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JEL Classification

E0, E6

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DID THE AMERICAN RECOVERY AND REINVESTMENT ACT HELP COUNTIES MOST AFFECTED BY THE GREAT RECESSION?

Mario J. Crucini* and Nam T. Vu†

July 30, 2019

Abstract

One of the statements of purpose of the American Recovery and Reinvestment Act (ARRA) was “to assist those most impacted by the recession.” To consider this facet, the ARRA is assessed along this dimension using the concept of risk-sharing. We estimate a trend-stationary autoregressive model of county-level wage income dynamics with each county subject to an idiosyncratic shock and a common shock (with county-specific factor loading). These shocks are used to estimate a redistributive fiscal policy function. The fiscal-offset is 33.6% for the common shock and 6.64% for the county-specific shock. Both of these fiscal policy parameters are statistically and economically significant.

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I INTRODUCTION

The American Recovery and Reinvestment Act (ARRA) was signed into law by then-President Barack Obama on February 17, 2009. As a discretionary peacetime fiscal measure, the total appropriation was the largest in American history. The impetus for the stimulus was, of course, the collapse of the stock market and a rapidly deteriorating macroeconomic situation in the United States and abroad, at the onset of the Great Recession. Unfortunately, the appropriate policy prescription and dosage were impossible to determine with any reasonable degree of accuracy given the lack of prior economic analyses to draw upon and the urgency to act. The economics profession was left in the unenviable position of having to assess the policy ex-post. This evaluation is ongoing and is proving to be a productive and challenging research area.

Much of the literature to date has focused on the question that macroeconomic models are best equipped to answer: How large is the expected change in GDP associated with an exogenous increase in government consumption? Studies of the fiscal multiplier have a long intellectual history, recent studies include: Feyrer and Sacerdote (2011), Wilson (2012), Chodorow-Reich et al. (2012), Nakamura and Steinsson (2014), and Dupor et al. (2018). A second branch of the post-ARRA literature has attempted to relate the stimulus to job creation (see, for example, Goodman and Mance (2011), Conley and Dupor (2013), Bohn (2013), and Dupor (2014)).¹ Finally, handful of papers deal with the subtle interactions of Federal stimulus, and fiscal spending and taxation, at the state and local level (see, for example, Johnson (2009), Cogan and Taylor (2010), and Leduc and Wilson (2017)).

Each of these studies has improved our understanding of fiscal policy and the role that specific parts of the ARRA stimulus package may have played in altering the paths of aggregate GDP and employment relative to a counterfactual without it. Largely absent from the literature is a systematic analysis of the heterogeneous impact of the Great Recession across

1) There is another related literature that deals specifically with the political economy aspect of the ARRA program. See, for example, Inman (2010), Gimpel et al. (2012), and Boone et al. (2014).

individuals and the role the ARRA may have had in mitigating or exacerbating income inequality during the Great Recession.

These issues relate directly to the second and indirectly to the fifth of the five stated purposes of the ARRA:² (1) to preserve and create jobs and promote economic recovery; (2) *to assist those most impacted by the recession*; (3) to provide investments needed to increase economic efficiency by spurring technological advances in science and health; (4) to invest in transportation, environmental protection, and other infrastructure that will provide long-term economic benefits and (5) *to stabilize State and local government budgets, in order to minimize and avoid reductions in essential services and counterproductive state and local tax increases*.

To address the success or failure of the legislation along the dimension of income inequality requires that we move from an analysis of the macroeconomic impact to the microeconomic impact – from a focus on the time series movements in aggregate income per capita to movements of individual income relative to the mean. Risk-sharing theory provides the relevant benchmark for understanding these types of policy choices. Positing a benevolent social planner, the policy prescription is to pool aggregate income in order to eliminate changes in the marginal utility of consumption across agents. As a practical matter, the instrument to achieve this is a policy of state-contingent transfers from those less affected by the recession to those more affected, as the Statement of Purpose suggests.

Assessing the effectiveness of the ARRA in mitigating income inequality is empirically demanding, requiring microeconomic panel data on both income and ARRA disbursements. In principle, the characterization of wealth inequality and income dynamics over the business cycle could be undertaken with longitudinal data such as the Panel Study of Income Dynamics (PSID) or the National Longitudinal Survey of Youth (NLSY). There are two reasons this is impractical. First, these familiar micro-panels are taken at an annual frequency which severely limits their value in business cycle analysis, particularly in the context of the

2) 111th Congress, Public Law 5, Statute 115, page 123, U.S. Government Printing Office.

ARRA which had a duration of only four years. Second, the ARRA payments cannot be traced directly back to individual recipients in most cases and in those rare cases in which this is possible, it will be very unlikely the individual will also be a respondent in either NLSY or PSID. This is because the discretionary component of the ARRA is almost entirely allocated to Federal departments and agencies who subsequently make grants to states and localities, non-profit organizations, and private businesses.

These considerations led us to the *Quarterly Census of Employment and Wages*, which ensures a nationally comprehensive accounting of both wage income and ARRA expenditure. As a consequence, the focus is on location-specific, not individual-specific, risks. Individual-specific risks will be averaged out as individual wages are aggregated to the county level. The basic implication of risk-sharing in this setting, then, is that more ARRA funds should be disbursed to counties that experienced larger income shocks during the Great Recession.

A necessary, but not sufficient condition for the ARRA to achieve this goal is that disbursements vary across counties. Establishing this fact is challenging because the ARRA was a complex mix of tax changes, grants to state governments and grants, contracts and loans to other private and public institutions. Our focus on counties rather than states is intended to preserve as much of the cross-sectional income variance as possible to identify the risk-sharing channel. Strict adherence in linking ARRA disbursements to county-level economic distress requires that each line-item disbursement has an associated zip code. This leads us to focus mostly on grants, which are the lion's share of the non-tax component of the ARRA.

We have two sets of novel results. The first has to do with the dynamics of county-level wage income relative to trend and its relationship to its aggregate U.S. business cycle counterpart (i.e., the median county). The second has to do with the relationship between discretionary grants and the relative veracity of business cycles across counties.

The econometric model of county wage income dynamics allows for three sources of business cycle heterogeneity: 1) differences in business cycle persistence; 2) differences in the

variance of the county-specific shock to wage income; and 3) differences in the factor-loading on a common macro-shock to wage income.

Turning to more details of the county-level wage income process, the half-life of a shock for the median county is reasonably short, 1.6 quarters, but ranges from 0.5 to 5 quarters at the 5th and 95th percentile of the cross-county distribution of persistence estimates. The county-specific shocks have a median standard deviation of 4.86% with the corresponding range from 2.59% to 12.57%. The macro-shock has a standard deviation that is slightly elevated relative to the median county-specific shock, 5.46%. The estimated county-specific factor loading ranges from 0.40 to 1.59, indicating that some counties have dampened responses to the macroeconomic shock while others' are amplified. Notice that these macro-factor loadings also imply a range of variation at the county level, from 2.18% to 8.68%. While interesting in their own right, these county-level income processes are particularly useful in thinking about the potential for monetary and fiscal policies to mitigate or exacerbate geographical income inequality at business cycle frequencies.

The focus of this paper is the evaluation of the discretionary component of the ARRA in helping those counties most affected by the Great Recession. To assess this objective we ask if counties experiencing either larger county-specific shocks or greater sensitivity to the common macro-shock received more funds during the Great Recession. Estimating a cross-county discretionary fiscal policy function, it is found that 33.6% of the macroeconomic shock is offset compared to 6.64% of the county-level shock. These elasticities are both statistically and economically significant. One important caveat of our findings is that the fitted policy function explains a small fraction of the variation in ARRA disbursements across counties. Low explanatory power is, of course, a common feature of cross-sectional empirical analysis and we discuss alternative explanations for it as well as the implications for the broader fiscal policy debate.

Our paper is related to the risk-sharing literature dealing with fiscal policy, most notably, Asdrubali et al. (1996). Their study focuses on the role of various automatic stabilizers in

mitigating the variance of income growth across U.S. states and finds that 13 percent of the unconditional variance of gross state product output growth is smoothed by the federal government. However, because they focus on automatic stabilizers, they do not estimate unexpected changes to income, but use raw growth rates instead.

In contrast, the discretionary appropriations in the ARRA were explicitly designed to overcome the perceived deficiencies of automatic stabilizers in the context of an extreme business cycle downturn. As such, unlike existing stabilizers, the stimulus was unprecedented in size and known to be a temporary measure: when the appropriated funds were disbursed, there was no expectation of a subsequent round of stimulus. In an interesting recent contribution, Oh and Reis (2012) study the ARRA with a focus on the redistributive components of the policy. Their focus is on the implication of incomplete markets (and other frictions, such as sticky prices) on the size of the aggregate multiplier, rather than the covariance between transfers and income shocks, which is our focus.

The paper proceeds in the following way. Section 2 describes our data sources. Section 3 presents a detailed picture of the time series and cross-county variation in ARRA grants, contracts, and loans. Section 4 reports our main results. This includes estimates of county-level wage income dynamics and the fiscal policy function relating disbursements at the county level to county-level and macroeconomic wage income shocks. Section 5 conducts robustness analysis, such as the sensitivity of the policy function to the exclusion of counties where state capitals reside. Section 6 concludes.

II THE DATA

We use two data sources.

Our wage income data are from the *Quarterly Census of Employment and Wages* (QCEW). The QCEW data set provides three measures of income: total quarterly wages, average weekly wages, and taxable wages. Our benchmark income measure is the total quarterly

wages.³ We seasonally adjust the raw data and then deflate by a GDP deflator (GDPDEF) available from the St. Louis' FRED database. The cross-sectional unit for the QCEW is the county-level Federal Information Processing Standards (FIPS) code. The cross-sectional unit of the ARRA data, on the other hand, is the zip code.⁴ The two data sets are spatially reconciled by aggregating all the stimulus payments across zip codes within the county using the corresponding area FIPS code in the QCEW data. As there are about 42,000 zip codes and about 3,000 counties in the United States, on average, there are 14 zip codes in a county. These data are essential in identifying economic distress in the labor market at the most spatially granular level possible.

The second source of data consists of the grants, contracts, and loans portion of the ARRA. For the purposes of identifying the risk-sharing channel, we purposely exclude any funds where it is not possible to identify the end recipient based on their zip code, which is necessary to evaluate the fiscal risk-sharing model at the most spatially granular level possible. As grants, contracts and loans may have quite different economic implications, the first thing we check is what dollar amounts fall into the three categories. Of the aggregate \$301 billion disbursements tracked back to the zip code level, almost all are grants. Only about 8% consist of loans and contracts, approximately \$4 billion and \$22 billion, respectively. The ARRA transfers data were initially collected by William Dupor at the Federal Reserve Bank of St. Louis and were supplemented with additional data from, the now defunct, Recovery.gov, a Federal government repository of all the ARRA data.⁵ A great deal of care is taken to identify the local zip code in which an individual ARRA transfer is finally distributed, as opposed to the zip code of the headquarters of the awarded company/organization with

3) We focus on the total quarterly wages as the main proxy for average income at each locality, as opposed to the other two measures to avoid having to deal with state and local taxes, which can vary significantly from one county to another.

4) There are two variables that indicate the location of the project in the data. The first variable is the zip code at which the firms/organizations were located at the time of the ARRA distribution. The second variable is the local zip code in which the project was carried out. We use the latter to match with the QCEW data set.

5) Data up to 2012:Q2 were initially collected from William Dupor's website and were extended to the end of our sample (2013:Q4) with supplemental data from recovery.gov

the goal of identifying the individuals (or, more precisely, the counties) most affected by the disbursement. These dollar amounts are then aggregated to zip code totals in each quarter and then aggregated across all zip codes within each county to arrive at our county-level panel of ARRA grants, contracts, and loans.

III THE ARRA OVER TIME AND ACROSS COUNTIES

One of the challenges of studying the ARRA is that it involves a complex array of fiscal policy measures. It is obviously well beyond the scope of any single paper to consider all of the economic implications of such a diverse set of tax and expenditure changes. Our risk-sharing model is intended to develop a better understanding of the large grants-in-aid portion of the ARRA and its relationship to the Great Recession, as experienced at the county level. The most instructive aggregate compilation of the impact of the ARRA on taxes and expenditures across time that we have encountered was produced by the Bureau of Economic Analysis. Table 1 reproduces most of the content of that compilation. Outlays from 2009:Q1 to 2013:Q1 totaled \$787 billion. To understand the composition of this total as well as the tax provisions, the line items of the table have been sorted into three groups. The first group, *discretionary spending*, are the categories that are thoroughly covered by our tracking of grants, loans and contracts down to the zip code level. The total in this category is \$312 billion. The lion's share of this total are grants, 75% of which are given to state and local governments who subsequently disburse the funds within their respective jurisdictions.

[Table 1 Here]

The second group are *enhanced stabilizers*, non-discretionary spending that serve to offset some of the negative effects of business cycle downturns on the most economically vulnerable. These funds supplemented pre-existing social insurance schemes, in the amount of \$97.8

billion. Of this total, about 60% was allocated to unemployment programs and the remaining 40% to the Supplemental Nutrition Assistance Program (SNAP).

The final category, *temporary tax provisions*, in the amount of \$305 billion are excluded from our analysis, but are briefly discussed here. About half of this amount is related to the Making Work Pay program and related tax credits provisions. One example is a 6.2% of income supplement up to \$400, with a phaseout dollar-for-dollar above incomes of \$75K (thus reaching zero at \$95K). As shown in the appendix, almost all counties would have qualified for the exact same \$400 per capita tax cut, leaving no cross-sectional variation to relate to the risk-sharing channel that is our focus.⁶

We turn now to a description of the ARRA grants, loans and contracts, in terms of their timeline of disbursements and variation across counties.

III.1 The ARRA Over Time

We begin with a macroeconomic view by presenting time series of the median (across counties) nominal wage income per capita and the median (across counties) of nominal income per capita when ARRA payments are excluded in Figure 1. The shaded area in the figure is the contraction phase of the Great Recession as decided by the NBER business cycle dating committee; it runs from the previous business cycle peak, December 2007, to the trough of the Great Recession, June 2009. In our construction, the gap between the two lines is the median per capita transfer disbursed through the grants, contracts and loans part of the ARRA program. As is by now well-known, at the macroeconomic level, it takes a considerable length of time for the appropriations to materialize in actual transfer payments and even longer for the funds to result in expenditure by end recipients on materials, labor, and capital. The first stimulus flow occurs in the third quarter of 2009, the maximum flow occurs in the second quarter of 2010 and the flows shrink rapidly toward zero by the end of 2013.

6) Specifically, Figure B.3 in the appendix plots a histogram of the fraction of counties that would receive the common maximum supplement, those that would receive less than the max, and those that would receive nothing (because average county income exceeds \$95K). To examine the within county effects on the income distribution would require administrative IRS data.

[Figure 1 Here]

This presentation implicitly assumes that the fiscal multiplier on wage income of the ARRA disbursements is one and is realized entirely within the quarter of the disbursement. The simplest example of this would be a grant-in-aid to a local government that pays the salary of a public school teacher who otherwise would have been laid off. In contrast, if the disbursement is a grant to a firm who places the money in the bank and does not hire a new worker or increase wages of existing workers, the gap created in subtracting the ARRA creates a reduction in wage income that simply does not exist. There is also the more abstract question of what would be the time profile of wage income if the stimulus had not been passed which lies at the heart of the debate on macroeconomic fiscal multipliers.

In contrast, the focus of this paper is on the unpredictable movements in county-level wage income and how ARRA disbursements correlate with the *innovations* to wage income. If every county received the same per capita transfer, there would not be any variation from the time-lines plotted in Figure 1 and the risk-sharing or redistributive implications of the ARRA could not be assessed. To get a sense of the variance across counties and over time of the ARRA grants, contracts and loans, we examine both the total county-level awards and awards on a per capita basis, by county and over time.

[Figure 2 Here]

Figure 2 presents the median, the 25th and 75th percentiles, as well as the minimum and maximum across counties. The figure focuses on the time period from the start of the stimulus to the period of its exhaustion (recall, 2009:Q3 to 2013:Q4). The median of the total transfer is approximately \$10 million per county (see the upper panel). The cross-county range is extraordinary, from a low of about \$100,000 to a high of roughly \$600 million dollars. Even the interquartile range is dramatic: \$3 million to \$50 million (approximately).

Since counties differ substantially in population, the lower panel of Figure 2 reports the amounts in per capita terms. The cross-sectional variance is still considerable, but now the

time series dimension is a bit more visible as well. The median per capita transfer averaged across years is \$184, the interquartile range is \$44 to \$537.

To get a sense of how wage income evolves during the course of the ARRA program, we examine, in Figure 3, both the county total wage income and county-level wage income per capita. Notice that given the massive amount of cross-sectional variation in wages (both total and per capita), the recovery of real wage income per capita is barely visible to the naked eye.

[Figure 3 Here]

Turning to the details, the range for aggregate wage income is from less than \$40 million for some counties at the lower end to more than \$3.5 billion for rich mega-counties (such as Cook County, Illinois). While macroeconomic analysis has been focusing almost exclusively on per capita income, it is important to also understand the heterogeneity of aggregate wage income since economically larger counties can potentially have more impact on the distribution of ARRA disbursements.

The lower panel of Figure 3 shows the evolution of the county-level wage income distribution on a per capita basis. Not surprisingly, the cross-sectional variance dominates the time series variation, at least as is evident in the median and interquartile ranges, which are bounded between \$10,682 and \$ 22,097 (or approximately \$40,000 and \$ 90,000 at annual rates).

III.2 The ARRA Across Counties

We next move on to a spatial view of wage income and the corresponding distribution of the ARRA stimulus package across counties.

To understand the extent to which the impact of the Great Recession differs across counties, we plot, in the upper panel of Figure 4, the peak-to-trough decline (mostly) of log wage income per capita. The first remarkable feature of this figure is that wage income is not

declining in a sizable fraction of counties – 29%, to be precise, did not experience declining real wages during this *national* business cycle. The second remarkable feature is just how much heterogeneity there is in the business cycle experiences of U.S. counties. Quite visible are the very large real wage declines in the Upper Midwest and the Southeast.

[Figure 4 Here]

The lower panel of Figure 4 plots the time-aggregated level of transfers per capita (in U.S. dollars per capita) across locations. To place this geographic distribution into perspective, if all individuals received the same transfer, the amount would be \$231 per capita on average. The variation in color in the heat map indicates considerable variation around this mean, including some counties that received no funds at all.

Our interest is in the spatial correlation of the business cycle experiences of each county and the disbursement they received from the ARRA. This is difficult to see in the two panels of the heat map, so we turn now to our formal empirical approach.

IV RESULTS

This section begins with an estimation of county-level growth trends and business cycles and their relationship to the macroeconomic trend and cycle. Specifically, we estimate a trend-stationary, first-order autoregressive model of county-level wage income dynamics. In what follows, wage income is seasonally adjusted log real wage income per labor force participant.

Our specification differs from the existing literature in that each county's wage equation includes a macroeconomic innovation and a county-specific loading parameter. This allows for heterogeneous amplification of common (i.e., macroeconomic) shocks at the county level. And, of course, each county is subject to a county-specific innovation which, by design is orthogonal to the macroeconomic shock. Importantly, the income processes are estimated using the longest available history of these data, 1990:Q1 to 2015:Q4.

The common and county-specific shocks are then regressed on the ARRA grants, contracts and loans the county receives during the period over which the stimulus is active. The estimated policy function recovers two elasticities. The first is the elasticity of discretionary fiscal transfers to an idiosyncratic county-level income shock and the second is the elasticity with respect to a given county's sensitivity to the aggregate, common, business cycle shock. The estimated historical income process is then combined with the ARRA fiscal policy functions to construct counterfactuals for each county that receives ARRA funds. These results are related to risk-sharing theory by combining the variance of wage income under *laissez-faire* to following the estimated policy function systematically across all counties.

IV.1 County-level Wage Income

As far as we know, there has been no systematic study of county-level business cycles or their relationship to the national business cycle. This section intends to fill this gap as a necessary preliminary step to estimating a county-level fiscal policy function.

The wage measure used in the estimation of labor income dynamics is the logarithm of the county-level nominal wage income divided by the product of an implicit price deflator and the county-level labor force:⁷

$$w_{it} = \ln \left(\frac{W_{it}}{L_{it}P_t} \right) .$$

This series is seasonally adjusted and is referred to simply as wage income.

The literature on growth and business cycles has long debated the question of whether aggregate GDP is trend stationary or difference stationary. Our preferred specification is a trend stationary model. The technical appendix reports results for the difference stationary alternative and the Im et al. (2003) (IPS) panel unit root test.⁸

7) For the implicit price deflator, we use the GDPDEF from the St Louis' FRED, which is the implicit price deflator used to deflate nominal GDP. County-level labor force data are from the Local Area Unemployment Statistics.

8) What we find is evidence of over-differencing in that the first differences exhibit negative auto-correlation of about -0.167, on average.

IV.2 County-level Wage Income Dynamics

County-level wage income is modeled as a trend-stationary process,

$$w_{it} = \alpha_i + \gamma_i t + \rho_i w_{i,t-1} + \lambda_i \varepsilon_t + \varepsilon_{it}. \quad (1)$$

The common shock is the estimated innovation from an analogous stochastic process followed by the cross-county mean wage level, w_t :

$$w_t = \alpha + \gamma t + \phi w_{t-1} + \varepsilon_t. \quad (2)$$

Recall from Figure 1 that wage income of the median county business cycle looks very much like the aggregate U.S. business cycle. How “representative” the median is of the more than 3,000 counties in the U.S. is central to the policy question that we address. If all counties have wage income profiles that track the median county perfectly, there are no gains from risk pooling, and there would be no “counties most in need” for the ARRA program to target.

Referring back to Equation (1), it is obvious that the specification has a rich menu of possible channels through which county wage income moves relative to the mean. Focusing on the cyclical component (i.e., ignoring the county-specific trends), there are three sources of county-level heterogeneity.

First, the shock identified by ε_{it} is, by construction, orthogonal to the common macroeconomic shock, ε_t and thus an idiosyncratic source of county-level variation. Second, the factor loading on the common macroeconomic shock, λ_i , allows county-level business cycles to be mitigated or amplified relative to the mean as this parameter ranges from values close to zero to above unity.⁹ Third, the persistence is allowed to be county-specific so that any stochastic perturbation from the trend growth path (from macroeconomic or microeconomic

⁹ The reader may be interested to know that the support of the estimated distribution of this parameter is entirely positive so there are no counties that are counter-cyclical to the aggregate cycle.

shocks) will result in different cumulative impacts on income across counties and thus imply different wealth effects of the underlying shocks.

Given the large dimensional parameter space, the exposition will focus on the median parameters and the 5th and 95th percentiles of their respective distributions. Concrete examples of counties with these parametric features will also be drawn from the panel for graphical examination.

[Table 2 Here]

Table 2 summarizes the parameter estimates and their standard errors arising from the estimation of Equations (1) and (2). We estimate this set of two equations jointly for each county i using the Newey-West estimator to account for potential auto-correlation and heteroscedasticity in the error terms.

The median county has real wage income that grows at a trend rate of about 0.48%. Cyclical deviations from trend for the median county have a persistence of 0.658 (a half-life of about 1.6 quarters). While, in theory, the cross-county median persistence and the persistence of the mean of the distribution need not be equal, the persistence of the cross-county mean wage (w_t) is, in fact, very close to the median – it equals 0.627. The fast trend reversion at the mean or median of the distribution needs to be carefully interpreted. Keep in mind, first of all, that trends may differ across counties indicating substantial long-run divergence in some parts of the cross-sectional distribution. The trend growth in real wages ranges from almost zero (0.16%) at the 5th percentile of the growth distribution to 1.2% at the 95th percentile.

Also, wage persistence around these county-specific trends ranges from 0.275 to 0.870 based on the 5th and 95th percentiles of the estimated distribution. These estimates translate into half-lives with a tenfold range: 0.5 quarters to 5 quarters. Heterogeneity of the conditional volatility of the wage processes by county arises from two sources. The first is the county-level shock, ε_{it} and the second is the county-specific response to the common (aggregate) shock $\lambda_i\varepsilon_t$. Typically, this coefficient, λ_i , is called a factor loading.

The idiosyncratic microeconomic shocks and common macroeconomic shocks are both economically significant. For the median county, the standard deviation of the idiosyncratic shock is 4.86% (Table 2). The median factor loading on the macroeconomic shock is indistinguishable from unity (0.989). This, combined with the fact that the common (macroeconomic) shock has a standard deviation of 5.46%, implies that the median county business cycle is driven by a roughly equal mix of macroeconomic and county-specific shocks.

Again, there is considerable heterogeneity around these medians. Beginning with the microeconomic or county-specific shocks (ε_{it}), the standard deviation ranges from 2.59% to 12.57%, a factor of just under 5 (4.85). The factor loading on the common shock (λ_i) range from 0.40 to a high of 1.59 (moving from the 5th to 95th percentile cutoffs). In words, a positive 10% macroeconomic wage income shock would induce a 4% impact response in county-level wages in the former case and a 15.9% wage advance in the latter case. This parameter range is a factor of about 4 (3.975), only slightly less cross-county heterogeneity compared to what arises from the microeconomic shocks.

[Figure 5 Here]

Figure 5 presents a complete statistical characterization of the heterogeneity of business cycles across counties. Specifically, it presents kernel densities of the full distributions of parameter estimates with vertical lines at the median, 5th and 95th percentiles of each parameter's distribution. Notice that all of the distributions are skewed with the exception of the factor loading parameter. Also of note is the long right tail of the standard deviation of county-specific shocks. In words: some counties suffer very dramatic cyclical episodes that appear to have little relationship to the national cycle. A classic example of this would be a discovery of recoverable reserves during the fracking boom or possibly fluctuations in oil and natural gas prices amplifying wage income variation in counties most specialized in their extraction or refining.

Given the heterogeneity in county-level business cycles, our results will be presented through the lens of nine “representative” U.S. counties that span the estimated parameter

space of persistence, microeconomic shock variance, and macroeconomic factor loading.

Figure 6 presents the complete history of real wage income per capita for these nine “representative” counties. The dashed lines are the estimated trends and the shaded areas are the NBER dated recessions. By “representative” counties we mean the following. We select six counties that have one business cycle characteristic that is in the upper or lower tail of the cross-sectional distribution, specifically at the 5th or 95th percentile of the distribution. These counties have the other two parameters close to the median value of their respective distributions. The county in the center of the figure, Randolph, Arkansas, is representative in an overall sense, matching all three parameters to the medians.¹⁰ That is, the persistence, idiosyncratic shock standard deviation and factor-loading on the macroeconomic shock are chosen as close as possible to 0.627, 0.0486 and 1, respectively. The graphic is oriented such that the parameter being varied (in bold) is indicated by the column and its value in the cross-sectional distribution is indicated by the row: the median or “representative” counties are in the middle row, the top row is the 95th percentile, and the bottom row is the 5th percentile.

[Figure 6 Here]

The first notable feature of the graphic is that the turning points of business cycles at the county level tend not to be aligned with NBER business cycle dates. An exception is the Great Recession, where most counties are either experiencing stagnation or negative real growth of wages. One way to think of the Great Recession in terms of these microeconomic data is the dominance of the macroeconomic innovation to the microeconomic innovation, which almost by definition will be true during deeper recessions.

Turning to the details, consider, Mohave county in the state of Arizona; it has a business cycle persistence close to the 95th percentile of the distribution, 0.82. Moving down the first column, the persistence drops to the national median of 0.67 and then to the 5th percentile, 0.28. In each case, the standard deviations of county-specific shock and macroeconomic

10) These three counties are the top three counties that match all three parameters to the medians.

factor loadings are close to the U.S. median, 0.05 and 1.02, respectively. Consistent with the selection criterion we see a tendency of Mohave to stay above or below trend for longer periods than Hempstead, Arkansas, while Beaverhead, Montana has even more cyclical oscillations over the same time period.

The middle column varies the size of the idiosyncratic shock. Hitchcock county, Nebraska is in the 95th percentile with a standard deviation of 0.14, it also has somewhat elevated persistence, despite our attempt to condition on that feature. The large idiosyncratic risk component combined with above median persistence decouples its cycle from the national cycle in both timing and duration.

The right-most column varies the loading on the common, macroeconomic shock. Marin, California for example, has a very high factor loading on the macroeconomic shock and tends to track the national business cycle (as indicated by the shaded NBER turning points) far better than Grant, New Mexico, which is actually booming during the Great Recession.

The fact that the time series profiles in these carefully orchestrated graphics are not more distinctive when comparing the 5th and 95th percentiles is a good rationale for the formal econometric modeling on which they are based. That is, any county will have some good or bad draws from the distribution in a given history and the mix of microeconomic and macroeconomic impulses is impossible to discern without first estimating the dynamic wage income model with the two shocks and independent trends.

IV.3 Estimated Fiscal Policy Function

The fiscal policy function is motivated by the risk-sharing literature. In that literature, a benevolent social planner transfers money across individuals in an attempt to equalize their marginal utility of consumption. In the international finance literature, the intent is to avoid *changes* in the marginal utility of consumption and thus allowing the pre-existing distribution of utility and consumption to be non-degenerate and yet have each agent's position in the

distribution be unaltered by asymmetric shocks.¹¹

The risk-sharing concept is explored in the context of the ARRA by seeking a functional relationship between the wage income shocks that a county experiences and the ARRA grants it receives.

The policy function that we estimate is given by:

$$g_{it} = \alpha + \beta_M(\lambda_i \varepsilon_t) + \beta_m \varepsilon_{it} + \nu_{it} \quad (3)$$

where g_{it} is the logarithm of real per capita total of grants received by county i in quarter t . We estimate the policy function in Equation 3 using a fixed effects panel regression with bootstrapped standard errors.¹² The coefficient β_M gives the percentage fiscal offset of a macroeconomic shock, including an accounting for the county's sensitivity to the aggregate cycle, $\lambda_i \varepsilon_t$. A county that is not affected by the macroeconomic shock ($\lambda_i = 0$) will receive no transfer while a county that moves in proportion to the cycle will receive an offset of β_M percent. Counties with a multiplier, $\lambda_i > 1$ will receive a larger transfer (and so forth). The coefficient β_m is the percentage offset of the idiosyncratic shock, ε_{it} .

Notice that by definition the idiosyncratic shocks average toward zero across counties and thus define a set of taxes and subsidies that could be balanced within each quarter. In contrast, the transfers associated with the macroeconomic shock are counter-cyclical (since, as we shall see, the betas are negative) and these would be expected to average out over time. That is, grants add to the Federal deficit during the Great Recession due to the offset of macroeconomic shocks (λ_i). These deficits would need to be financed using some combination of future tax increases and spending reductions, effectively reversing the process during the subsequent boom. Whatever the excess burden of the ARRA may be (due to those deficit-balancing actions), the point of this paper is to determine if the current beneficiaries

11) Because of potential labor market spillovers across adjacent counties (e.g., one can work in a county but lives in another), we provide estimates of our results using labor market areas (LMAs) instead of counties as the unit of locality in the appendix.

12) We provide, in a separate technical appendix, estimates using GMM. Overall, we find our estimates to be generally consistent across these different methodologies.

are those most affected by the Great Recession.

[Table 3 Here]

Table 3 reports the results of the policy function estimation. Observations with zero-dollar ARRA transfers are included in Table 3.¹³ The first row shows the fiscal offset to be 13.9%; that is, a 10% “shock” at the county level will be reduced to 8.61% on impact. The shock used to estimate this policy function is one that does not distinguish between the microeconomic (i.e., the county-level component, ε_{it}) and the macroeconomic component (i.e., the county-specific response to the macroeconomic shock, $\lambda_i\varepsilon_t$).¹⁴

Turning to more details of Table 3, the middle two columns are policy functions with only one of the two shocks included, not both. Clearly, the common shock is the more important of the two, with 32.4% (column 2) of the county-level response to a macro-shock offset, compared to just 4.03% (column 3) for the micro-shock.

The fourth column reports our benchmark policy function as it includes both shocks. It is important to note that ε_{it} and ε_t are orthogonal by construction, so we would not expect a large difference in the coefficients in the move from the single-regressor cases to the two-regressor case. In fact, the policy function coefficients are both a bit larger in column (4), than in columns (2) and (3). The policy response to the macro-shock increases from 32.4% to 33.6% while the policy response to the micro-shock increases from 4.03% to 6.64%. Based on the standard omitted variable bias formula, these parameter estimates indicate a mildly positive cross-county co-variance between the micro-shocks and the factor-loadings. In words: there is a tendency for a county with a larger micro-shock to also be somewhat more cyclically sensitive to the macro-shock (as measured by a higher λ_i).

13) Excluding the zeros has very little impact on the coefficients of the estimated policy function. Bootstrapped standard errors are reported to account for the use of generated regressors.

14) This is approximately what one would get by estimating a first-order auto-regressive model of wage income dynamics: $w_{it} = \alpha_i + \gamma_i t + \rho_i w_{i,t-1} + \eta_{it}$ and then regressing g_{it} on a constant and η_{it} .

IV.4 Cumulative Impulse Responses

By combining the estimated wage income processes by county and the estimated policy functions, it is possible to convey: 1) how the Great Recession impacted the distribution of wage income across counties and 2) the role of the ARRA disbursements in mitigating those effects.

To illustrate this we return to the representative nine counties discussed earlier and present the cumulative impulse response (CIR) functions of each county to either a microeconomic or a macroeconomic shock in Figure 7 and Figure 8. Moreover, in each case, we show the predicted path of future wage income under *laissez-faire* (letting the cycle take its course) or active policy, where the estimated fiscal policy function guides redistribution via g_{it} , dampening the macro-shock, by 33.6%, and the micro-shock, by 6.64%.

[Figure 7 Here]

Figure 7 presents the cumulative impulse responses to a micro-shock with the shock calibrated to the historical standard deviation by county (again, as shown in the middle number in the triplet of values in the parentheses below the county name). The cumulative impulse response for county i is therefore: $\sum_{k=1}^{20} \rho_i^k (\sigma_i)$, where ρ_i and σ_i are the persistence parameter and the standardized shock for county i . There are two sources of asymmetry in these responses across counties: the size of a typical county-specific shock and the rate at which a county recovers back to its trend growth path.

For example, the standard deviation of the microeconomic (county-specific) shock in Mohave county, Arizona is close to the median of all counties (0.05) but the persistence of its business cycle is in the 95th percentile of the cross-county distribution (0.82). Combining these two business cycle features, the cumulative impulse response is therefore: $\sum_{k=1}^{20} 0.82^k (-0.05)$. The dashed lines give the counter-factual path where the initial shock is offset by 6.64% of its initial value based upon the estimated policy coefficient for that type of shock. This will also reduce the cumulative effect by the same proportion (from about -27% to -25%).

The case of Beaverhead, Montana, in contrast, has a relatively fast revision to trend with a cumulative wage loss of only -6.5% relative to trend compared to about -6% as a result of the ARRA offset.

[Figure 8 Here]

Figure 8 presents analogous results for the macro-shock. Here the macro-shock is a one-standard-deviation of ε_t which, recall, is 5.49%. The cumulative impulse response in this case is: $\sum_{k=1}^{20} \rho_i^k \lambda_i (-0.0549)$. Notice, again, there are two sources of asymmetry in these responses: the novel dimension here is the sensitivity of a county's response to a macroeconomic shock and, as before, the rate at which a county typically recovers back to its trend growth path. Comparing Figure 7 to Figure 8 yields a key insight: across these nine "representative" counties, in theory, the ARRA transfers can greatly offset the negative impact of the Great Recession and significantly more so for the macroeconomic innovations.

[Table 4 Here]

To see this all in one place, Table 4 summarizes 20-quarter cumulative impulse responses using the median, the 5th and the 95th percentiles of the parameters governing the wage income processes. The top panel reports results for a one-standard-deviation macroeconomic shock (5.49%) which results in 20-quarter cumulative impulse responses ranging from a low of -2.85% for the 5th percentile factor loading (0.4) and persistence (0.275) to a high of -28.14% for the case of the 95th percentile of persistence and factor loading (0.87 and 1.5). The upper and lower range of cumulative impacts, across this two-dimensional parameter vector, differ by a factor of 10.

At the median of the estimated parameters (persistence of 0.628 and factor loading of around one), the cumulative impulse response to a macroeconomic shock is -10.69%. The ARRA transfers are predicted to offset 33.6% of these impacts, which reduces the median response from -10.69% to -7.10%, which is economically significant. Notice that this policy

does exactly what risk-pooling requires: it reduces wage income dispersion that would otherwise rise due to the asymmetric factor loadings on the common shock. Put differently, the cross-county income distribution does not fan out as significantly with the active policy in place as it does under *laissez-faire*.

The lower panel of Table 4 reports the 20-quarter cumulative impulse responses using the median, the 5th and the 95th percentile of the persistence parameters and standard deviations of the micro-shocks. The cumulative impulse responses range from a low of -3.24% for counties at the 5th percentile persistence (0.275) and shock standard deviation (0.025) to as high as -42.7% for counties at the 95th percentile persistence (0.870) and shock standard deviation (0.125). All in all, these numbers imply a roughly tenfold increase in the impact of the shock at the microeconomic level moving from one extreme point in the parameter distribution to another. Taking into account the 6.64% ARRA offsets at the micro level (Table 3, column (4)), these cumulative impulse responses are -3.03% and -39.88%, implying a cumulative fiscal offset by the ARRA ranging from 0.27% to 2.84%, moving from the 5th percentile county to the 95th percentile county. At the median, the ARRA program offsets the negative micro level shock by 0.62%, reducing the cumulative response from -9.35% to -8.73%.

[Figure 9 Here]

Figure 9 provides a more comprehensive view. Each panel is a histogram of cumulative impulse responses across the entire distribution of counties for *laissez-faire* and active policy (ARRA). Both distributions are truncated at a bin for cumulative responses equal to or greater than 35% for readability.

The first, and most obvious feature of the distributions of CIRs to the macroeconomic and microeconomic shocks is that both are strongly left-skewed, but the macroeconomic impulses are considerably more skewed. The medians of the CIRs, given the historical income dynamics, turn out to roughly be identical across the two shocks, at -15%.

The counterfactuals using the ARRA policy function shift the mass of the CIR distribution to the right. Because the offset coefficient is only 6.64% for the microeconomic shocks and 33.6% for the macroeconomic shocks (Table 3, specification (4)), the latter is far more important given the estimated ARRA policy function. The policy response shifts the median CIR from -15% to -10% and moves the fraction of counties experiencing extreme distress (-35% or more from 6% of the counties to less than 3%). More importantly, from a risk-sharing perspective, the resulting CIR distribution is much more concentrated around -10% with the full treatment of the asymmetric effects of the macroeconomic shocks as the mass to the left of the laissez-faire median is shifted toward zero.

V ROBUSTNESS

This section focuses on the robustness of our benchmark trend-stationary specification to selection into treatment and mis-measurement of the treatment. A battery of other econometric issues are also considered.

V.1 Selection into Treatment

It is beyond the scope of the data to know why some counties received treatment (positive grants) and others did not. However, given the historically estimated income processes, it is possible to ask if the stochastic properties of the treated and non-treated counties differ in obvious ways. To accomplish this, the distribution of the CIR functions in response to both the macroeconomic shock and the microeconomic shock are parsed into two groups, those who receive grants and those who do not.

Figure 10 contains four panels of CIRs histograms. As with Figure 9, the top row is the distribution of CIR for the macroeconomic shock while the bottom row is the counterpart for the county-specific shock. The new partition divides the population of counties into those receiving treatment (i.e., positive ARRA transfers) on the left-hand side and on the right-hand side would be what is considered the *control* or untreated group if this was indeed a

controlled experiment.

[Figure 10 Here]

What we are looking for when comparing the raw CIRs (the *laissez-faire*, red bars) is evidence of a difference across the treated and non-treated, but there does not seem to be one. The median CIR is 15% in both panels for the macroeconomic shock. Both distributions are quite similar in shape as well, with substantial left-tails. The fraction of counties with very strong responses to macroeconomic shocks historically is also similar. Note that the fraction of counties with CIRs of 35% or more is about 6% in both cases.

The CIRs for the microeconomic shocks are also quite similar across the treated and non-treated groups. The median CIR is again close to 15% for both groups. The CIRs of the treated counties are a bit more concentrated about the mode, but otherwise look much like the non-treated, skewing strongly left. Note that we would expect more differences in the lower panel of the simple fact that the microeconomic shocks are idiosyncratic to the county, so it is a bit heroic to think the distribution will preserve itself exactly when parsed into two groups.

Taken at face value, these figures strongly suggest that the treatment and control look quite similar in business cycle characteristics. This is important given the discussion in the macroeconomic literature about the decision to treat at the macroeconomic level. As the argument goes, if we invoke discretionary stimulus only in the worst states of the world, the multiplier will be downward biased in the sense that the counter-factual output decline would have been much worse. In a sense, our study provides 2,479 cases of fiscal stimulus and 657 cases of no fiscal stimulus. There is no sense in which things are worse in the non-treated group in terms of the sensitivity of business cycles to the aggregate shock.

The corollary of this is that they should be treated. The black bars are repeating exactly what we did in the benchmark case, but now with the treatment extended to counties that failed to receive any grants. Consistent with the treated group, the treatment arising in

the observed responses to the macroeconomic shocks would have been similarly effective in the 657 counties that did not receive any transfers. This can be seen by the comparable rightward shift (i.e., toward smaller CIR recessions) in both of the upper panels. Since the policy responses to the microeconomic shocks were small to begin with, the distribution of the CIRs is not dramatically affected by the active policy scenario.

V.2 Mismeasurement of Treatment

An important contribution of our paper is tracking the funds appropriated by the U.S. Congress, to the Federal Agencies and Departments charged with their allocations to state and local governments and to the private for-profit and not-for-profit businesses and institutions at the zip code level. The state government is a key intermediary in these flows of funds. As such, they are typically the primary recipient of record in the recovery.gov data. Reporting of sub-awards and contracts from the state to final recipients is the responsibility of the state government.

To the extent that there are delays in the movement of funds from the state level and beyond or the state government fails to completely or accurately report those allocations, the grants will be geographically misallocated. To effectively deal with the possibility it is first useful to parse the grants to counties in which the capital of each state resides and others.

[Table 5 Here]

Table 5 shows the accounting of grants, contracts, loans in the state capital (county), other counties and the totals. Of the \$ 301 billion tracked to the county level, \$108 billion is assigned to the state capitals and \$ 193 billion to counties that do not contain the state capital. Roughly a factor of 2 to 1 favoring state capitals. This seems to suggest the possibility of over-attribution to state capitals.

Another relevant metric is dollars per capita since counties with state capitals vary in population at least as much as those without state capitals. Panel B of Table 5 shows the

per capita dollar amount of grants going to the state capitals is \$ 3,983 compared to \$ 964 – a factor of more than 4 to 1 favoring state capitals.

[Table 6 Here]

While state capitals may retain more funds per capita due to their role in managing various programs, these numbers suggest over-attribution of funds to state capitals. To see what difference this makes, Table 6 re-estimates all of the policy functions excluding the counties in which the state capitals reside. As is evident, the coefficients are virtually unaffected. This is perhaps not entirely unexpected. The excluded counties may account for 2 out of 3 dollars in our micro-panel, but they are only 1.6% of the sample of counties in the cross section.

Moreover, if one assumed that the over-attribution to the state capitals is distributed in the same proportion to the counties as the funds that are reported to sub-recipients, there would be no effect on the fiscal policy slope parameter. From an econometric point of view, recovering the policy parameter does not require a full accounting of the disbursements, what is required is a random sample from the disbursement data large enough to estimate the coefficient of interest. This, of course, is generally the case in applied microeconomics where a 1% random sample of U.S. Census data is sufficient to estimate parameters of interest at a very high level of precision. Nonetheless, it is reassuring in the context of a policy evaluation to track such large fractions of the total disbursements down to the county level and relate them to economic conditions faced by individuals, firms and public officials in those counties.

V.3 Additional Sensitivity Analyses

In addition to the two main robustness exercises that we have alluded to in this section, a battery of additional econometric issues are considered, with more details to follow in the appendices.

First, panel unit-root tests are reported and provide evidence that not all counties exhibit non-stationarity in their real wage levels. In particular, we test for unit root in wage income

using the Im et al. (2003) (IPS) panel unit root test and are able to reject the null hypothesis that all panels contain unit roots for wage income.

Second, due to the inherent difficulty in distinguishing trend-stationary and difference stationary stochastic processes, a difference-stationary wage process and the associated fiscal policy functions are also estimated and reported. Here we find the average persistence of wage growth is -0.167, with a range from -0.592 and 0.233 based on the 5th and 95th percentiles of the distribution. This result points to the evidence of over differencing, which favors our benchmark trend-stationary specification.

Third, the data are aggregated to Local Market Areas (which define labor-market-integrated areas comprised of adjoining counties). This helps to ensure the results are not sensitive to the level of spatial aggregation as might be true when the places of work (wages and grants) differ from the places of residence (consumption) due to commuting. Here we find that our fiscal offset estimates to be insensitive to the use of this alternative unit of locality.

Fourth, given the panel structure of our wage income dataset, we provide the fiscal offset estimates using income shocks arising from estimating an alternative to the benchmark wage income process using panel GMM. We find our benchmark estimates to be consistent with the alternative results, despite the change in the estimation method of the wage income process.

Fifth, we explore the extent to which our fiscal offset estimates are sensitive to either (i) not having any particular county in the sample or (ii) not having any particular quarter in the data. The impetus of this exercise is to understand how our estimates are sensitive to outliers across time and counties. We find that our benchmark estimates are generally not driven solely by data from any particular county or quarter of the ARRA's implementation.

Last but not least, we explore the extent to which our estimates of the effects of the ARRA program in offsetting income shocks at the county level are sensitive to the size of the transfers. Here we find that our result that ARRA transfers are largely offsetting national

shocks to be consistent across samples with varying transfers sizes.

VI CONCLUSION

As Oh and Reis (2012) have correctly pointed out, much of the ARRA stimulus came in the form of transfers rather than increases in government consumption. This paper studies the role of the discretionary part of the stimulus in terms of mitigating wage income variance across counties, finding evidence of a particularly strong fiscal offset of the asymmetric county-level responses to a common macroeconomic shock.

Future work should aim at establishing a structural framework that can account for these collinear, asymmetric-sized wage income movements. Doing so may suggest both an improvement in the design of social insurance programs such as the unemployment insurance program and also a more efficient allocation of discretionary funds such as the ARRA. The fact that the policy function explains a small fraction of the cross-county variation in the ARRA suggests that following the protocol of the empirical model developed here in the future could bring about significant policy efficiency gains and more success in helping counties most affected by recessions.

By the same token, it seems problematic to rely on models with a single representative agent to guide discretionary fiscal policy discussions of fiscal multipliers. With asymmetric business cycles and incomplete markets (more than one representative agent), the fiscal multipliers and optimal policies will look very different.

Much remains to be done.

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TABLE 1: ARRA CUMULATIVE OUTLAYS FROM 2009:Q1 TO 2013:Q1

Item	\$ millions
Deficit	-787,300
Receipts	-114,975
Less expenditures	672,325
Discretionary spending:	312,450
Grants-in-aid to state and local governments:	233,700
Medicaid	95,250
Education	75,825
Other ¹	62,725
Capital grants and transfers to business	78,750
Enhanced stabilizers:	97,825
Unemployment programs	58,650
Supplemental Nutrition Assistance Program	39,175
Temporary tax provisions:	304,775
Making Work Pay, American Opportunity and other tax credits ²	152,050
AMT exemption increase and business tax incentives ³	118,200
Other programs ⁴	20,700
One-time \$250 payments ⁵	13,825

Notes: ¹Includes grants to fund programs related to national defense, public safety, economic affairs, housing and community services, income security, and unemployment. ²Includes reductions to tax withholdings associated with the Make Work Pay (MWP) refundable tax credit and outlays and offsets to tax liabilities associated with the MWP, American Opportunity, and other refundable tax credits as well as an expansion of the earned income and child tax credits. ³Includes an increase to the individual AMT exemption amount and business tax incentives claimed by individuals and special allowances for certain property acquired during 2009 and other business tax incentives. ⁴Student financial assistance (16,500) and Includes funding for COBRA premium assistance payments and veterans' benefits, and payments to cover digital converter box redemption. ⁵Payments to recipients of Social Security, Supplemental Security Income, veterans' benefits, and railroad retirement benefits. *Not separately displayed are other expenditures (113,825): Capital grants and transfers to business and gross investment and transfers to the rest-of-the-world and consumption expenditures 42,900.

TABLE 2: ESTIMATES OF COUNTY-LEVEL INCOME DYNAMICS

Description	Symbol	Mean	Median	5%	95%	std. dev.
County-specific shock (ε_{it})	σ_i	0.0590	0.0486	0.0259	0.1257	0.0385
Common shock (ε_t)	$\lambda_i\sigma$	0.0549	0.0546	0.0221	0.0880	0.0225
Loading on common shock	λ_i	0.995	0.989	0.400	1.594	0.407
	s.e.	(0.108)	(0.088)	(0.046)	(0.232)	(0.073)
County-level persistence	ρ_i	0.627	0.658	0.275	0.870	0.184
	s.e.	(0.054)	(0.048)	(0.025)	(0.101)	(0.025)
County-level trend	γ_i	0.0023	0.0019	0.0000	0.0055	0.0018
	s.e.	(0.0004)	(0.0003)	(0.0001)	(0.0010)	(0.0003)
County fixed-effects	α_i	3.160	2.949	1.007	6.186	1.604
	s.e.	(0.453)	(0.405)	(0.199)	(0.864)	(0.213)

Note: The estimated county-level equation is $w_{it} = \alpha_i + \gamma_i t + \rho_i w_{i,t-1} + \lambda_i \varepsilon_t + \varepsilon_{it}$ where the macroeconomic shock ε_t is estimated from the process governing the median county wage growth, $w_t = \alpha + \gamma t + \phi w_{t-1} + \varepsilon_t$.

TABLE 3: FISCAL POLICY FUNCTION ESTIMATES

Policy response to:	Parameter	(1)	(2)	(3)	(4)
Composite shock ($\lambda_i \varepsilon_t + \varepsilon_{it}$)	β	-0.139 (0.0108)			
Common shock ($\lambda_i \varepsilon_t$)	β_M		-0.324 (0.0187)		-0.336 (0.0189)
County shock (ε_{it})	β_m			-0.0403 (0.0122)	-0.0664 (0.0123)
Constant	α	2.465 (0.00841)	2.449 (0.00851)	2.485 (0.00827)	2.445 (0.00854)
R^2		0.003	0.006	0.005	0.006

The number of observations (N X T) is 56,223 in all cases.

Note: The estimated equation in column (4) is $g_{it} = \alpha + \beta_M(\lambda_i \varepsilon_t) + \beta_m \varepsilon_{it} + \nu_{it}$ where $\lambda_i \varepsilon_t$ is the estimated impact of the macroeconomic shock on county i and ε_{it} is the county-specific shock (both estimated residuals from estimating income processes (Table 2)). Specifications (2) and (3) consider each shock exclusively, while specification (1) restricts the policy response to be symmetric across the macroeconomic and microeconomic shocks. All specifications (2009:Q3 to 2013:Q4) are estimated using panel fixed effects regressions with bootstrapped standard errors to account for the use of generated regressors. Standard errors in parentheses.

TABLE 4: CUMULATIVE WAGE INCOME EFFECT OF A ONE- σ SHOCK

Panel A: Macroeconomic Shock $\sigma = 0.0549$						
ρ_i	$\lambda_i = 0.40$		$\lambda_i = 1.00$		$\lambda_i = 1.50$	
	Laissez-Faire	Active Policy	Laissez-Faire	Active Policy	Laissez-Faire	Active Policy
0.275	-0.0285	-0.0189	-0.0712	-0.0473	-0.1067	-0.0709
0.628	-0.0428	-0.0284	-0.1069	-0.0710	-0.1604	-0.1065
0.870	-0.0750	-0.0498	-0.1876	-0.1246	-0.2814	-0.1869

Panel B: Microeconomic Shocks						
ρ_i	$\sigma = 0.025$		$\sigma = 0.048$		$\sigma = 0.125$	
	Laissez-Faire	Active Policy	Laissez-Faire	Active Policy	Laissez-Faire	Active Policy
0.275	-0.0324	-0.0303	-0.0622	-0.0303	-0.1620	-0.1513
0.628	-0.0487	-0.0455	-0.0935	-0.0873	-0.2434	-0.2273
0.870	-0.0854	-0.0798	-0.2273	-0.1531	-0.4272	-0.3988

Note: The cumulative impulse response for county i is $\sum_{k=1}^{20} \rho_i^k(\sigma_i)$, where ρ_i and σ_i are the persistence parameter and standardized shock for county i .

TABLE 5: ARRA FROM THE DATA

Panel A: Amounts in \$ billions				
	Grants	Contracts	Loans	Total
State capital	104.40	2.61	0.81	107.82
Other counties	171.07	19.08	3.01	193.15
Total	275.47	21.69	3.82	300.97

Panel B: \$ Per Capita				
	Grants	Contracts	Loans	Total
State capital	7,297	1,124	3,527	3,983
Other counties	1,258	724	911	964
Average	4,278	924	2,219	2,474

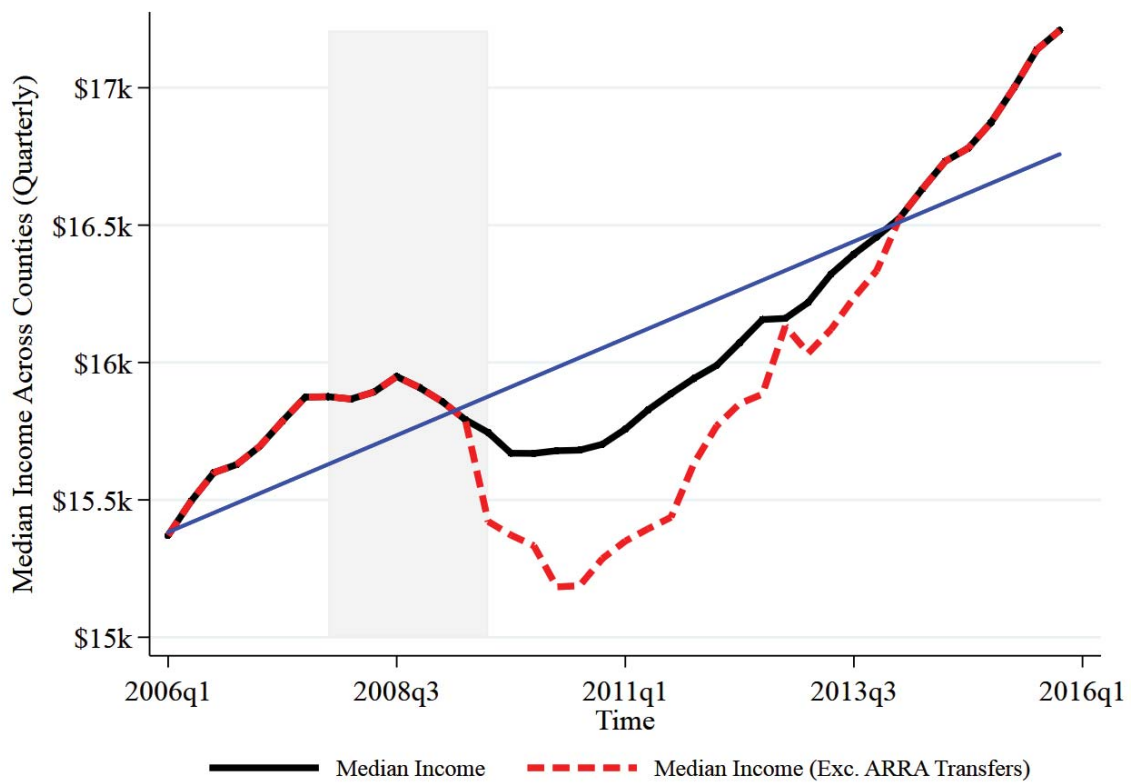
TABLE 6: FISCAL POLICY FUNCTION - EXCLUDING STATE CAPITALS

Policy response to:	Parameter	(1)	(2)	(3)	(4)
Composite shock ($\lambda_i \varepsilon_t + \varepsilon_{it}$)	β	-0.139 (0.0109)			
Common shock ($\lambda_i \varepsilon_t$)	β_M		-0.327 (0.0188)		-0.339 (0.0189)
County shock (ε_{it})	β_m			-0.0384 (0.0123)	-0.0646 (0.0123)
Constant	α	2.254 (0.00847)	2.437 (0.00857)	2.474 (0.00823)	2.433 (0.0086)
R^2		0.003	0.006	0.0051	0.006

The number of observations (N X T) is 55,116 in all cases.

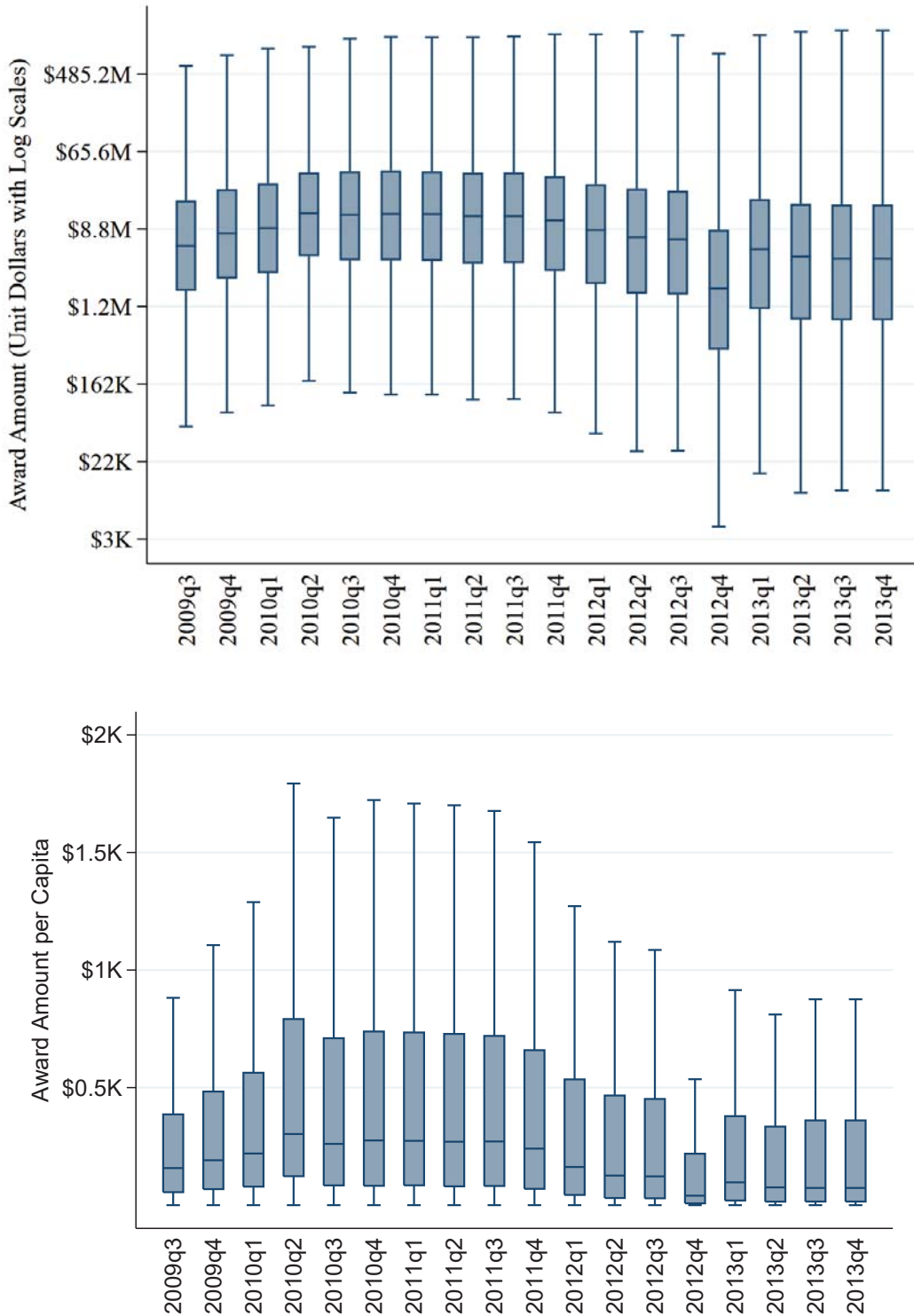
Note: The estimated equation in column (4) is $g_{it} = \alpha + \beta_M(\lambda_i \varepsilon_t) + \beta_m \varepsilon_{it} + \nu_{it}$ where $\lambda_i \varepsilon_t$ is the estimated impact of the macroeconomic shock on county i and ε_{it} is the county-specific shock (both estimated residuals from estimating income processes (Table 2)). Specifications (2) and (3) consider each shock exclusively, while specification (1) restricts the policy response to be symmetric across the macroeconomic and microeconomic shocks. All specifications (2009:Q3 to 2013:Q4) are estimated using panel fixed effects regressions with bootstrapped standard errors to account for the use of generated regressors. Here we exclude state capitals. Standard errors in parentheses.

FIGURE 1: Median Wage Income and ARRA Transfers



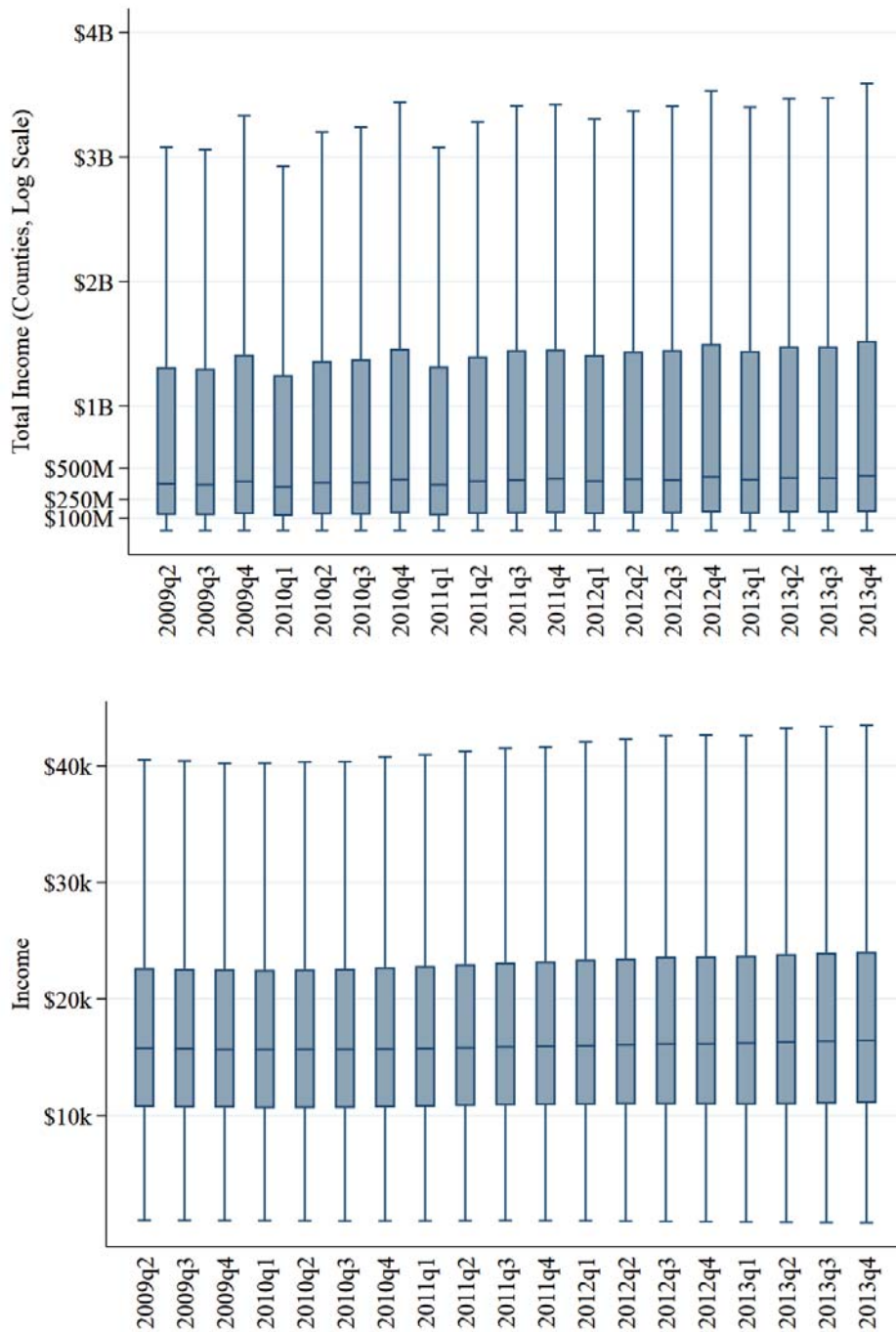
Note: Figure 1 plots the gross wage income per capita and gross wage income per capita less the transfers amount disbursed in each quarter. The official NBER recession is the shaded area. The blue line denotes a fitted linear trend for the median income.

FIGURE 2: Transfers to Counties (Total and Per Capita)



Note: These figures are box and whisker plots of the cross-sectional distribution of transfers to counties in each quarter: the maximum, minimum, 25th and 75th percentiles (shaded bars) and the medians (horizontal line within each bar). The upper figure is the total quarterly transfer to each county while the lower figure is the per capita county amount.

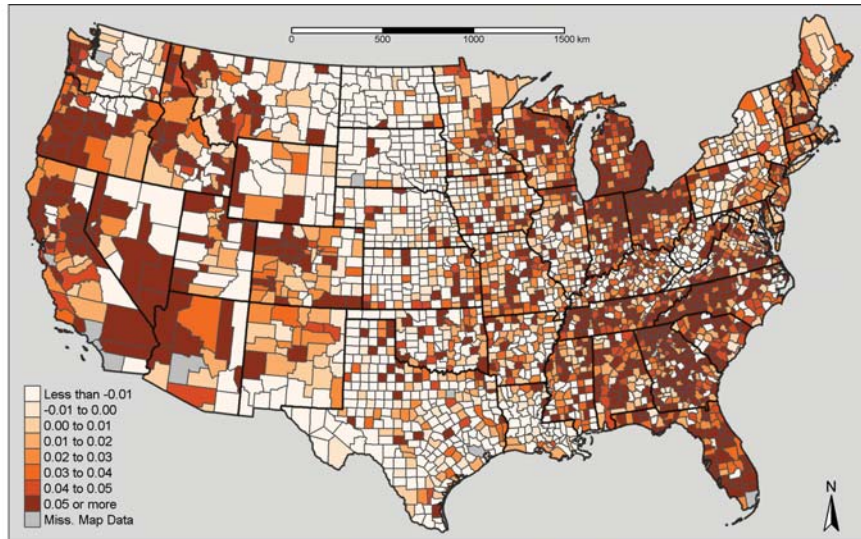
FIGURE 3: Wage Income of Counties (Total and Per Capita)



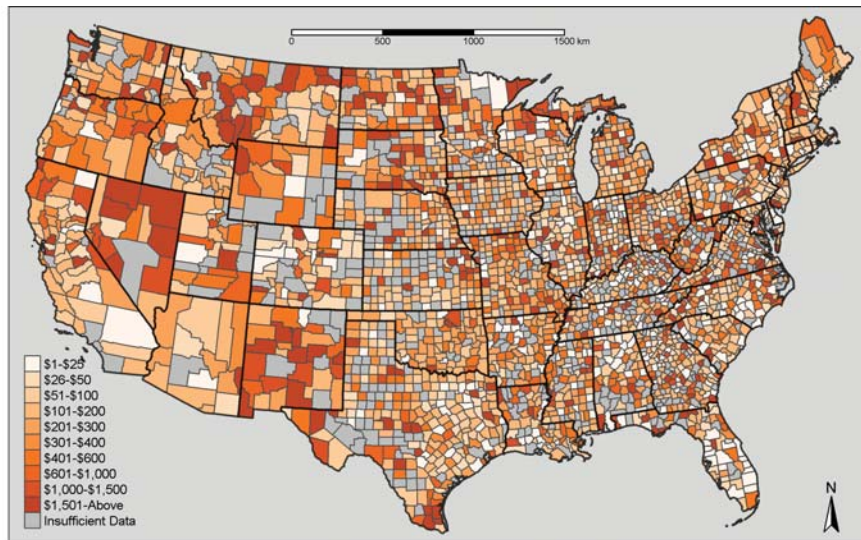
Note: These figures are box and whisker plots of the cross-sectional distribution of wage income across counties in each quarter: the maximum, minimum, 25th and 75th percentiles (shaded bars) and the medians (horizontal line within each bar). The upper figure is the total quarterly incomes to each county while the lower figure is the corresponding per capita county amount.

FIGURE 4: Geography of Economic Contraction and ARRA Transfers

(a) Peak-to-Trough Percentage Decline in Wage Income Per Capita

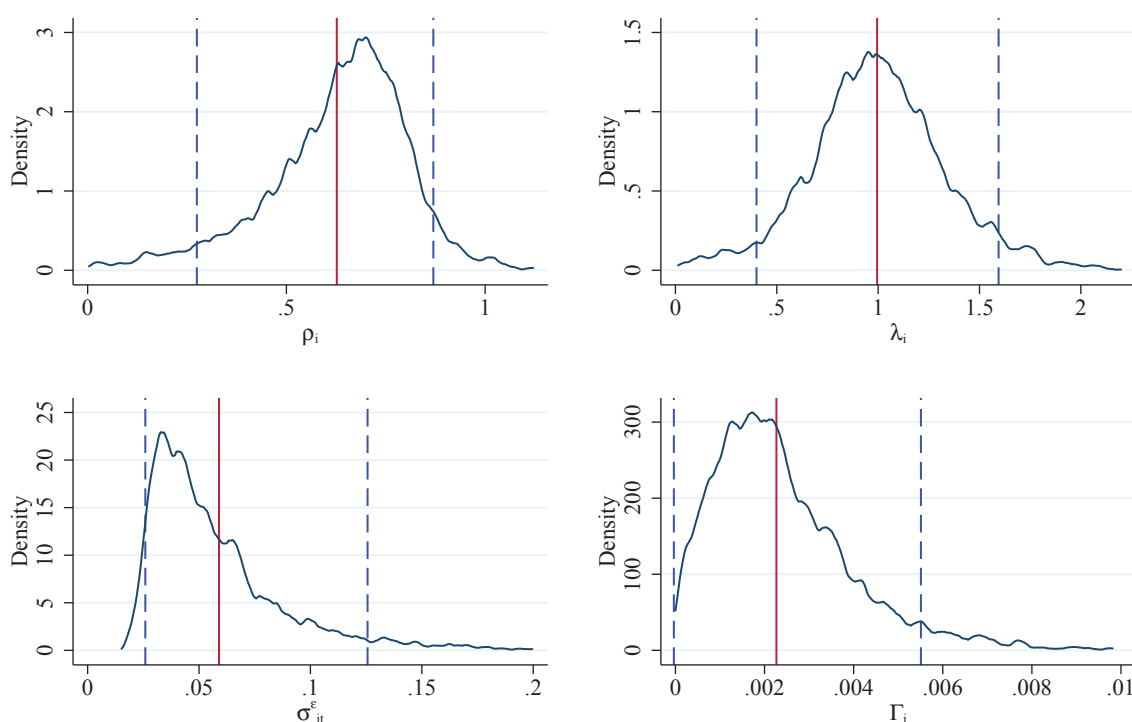


(b) Average Quarterly Transfers Per Capita (2009:Q2-2013:Q4)



Note: The upper panel plots the negative of the difference in real wage income per capita (in log) between the official peak (2007Q4) and the official trough (2009Q3) of the Great Recession. Map data are from the U.S. Census (2010 Map). We use official NBER cycles for peaks and troughs. Warmer colors imply larger negative impacts. The lower figure plots the level of transfers per capita (G_{it}) across all counties. Locations denoted with “insufficient data” include ones with zero transfers and ones that were not reported. Data are averaged over every quarter from 2009Q2 to 2013Q4.

FIGURE 5: Kernel densities of key estimated parameters



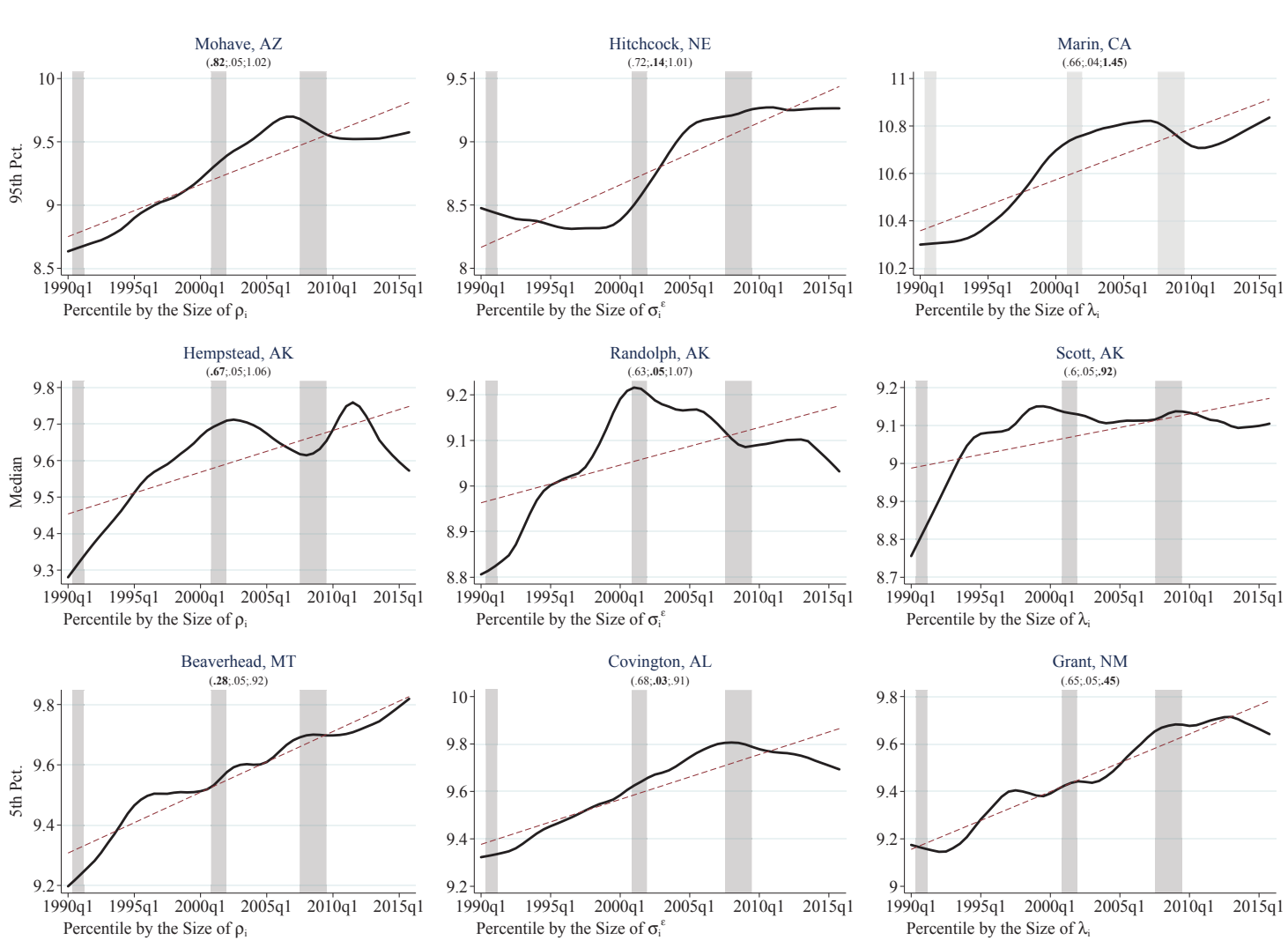
Two-step Estimation (1990Q1-2015Q4).

1st Step: $Y_t = \alpha + \rho Y_{t-1} + \varepsilon_t + \gamma t$

2nd Step: $Y_{it} = \alpha_i + \Gamma_i t + \rho_i Y_{it-1} + \lambda_i \varepsilon_t + \varepsilon_{it}$

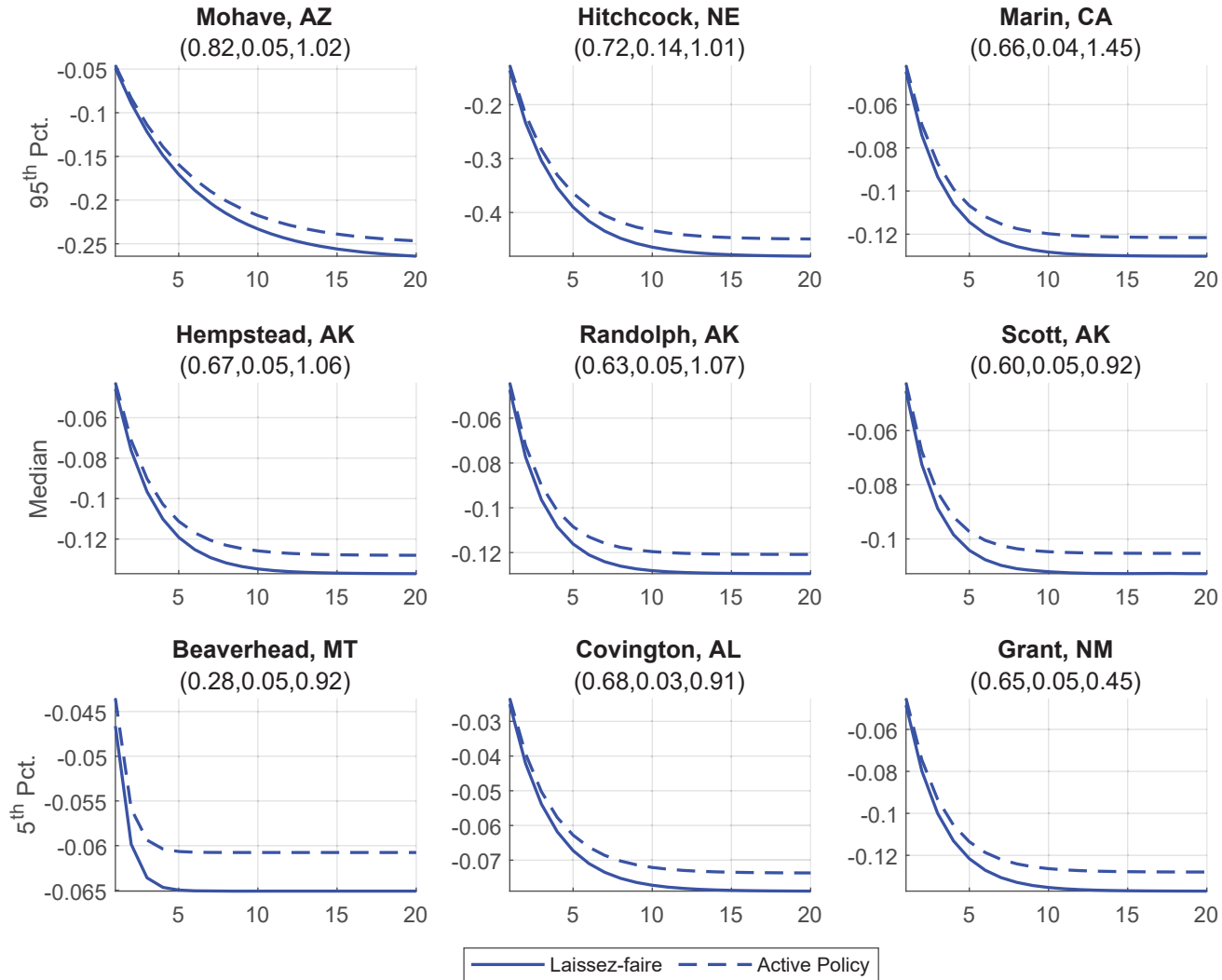
Note: This figure plots the kernel density distribution of estimates of selected parameters across all counties i . σ_i^ε denotes the standard deviation of the income innovation ε_{it} over time for county i . Y_{it} is the logarithm of real per capita wage income (w_{it}) for county i in quarter t and Y_t is the average number across counties.

FIGURE 6: Selected County Wage Income



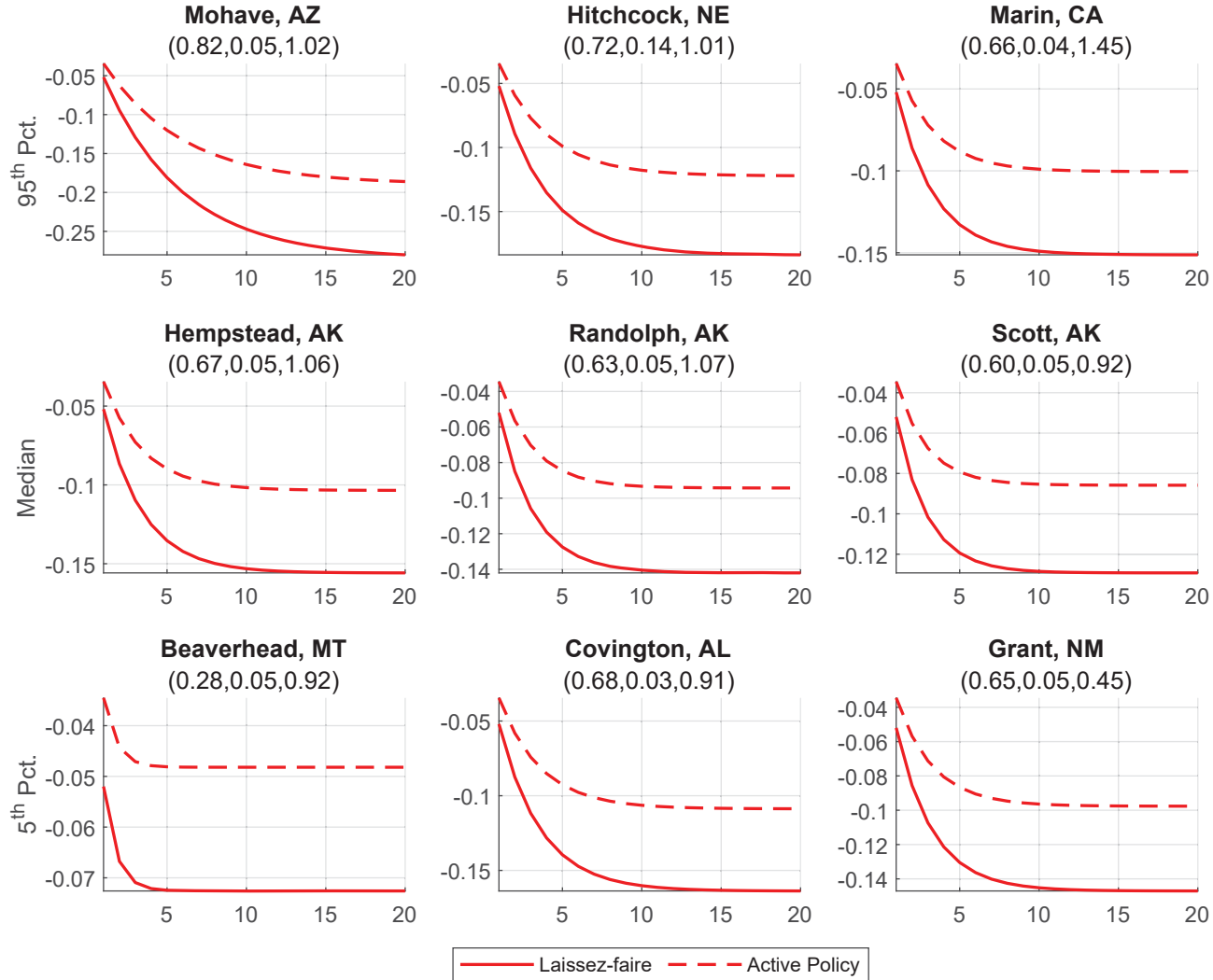
Note: This figure plots the wage income processes for selected counties. These counties are selected such that they are closest to the 5th pct., the median, and the 95th pct of three estimated parameters: ρ_i , σ_i^e , and λ_i . These parameters are estimated from the two-step process noted in Figure 5.

FIGURE 7: Cumulative Micro Impacts of Wage Income Shocks



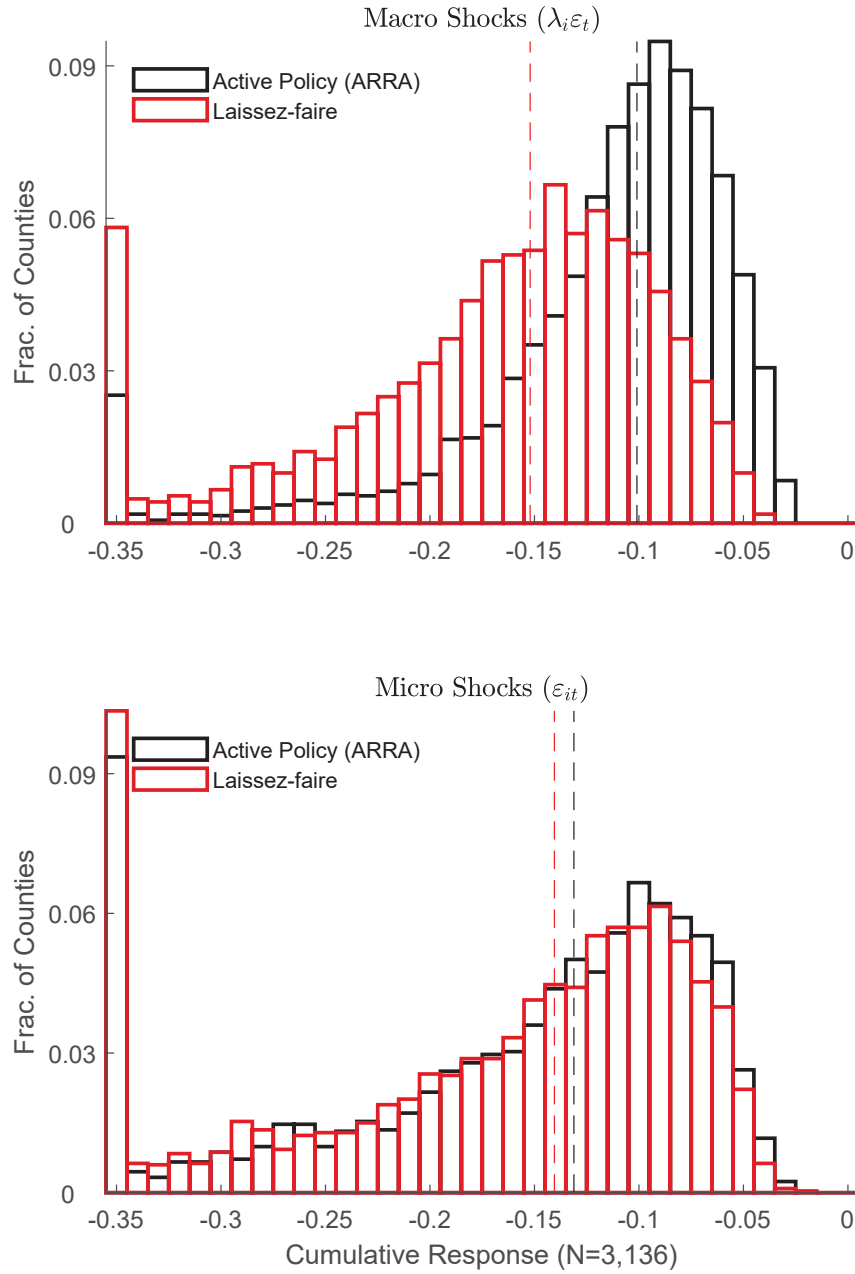
Note: This figure plots the cumulative impact of a negative one-standard-deviation micro-shock (ε_{it}) to wage income for selected counties. These counties are selected such that they are closest to the 5th pct., the median, and the 95th pct of three estimated parameters: ρ_i , σ_i^e , and λ_i . These parameters are estimated from the two-step process noted in Figure 5.

FIGURE 8: Cumulative Macro Impacts of Wage Income Shocks



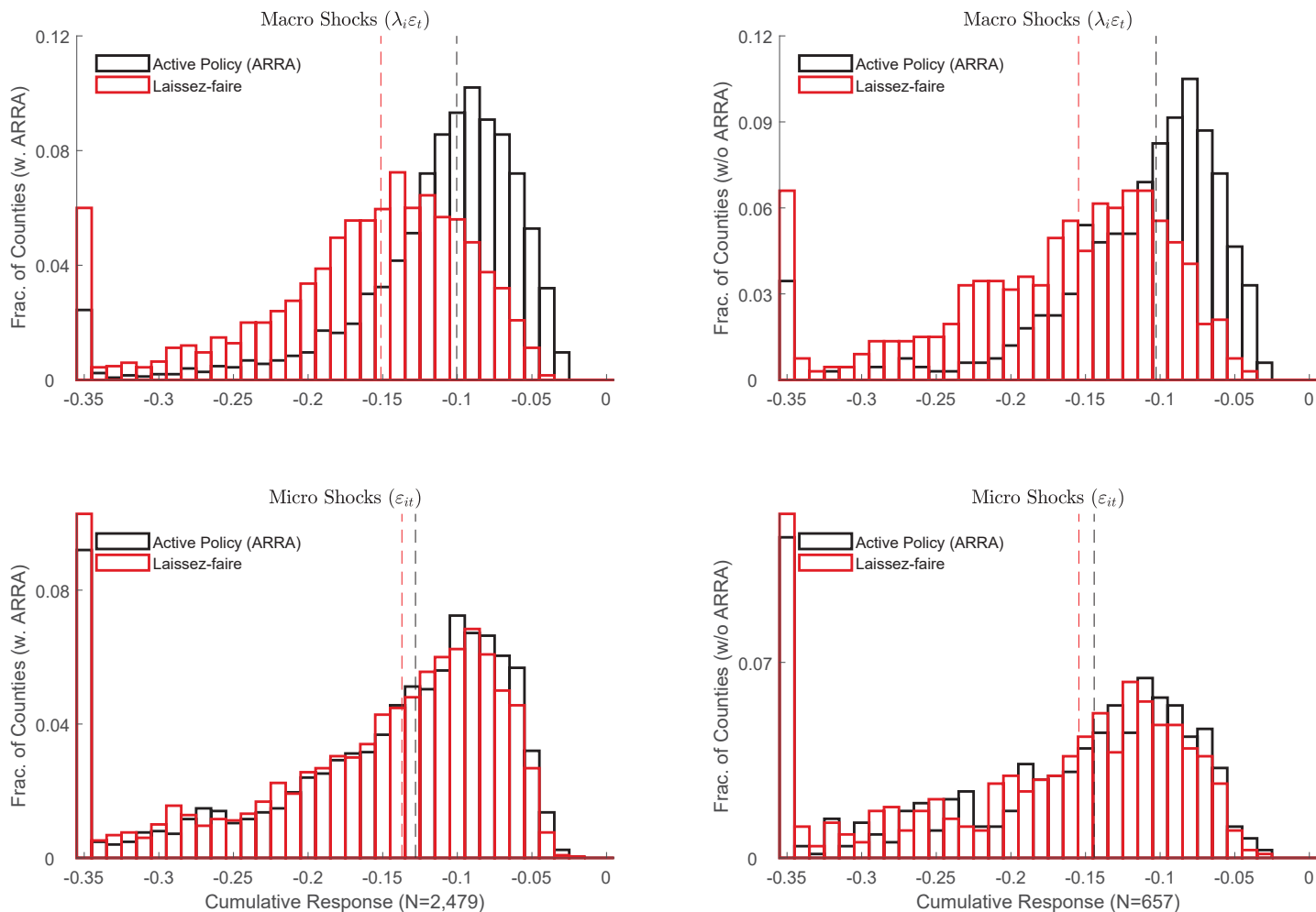
Note: This figure plots the cumulative impact of a negative one-standard-deviation macro-shock ($\lambda_i \varepsilon_t$) to wage income for selected counties. These counties are selected such that they are closest to the 5th pct., the median, and the 95th pct of three estimated parameters: ρ_i , σ_i^ε , and λ_i . These parameters are estimated from the two-step process noted in Figure 5.

FIGURE 9: Cumulative Impacts of Wage Income Shocks: All Counties



Note: This figure plots the cross-sectional distribution of the cumulative responses of wage incomes to a one-standard-deviation of macro-shock ($\lambda_i \varepsilon_t$) and micro-shock (ε_{it}) without fiscal offset (i.e., Laissez-faire) and with fiscal offsets (i.e., Active Policy). Both ARRA-recipients and non-recipients are included. Vertical lines denote the means of the corresponding distributions.

FIGURE 10: Cumulative Impacts of Income Shocks: Counties w and w/o ARRA



Note: This figure plots the cross-sectional distribution of the cumulative responses of wage incomes to a one-standard-deviation of macroshock ($\lambda_i \varepsilon_t$) and micro-shock (ε_{it}) without fiscal offset (i.e., Laissez-faire) and with fiscal offsets (i.e., Active Policy). ARRA-recipient counties are plotted on the left and non-recipient counties are plotted on the right. Vertical lines denote the means of the corresponding distributions.

APPENDIX NOT INTENDED FOR PUBLICATION

A APPENDIX: DATA SOURCES

A.1 Wage Income Data

The *Quarterly Census of Employment and Wages (QCEW)* is the tabulation of employment and wages of establishments, which report to the Unemployment Insurance (UI) programs of the United States. Employment covered by these UI programs represents about 97% of all civilian employees that receive wages or salaries in the county. The lowest level of spatial aggregation available is what we use, the (county-level) Area-FIPS codes (by the Geography Division of the U.S. census).

The *QCEW* reports four different wage income measures: total quarterly wages, taxable quarterly wages, average weekly wages, and quarterly contributions. We use total quarterly wages, which according to the *U.S. Bureau of Labor Statistics*,

“Wages include bonuses, stock options, severance pay, profit distributions, cash value of meals and lodging, tips and other gratuities, and, in some States, employer contributions to certain deferred compensation plans such as 401(k) plans. Covered employers in most States report total compensation paid during the calendar quarter, regardless of when the services were performed. A few State laws, however, specify that wages be reported for or based on the period during which services are performed rather than the period during which compensation is paid.”

A.2 ARRA Data on Grants, Contracts and Loans

How Locations Are Recorded Two variables indicate locations in the ARRA data set. The first is “recipient_zip_code,” which denotes the location of the agency/organization that

receives the ARRA transfers and the second is “dest_zip code,” which denotes the destination of the ARRA transfers. Here we use the latter to identify the location in which the award was disbursed.

In the publicly available ARRA data, two variables indicate the amount of the award. The first is “total_award_amount”, which denotes “The amount of the award as issued by the Federal agency to the Prime recipient. The field is left blank for sub-recipients and vendors,” and the second is the “local_award_amount,” which denotes the amount that is awarded to the “local” sub-contractor.¹⁵

Data Transformations The nominal wage income and ARRA grants, contracts and loans are both deflated by the GDP deflator series GDPDEF (which is the implicit price deflator used to deflate nominal GDP), retrieved from the St. Louis’ FRED. In the empirical applications, they are also normalized by the county labor force. The wage income data are seasonally adjusted at the quarterly frequency. We also find that using population, as opposed to labor force, does not have any significant effects on our estimates of fiscal offset.

Matching Wage Income Data to ARRA Data at the County Level Since the QCEW data are aggregated to the county level (as designated by the area county-level FIPS codes) whereas the ARRA data are by zip-code, we aggregate the ARRA data to the county level using Census data files that allocate zip codes to county level FIPS codes.

Distribution of ARRA Transfers per Capita: A Closer Look As our analysis focuses on variation in income and ARRA disbursements in the cross-section of counties, it is important that we have a spatially diverse sample. In particular, we should ideally have ARRA recipient counties well mixed with the non-recipients. This requirement is well supported by the spatial distribution of the ARRA transfers, as demonstrated by Figure 4b. For example, Davidson county in Tennessee (the orange dot in the middle of Figure A.1b in

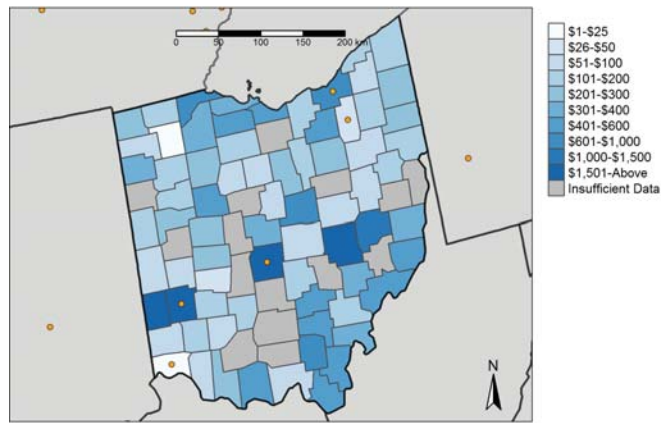
15) Source: www.recovery.gov. Retrieved 2015-02-25

the appendix) received a significant amount of ARRA transfers per capita, yet the adjacent counties either received far less or nothing at all during the course of the ARRA program. Such variation is important, especially if we consider the ARRA program to be a “treatment”, in which Davidson county is “treated” and the adjacent non-recipient counties are “non-treated.” Another insight from Figure A.1b is that ARRA transfers do not necessarily concentrate solely on big cities. Indeed, comparing Figure A.1b (Tennessee) and Figure A.1a (Ohio), large ARRA distributions can happen in both rural and urban counties.

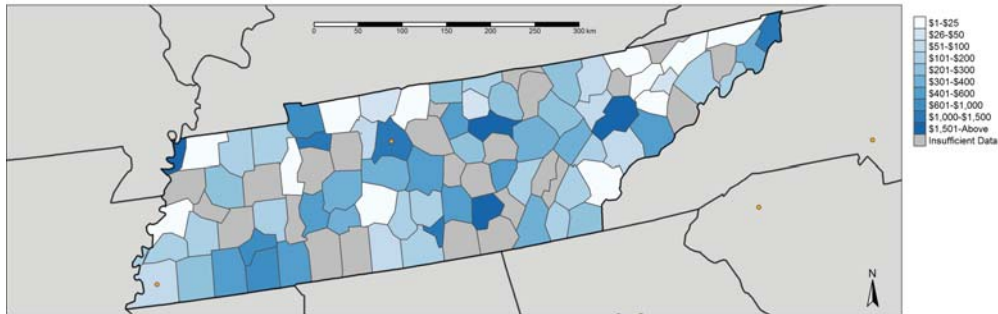
Figure A.2 plots the ratio of the level of transfers per capita G_{it} relative to the level of wage income per capita across locations. The first thing to note about this figure is that 26.5% of the counties received nothing at all. The picture that emerges again is a very skewed distribution, even after normalizing by income. The lion’s share of transfers seem to accrue to a corridor running north from Florida to Ohio and east from Atlanta and from the western edge of the state of Tennessee eastward through the state of Virginia. Notably, the variations in ARRA distribution becomes even more pronounced than the raw transfers themselves, with some locations receiving far less than 10% of their per capita income and some locations receiving as much as 40% of their per capita income.

FIGURE A.1: ARRA Transfers per Capita: A Closer Look

(a) ARRA Transfers per Capita (Ohio)

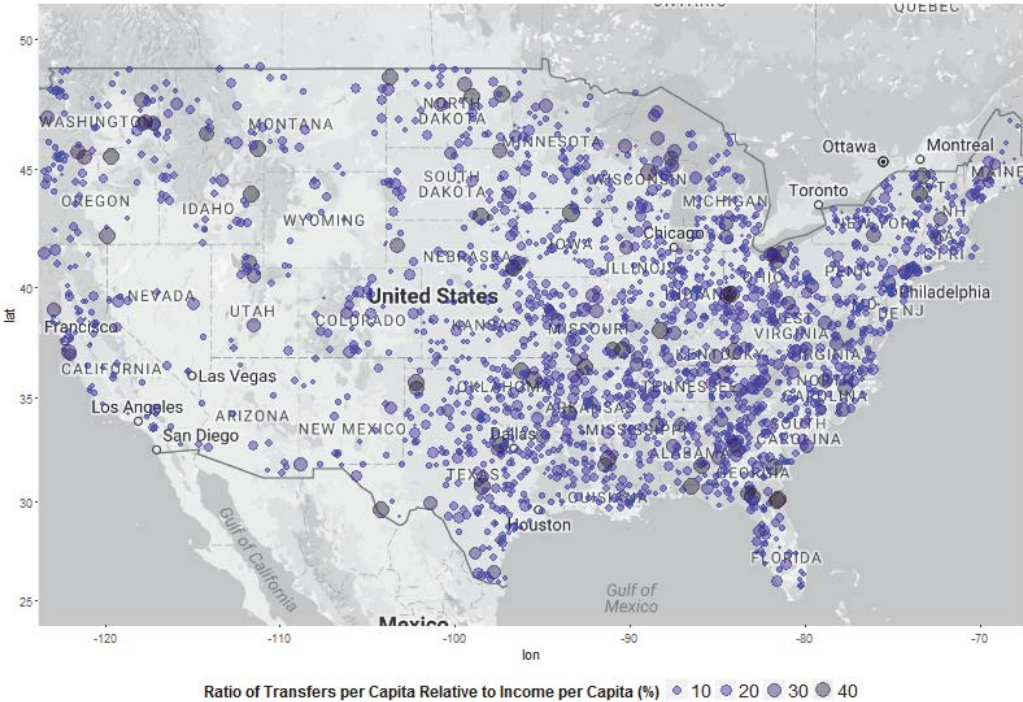


(b) ARRA Transfers per Capita (Tennessee)



Note: This figure plots transfers per capita (G_{it}) for the state of Ohio and Tennessee. Data are averaged over every quarter from 2009Q2 to 2013Q4. The orange dots represent major cities with population of more than 200K.

FIGURE A.2: Ratio of Transfers per capita Relative to Income per capita



Note: This figure plots the ratio of transfers per capita relative to income per capita. Data are averaged over every quarter from 2009Q2 to 2013Q4.

B DIFFERENCE STATIONARY WAGE INCOME

At the macroeconomic level, there is much discussion of whether income is trend-stationary or difference stationary. As this question may be relevant to our county-level analysis, we also considered a first-difference specification. This appendix reports all the results following this alternative income specification.

The bottom line is that the county-level income has an average auto-correlation of -0.167, which is econometric evidence of over-differencing. As a practical matter, this reflects the unfortunate fact that real wage growth in the median county has stagnated which ends up being reflected in a stationary level of the logarithm in wage income per worker (or per capita).

B.1 Im et al. (2003) Panel Unit-root Test

Since our wage income data is a panel across counties, we test for unit roots of wage income a panel setting using the Im et al. (2003) (Im-Pesaran-Shin, or IPS) panel unit root test. As shown in Table B.1, we can reject the null hypothesis that all panels contain unit roots for wage income, which favors our trend-stationary specification in the main text.

TABLE B.1: Im-Pesaran-Shin (IPS) Unit Root Test

Variable	$t - bar$	$\tilde{t} - bar$	$Z_{\tilde{t} - bar}$
Wage Income	-3.4130	-2.8203	-89.1772

H_o : All panels contain unit roots.

H_a : Some panels are stationary.

B.2 Difference stationary wage income

The specification is a difference-stationary process,

$$\Delta w_{it} = \mu_i + \phi_i \Delta w_{i,t-1} + \beta_i \varepsilon_t + \varepsilon_{it}$$

TABLE B.2: Estimated Income Dynamics (Difference stationary)

Description	Symbol	Mean	5%	95%	std. dev.
Persistence	ϕ_i	-0.167	-0.592	0.233	0.242
	s.e.	(0.084)	(0.044)	(0.142)	(0.033)
Micro variance	σ_i^2	0.0616	0.0266	0.1365	0.0458
Macro variance	σ^2	0.0617			
Macro loadings	λ	0.873	0.207	1.554	0.454
	s.e.	(0.125)	(0.055)	(0.254)	(0.086)
Fixed-effects	μ	0.008	0.002	0.017	0.005
	s.e.	(0.006)	(0.003)	(0.014)	(0.005)

along with an auxiliary equation for the average growth of labor income across counties,

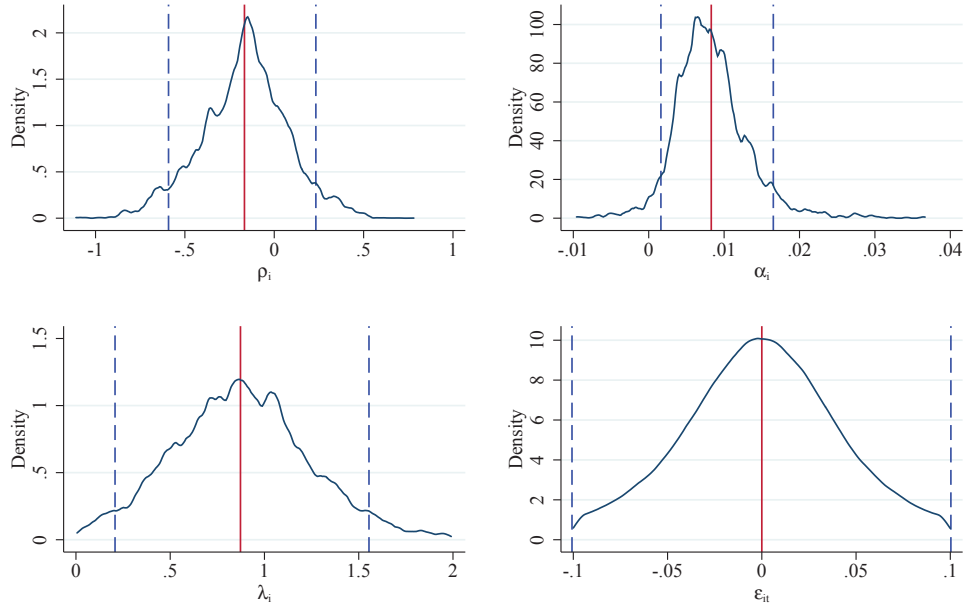
$$\Delta w_t = \mu + \phi \Delta w_{t-1} + \varepsilon_t$$

The average persistence of wage growth is -0.167 and ranges from -0.592 to 0.233 across counties based on the 5th and 95th percentiles of the distribution. Negative autocorrelation in growth rates is typically an indication of over-differencing which is consistent with the stagnation of real wage growth in most counties that we find using our empirical benchmark, trend-stationary, specification. Despite the fact that the microeconomic (county-specific) and the macroeconomic (mean wage shock) innovations are orthogonal by construction, the cross-county average time series variation of the idiosyncratic shock is very close in magnitude to the macroeconomic shock, 6.16% per quarter for the average microeconomic shock compared to 6.17% for the macroeconomic shock.

Heterogeneity of the conditional volatility of the wage processes by county comes in a number of forms. Notice that the standard deviation of the county-specific shock ranges from 2.66% to 13.65%.

The second source of heterogeneity is the response coefficient, λ_i , on the common shock.

FIGURE B.1: A Difference-Stationary Process



Two-step Estimation: Difference Equation (1990Q1-2015Q4)
 1st Step: $\Delta Y_{it} = \alpha_i + \epsilon_{it}$
 2nd Step: $\Delta Y_{it} = \alpha_i + \rho_i \Delta Y_{it-1} + \lambda_i \epsilon_{it} + \epsilon_{it}$

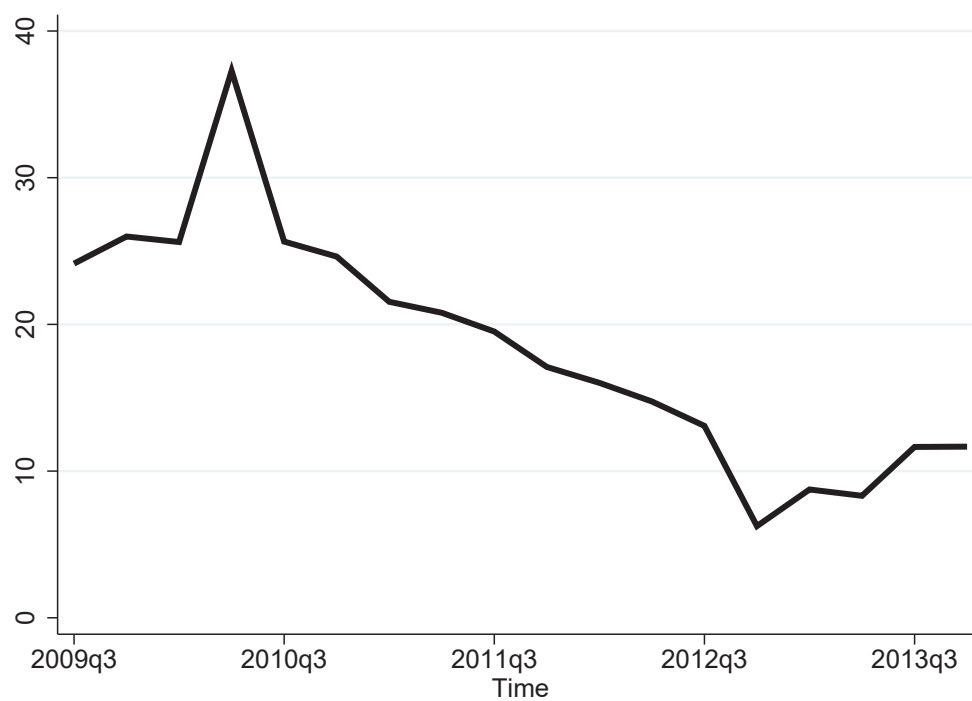
The mean is close to 0.9 indicating a slightly less than proportional response at the county level to a macroeconomic wage shock (though the value of unity also cannot be rejected). The range of responses is diverse from a low of 0.207 to a high of 1.55. In words, a 10% macroeconomic wage shock would induce a 2% adjustment in county-level wages in the former case and a 15.5% wage adjustment in the latter case. We expect these coefficients to in part reflect the industry structure of the county in question with service sector (education, medicine and government) based counties at the low end and agriculture, resource and durable manufacturing based counties at the high end. Figure B.1 presents kernel densities of the full distributions of parameter estimates.

TABLE B.3: Fiscal Policy Functions

	(1)	(2)	(3)	(4)
β	-0.0971*** (0.0186)			
β_M		-0.102*** (0.0189)		-0.102*** (0.0189)
β_m			0.0428 (0.0979)	0.0417 (0.0979)
Constant	5.055*** (0.0115)	5.053*** (0.0116)	5.096*** (0.00840)	5.053*** (0.0116)
R^2	0.00109	0.00117	0.00000765	0.00118

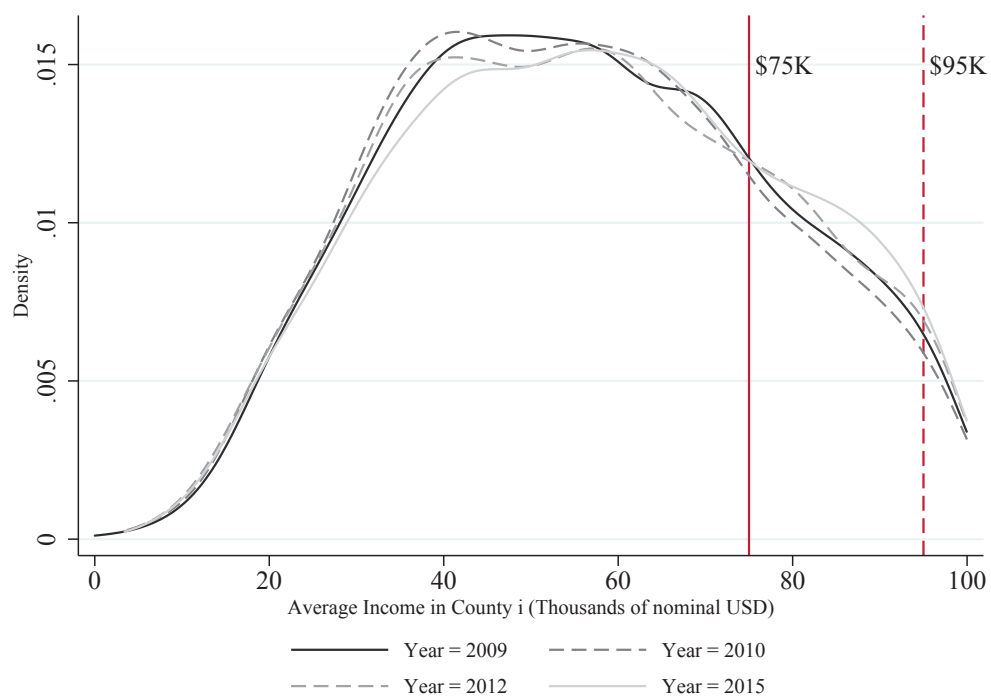
Note: The number of observations (N X T) is 56,223 in all cases.

FIGURE B.2: Percentage of Counties Receiving ARRA Transfers (%) Over Time



Note: This figure plots the percentage of counties receiving ARRA transfers over time.

FIGURE B.3: Average Income Distribution



Note: This figure plots the distribution of wage income (at annual rates) for selected years. The red vertical lines denote the eligibility cutoffs for the Making Work Pay program.

C SENSITIVITY ANALYSES

This appendix contains a battery of econometric sensitivity analysis, but maintains the benchmark specification, the trend-stationary model, for wage dynamics in all cases. The difference stationary specification is reported in Appendix B.

C.1 Labor Market Areas

Because two or more adjacent counties may be integrated into the same labor market (e.g., one can live in one county and commute to work in another), the distribution of ARRA transfers in one county may have spill-over effects into other counties that presumably belong to the same labor market (or metro area). In this section, we test the robustness of our estimates using 1,792 *Labor Market Areas* (LMAs) from the Bureau of Labor Statistics as our unit of locality.¹⁶ In particular, instead of using the county-level FIPS code as our cross-sectional unit, here we match the *Labor Market Areas* to their corresponding county-level FIPS codes. Our estimates of the composite fiscal offset (β) using LMAs as the unit of locality are reported in Table C.1 (Column (1)).

TABLE C.1: Fiscal Offset Sensitivity Analyses

	(1)	(2)
	LMAs	GMM
Fiscal Offset	-0.136 (0.026)	-0.135 (0.022)
Constant	5.170 (0.004)	5.149 (0.001)
Observations	20,519	56,223

Standard errors in parentheses.

For specification (1), the unit of locality is LMAs.

$p < 0.10$, $p < 0.05$, $p < 0.01$

¹⁶) Retrieved from <https://www.bls.gov/lau/lmadir2015.xlsx> on Nov. 02, 2017

C.2 Panel GMM Estimation

Here we replicate our baseline estimate of the fiscal offset using income innovations from a panel GMM estimation (see Judson and Owen (1999) for a discussion of the applicability of using panel GMM when the cross-sectional dimension is large). In particular, we estimate an alternative wage income process with a common persistence across all counties

$$w_{it} = \alpha + \gamma t + \rho w_{i,t-1} + u_{it} \quad (4)$$

using the Arellano and Bond (1991) estimator. While we use up to 6 lags for the instrument for computational simplicity, our estimates are not sensitive to larger sets of instruments. Given the estimates of the combined unexpected income shock u_{it} arising from this procedure, we next estimate the equivalent of our benchmark composite fiscal offset β using

$$g_{it} = \beta u_{it} + \nu_{it}$$

We present the estimates of fiscal offset using GMM in Table C.1 (Column (2)). Here the innovations u_{it} is the equivalent of the composite wage income shock in the main text ($\lambda_i \varepsilon_t + \varepsilon_{it}$). All in all, these estimates are consistent with our estimate of fiscal offset in the main text (which, recall, is -0.139).

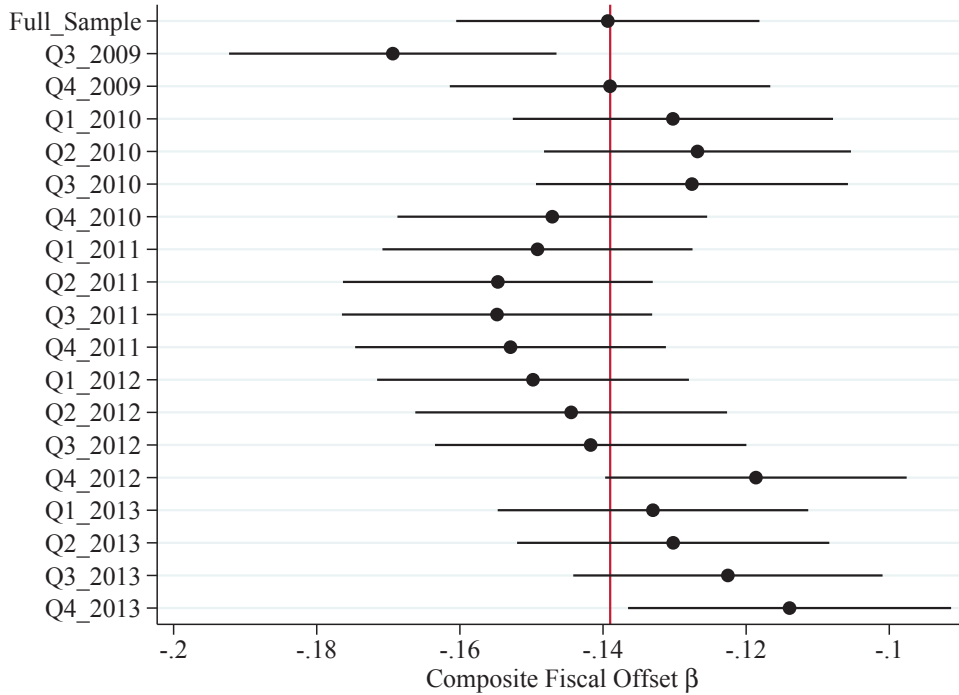
C.3 Sensitivity of Fiscal Offset Estimates to Outliers

This section examines the sensitivity of our fiscal offset estimates to outliers. To that end, we estimate our baseline composite fiscal offset β using

$$g_{it} = \beta u_{it} + \nu_{it}$$

for the full sample and for individual samples in which we drop each quarter in the data one by one. We plot, in Figure C.1, the composite fiscal offset estimates for these “leave-one-

FIGURE C.1: Sensitivity of the Composite Fiscal Offset to Time Outliers



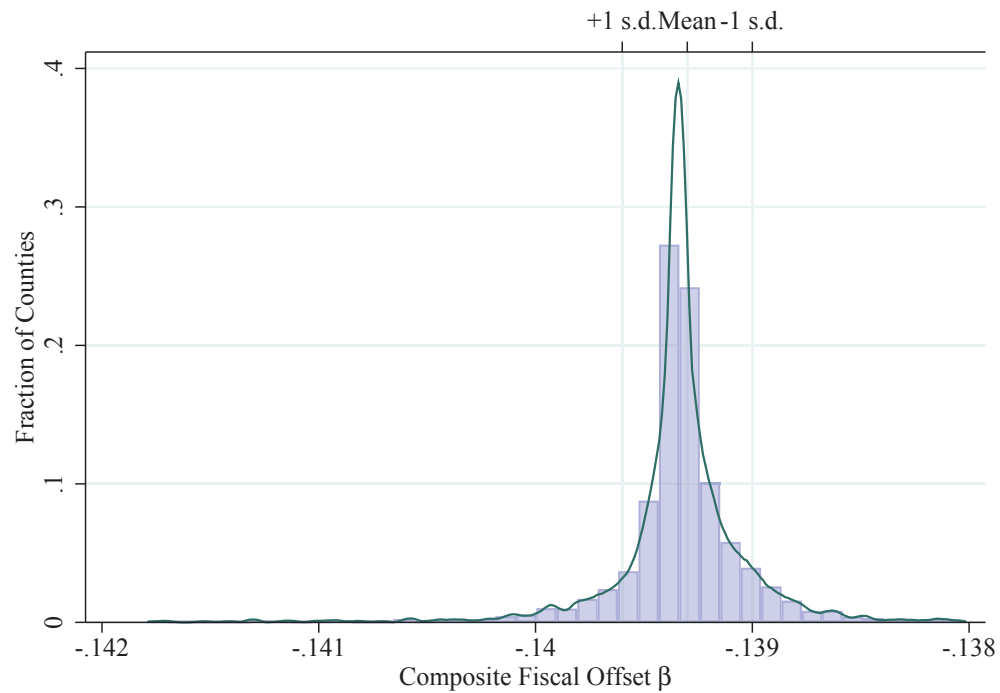
quarter-out” samples. The quarter that is left out is denoted in the vertical axis. Overall, we find our full-sample estimate of β in the main text to be generally insensitive to the presence of outliers in any particular quarter.

We next conduct the same exercise, leaving one county out at a time, and plot the corresponding distribution of the composite fiscal estimates β across these “leave-one-county-out” samples in Figure C.2. Similar to the result when shrinking the time dimension quarter by quarter, we find that our composite fiscal offset estimate is not driven by having any particular county in the sample (for example, Cook County, IL in which the City of Chicago is located).

C.4 Sensitivity of the Fiscal Offset Effects: by Size of Transfers

We next examine the extent to which the estimated redistributive effects of the ARRA are sensitive to the size of the transfers. To that end, we plot, in Figure C.3, the distribution

FIGURE C.2: Sensitivity of the Composite Fiscal Offset to County Outliers



of the cumulative effects of wage income in the under active policy (i.e., with the offset) and under laissez-faire (i.e., without the offset). We present these results under the national (macro, upper subfigures) and the county-level (micro, lower subfigures) shocks for transfers that are at least, from left to right, (i) \$1 per capita, (ii) \$ 500 per capita, and (iii) \$ 1,000 per capita. All in all, we find our main result that ARRA transfers are largely offsetting national shocks to be consistent across these samples with varying sizes of minimum transfers.

FIGURE C.3: Cumulative Effects of ARRA Transfers: Sensitivity by Size of Transfers

