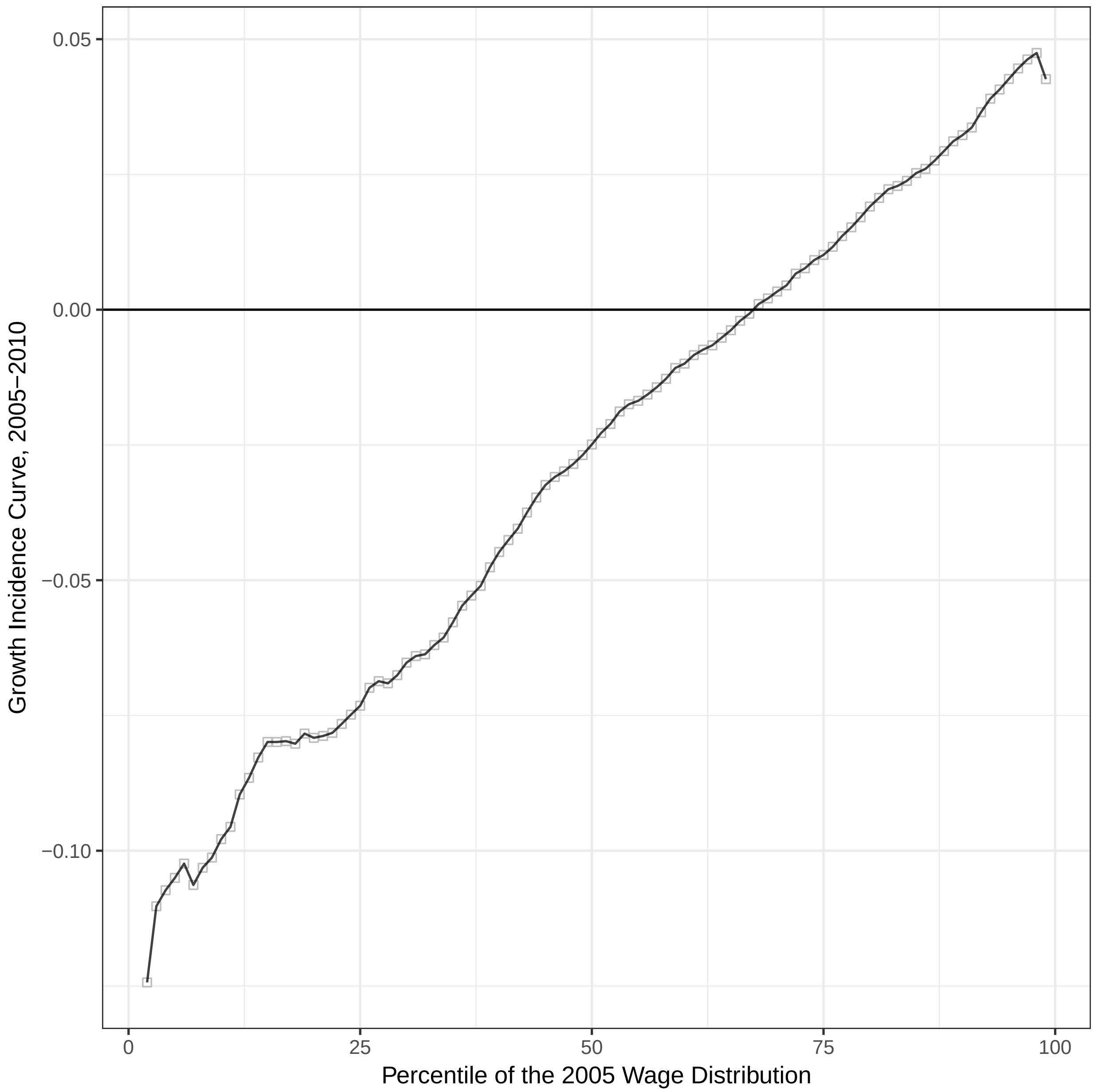
Figures

Figure 1: Variation in State Minimum Wage Laws, 1974-2016



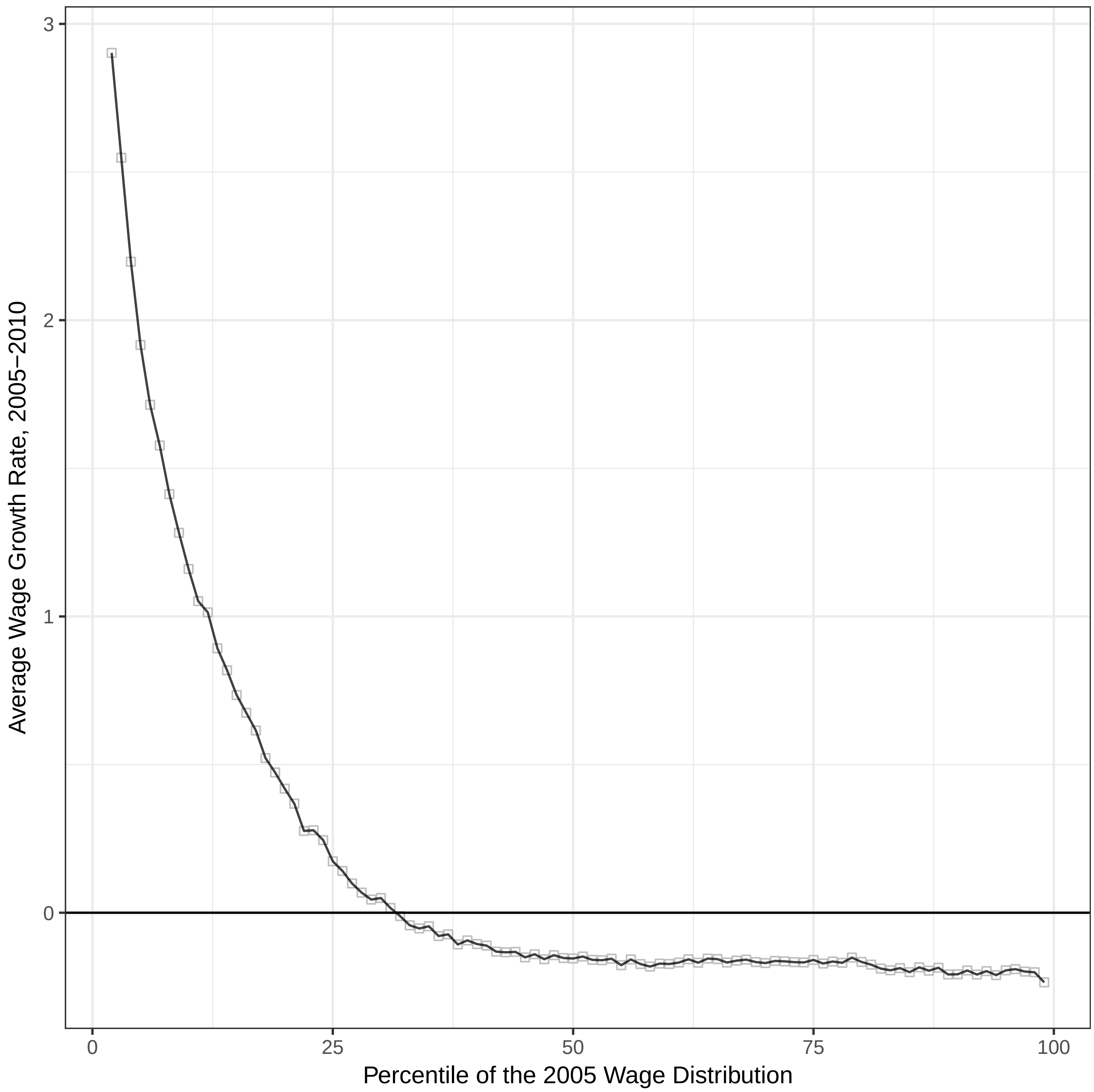
Source: Author's calculations based on Vaghul and Zipperer (2016) state minimum wage data.

Figure 2: Growth Incidence Curve, 2005-2010



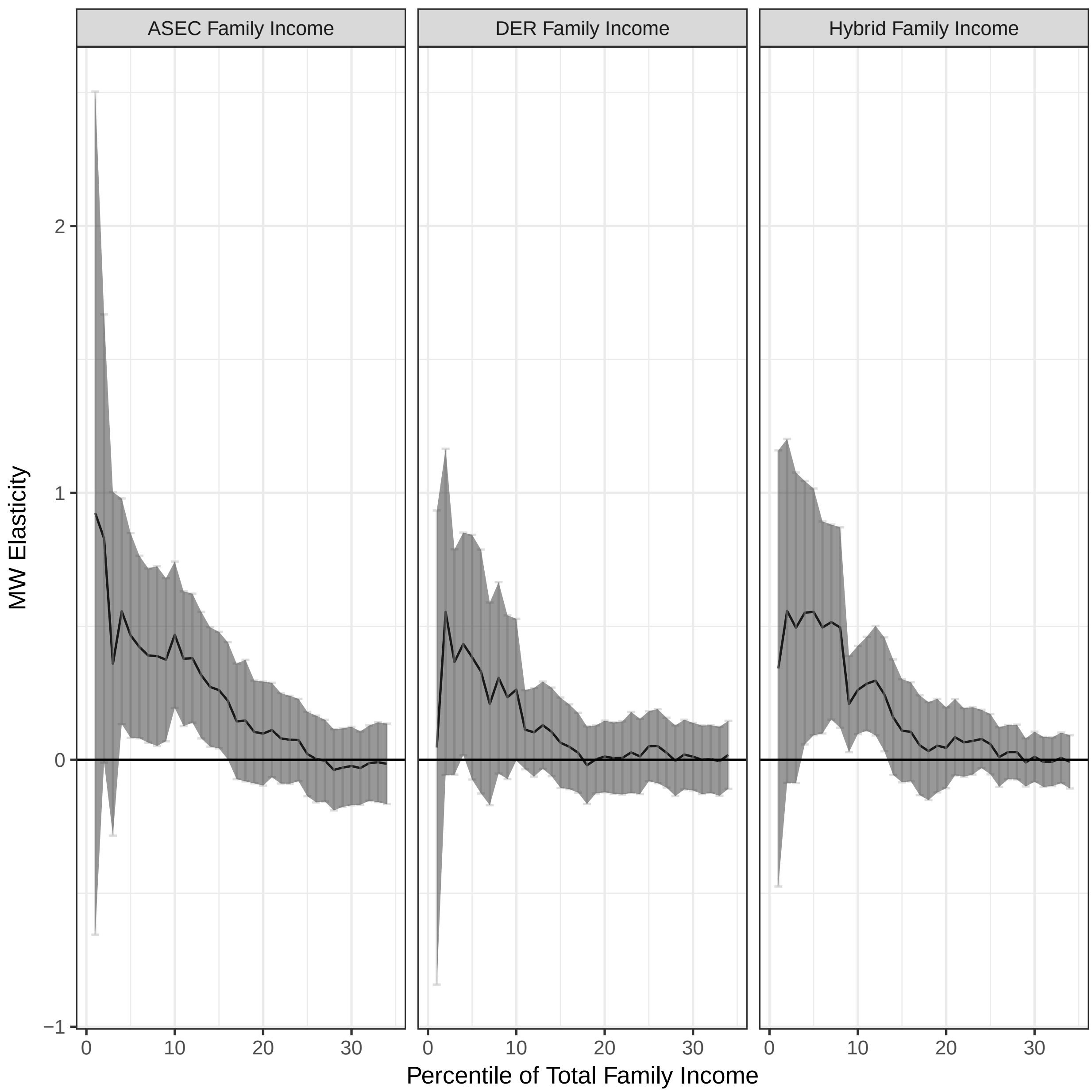
Source: CPS ASEC and SSA DER, 1991-2013
Note: Each plotted point represents and ordinate of a growth incidence curve, described in Section 3.2, depicting the percent change in the dollar values associated with each percentile of the wage earnings distribution between 2005 and 2010.

Figure 3: Income Mobility Profile, 2005-2010



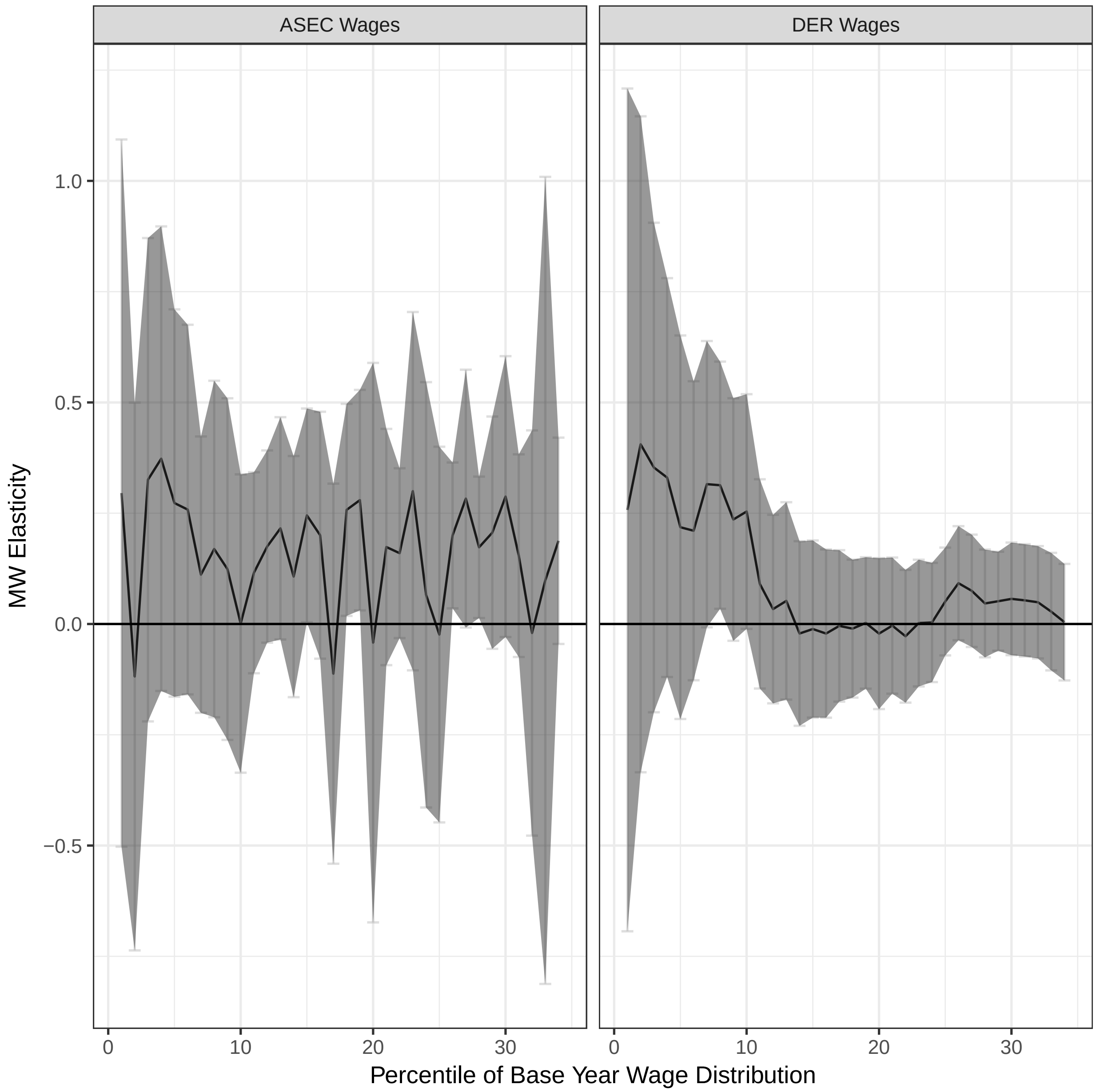
Source: CPS ASEC and SSA DER, 1991-2013
Note: Each plotted point represents an ordinate of an income mobility profile, described in Section 3.3, depicting average wage growth between 2005 and 2010 among individuals with wage earnings at the indicated percentile of the 2005 wage earnings distribution.

Figure 4: Recentered Influence Function Quantile Regressions, by Income Measure



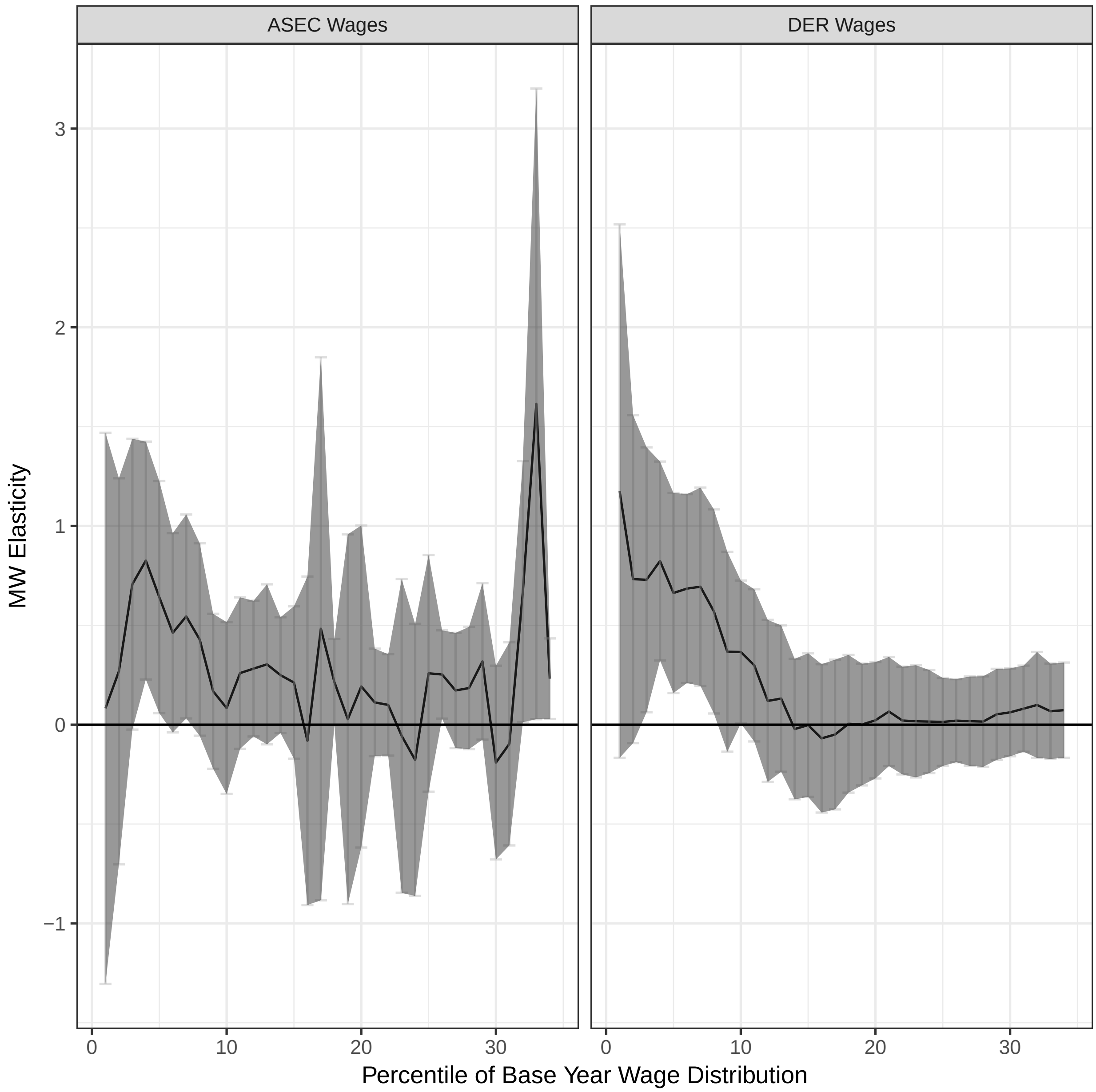
Source: CPS ASEC and SSA DER, 1991-2013
Note: Each plotted point represents a separate regression estimated as described in Section 3.1. The left panel of the figure uses the survey-based measure of family income reported in the CPS ASEC. The measure of family income used in the middle panel aggregates individual measures of wage and salary earnings from the DER for all members of each family observed in the CPS ASEC; other sources of income reported in the CPS ASEC are ignored. In the right panel, family income includes administrative measures of wage and salary earnings from the DER, as well as CPS ASEC measures of income from other sources.

Figure 5: Recentered Influence Function Growth Incidence Curve Regressions, One Year Ahead, by Income Measure



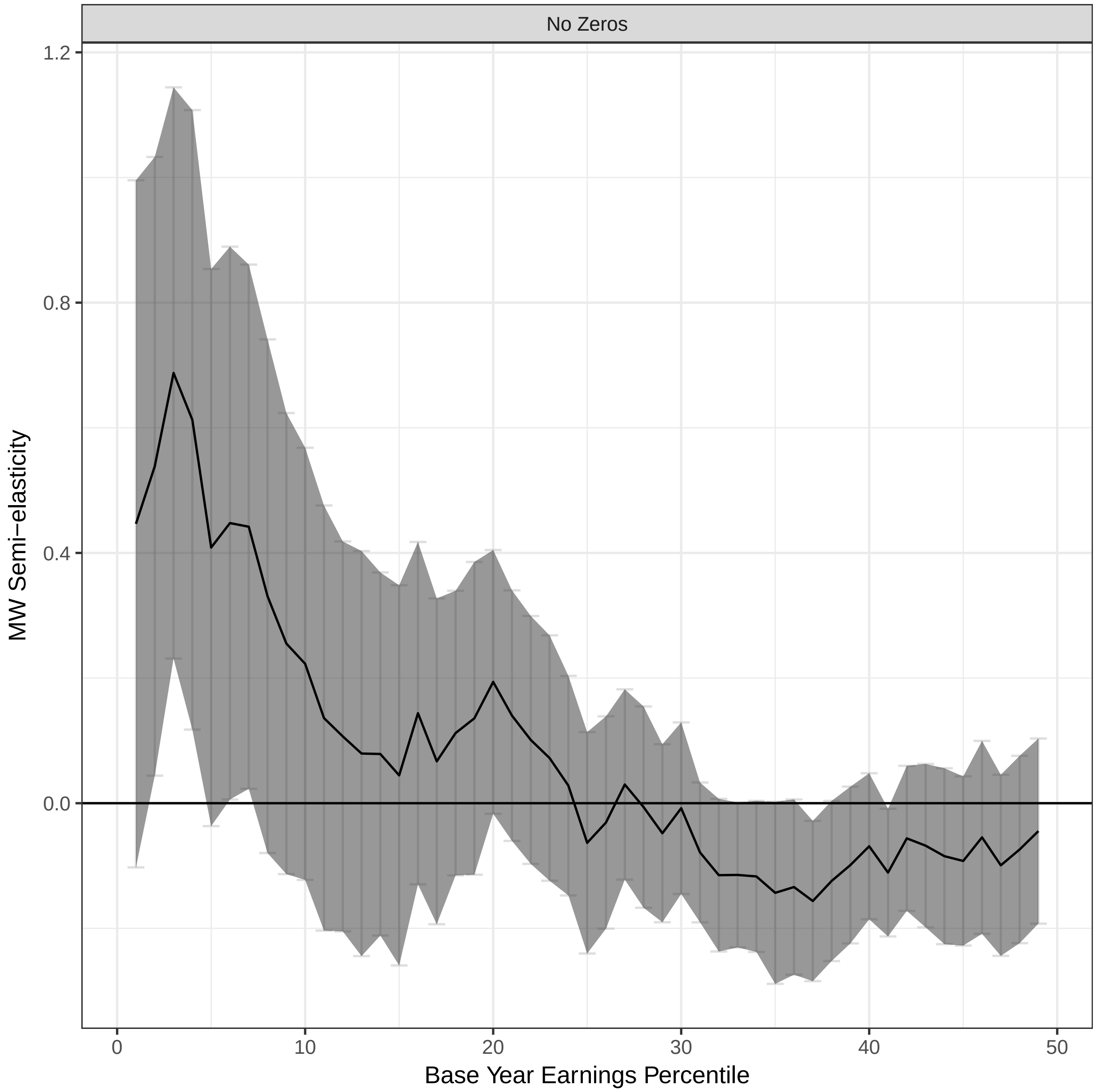
Source: CPS ASEC and SSA DER, 1991-2013
Note: Each plotted point represents a separate regression estimated as described in Section 3.2. The left panel uses the CPS ASEC measure of annual wage and salary earnings. The right panel uses the DER measure of annual wage and salary earnings. Both measures are aggregated across all jobs.

Figure 6: Recentered Influence Function Growth Incidence Curve Regressions, Five Years Ahead, by Income Measure



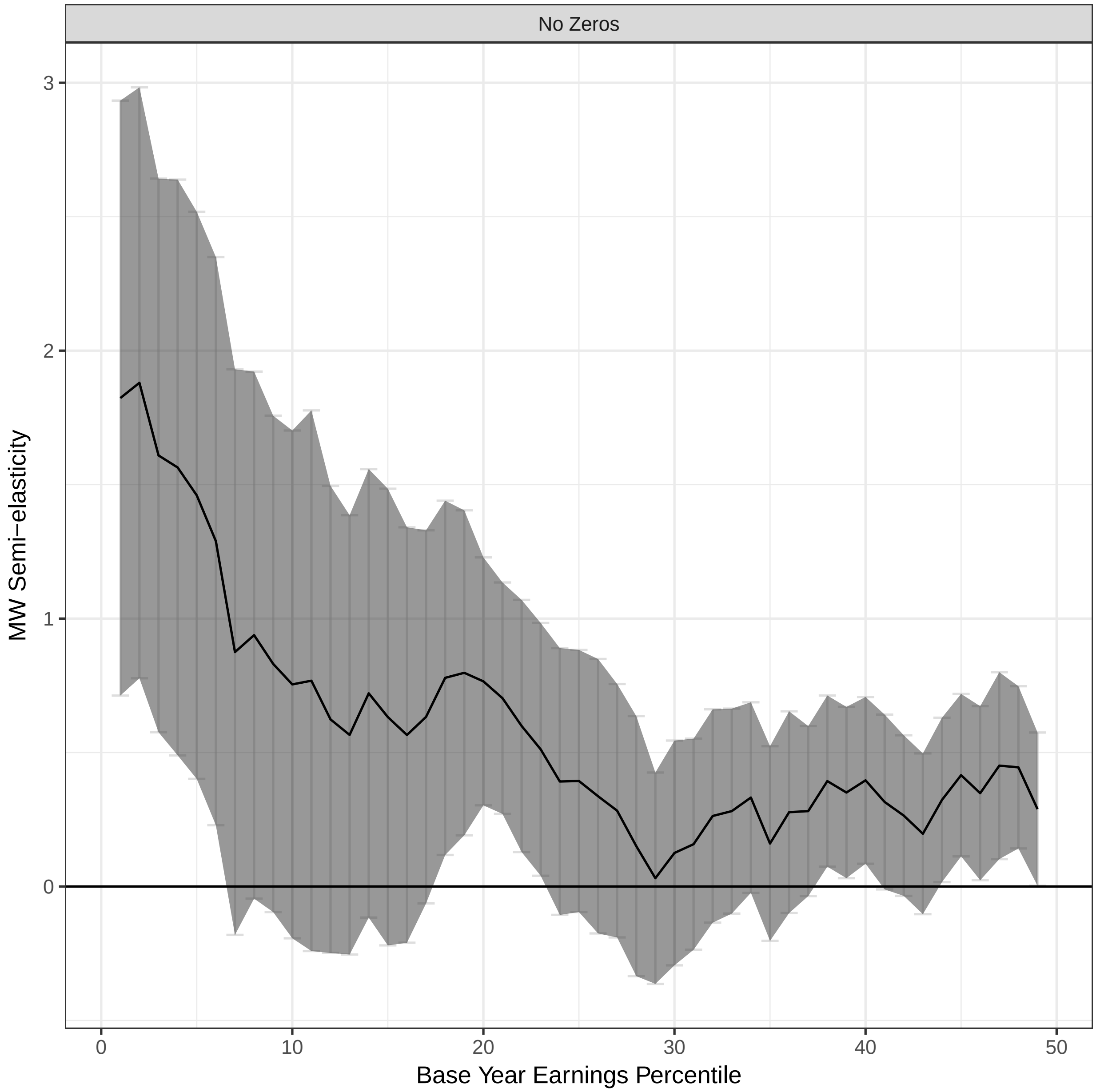
Source: CPS ASEC and SSA DER, 1991-2013
Note: Each plotted point represents a separate regression estimated as described in Section 3.2. The left panel uses the CPS ASEC measure of annual wage and salary earnings. The right panel uses the DER measure of annual wage and salary earnings. Both measures are aggregated across all jobs.

Figure 7: Income Mobility Profile Regressions, One Year Ahead, Baseline Specification



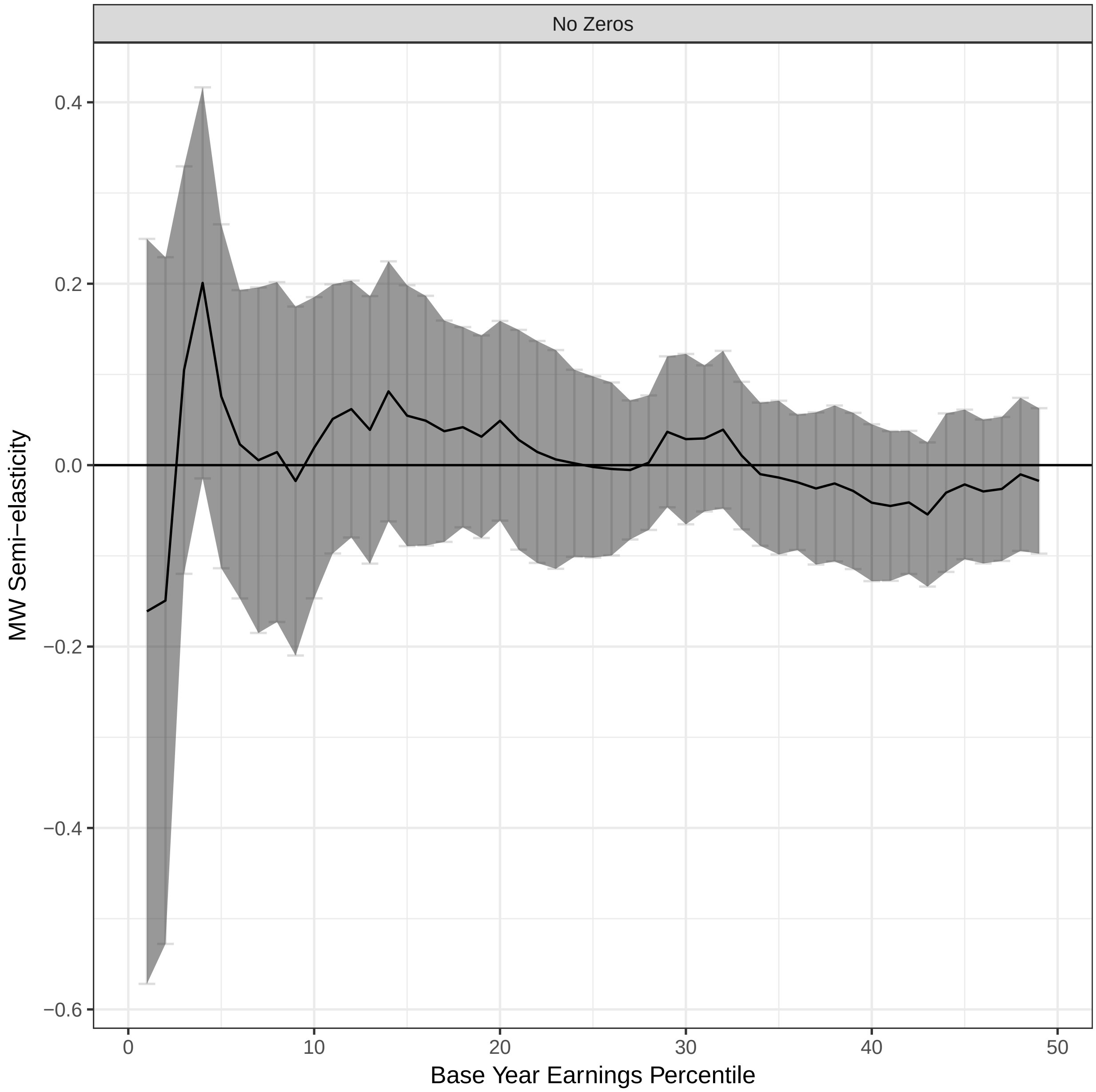
Source: CPS ASEC and SSA DER, 1991-2013
Note: Each plotted point represents a separate regression estimated as described in Section 3.3. Earnings growth is defined as the change in log earnings between the base year and t years later, so individuals with zero earnings in either year are excluded from this analysis.

Figure 8: Income Mobility Profile Regressions, Five Years Ahead, Baseline Specification



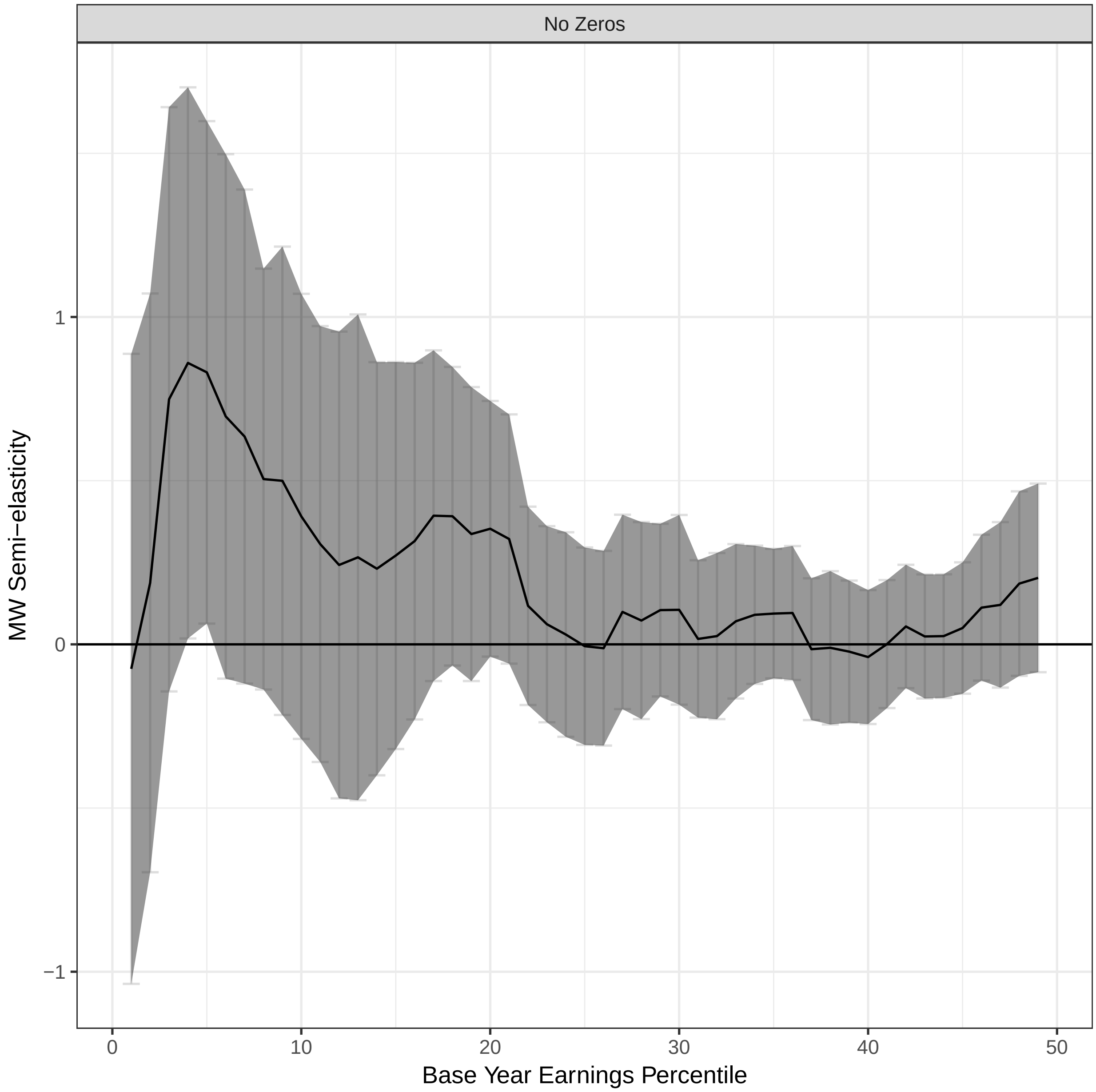
Source: CPS ASEC and SSA DER, 1991-2013
Note: Each plotted point represents a separate regression estimated as described in Section 3.3. Earnings growth is defined as the change in log earnings between the base year and t years later, so individuals with zero earnings in either year are excluded from this analysis.

Figure 9: Income Mobility Profile Regressions, One Year Ahead, Parsimonious Specification



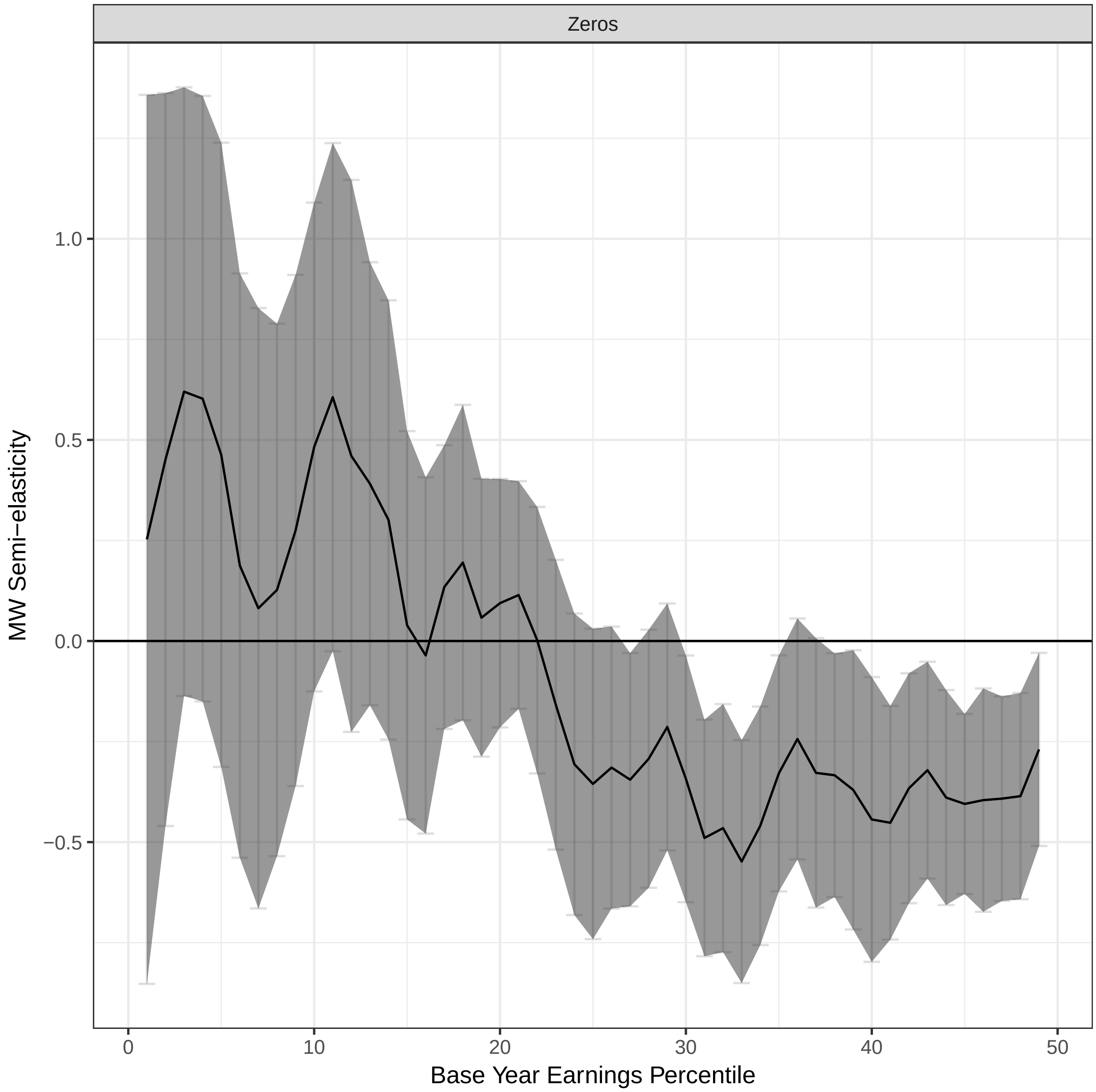
Source: CPS ASEC and SSA DER, 1991-2013
Note: Each plotted point represents a separate regression estimated as described in Section 3.3, but without controls for time-varying heterogeneity, as described in Section 4.3.1. Earnings growth is defined as the change in log earnings between the base year and t years later, so individuals with zero earnings in either year are excluded from this analysis.

Figure 10: Income Mobility Profile Regressions, Five Years Ahead, Parsimonious Specification



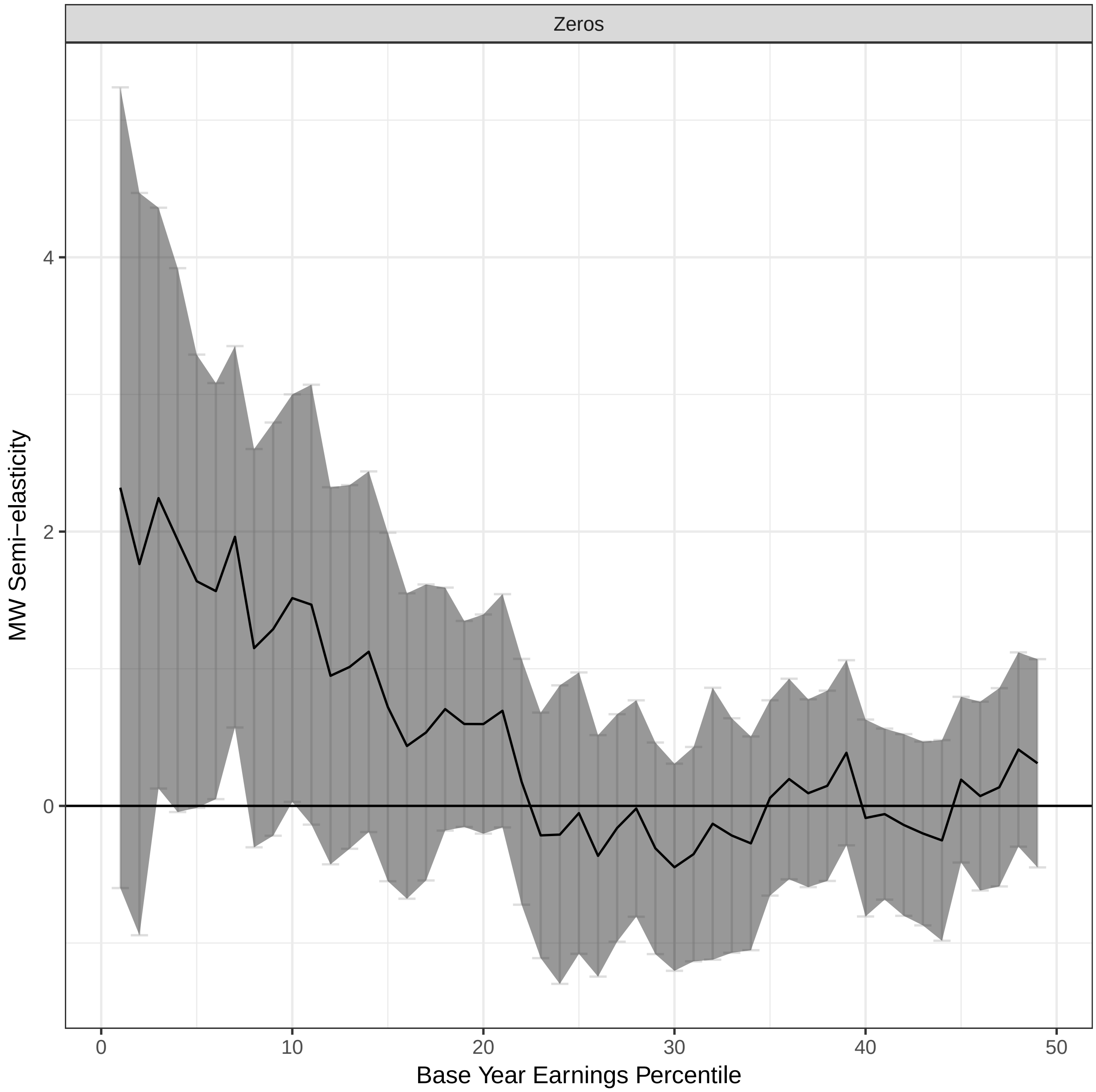
Source: CPS ASEC and SSA DER, 1991-2013
Note: Each plotted point represents a separate regression estimated as described in Section 3.3, but without controls for time-varying heterogeneity, as described in Section 4.3.1. Earnings growth is defined as the change in log earnings between the base year and t years later, so individuals with zero earnings in either year are excluded from this analysis.

Figure 11: Income Mobility Profile Regressions, One Year Ahead, Inverse Hyperbolic Sine Specification



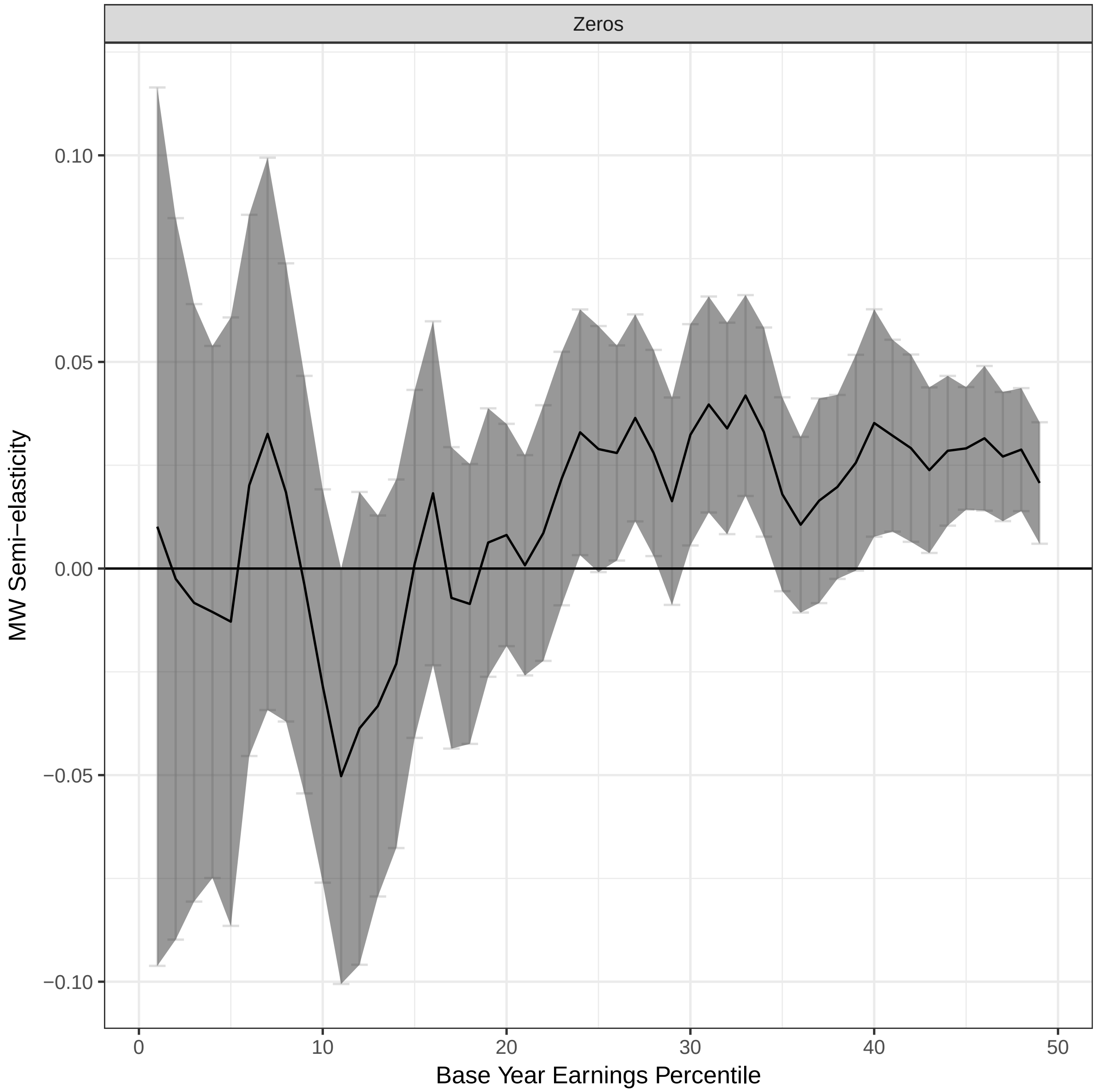
Source: CPS ASEC and SSA DER, 1991-2013
Note: Each plotted point represents a separate regression estimated as described in Section 3.3, but using an alternative definition of earnings growth. Here, earnings growth is defined as the change in the inverse hyperbolic sine of earnings between the base year and t years later, so individuals with zero earnings in either year are included in this analysis.

Figure 12: Income Mobility Profile Regressions, Five Years Ahead, Inverse Hyperbolic Sine Specification



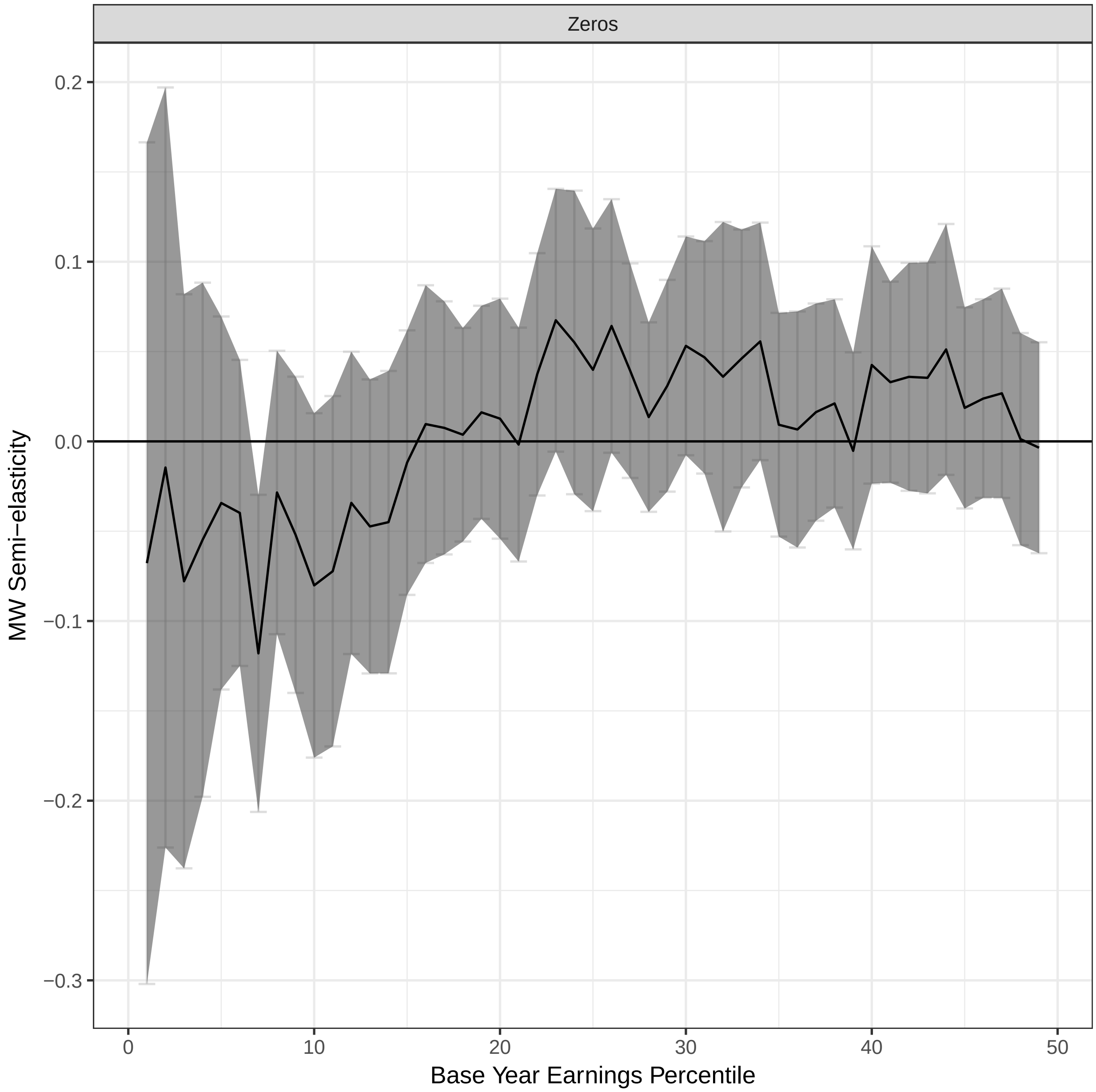
Source: CPS ASEC and SSA DER, 1991-2013
Note: Each plotted point represents a separate regression estimated as described in Section 3.3, but using an alternative definition of earnings growth. Here, earnings growth is defined as the change in the inverse hyperbolic sine of earnings between the base year and t years later, so individuals with zero earnings in either year are included in this analysis.

Figure 13: Probability of Zero Earnings, One Year Ahead, Baseline Specification



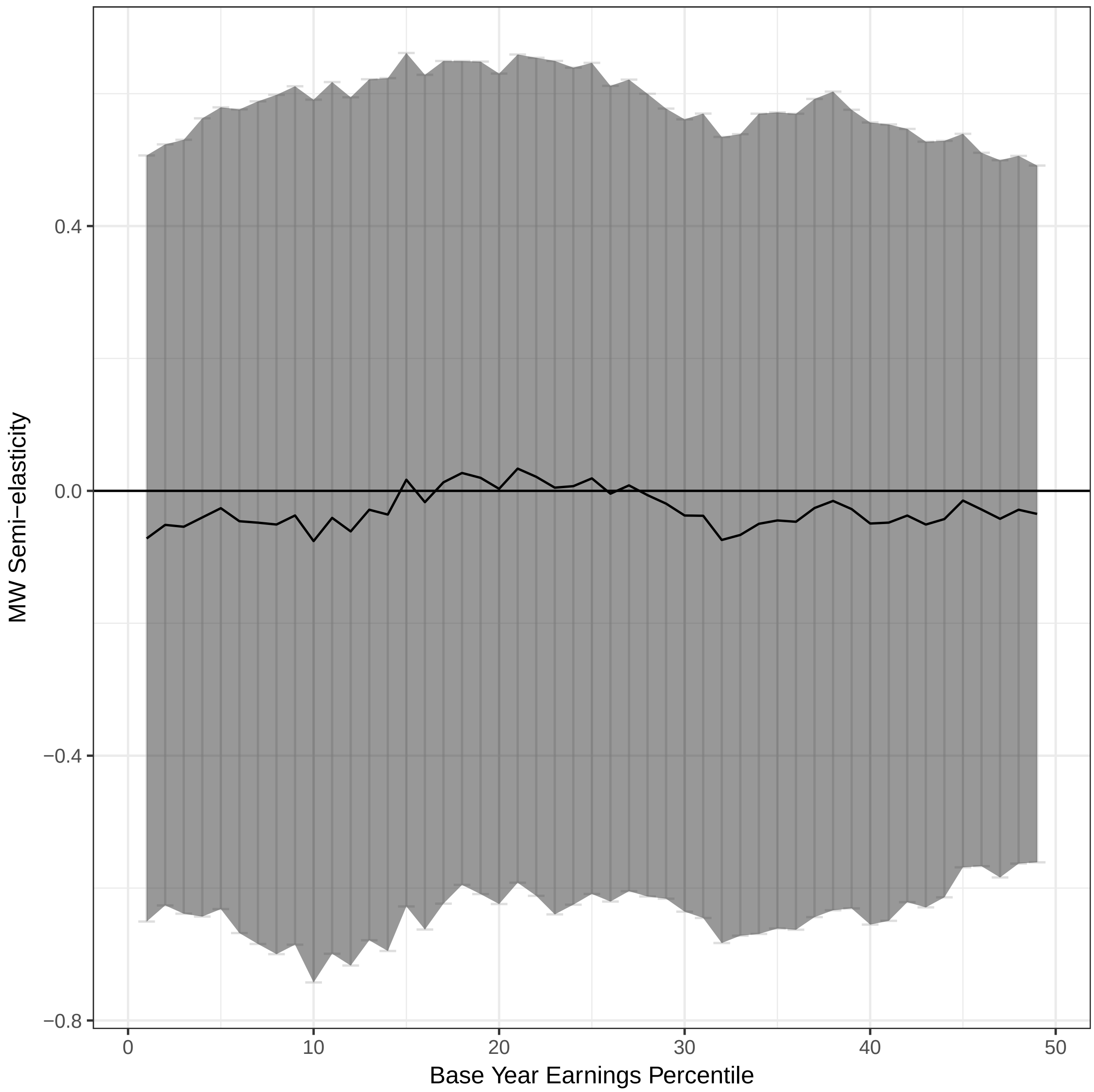
Source: CPS ASEC and SSA DER, 1991-2013
Note: Each plotted point represents a separate regression estimated as described in Section 3.3, but the dependent variables is an indicator for whether an individual has exactly zero wage and salary earnings t years later.

Figure 14: Probability of Zero Earnings, Five Years Ahead, Baseline Specification



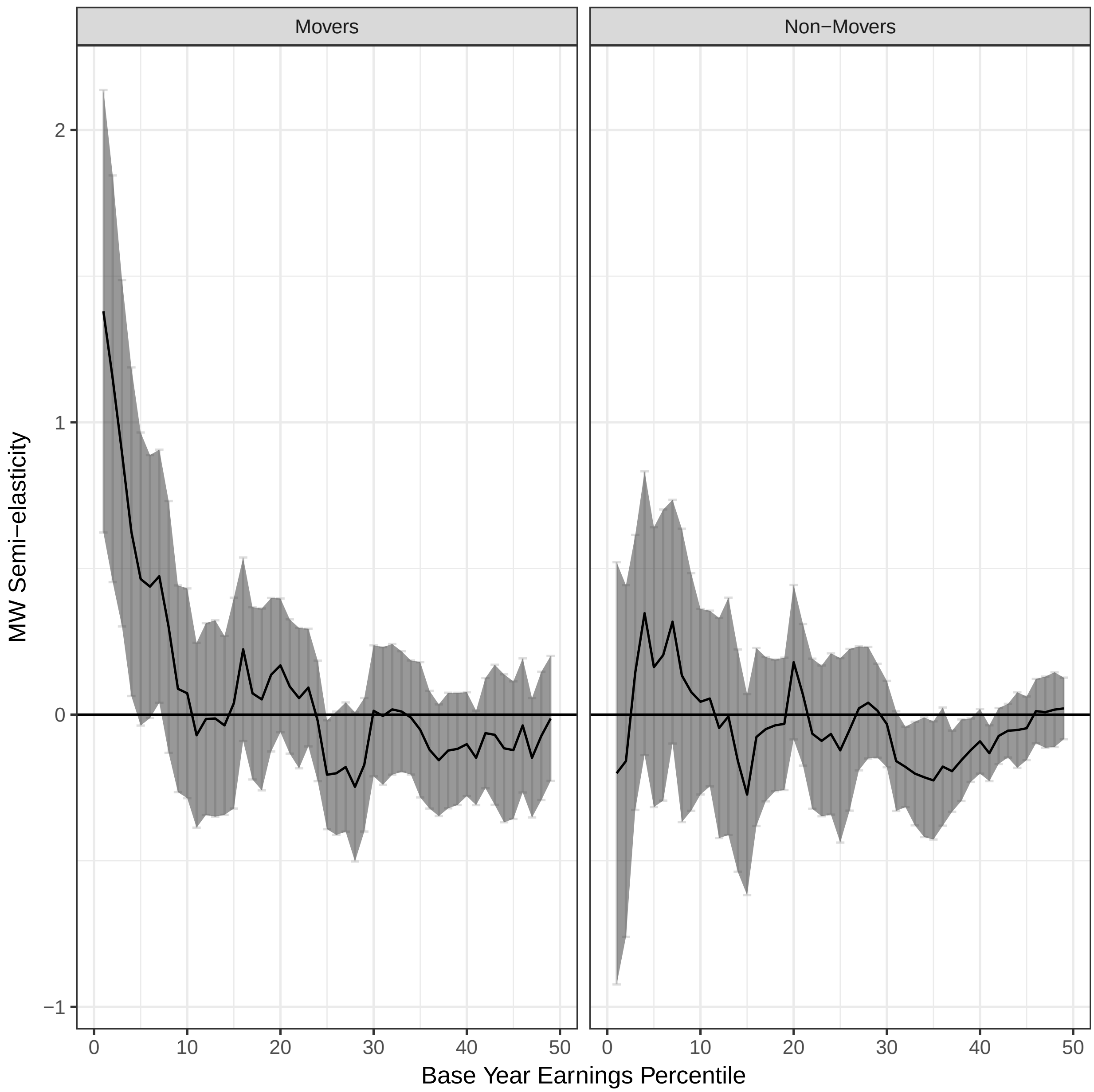
Source: CPS ASEC and SSA DER, 1991-2013
Note: Each plotted point represents a separate regression estimated as described in Section 3.3, but the dependent variables is an indicator for whether an individual has exactly zero wage and salary earnings t years later.

Figure 15: Effect of Minimum Wages on Mobility, One Year Ahead



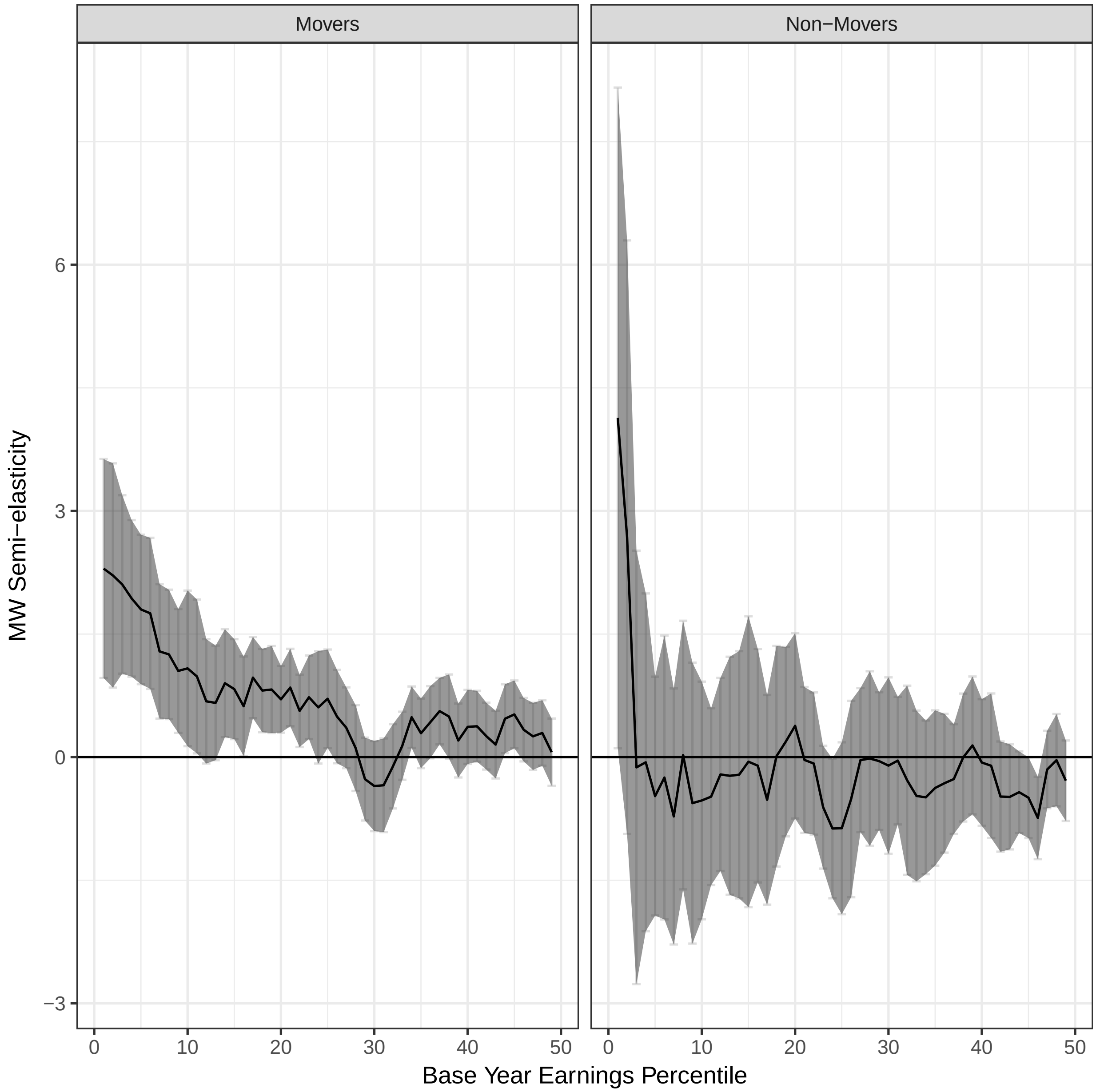
Source: CPS ASEC and SSA DER, 1991-2013
Note: Each plotted point represents a separate regression estimated as described in Section 3.3, but the dependent variables is an indicator for whether an individual has moved to a different state between the base year and t years later.

Figure 16: Income Mobility Profile Regressions, One Year Ahead, by Mobility Status (Ever Moved)



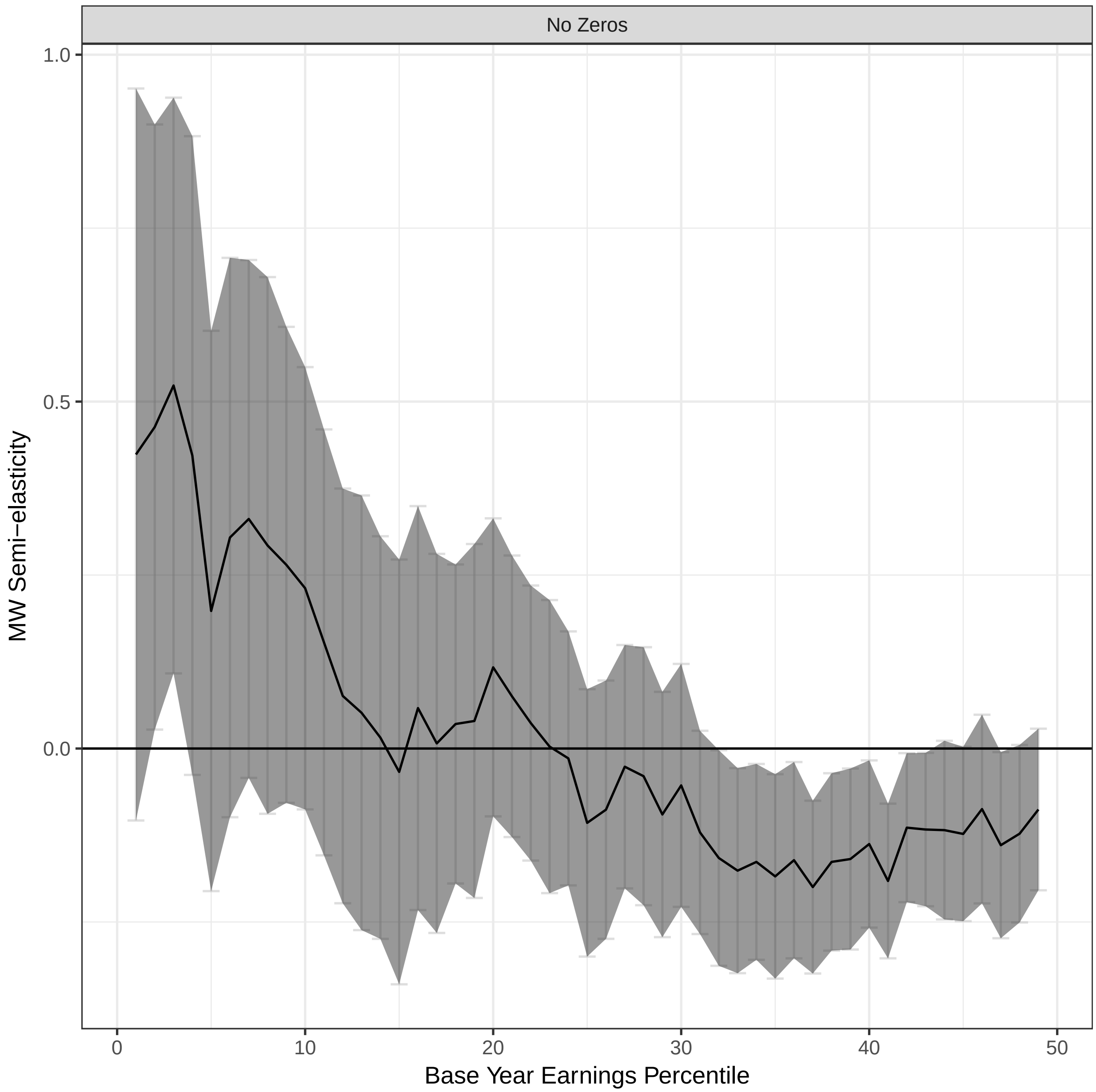
Source: CPS ASEC and SSA DER, 1991-2013
Note: Each plotted point represents a separate regression estimated as described in Section 3.3. Earnings growth is defined as the change in log earnings between the base year and t years later, so individuals with zero earnings in either year are excluded from this analysis. The left panel presents estimates for individuals who lived outside their base-year state of residence in any year between the base year and t years later, while the right panel presents estimates for individuals observed in their base-year state of residence in all years between the base year and t years later.

Figure 17: Income Mobility Profile Regressions, Five Years Ahead, by Mobility Status (Ever Moved)



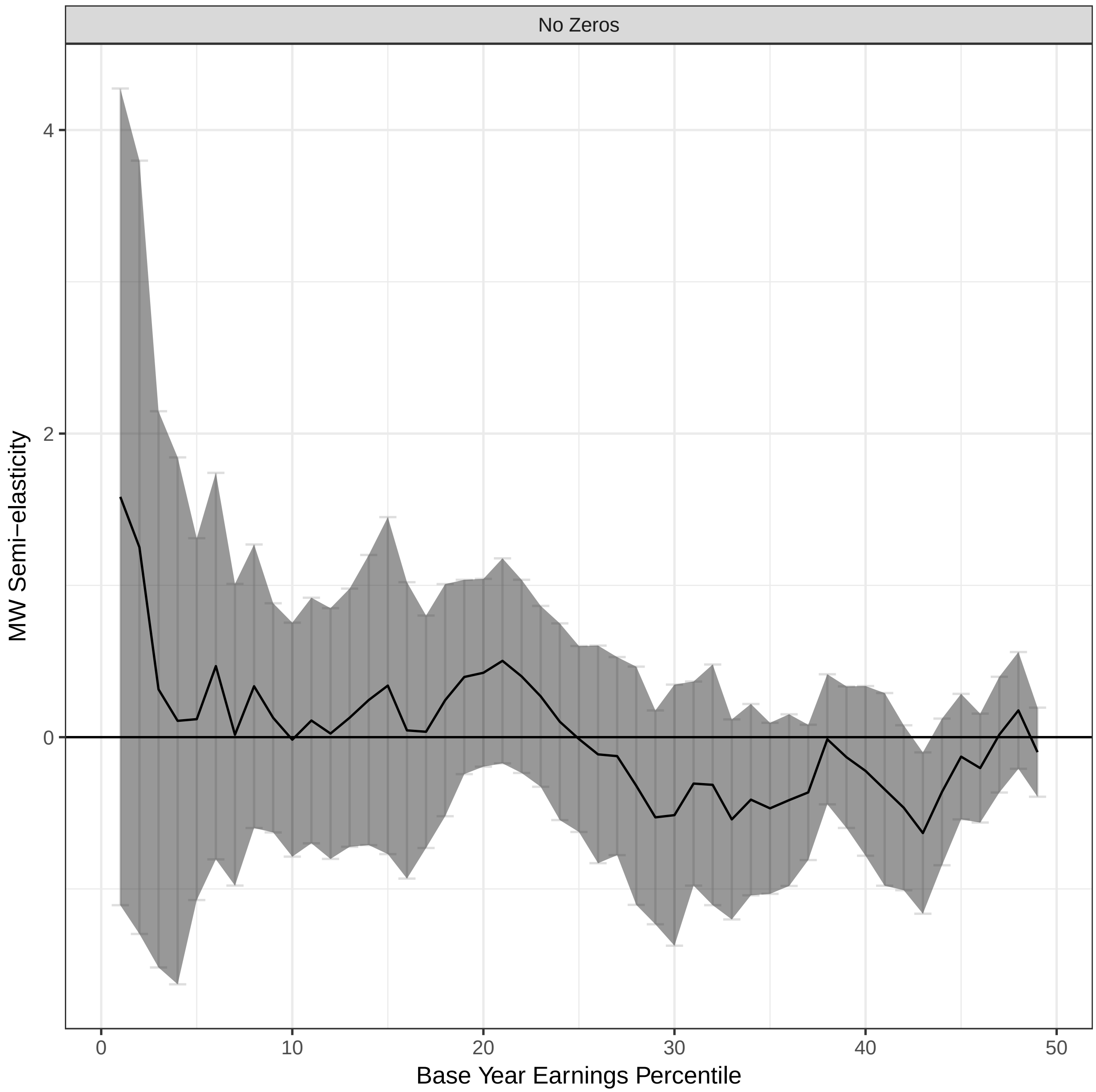
Source: CPS ASEC and SSA DER, 1991-2013
Note: Each plotted point represents a separate regression estimated as described in Section 3.3. Earnings growth is defined as the change in log earnings between the base year and t years later, so individuals with zero earnings in either year are excluded from this analysis. The left panel presents estimates for individuals who lived outside their base-year state of residence in any year between the base year and t years later, while the right panel presents estimates for individuals observed in their base-year state of residence in all years between the base year and t years later.

Figure 18: Instrumental Variables Regressions, One Year Ahead, Baseline Specification



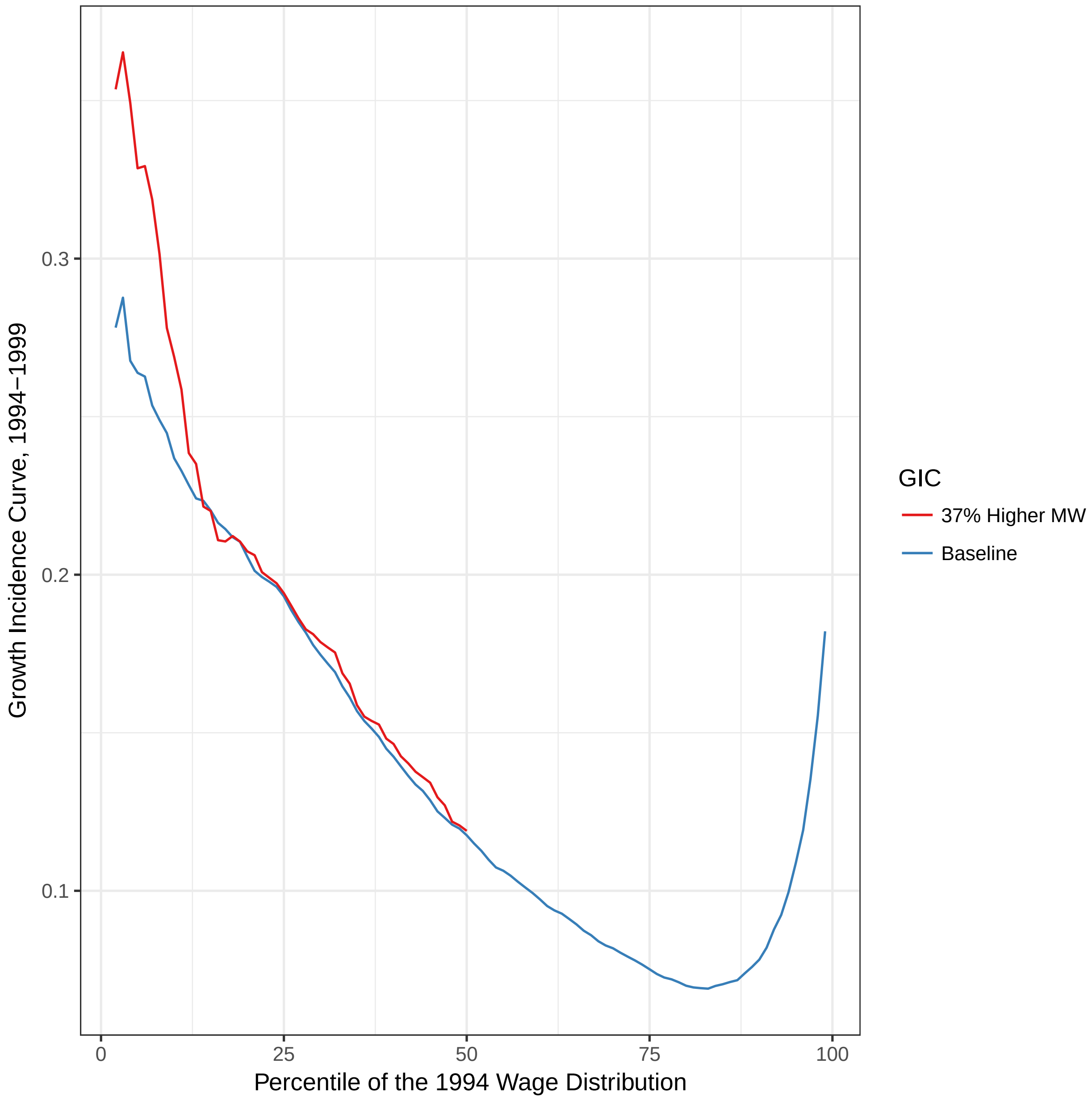
Source: CPS ASEC and SSA DER, 1991-2013
Note: Each plotted point represents a separate regression estimated as described in Section 3.3, except actual minimum wage exposure in years following the base year is instrumented for using the minimum wage exposure an individual would have experienced living in her state of residence in the base year until t years later. Earnings growth is defined as the change in log earnings between the base year and t years later, so individuals with zero earnings in either year are excluded from this analysis.

Figure 19: Instrumental Variables Regressions, Five Years Ahead, Baseline Specification



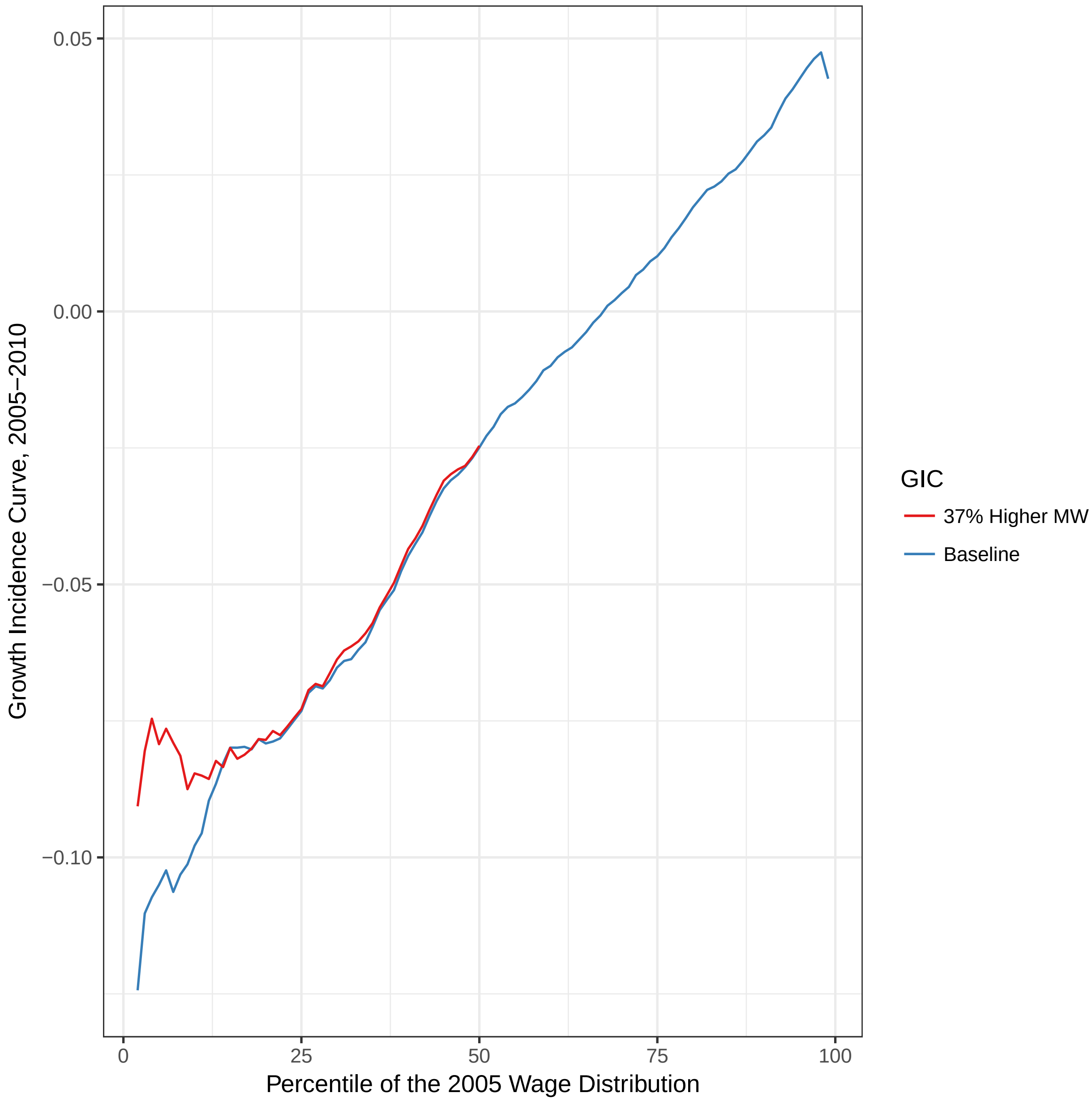
Source: CPS ASEC and SSA DER, 1991-2013
Note: Each plotted point represents a separate regression estimated as described in Section 3.3, except actual minimum wage exposure in years following the base year is instrumented for using the minimum wage exposure an individual would have experienced living in her state of residence in the base year until t years later. Earnings growth is defined as the change in log earnings between the base year and t years later, so individuals with zero earnings in either year are excluded from this analysis.

Figure 20: Implications of Growth Incidence Curve Estimates for a Large Minimum Wage Change, 1994 Baseline



Source: CPS ASEC and SSA DER, 1991-2013
Note: The red line represents a counterfactual growth incidence curve generated by applying the estimates presented in the right panel of Figure 6 and a hypothetical 37 percent increase in the minimum wage to the baseline 1994–1999 growth incidence curve, which is presented in blue.

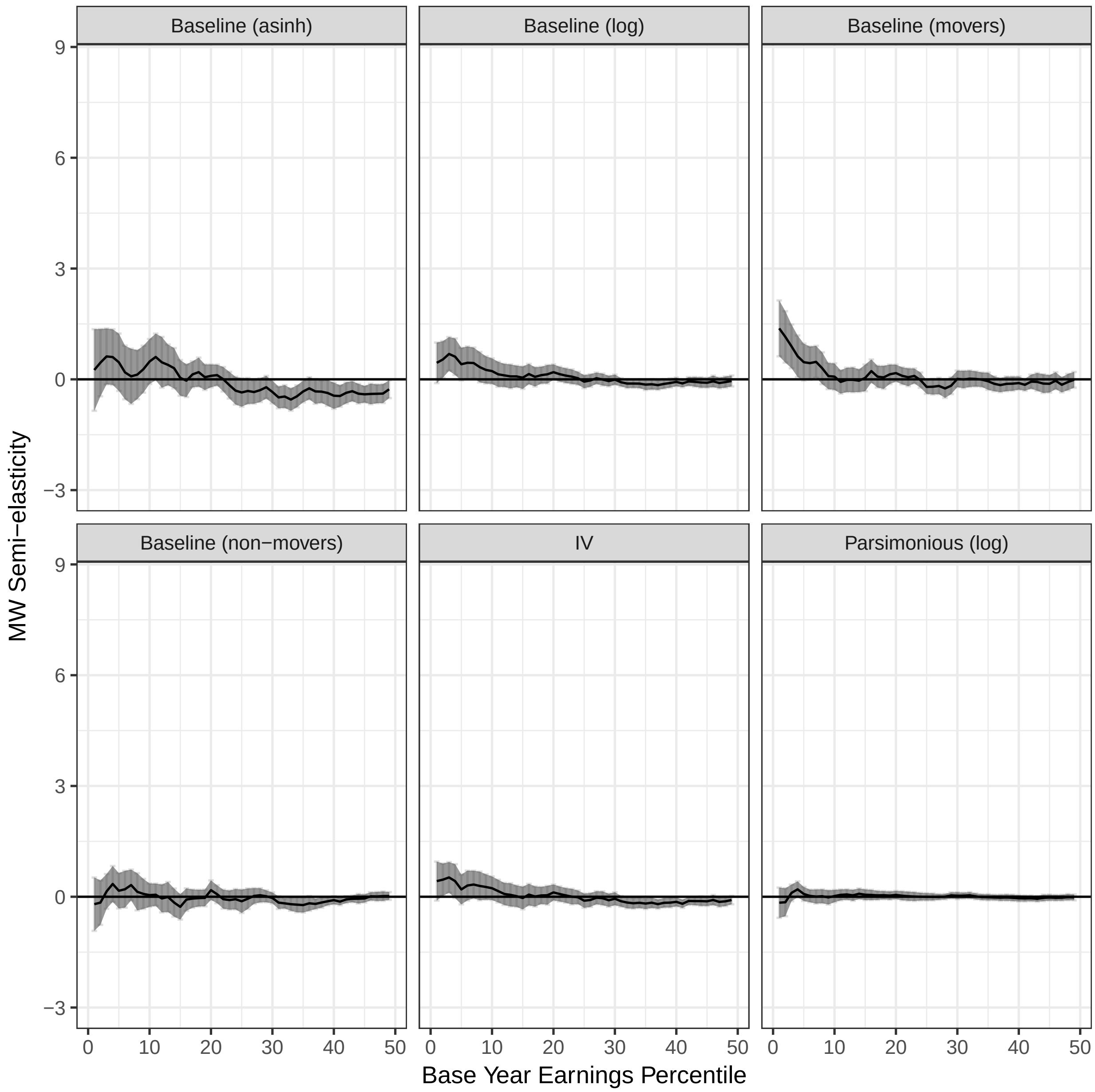
Figure 21: Implications of Growth Incidence Curve Estimates for a Large Minimum Wage Change, 2005 Baseline



Source: CPS ASEC and SSA DER, 1991-2013
Note: The red line represents a counterfactual growth incidence curve generated by applying the estimates presented in the right panel of Figure 6 and a hypothetical 37 percent increase in the minimum wage to the baseline 2005–2010 growth incidence curve, which is presented in blue.

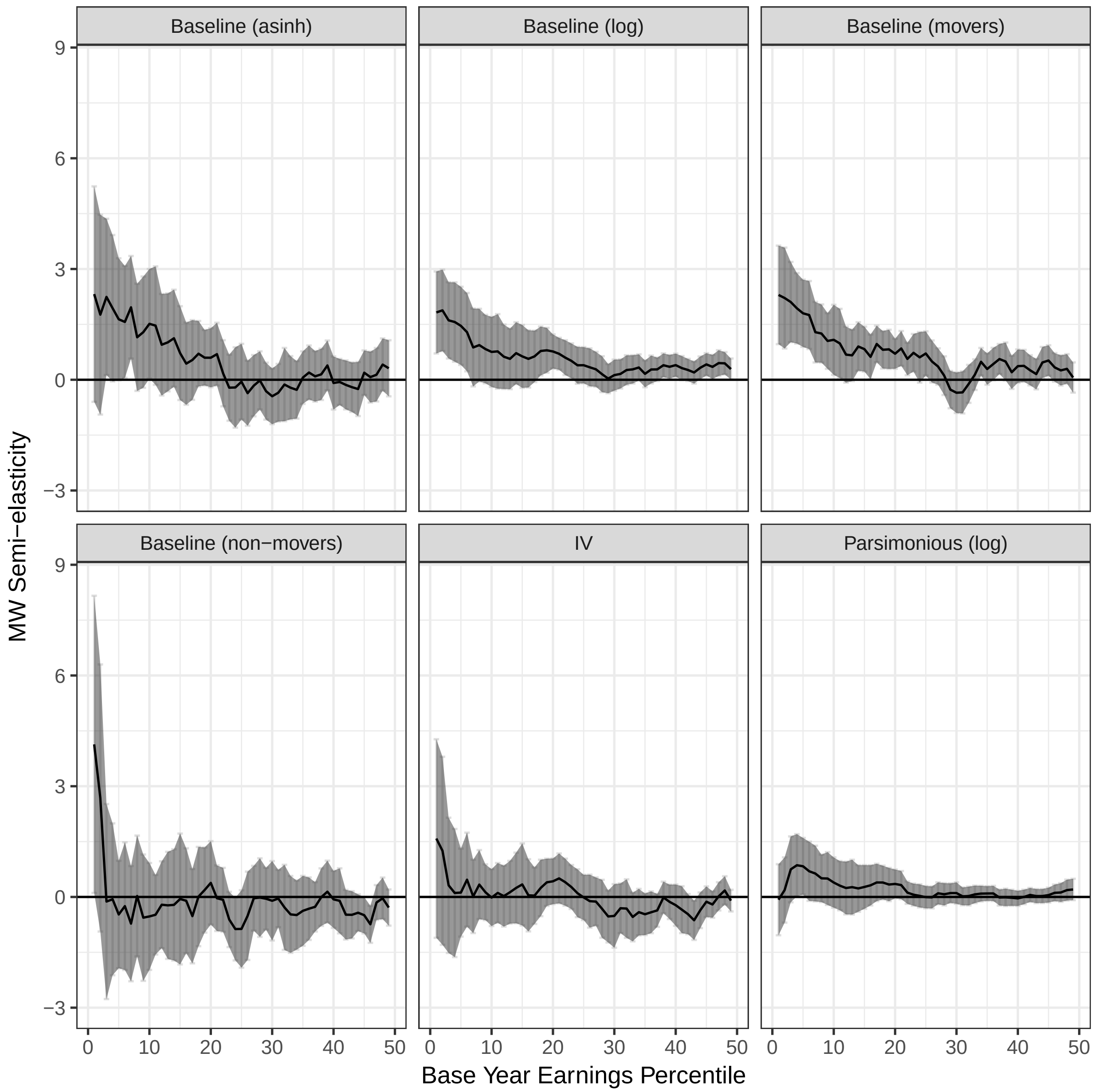
Appendix A Fixed Scale Figures

Figure A1: Income Mobility Profile Regressions, One Year Ahead, Fixed Scale



Source: CPS ASEC and SSA DER, 1991-2013
Note: Each plotted point represents a separate regression estimated as described in the specifications described in Section 3.3. All results are presented on a fixed scale for comparability.

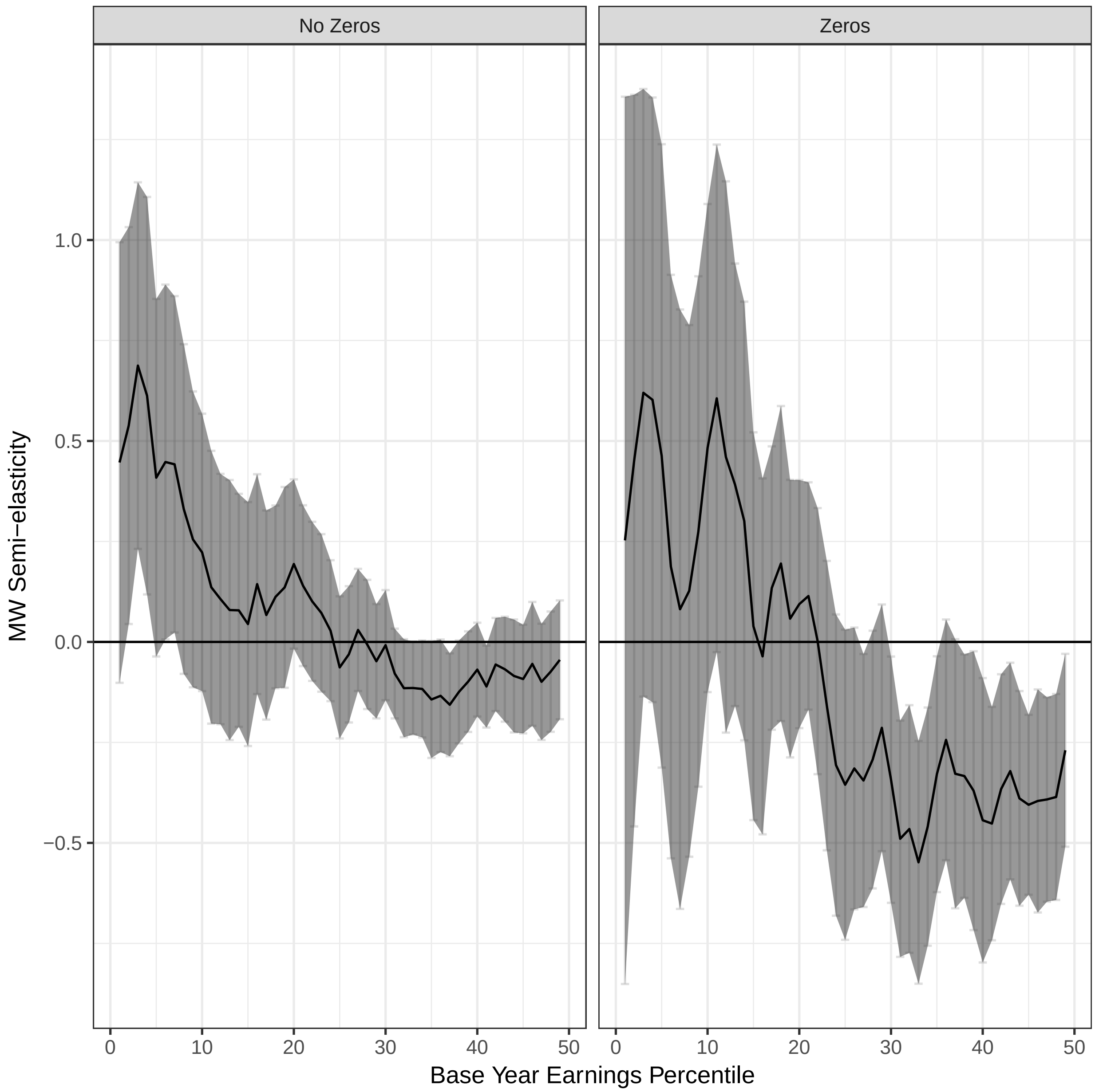
Figure A2: Income Mobility Profile Regressions, Five Years Ahead, Fixed Scale



Source: CPS ASEC and SSA DER, 1991-2013
Note: Each plotted point represents a separate regression estimated as described in the specifications described in Section 3.3. All results are presented on a fixed scale for comparability.

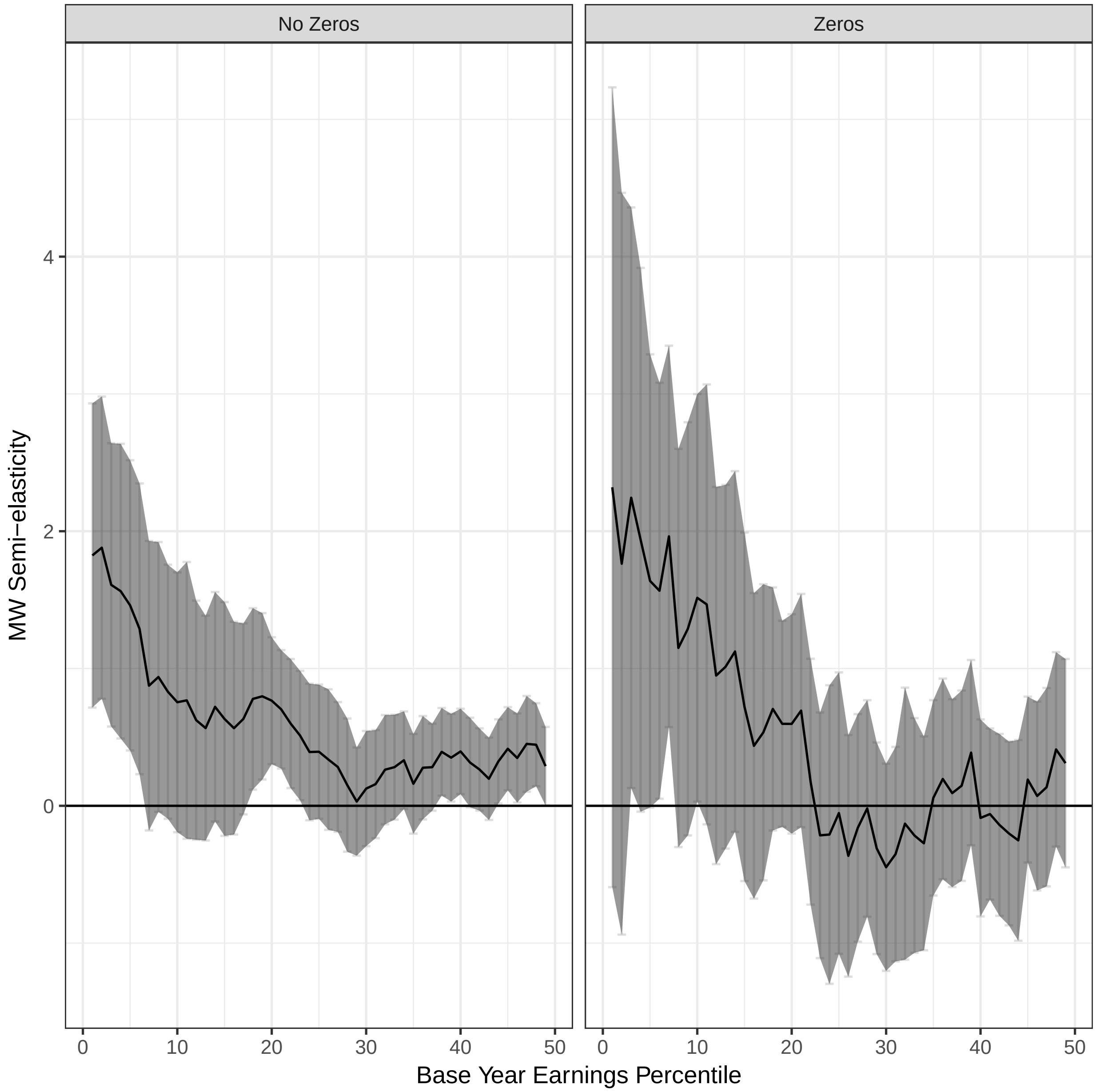
Appendix B Analysis using Real Minimum Wages

Figure B1: Income Mobility Profile Regressions, One Year Ahead, Real Minimum Wages



Source: CPS ASEC and SSA DER, 1991-2013
Note: Each plotted point represents a separate regression estimated as described in Section 3.3. In the left panel, earnings growth is calculated using differences in logs, analogous to Figure 7. In the right panel, earnings growth is calculated using differences in the inverse hyperbolic sine, analogous to Figure 11.

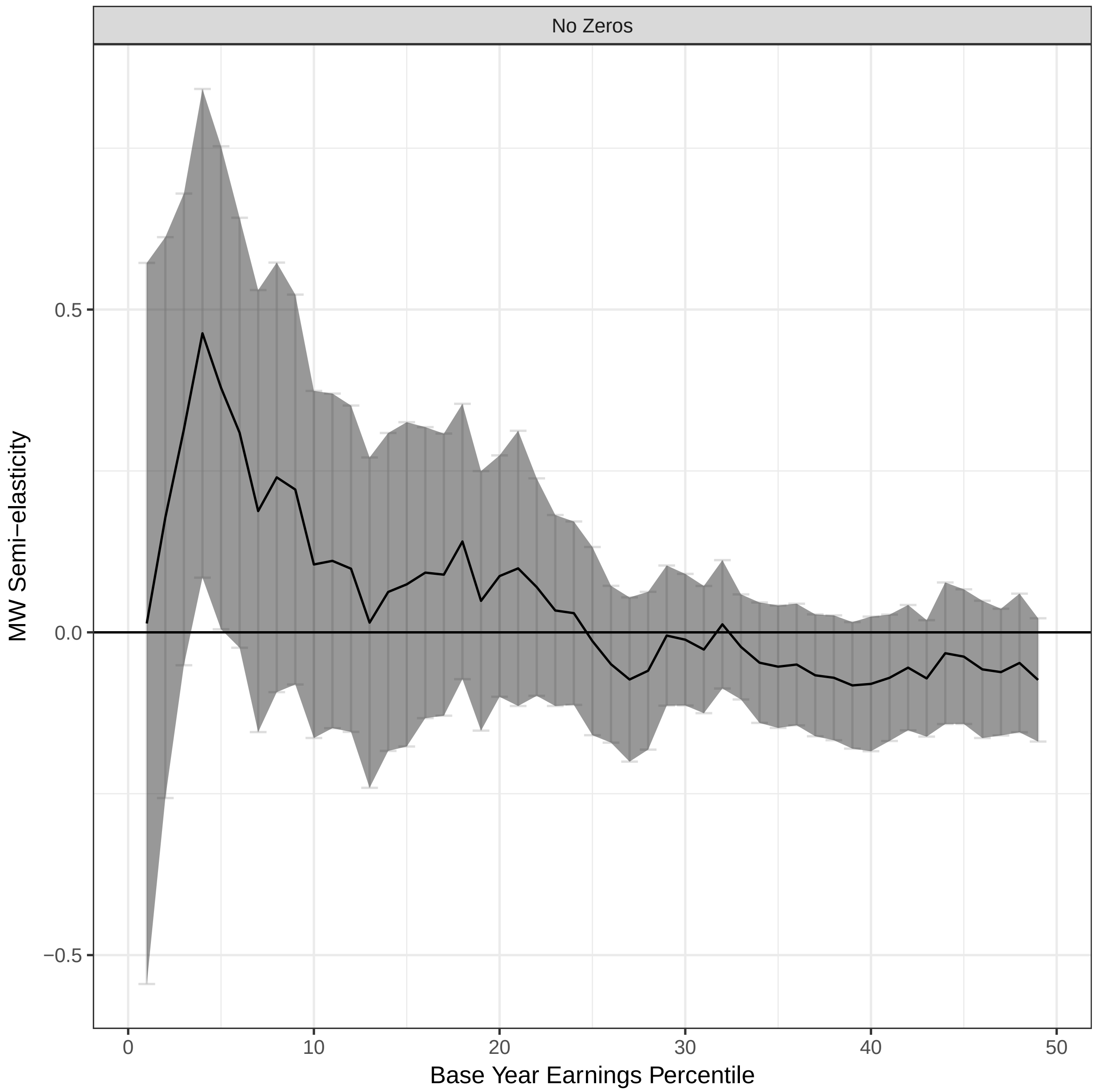
Figure B2: Income Mobility Profile Regressions, Five Years Ahead, Real Minimum Wages



Source: CPS ASEC and SSA DER, 1991-2013
Note: Each plotted point represents a separate regression estimated as described in Section 3.3. In the left panel, earnings growth is calculated using differences in logs, analogous to Figure 8. In the right panel, earnings growth is calculated using differences in the inverse hyperbolic sine, analogous to Figure 12.

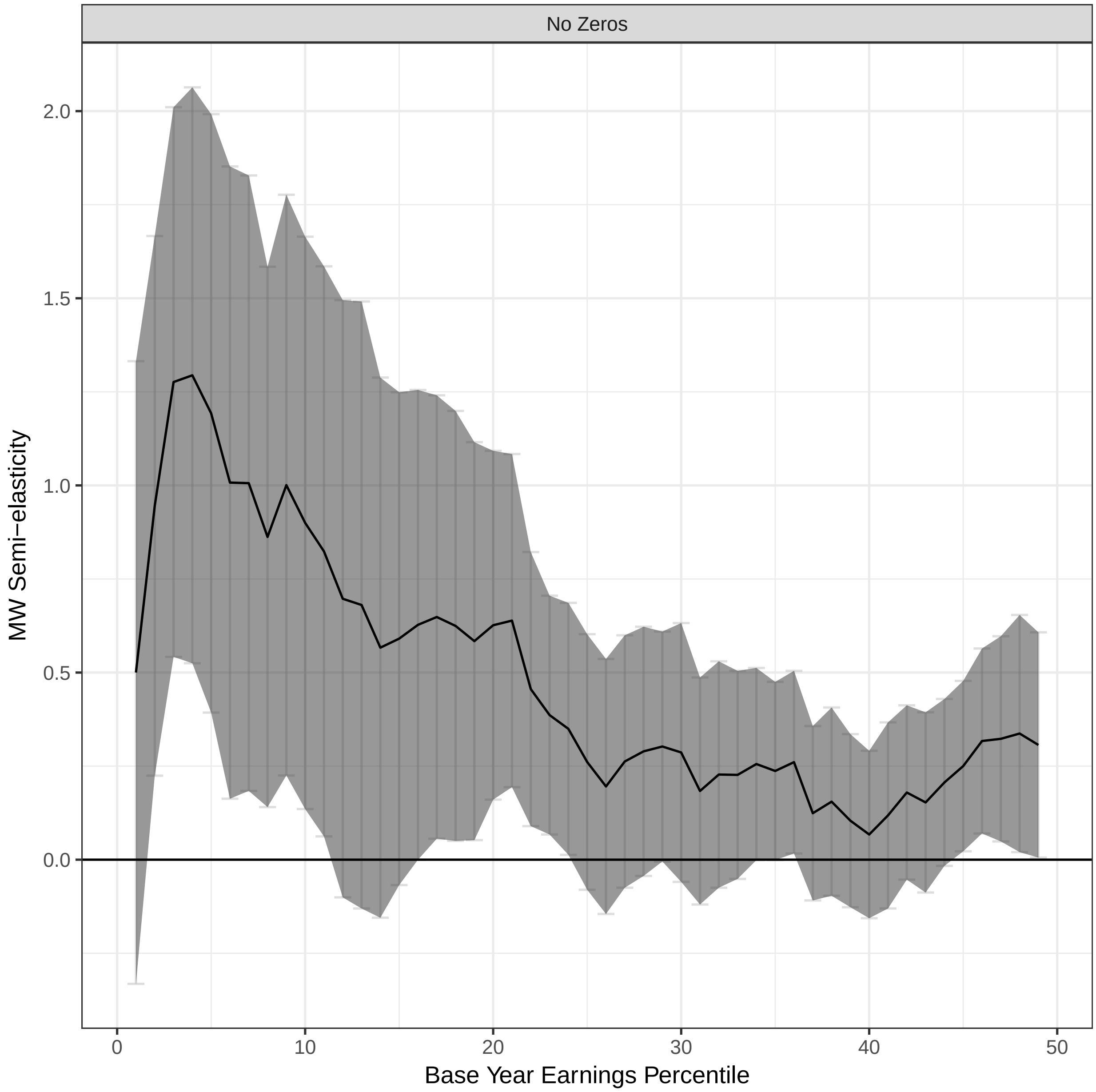
Appendix C Intermediate Saturation Estimates

Figure C1: Income Mobility Profile Regressions, One Year Ahead, Intermediate Saturation Specification



Source: CPS ASEC and SSA DER, 1991-2013
Note: Each plotted point represents a separate regression estimated as described in Section 3.3, but with census division by year fixed effects instead of state-specific linear trends. Earnings growth is defined as the change in log earnings between the base year and t years later, so individuals with zero earnings in either year are excluded from this analysis.

Figure C2: Income Mobility Profile Regressions, Five Years Ahead, Intermediate Saturation Specification



Source: CPS ASEC and SSA DER, 1991-2013

Note: Each plotted point represents a separate regression estimated as described in Section 3.3, but with census division by year fixed effects instead of state-specific linear trends. Earnings growth is defined as the change in log earnings between the base year and t years later, so individuals with zero earnings in either year are excluded from this analysis.