

The Distributional Effects of Minimum Wages

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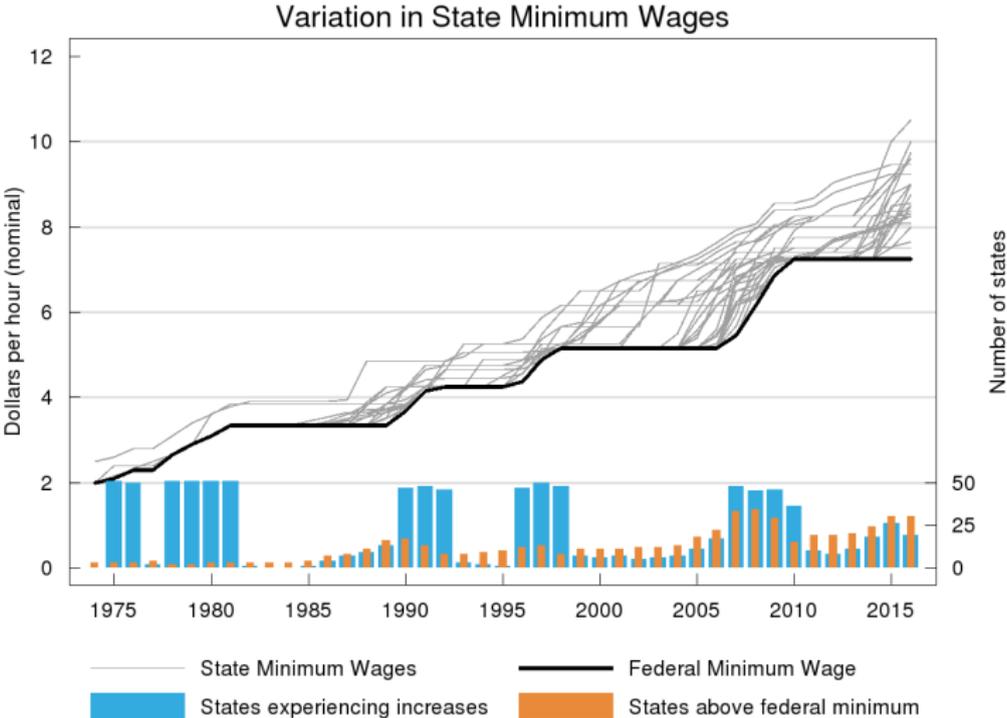
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Motivation



Source: Authors' calculations from Vaghul and Zipperer (2016)

Motivation

- ▶ Great deal of debate about (dis)employment effects of minimum wages
 - ▶ Neumark & Wascher (1992, 2002); Card & Krueger (1994); Dube, Lester, Reich (2010); Sabia, Burkhauser, Hansen (2012); Neumark, Salas, Wascher (2014); Dube & Zipperer (2015); Allegretto, et al (2017); Totty (2017)
- ▶ Some focus on income distribution/growth, more so recently
 - ▶ DiNardo et al (1996); Lee (1999); Lemieux (2008); Autor, Manning & Smith (2016)
 - ▶ Brochu et al (2015); Dube (2017); Cengiz et al (2017); Phelan (2018)
 - ▶ Neumark, Schweitzer, Wascher (2004); Clemens & Wither (2016)
- ▶ Studies of employment effects provide reason to think income growth/mobility could be affected
 - ▶ Changes in labor market transitions (Dube, Lester, Reich 2016)
 - ▶ Changes in employment growth (Meer & West 2016)

Motivation

- ▶ Difficult to consider income growth/mobility with publicly available data
 - ▶ Repeated CPS cross-sections, or aggregate administrative data
 - ▶ Exception: Clemens & Wither use SIPP, but only one panel during Great Recession
- ▶ Analyzing bottom of the distribution income mobility with survey data could be problematic
 - ▶ Abowd & Stinson (2013); Bollinger et al (2015); Chenevert et al (2016); O'Hara et al (2016); Brummet, et al. (2018)
- ▶ Linking the CPS to longitudinal administrative income data addresses measurement issue and enables consideration of mobility questions

Questions

1. Does using administrative earnings data alter estimated cross-sectional distributional effects of minimum wages?
2. Do minimum wages affect growth rate of low percentiles of the income distribution?
3. Do minimum wages affect income growth for individuals who start at low percentiles of the income distribution?

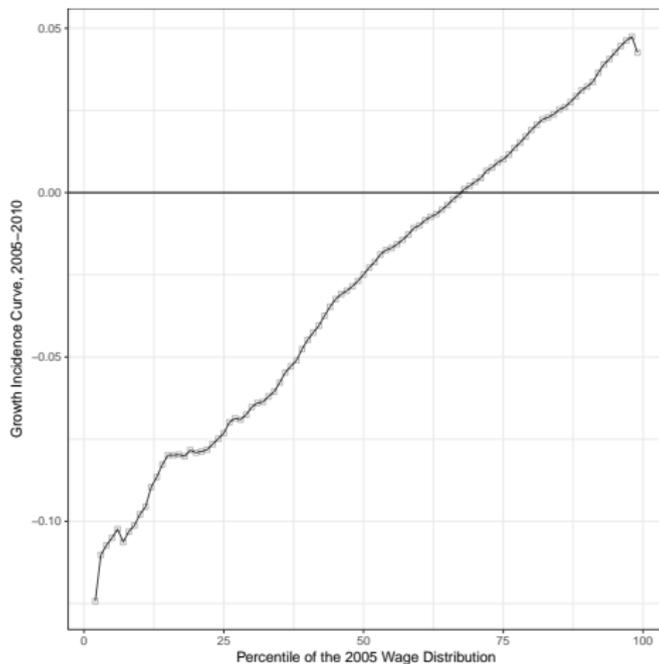
Data

- ▶ Minimum Wages
 - ▶ Vaghul and Zipperer (2016)
- ▶ Demographics
 - ▶ CPS ASEC
 - ▶ 1991-2013
- ▶ Earnings
 - ▶ SSA Detailed Earnings Record CPS Extract
 - ▶ Annual earnings from 1978-2012 for respondents to 1991-2013 CPS ASEC
- ▶ Geography
 - ▶ IRS 1040s, information returns
 - ▶ 1998-2012

Measuring (Absolute) Income Mobility

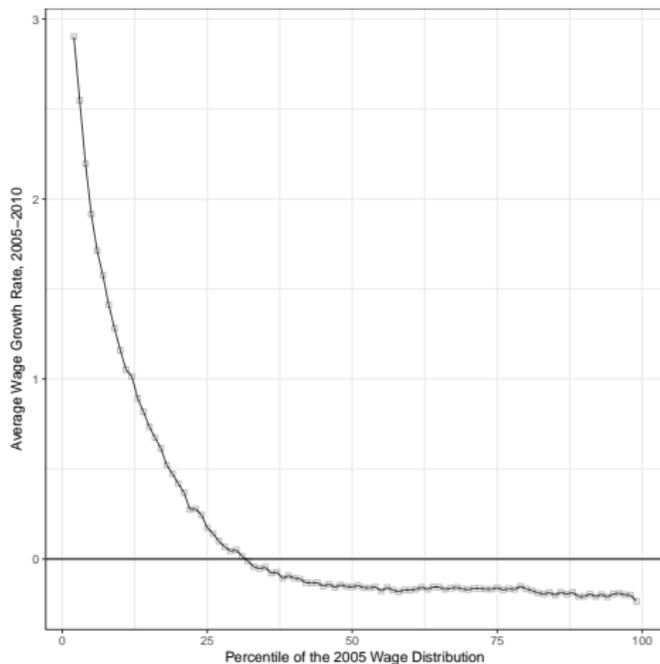
- ▶ Two ways of thinking about absolute income mobility
 1. What was the income growth rate of the p th percentile of the income distribution?
 2. What was the average income growth rate for an individual who started at the p th percentile of the income distribution?
- ▶ Growth Incidence Curves are a way of capturing the first concept:
 - ▶ $GIC(F_1, F_2, p) = \log(F_2^{-1}(p)) - \log(F_1^{-1}(p))$
- ▶ Income Mobility Profiles capture the second:
 - ▶ $IMP(p; x, y, F_1) = E(\log(y) - \log(x) | x = F_1^{-1}(p))$

Growth Incidence Curves



Source: CPS ASEC and SSA DER, 1991-2013

Income Mobility Profiles



Source: CPS ASEC and SSA DER, 1991-2013

Empirical Strategy

- ▶ Goal: 1) replicate Dube (2017)'s cross-sectional results and 2) extend this analysis to consider how MW affects income mobility
- ▶ Need some way to estimate the effect of MW on a functional of the income (or wage) distribution
- ▶ When analyzing quantiles and GICs, we extend the recentered influence function approach of Dube (2017)
- ▶ For IMPs, we adopt a local linear regression type approach

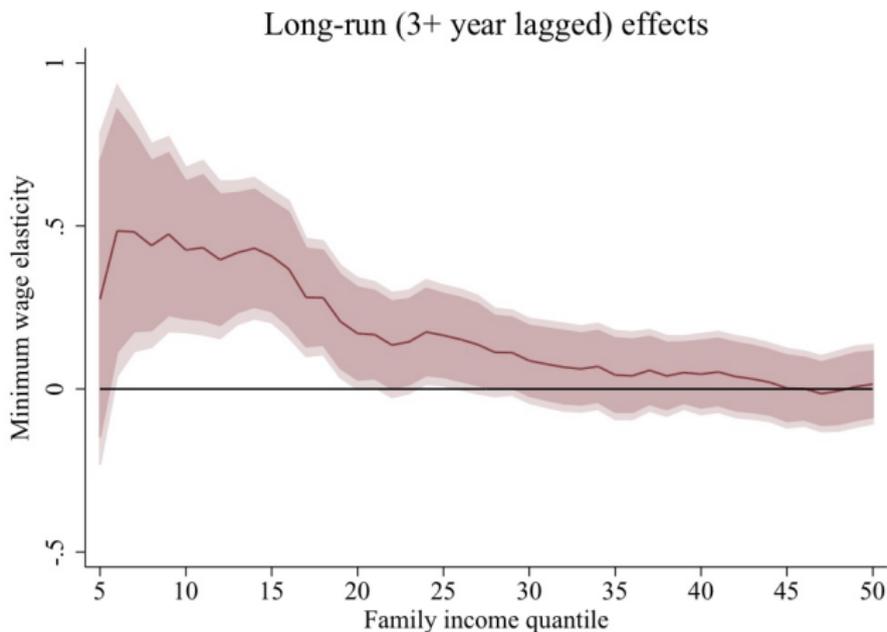
RIF Regressions

- ▶ We then estimate the effect of minimum wages on quantiles and GIC ordinates via RIF regressions of the form:

$$RIF(y_{i,s,t}) = \alpha_s + \alpha_t + f(t)\delta + \sum_{j=3}^{-k} \beta_j \log(MW_{s,t-j}) + \Gamma X_{i,s,t} + \epsilon_{i,s,t}$$

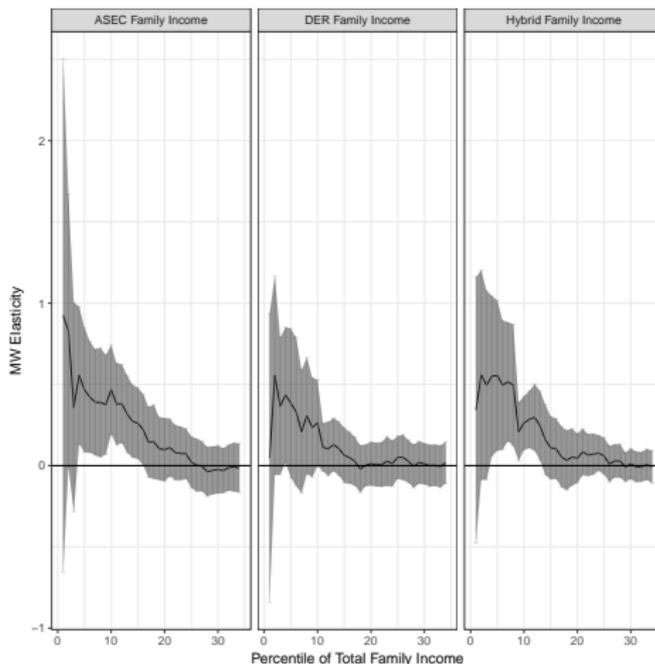
- ▶ $f(t)$ includes division-by-year FE, state-specific linear trends and state-specific recession year FE, and k is equal to 1 for quantiles, and equal to the number of years ahead for the GIC.
- ▶ We estimate these regressions using both CPS ASEC survey income/wages and DER adrec income/wages for the repeated cross section of CPS ASEC respondents 1991-2013

For Reference: Dube (2017), Figure 5



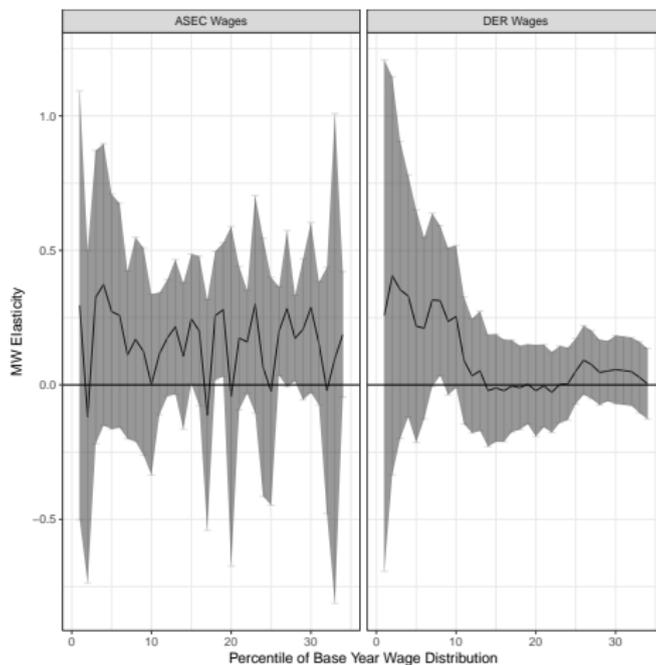
Source: Dube (2017), Figure 5

Results: RIF Quantile Regressions



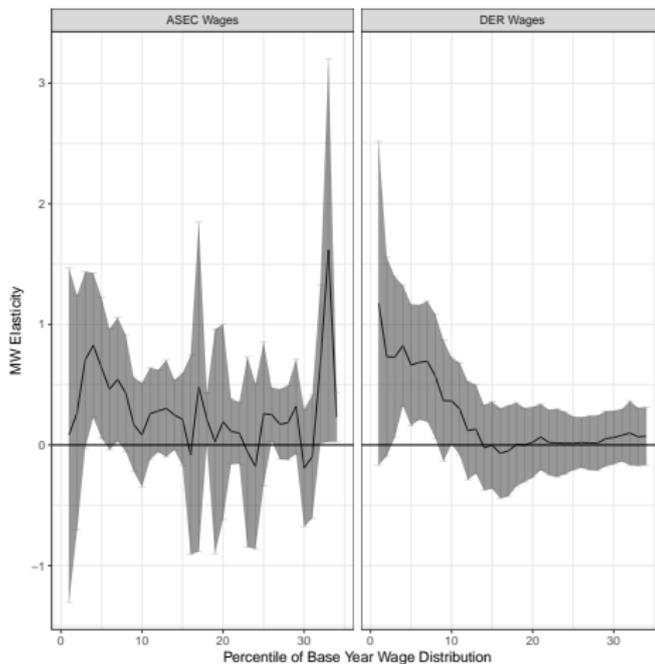
Source: CPS ASEC and SSA DER, 1991-2013

Results: RIF GIC Regressions - 1 Year



Source: CPS ASEC and SSA DER, 1991-2013

Results: RIF GIC Regressions - 5 Year

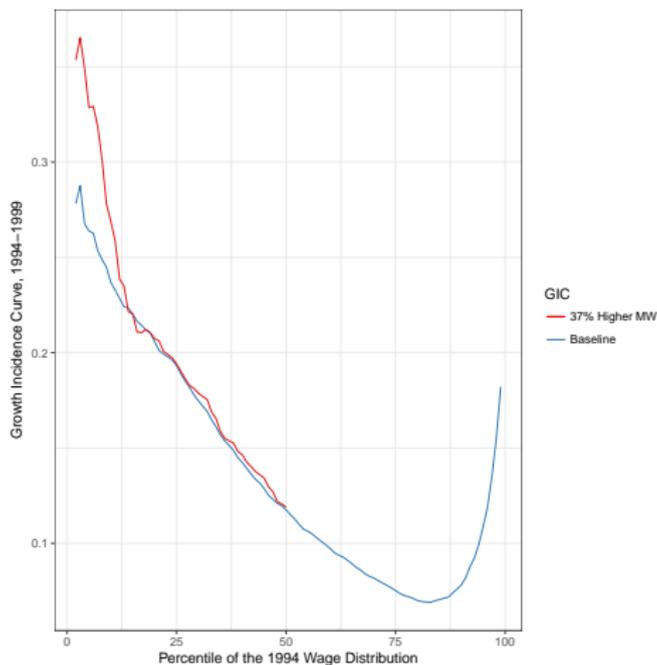


Source: CPS ASEC and SSA DER, 1991-2013

Analysis: A Large MW Change

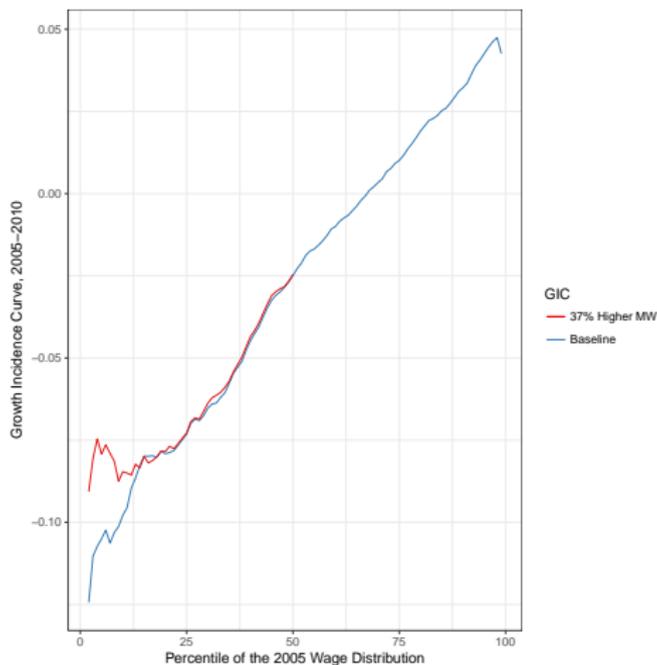
- ▶ Recently, some states and localities have enacted large changes in the minimum wage
 - ▶ Ex: Seattle increased its minimum wage from \$9.47 to \$13 for most employers ($\approx 37\%$ \uparrow) from 2013-2016
- ▶ What do our results imply about the effects of a large increase in MW on income mobility?
 - ▶ To do this, we compare two baseline 5-year ahead GICs (1994-1999 and 2005-2010) to counterfactual GICs with 37% increases in MW

Analysis: A Large MW Change



Source: CPS ASEC and SSA DER, 1991-2013

Analysis: A Large MW Change



Source: CPS ASEC and SSA DER, 1991-2013

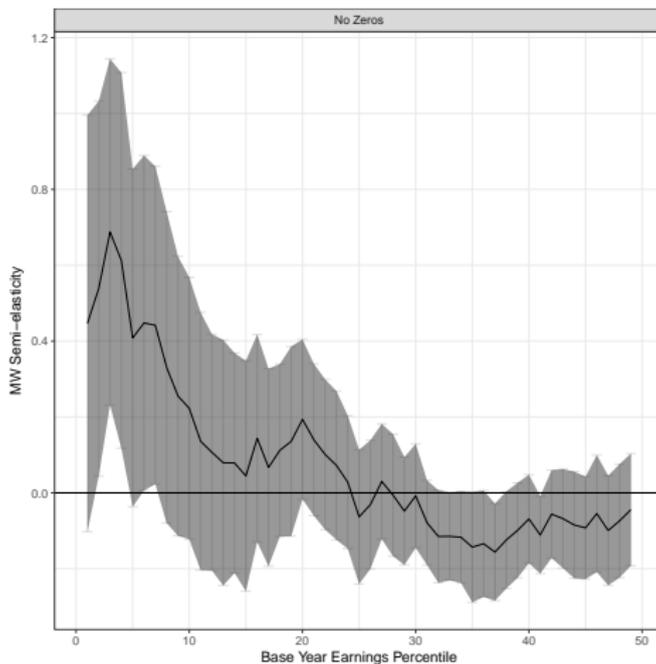
IMP Regressions

- ▶ IMPs are not amenable to the RIF regression approach
- ▶ Our approach is then to estimate regressions of the form:

$$d(y_{i,s,t+k}, y_{i,s,t}) = \alpha_s + \alpha_t + f(t)\delta + \sum_{j=3}^{-k} \beta_j \log(MW_{s,t-j}) + \Gamma X_{i,s,t} + \epsilon_{i,s,t}$$

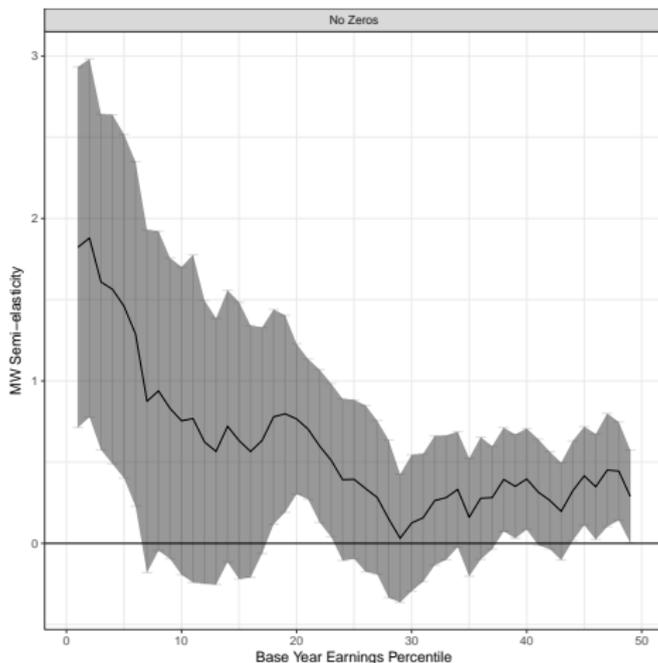
- ▶ For our baseline regressions, $d(x, y) = \log(x) - \log(y)$
- ▶ We estimate these regressions in moving windows across the percentiles of the base year distribution, with a bandwidth of 2.5 percentiles
 - ▶ So to estimate the effect at the 5th IMP point, we estimate the regression for the subsample between the 2.5 and 7.5 percentiles of the base year distribution.
- ▶ We estimate these regressions using DER adrec earnings for the panel of all CPS ASEC respondents 1991-2013

IMP Regressions - 1 Year



Source: CPS ASEC and SSA DER, 1991-2013; IRS 1040s 1998-2012

IMP Regressions - 5 Year



Source: CPS ASEC and SSA DER, 1991-2013; IRS 1040s 1998-2012

Other Specifications

- ▶ Parsimonious controls for time-varying local heterogeneity
- ▶ Intermediate controls for time-varying local heterogeneity
- ▶ Inverse hyperbolic sine
- ▶ Probability of zero earnings
- ▶ Real minimum wage
- ▶ Geographic mobility

Conclusion

- ▶ Evidence mostly points towards minimum wages increasing earnings and wage growth/income mobility at the bottom of the wage distribution, at least modestly
- ▶ Although estimates are sometimes imprecise, we can usually rule out large negative effects on wage growth
- ▶ IV results suggest that mobility may be important part of the story, and subsample analyses show larger IMP response to minimum wage among movers
- ▶ Highlights the importance of using administrative records when estimating the effects of minimum wages

Conclusion

Thanks!

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Recentered Influence Function theory

- ▶ Consider a functional T of distribution F for outcome y . The influence function of this functional is

$$IF(y, T, F) = \nabla T_{F \rightarrow \Delta_y}$$

where Δ_y is a degenerate CDF with mass only at y

- ▶ $IF(\cdot)$ captures the “influence” of a single observation – y – on the distributional statistic T
- ▶ If we add back the distributional statistic, we obtain the re-centered IF $RIF(y, T, F) = IF(y, T, F) + T(F)$. Note:

$$T(F) = E(RIF(y, T, F)) = E[E(RIF(y, T, F)|X)]$$

- ▶ So when we estimate a regression $RIF(y, T, F) = X'\beta + \epsilon$ we recover parameters that describe how X affects $T(F)$

RIF theory

- ▶ RIFs are well defined for quantiles and GIC (Essama-Nssah and Lambert, 2010)
- ▶ RIF for quantile point $v_p = F^{-1}(p)$:

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

- ▶ RIF for GIC ordinate $GIC(p) = \gamma q(v_p)$, where $q(x)$ is the growth pattern, γ is the average growth rate:

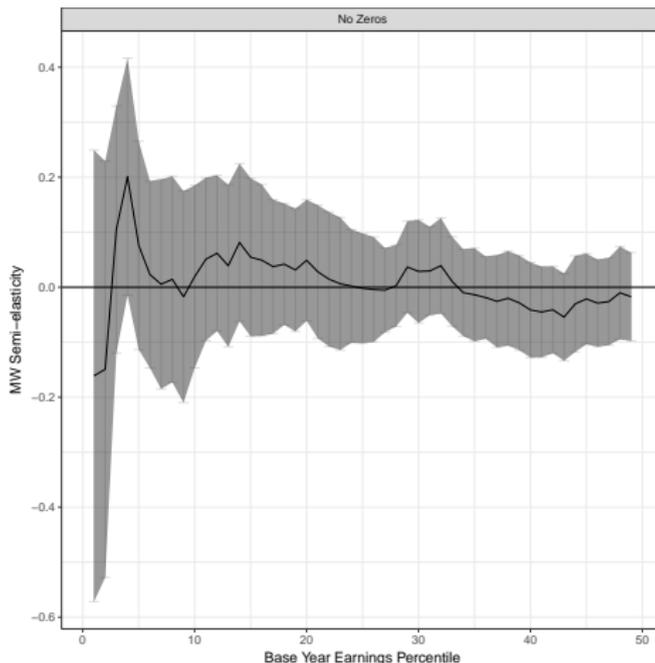
$$RIF(y, GIC(p), F) = \begin{cases} \gamma \left\{ \left[\frac{y}{\mu_F} + 1 \right] q(v_p) + \frac{pq'(v_p)}{f(v_p)} \right\} & y > v_p \\ \gamma \left\{ \left[\frac{y}{\mu_F} + 1 \right] q(v_p) - \frac{(1-p)q'(v_p)}{f(v_p)} \right\} & y < v_p \end{cases}$$

How much heterogeneity should we control for?

- ▶ Academic minimum wage/employment debate hinges on this question
- ▶ By following Dube (2017), we start from the maximalist position
 - ▶ Control for as much local, time-varying heterogeneity as possible
 - ▶ State-specific trends, division by year FEs
 - ▶ Some support for this approach from Totty (2017)
- ▶ What do estimates look like at the opposite extreme?
 - ▶ Neumark, et al (2014)
 - ▶ Just state and year FEs

IMP Regressions - Parsimonious Specification

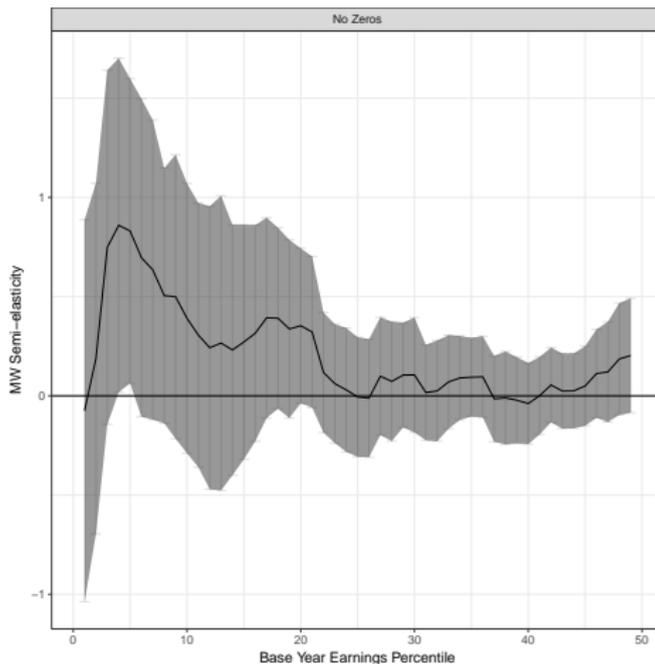
One year ahead



Source: CPS ASEC and SSA DER, 1991-2013; IRS 1040s 1998-2012

IMP Regressions - Parsimonious Specification

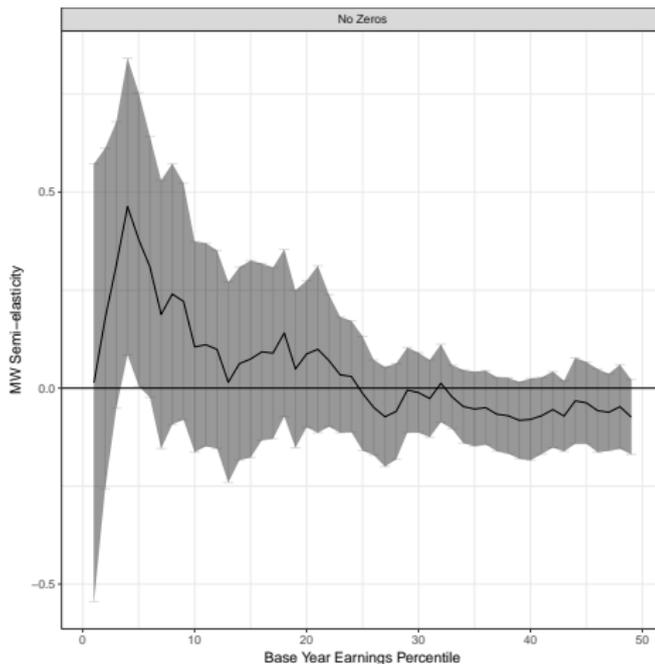
Five years ahead



Source: CPS ASEC and SSA DER, 1991-2013; IRS 1040s 1998-2012

IMP Regressions - Intermediate Saturation

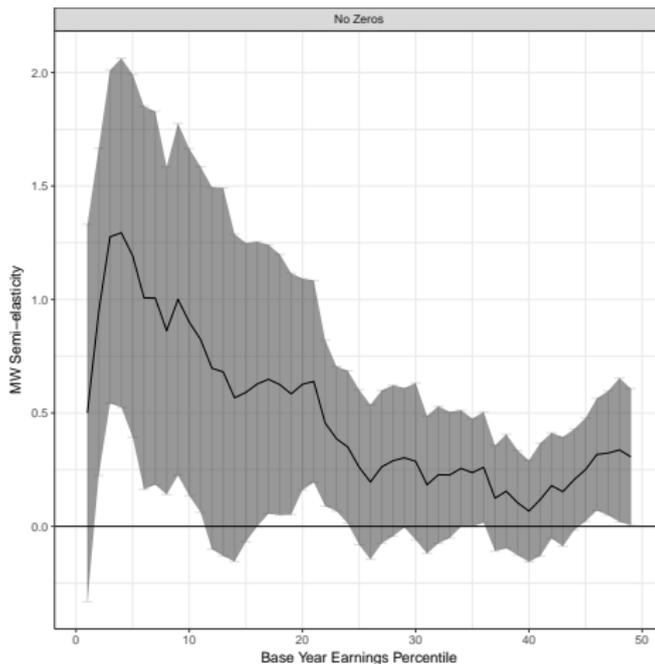
One year ahead



Source: CPS ASEC and SSA DER, 1991-2013; IRS 1040s 1998-2012

IMP Regressions - Intermediate Saturation

Five years ahead



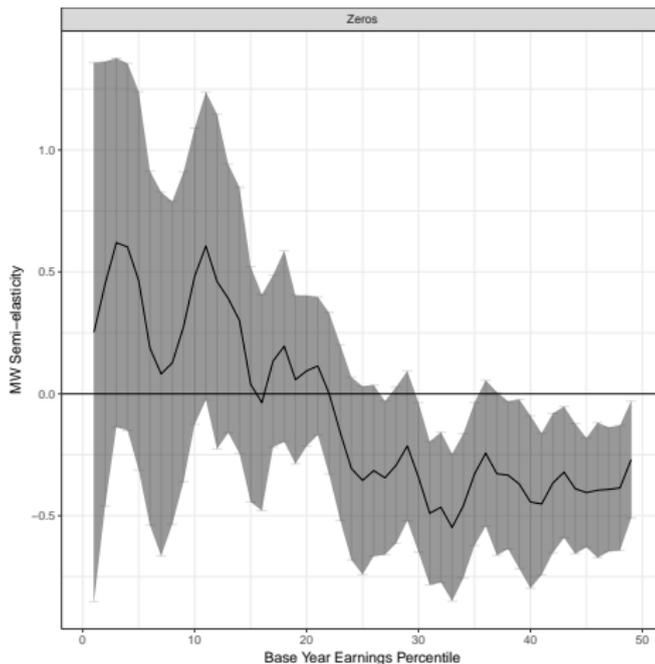
Source: CPS ASEC and SSA DER, 1991-2013; IRS 1040s 1998-2012

Full-Year Non-Employment

- ▶ Baseline analysis uses log differences to calculate earnings growth
- ▶ Individuals with zero earnings in year t or $t + k$ not included in that analysis (log not defined at zero)
- ▶ To the extent minimum wage increases induce zero earnings in measurement years, estimates could be biased
- ▶ Re-estimate using inverse hyperbolic sine to calculate earnings growth

IMP Regressions - asinh Specification

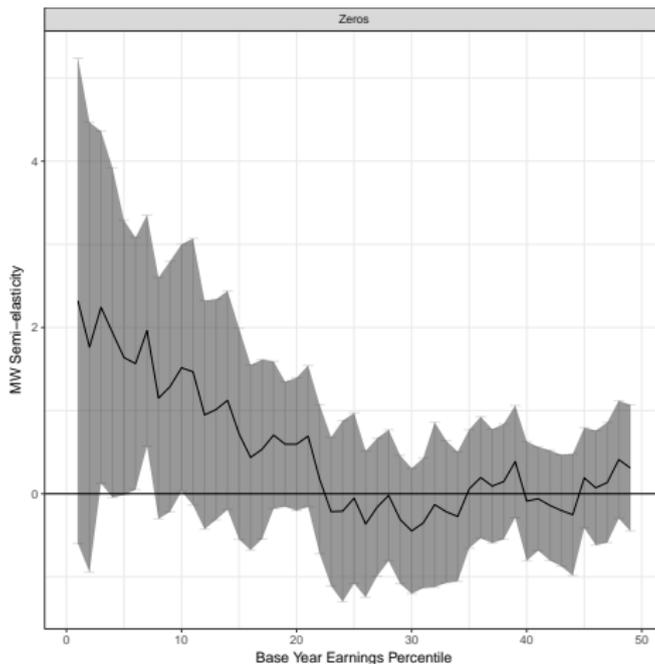
One year ahead



Source: CPS ASEC and SSA DER, 1991-2013; IRS 1040s 1998-2012

IMP Regressions - asinh Specification

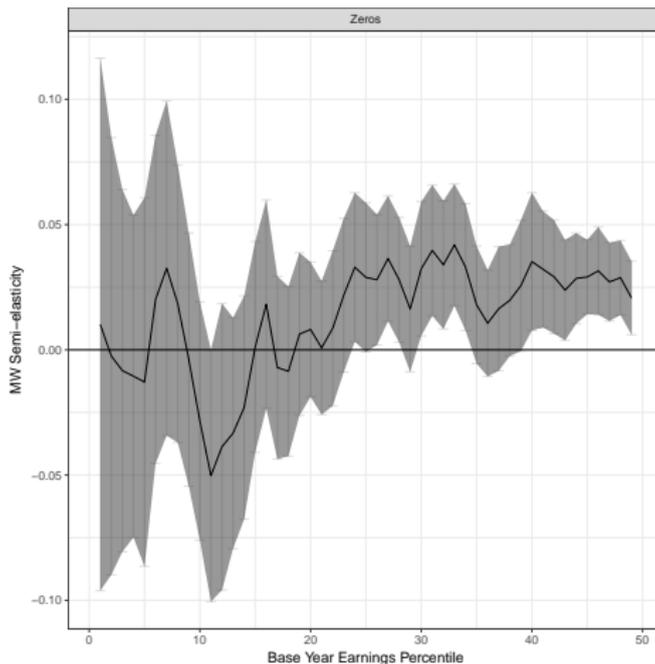
Five years ahead



Source: CPS ASEC and SSA DER, 1991-2013; IRS 1040s 1998-2012

Probability of Zero Earnings

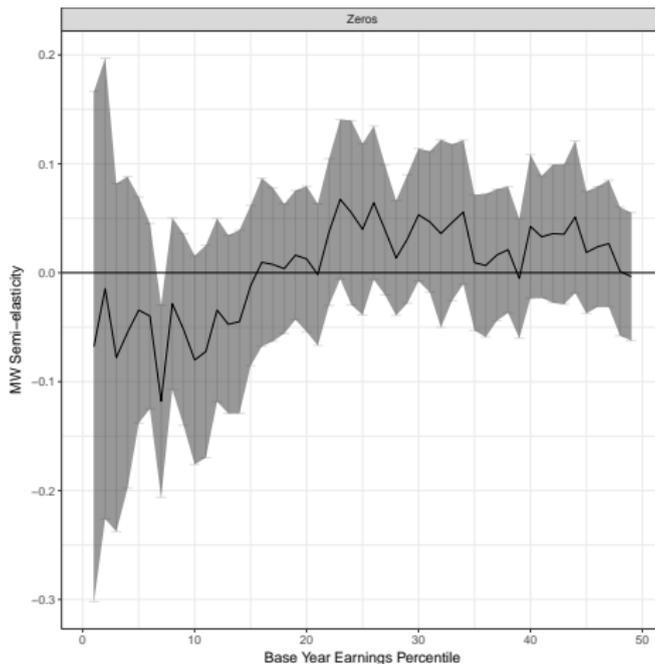
One year ahead



Source: CPS ASEC and SSA DER, 1991-2013; IRS 1040s 1998-2012

Probability of Zero Earnings

Five years ahead



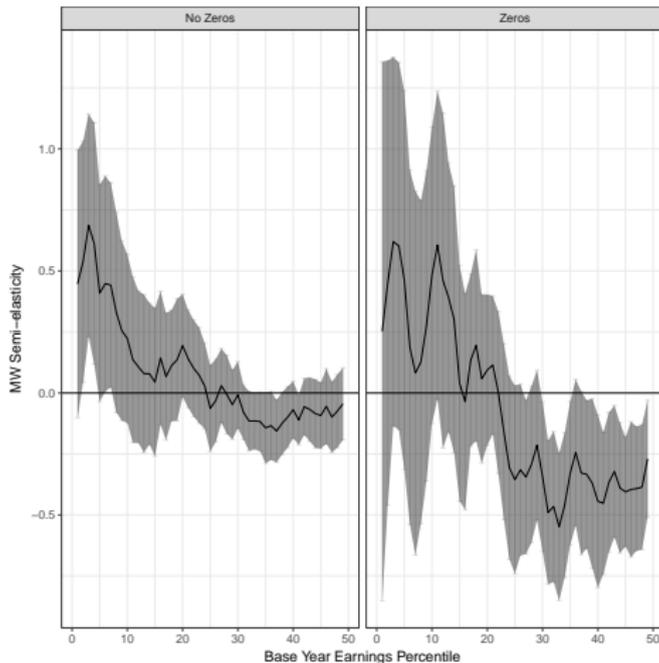
Source: CPS ASEC and SSA DER, 1991-2013; IRS 1040s 1998-2012

Real Minimum Wage

- ▶ Baseline estimates analyze the nominal minimum wage, as do many other quasi-experimental studies using state-level variation
- ▶ Work considering relationship between inequality and minimum wage often considers real minimum wage
- ▶ Does using the real minimum wage change our estimates?

IMP Regressions - Real Minimum Wage

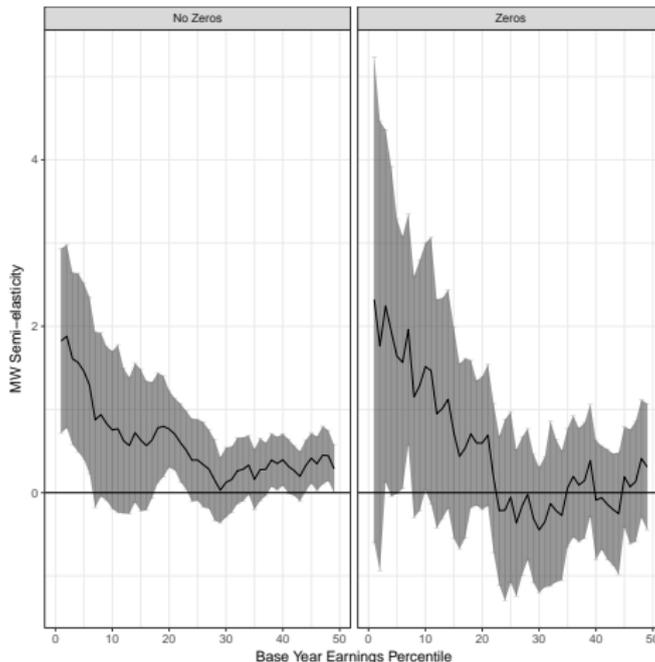
One year ahead



Source: CPS ASEC and SSA DER, 1991-2013; IRS 1040s 1998-2012

IMP Regressions - Real Minimum Wage

Five years ahead



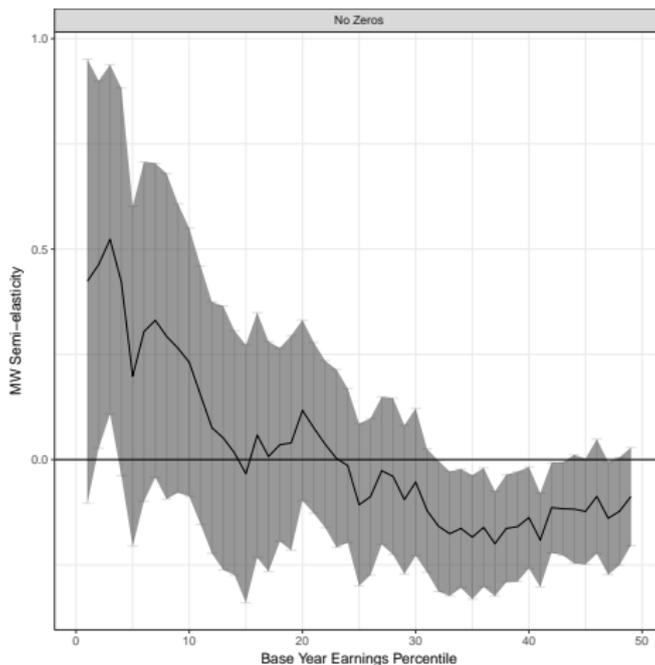
Source: CPS ASEC and SSA DER, 1991-2013; IRS 1040s 1998-2012

Mobility

- ▶ Considering earnings growth raises questions about geographic mobility
 - ▶ People may move toward higher wages
 - ▶ To what extent does this contribute to earnings growth?
- ▶ One approach: instrument for the leading MW terms $t + k$ with the minimum wage in the base year state in $t + k$
- ▶ Another approach: Estimate separately for movers and stayers

IMP Regressions - Simple IV Specification

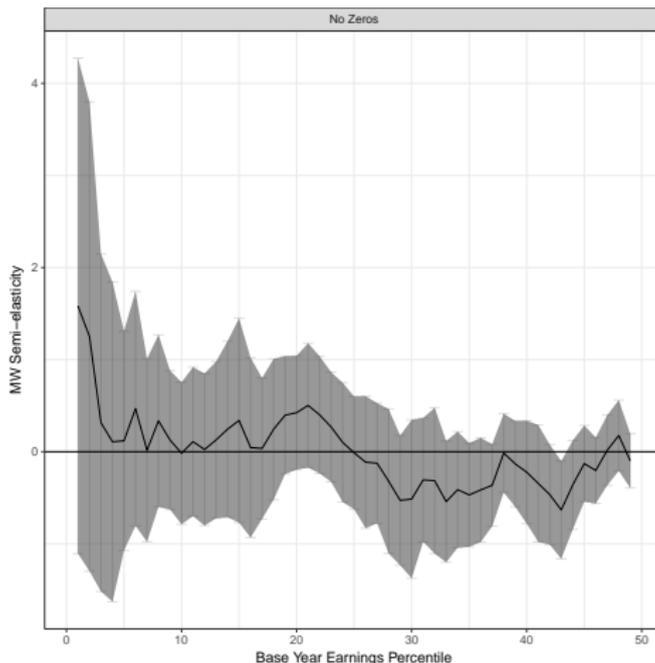
One year ahead



Source: CPS ASEC and SSA DER, 1991-2013; IRS 1040s 1998-2012

IMP Regressions - Simple IV Specification

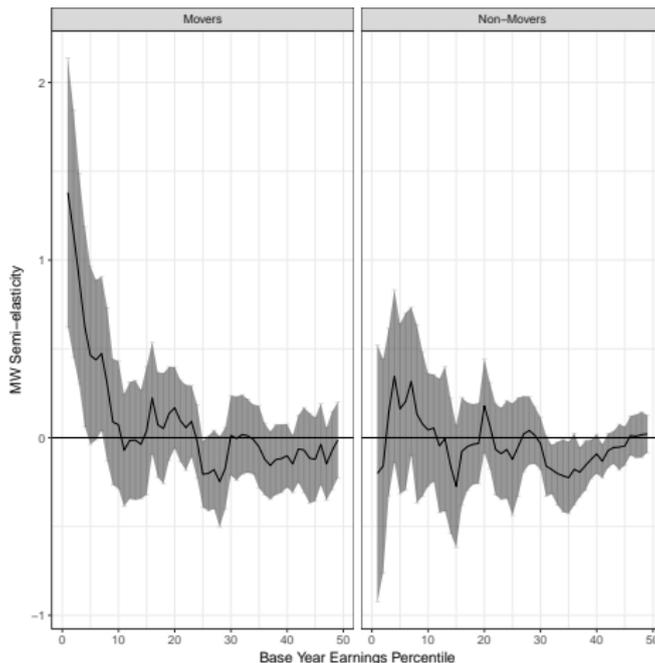
Five years ahead



Source: CPS ASEC and SSA DER, 1991-2013; IRS 1040s 1998-2012

IMP Regressions - By Mobility Status

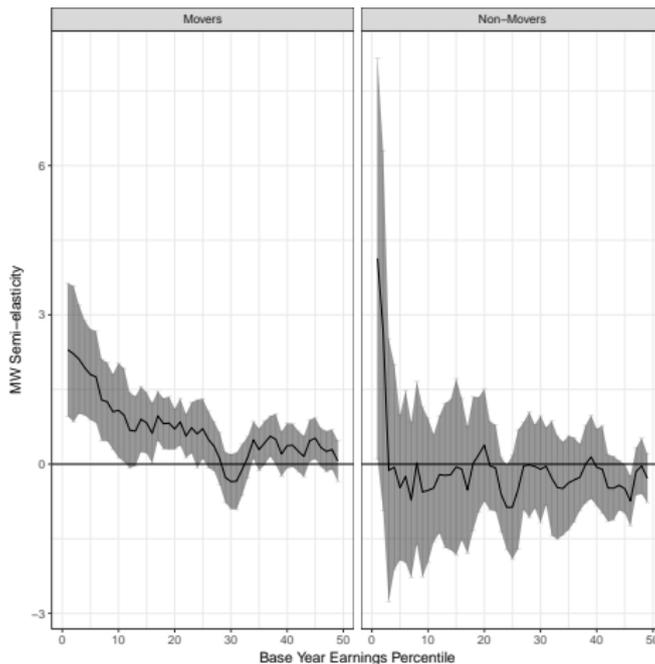
One year ahead



Source: CPS ASEC and SSA DER, 1991-2013; IRS 1040s 1998-2012

IMP Regressions - By Mobility Status

Five years ahead



Source: CPS ASEC and SSA DER, 1991-2013; IRS 1040s 1998-2012