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MOST IN NEED? A COUNTY-LEVEL ANALYSIS

Mario J. Crucini  
Nam T. Vu

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Did the American Recovery and Reinvestment Act Help Those Most in Need? A County-Level Analysis

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**ABSTRACT**

One of the statements of purpose of the American Recovery and Reinvestment Act (ARRA) was “to assist those most impacted by the recession.” The ARRA is assessed along this dimension using theoretical concepts from the risk-sharing literature. We estimate a model of income dynamics using a county-level panel of wage income in order to isolate the innovation to income. We then regress these income shocks on ARRA transfers and find 13.1% of the shock is offset by the transfer. While this is a long way from complete risk-sharing, the impacts are economically and statistically significant. Surprisingly, there are large state-contingent effects in the second and third quartiles 25.6% and 15.7% versus a mere 8.5% in the first quartile. By this metric, the policy of helping those most in need was not achieved.

Mario J. Crucini  
Department of Economics  
Vanderbilt University  
Box 1819 Station B  
Nashville, TN 37235-1819  
and NBER  
mario.j.crucini@vanderbilt.edu

Nam T. Vu  
Miami University  
Farmer School of Business  
Economics Department  
800 E. High St.  
Oxford, OH 45056  
vunt@miamioh.edu

## 1 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 expenditure was the largest in American history. The impetus for the stimulus was, of course, the collapse of the stock market and rapidly deteriorating macroeconomic situation in the United States and abroad. Unfortunately, the exact policy prescription and dosage was difficult to decide given the lack of historical precedent. The economics profession was left in the unenviable position of having to evaluate the policy *ex post*. From virtual obscurity, the literature on fiscal multipliers re-emerged with a flurry. Recent papers focusing on estimating the fiscal multiplier include, [Nakamura \(2014\)](#); [Wilson \(2012\)](#); [Adams \(2010\)](#); [Chodorow-Reich et al. \(2012\)](#); [Feyrer and Sacerdote \(2011\)](#). Another branch of the literature focuses on the extensive margin of the labor market, the number of jobs created (see, for example, [Dupor \(2014\)](#); [Conley and Dupor \(2013\)](#); [Goodman and Mance \(2011\)](#); [Bohn \(2013\)](#)). A handful of papers focus on the interactions of Federal stimulus and fiscal spending at the state and local levels (see, for example, [Johnson \(2009\)](#) and [Leduc and Wilson \(2017\)](#)).

The focus of this paper is different. In the Statement of Purpose attached to the bill was the following phrase: “To assist those most impacted by the recession.” To address the success of the legislation along this dimension 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. The theoretical underpinnings of risk-sharing theory provides a useful benchmark for understanding such a policy. Positing a benevolent social planner the policy prescription is to reallocate income *ex post* across agents in order to equate their marginal utility of consumption. Since marginal utility is not directly observable, the empirical literature has used actual consumption changes as a proxy. As such, the benchmark of full consumption insurance (for example, [Mace \(1991\)](#)) is that consumption growth is perfectly correlated across agents, though the long-run level of their income and consumption may differ. In an endowment economy with perishable goods the full-insurance policy prescription would entail state-contingent transfers from those less affected by the recession to those more affected, as suggested by the Statement of Purpose.

The closest antecedent to our paper is the empirical 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 cross-state variance of income growth and finds that 13 percent of the unconditional variance of gross state product output growth are smoothed by the federal government. However, because they focus on automatic stabilizers, they do not estimate unexpected changes to income, but rather use raw growth rates. In contrast, the ARRA was 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 stimu-

lus 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.

Our analysis seeks the answer to the question: Did expenditures end up being higher for individuals who experienced a greater loss of income at the outset of the downturn? This is, after all, the relevant question to the second statement of purpose attached to the legislation. We refer to this as state-contingent fiscal federalism. The fiscal federalism dimension is the notion that national governments tax regions at similar rates, but either spend more and transfer more of the revenue back to the poorer sub-jurisdictions. When such policies become enshrined in law, they are called demigrant policies. Canada's system of federal equalization payments constitutes such a policy. Note that this type of equalization tends not to distinguish long-term differences in wealth from short-term fluctuations of income. The state-contingent part of our description is that the expenditure is triggered by a sufficiently large macroeconomic shock that it compels policymakers to do something. In our case, the shock was the announcement by top government officials that the financial system was on the brink of collapse.

Assessing state-contingent fiscal federalism requires spatially granular data on both income and ARRA disbursements. We focus on the county level in order to ensure a nationally comprehensive accounting of income and ARRA expenditure and to consider the possibility of political economy motives in the implementation by contrasting majority Republican and Democrat jurisdictions (both in terms of voter registration and actual voting outcomes). The implication for a state-contingent fiscal stimulus, then, would be to distribute the ARRA funds such the idiosyncratic income changes associated with the onset of the Great Recession are at least partially offset. That is, the risk-sharing theory calls for transfers from those whose incomes fell less than the national average to those whose incomes fell by more than the national average. If fully implemented, expenditure in a given county should be equal in amount and opposite in sign to the income shock that county experienced relative to the national aggregate. Put differently, if fully implemented, the cross-county dispersion of income after the onset of the Great Recession should not be larger than beforehand.<sup>1</sup>

To examine the cross-sectional implications of the fiscal stimulus we construct a unique data set of wage income and ARRA payments at the county level. We measure wage income shocks as the residuals from panel estimates of county-level income dynamics. Our estimate of the persistence of county-level income deviations from the national mean is 0.915 (a half-life of 7.8 quarters) when the entire sample from 1990 to 2015 is used in the estimation. The persistence indicates that divergence of county-level income from the aggregate cycle takes a considerable amount of time to work its way back to its original position relative to the national cycle. As far as we know this property of county-level deviations from the national average has not been previously documented.

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<sup>1</sup>This statement assumes that the economy was close to its long-run steady-state geographic distribution of income.

In the period from the onset of the Great Recession (first quarter of 2008) to the end of the sample, the estimated persistence drops dramatically to 0.611 (a half-life of 1.4 quarters). There are at least three possible explanations for the decline in persistence. First, the transitory ARRA payments themselves contributed to the reduced persistence of the income processes. Second, the income movements relative to the aggregate may in fact have become less persistent than was the case historically (possibly pre-dating the onset of the Great Recession). Third, the estimates may be downward biased due to the relatively short time period of the post-recession panel. We can effectively rule out the first explanation because counties not receiving ARRA funds experience the roughly the same drop in income persistence.

The ARRA was a complex mix of tax changes, grants to state governments and grants, contracts and loans to other private and public institutions. We focus on the latter part of the stimulus as it is possible to follow the money from the Treasury to the recipient's zip code. Delving into the geographic distribution of ARRA funds reveals large differences in the cross-section. The most obvious is that fact that in any given quarter of the year, 71.2% of U.S. counties received no funds at all. Consequently, if every county shared equally in the funds on a consistent basis each period, the value of transfers per capita would be \$93.20 per quarter. In contrast, the average amount received per county including only counties that receive at least one dollar is \$1,839 per quarter. The recipient counties are more affluent, on average, than their non-recipient counterparts (\$21,732 vs. \$18,525). There are a number of counties that receive an extraordinary \$80,000 or more per capita, which tend to be large grants to counties with relatively few residents. An example of this contrast is New Castle County of Delaware which received an amount of transfers roughly 6.4% of their income and Prowers County of Colorado that received an amount of transfers equal to 79.8% of their average income.

Our goal is to estimate a scalar parameter that represents the proportion of county-level income shocks that are offset by ARRA payments. Full public insurance of idiosyncratic wage income movements would predict a coefficient of -1 when the income shock is projected on the ARRA disbursement. Pooling all counties, we estimate the insurance parameter to be -0.131 such that about 13.1% of idiosyncratic income variation is offset payments. This value is consistent in sign with the goal of helping those most in need, though very far from the complete insurance benchmark of -1 (100% offset).

Stratifying by quartile of the income distribution reveals that the most of the offset occurs in the middle quartiles of the distribution. The insurance parameter is -0.242 for the second quartile of the county-level income distribution and -0.198 for the third quartile of the distribution. The parameter is close to zero and statistically insignificant in the first and fourth quartiles, 0.013 and -0.078, respectively.

Keeping in mind that these results pertain only to counties that received positive amounts of funding, begs the broader question of whether the counties that did not receive funding were close to the aggregate business cycle trend and thus would not be expected to receive funds

based on the risk insurance motivation.

Estimates are also provided stratifying by the poverty level and majority party affiliation of the county. For counties below the poverty line, the funds actually increase the cross-sectional variance of income from 0.03 to 0.056. In contrast full fiscal insurance would be predicted to result in a cross-sectional variance of just 0.015 (equal to the long-run dispersion of income across counties for this strata of the income distribution). For counties above the poverty line, income variance is predicted to be reduced from 0.057 to 0.040. This compares with the long-run dispersion of 0.028 across counties for this strata of the income distribution.

The perverse signs of the effects – income shock exacerbation among the poor and mitigated for others – is consistent across Democrat and Republican counties but the magnitudes are much larger for the Democrat counties. This means the income dispersion is exacerbated by more among the poor and mitigated for the rest of the income distribution and more so in Democrat counties than in their Republican counterparts.

We also find important historical changes in the relationship between the aggregate state of the U.S. business cycle and income dispersion across counties. The first recession in our sample is the 1990 recession. As conventional wisdom might suggest as the median county moves from recession to boom, dispersion of income shocks fall. That is, the cyclical component of income inequality is counter-cyclical – good times in the aggregate sense of the word are associated with less income inequality across counties. In contrast, beginning with the Bush tax rebates, dispersion of income shocks across counties has become pro-cyclical. While this broader evolution of income dispersion over the business cycle is beyond the scope of the current investigation, we discuss these anomalies and the potential role of government policy in their evolution in the concluding section.

## 2 The ARRA Over Time and Across Counties

This section describes our data sources and presents some facts about the ARRA stimulus payments in the aggregate, across counties and over time.

### 2.1 The Data

We use two data sources.

The first is the ARRA transfer data consisting of all grants, contracts, and loans that have been extended to various organizations at the local level (which is denoted by zip code in the original data).<sup>2</sup> This purposely excludes all 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.

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<sup>2</sup>See Table A1 for a summary of the average amount of transfers per capita (in real 2005 U.S. dollars) for each of the three categories over the duration of the ARRA program.

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 Recovery.gov, a Federal government repository of all the ARRA data. A great deal of care is taken here to identify the local zip code in which an individual ARRA transfer is finally distributed as opposed to the zip code of the headquarter of the awarded company/organization as there are often many establishments that receive ARRA transfers with varying magnitudes. To arrive at the amount of ARRA transfers in each of these local zip codes, we sum up all ARRA transfers in each zip code over one quarter.

Our second source of data, the *Quarterly Census of Employment and Wages* (QCEW), measures income at the county level in nominal U.S. dollars. We seasonally adjust the raw data and then deflate by a GDP deflator (GDPDEF) available from the St. Louis' FRED database. 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.<sup>3</sup> 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.<sup>4</sup> 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.

The last three transformations we make to the data are: 1) conversion to per capita values using the size of the labor force from the *U.S. Census*; 2) conversion to relative income by dividing by average per capita income across all U.S. counties and 3) taking the natural logarithm.<sup>5</sup> Because two or more adjacent counties can be integrated into the same labor market, the distribution of ARRA transfers in one county may have spill-over effects over other county that presumably belongs to the same labor market (or metro area). As a final robustness check, the Labor Market Area (LMA) replaces the county as an alternative spatial unit of account.<sup>6</sup>

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<sup>3</sup>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.

<sup>4</sup>There two variables that indicate the locations 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.

<sup>5</sup>We also examine the robustness of our results by using both the size of the labor force  $L_{it}$  in each county and total population, the data of which are available from the *U.S. Census*.

<sup>6</sup>Data that convert county-level FIPS codes to the MSA-level were downloaded from the NBER at <http://www.nber.org/data/cbsa-msa-fips-ssa-county-crosswalk.html>. We use the 2015 conversion of MSA to FIPS in our exercises.

Table 1: Descriptive Statistics by ARRA Recipients Status

(a) Number of counties receiving ARRA funds in a typical quarter (2009Q2-2013Q4)

|                                           | Counties | Percent | Cumulative |
|-------------------------------------------|----------|---------|------------|
| Non-recipients                            | 2,264    | 72.19   | 72.19      |
| ARRA Recipients (at least \$1 per capita) | 872      | 27.81   | 100.00     |
| Total                                     | 3,136    | 100.00  |            |

(b) Number of counties receiving ARRA funds in at least one quarter (2009Q2-2013Q4)

|                                           | Counties | Percent | Cumulative |
|-------------------------------------------|----------|---------|------------|
| Non-recipients                            | 657      | 19.98   | 19.98      |
| ARRA Recipients (at least \$1 per capita) | 2,479    | 79.02   | 100.00     |
| Total                                     | 3,136    | 100.00  |            |

(c) Full Sample (1990Q1-2015Q4)

|                                        | ARRA Recipients    | Non-Recipients     | All                |
|----------------------------------------|--------------------|--------------------|--------------------|
| Total Qtr. Real Income Per Capita (\$) | 16,838<br>(12,071) | 14,448<br>(14,825) | 16,366<br>(12,697) |
| Pct. Registered Democrats (%)          | 29<br>(45.4)       | 22.2<br>(41.5)     | 27.7<br>(44.7)     |
| Pct. Below Poverty (%)                 | 9.95<br>(29.9)     | 14.7<br>(35.4)     | 10.9<br>(31.1)     |
| Obs.                                   | 260,911            | 64,101             | 325,012            |

mean coefficients; sd in parentheses

(d) ARRA Periods (2009Q2-2014Q1)

|                                        | ARRA Recipients    | Non-Recipients     | All                |
|----------------------------------------|--------------------|--------------------|--------------------|
| Total Qtr. Real Income Per Capita (\$) | 19,662<br>(13,639) | 16,888<br>(19,832) | 19,118<br>(15,097) |
| Pct. Registered Democrats (%)          | 29<br>(45.4)       | 21.9<br>(41.3)     | 27.6<br>(44.7)     |
| Pct. Below Poverty (%)                 | 4.68<br>(21.1)     | 7.48<br>(26.3)     | 5.23<br>(22.3)     |
| Obs.                                   | 45,206             | 11,034             | 56,240             |

mean coefficients; sd in parentheses

**Note:** ARRA-recipients are defined as counties that receive at least \$1 per person at anytime during the ARRA program. We report real income using the appropriate CPI deflator for each quarter.



## 2.2 The ARRA Over Time

We begin with a macroeconomic view by presenting time series of the median (across countries) nominal income per capita and median (across countries) of nominal income per capita when ARRA payments are excluded in Figure 1a. The NBER dates the peak of the previous business cycle as December 2007 and June 2009 as the trough. The divergence of total per capita income at the county level and net of ARRA income begins with the first stimulus flow in the third quarter of 2009. The maximum flow occurs during 2010 and starts to fall off rapidly in 2013. This figure is simply used to get a visual sense of the pre- and post-ARRA cyclical movements. If one were to assume that the ARRA payments had no direct effect on wage income aside from the payments themselves (which are arguably financed by higher future taxes and/or lower spending), the depth and duration of the recession were both substantively mitigated. The debate about fiscal multipliers and crowding out, of course, lies at the heart of this discussion.

The focus in this paper is the income dispersion around the cross-county medians at each date. To get a sense of the variance across counties and over time of the ARRA stimulus package we examine the amounts awarded by county in total nominal dollars (not per capita) and the same values deflated by county population (per capita). Figure 1b presents the median, 25th and 75th percentile and 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 (2009:Q3 to 2013:Q4).

The median of the transfer is approximately \$1.2M per county. This, of course, tracks the aggregate picture. Of more interest to us is the variance across counties, which is quite extraordinary. The range is consistently from a high of about one-half of a billion dollars, to a few thousand at the low end of the county distribution. Even the middle two quartiles have a substantial range in the neighborhood of \$175,000 to \$ 7.5 million (approximately). Since counties in the U.S. differ substantially in population, a better measure of the economic impact of the stimulus is the one we employ in our estimation, award amounts per capita. These numbers are presented in the lower panel of Figure 1b. The cross-county range from minimum to maximum is from an unexpected ten dollar bill on the sidewalk to nearly two thousand dollars.

## 2.3 The ARRA Across Counties

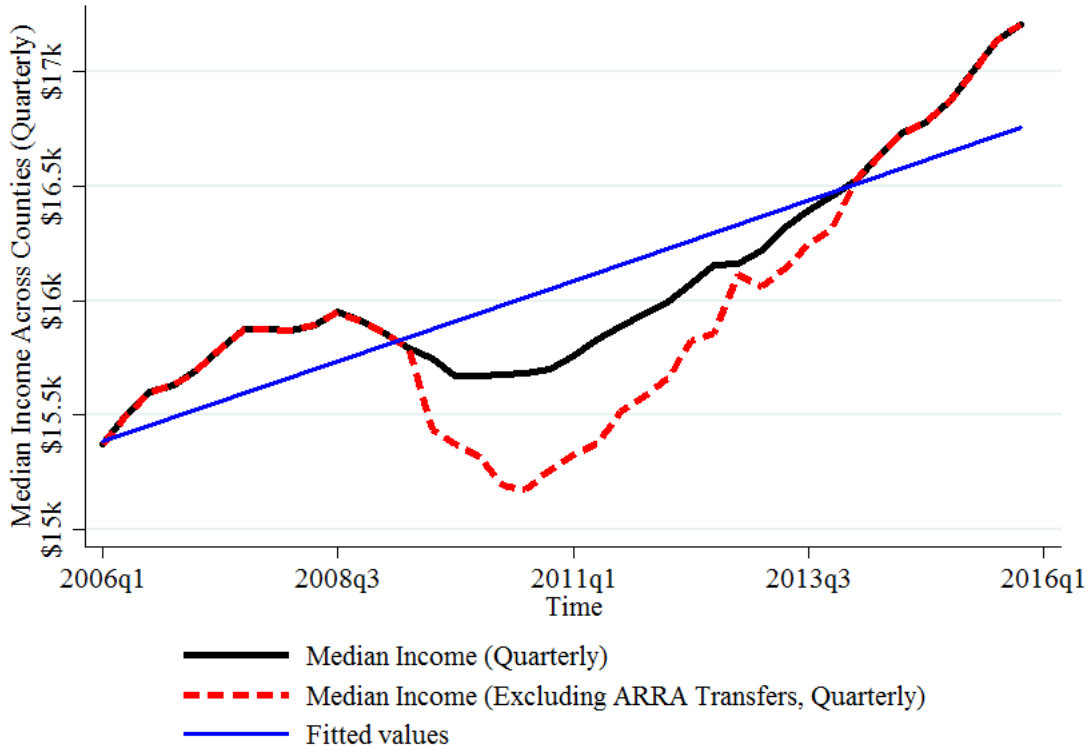
Averaging our real income per capita net of ARRA stimulus,  $Z_{it}$ , over time, Figure 2a displays the spatial distribution using mapping data from the U.S. Census. The amount of income inequality across counties is striking: a large number of counties have wage income below \$ 4,914 per quarter (about \$20,000 per year) while a number have income ten times that level. Put differently, there is an extraordinary amount of spatial income segregation in the U.S. even at the county level.<sup>7</sup> The risk-sharing perspective and the estimation is explicitly designed to exploit time series variation around these substantial “long-run” differences in per capita income

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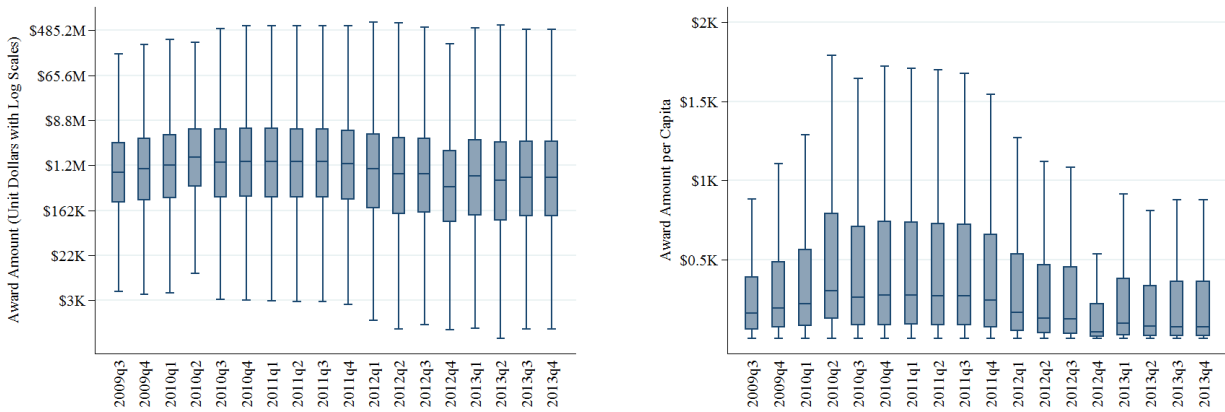
<sup>7</sup>The variation of income and wealth across zip codes within counties is also very significant.

Figure 1: Median Income and ARRA Transfers

(a) Median Income and ARRA Transfers over the Business Cycle



(b) Distribution of Transfers over Time



**Note:** Figure 1a plots the level of net income per capita ( $Z_{it}$ ) and the gross income per capita ( $W_{it}$ ) over the cycles. We define the level of net income per capita as the level of gross income per capita, measured by the level of total quarterly wages aggregated at the county level, minus the amount of ARRA transfers. Figure 1b plot the median and range of transfers per capita over time. The left figure plots transfers in terms of per capita in each zipcode and right figure plots the aggregate value of transfers.

across counties.

Figure 2b plots the level of transfers per capita  $G_{it}$  (in U.S. dollars per capita) across locations. This presentation emphasizes the size of grants without reference to differences in per capita income across counties (which we consider next). Almost all counties receive ARRA transfers that are less than \$20,000 per capita, which is not surprising given the total amount of funds distributed. That said, there are a number of counties receiving transfers of \$80,000 or more per capita, which may be large grants to counties with few residents. Two examples of this contrasting pattern are New Castle County of Delaware (population of 556,779) which received an amount of transfers roughly 6.4% of their income and Prowers County of Colorado (population of 11,954) that receives to an amount of transfers to the tune of 79.8% of their average income.

As our business cycle analysis at the county level critically hinges on the contrast between ARRA recipients and non-recipients over the Great Recession, 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 2b. For example, Davidson county in Tennessee (the orange dot in the middle of Figure 4 in 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 4 is that ARRA transfers do not necessarily concentrate solely on big cities. Indeed, comparing Figure 4 (Tennessee) and Figure 3 (Ohio), large ARRA distributions can happen in both rural and urban counties.

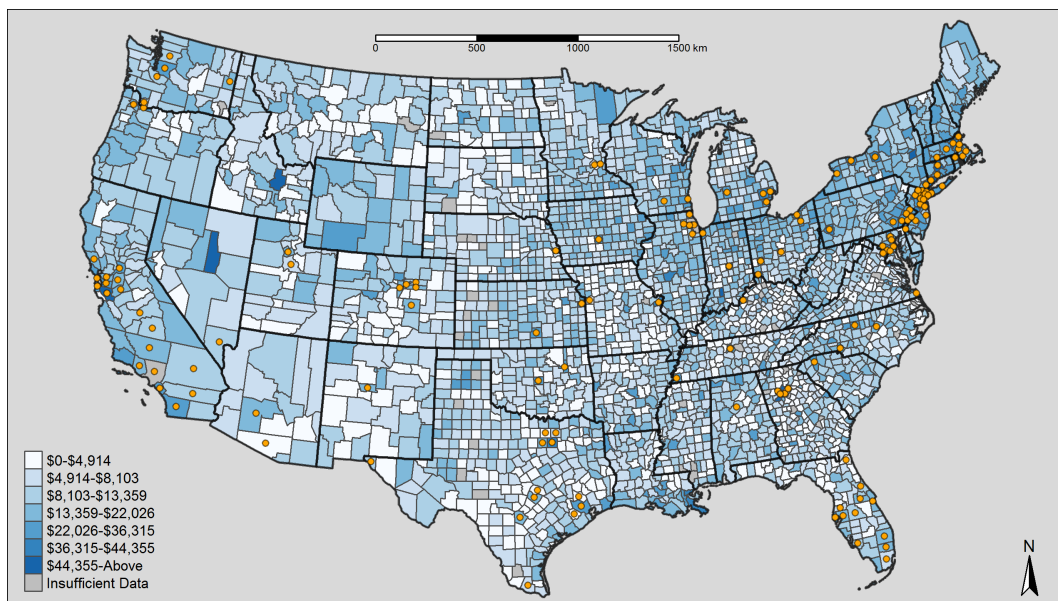
Figure 5 plots the ratio of the level of transfers per capita  $G_{it}$  relative to the level of the net income per capita  $Z_{it}$  across locations. The first thing to note about this figure is that 26.5% of the counties received nothing at all.<sup>8</sup> The picture that emerges again is a very skewed distribution, even after normalizing by income. The lions 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 location receiving as much as 40% of their per capita income.

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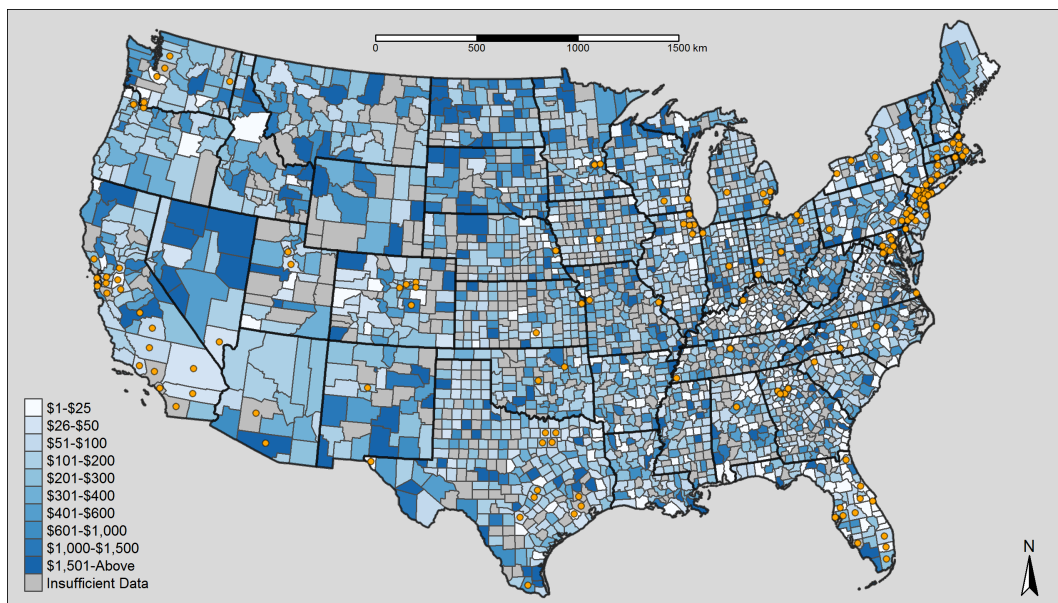
<sup>8</sup>It could be the some of the payments are to state governments or government agencies that subsequently distribute the funds across counties. In this case, the distribution of stimulus that we are using is overly spatially concentrated. We leave this issue to future research.

Figure 2: Spatial Distribution of Incomes and ARRA Transfers

(a) Quarterly Net Income Per Capita (in level of  $Z_{it}$  - U.S. Dollars per capita)

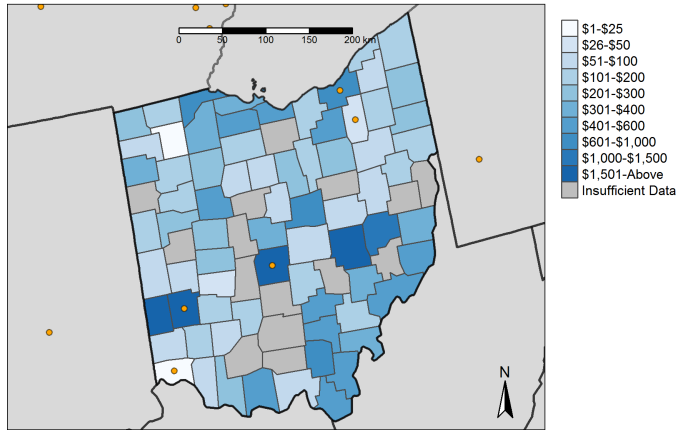


(b) Distributions of Quarterly Transfers per Capita



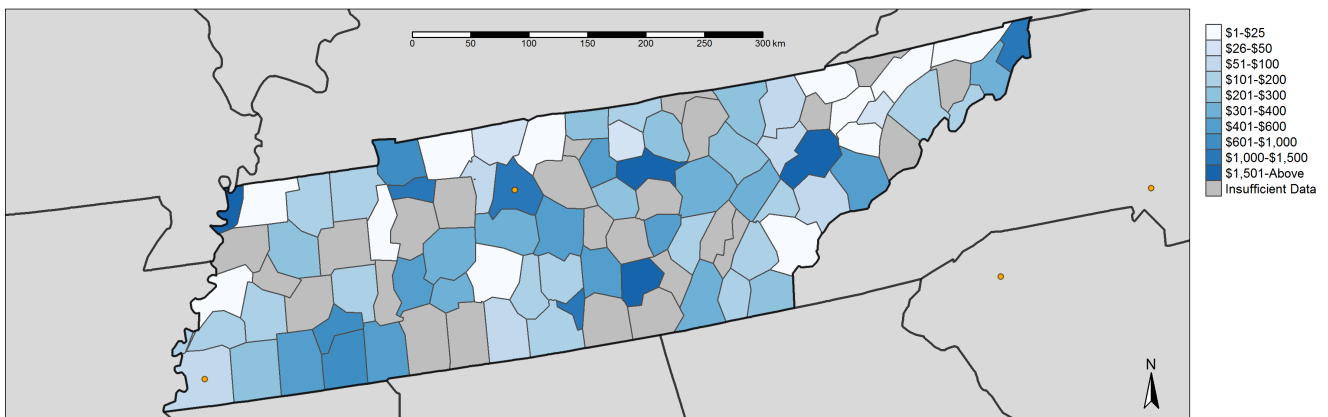
**Note:** The upper figure plots the distribution of total quarterly income per capita by county. Here we take the average of total quarterly income over time, net of national cycle and ARRA stimulus money ( $G_{it}$ ). In terms of notation in the main text, the data presented here are the equivalent of  $\hat{Z}_{it}$  in level. Map data are from the U.S. Census. The orange dots denote the top 100 counties by population. The lower figure plots the ratio 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 3: ARRA Transfers per Capita (Ohio)



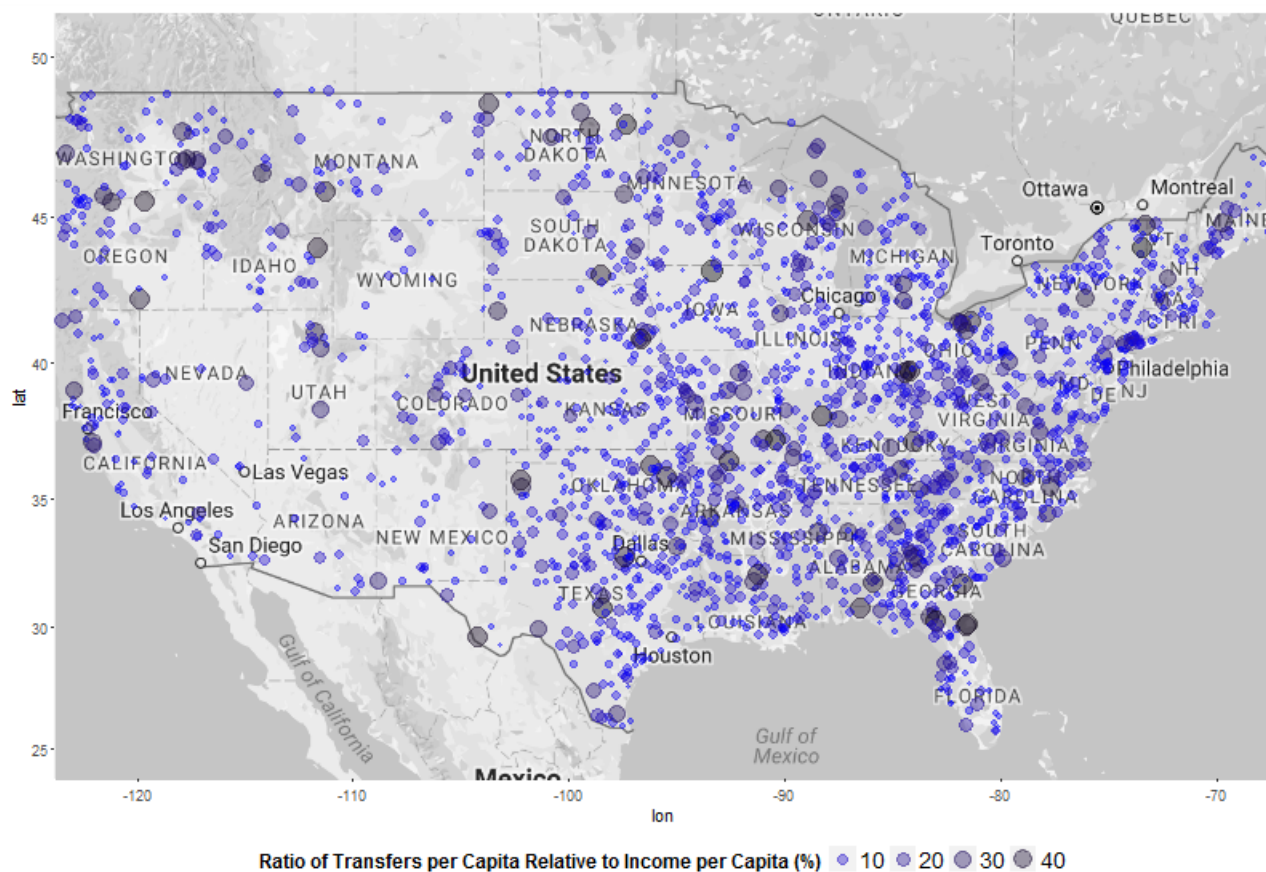
**Note:** This figure plots transfers per capita ( $G_{it}$ ) for the state of Ohio. Data are averaged over every quarter from 2009Q2 to 2013Q4. The orange dots represent major cities with population of more than 200K.

Figure 4: ARRA Transfers per Capita (Tennessee)



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

Figure 5: Ratio of Transfers per Capita Relative to Income per Capita



**Note:** This figure plots the ratio of transfers per capita ( $G_{it}$ ) relative to income per capita ( $Z_{it}$ ). Data are averaged over every quarter from 2009Q2 to 2013Q4.



### 3 ARRA as State-Contingent Fiscal Federalism

The benchmark model is a simple endowment economy in which individuals face uncertain income streams and a benevolent government (social planner) redistributes income to partially or fully offset the idiosyncratic component of county-level income variation. This model is used to describe how the cross-sectional variance of income may be parsed into long-run differences and transitory variation around those long-run differences. The risk-sharing facet of policy operates on the transitory variation by definition and is thus state-contingent.

#### 3.1 Risk-sharing Theory

Following Mace (1991), consider a social planner who maximizes the welfare-weighted sum of expected utility across  $N$  individuals. Here, individuals are indexed by county to comport to our micro-data and should thus be viewed as representative agents in their respective locations.

Formally, the social planner maximizes

$$\sum_{i=0}^N \omega_i \sum_{t=0}^{\infty} \beta^t \sum_{j=0}^S \Pi(s_{jt}) U[C_{it}(s_{jt})]$$

where the planner's weights,  $0 < \omega_i < 1$  and  $\sum_i^N \omega_i = 1$  and  $\Pi(s_{jt}) \in [0, 1]$  is the probability that event  $s_{jt}$  occurs with  $\sum_j^S \Pi(s_{jt}) = 1$ .

This maximization problem is subject to an economy-wide aggregate resource constraint which must be satisfied, state-by-state and date-by-date,

$$\sum_{i=0}^N C_{it}(s_{jt}) = \sum_{i=0}^N W_{it}(s_{jt}),$$

where  $C_{it}(s_{jt})$  is consumption per capita in county  $i$ , when the realized state is  $s_{jt}$ .

The income process for each county is governed by

$$W_{it} = \alpha_i + \rho W_{it-1} + \varepsilon_{it}(s_{jt}).$$

Here  $W_{it}$ , is measured as the difference between wage income per capita in county  $i$  and the cross-sectional average. This normalization is rationalized by the fact that the social planner cannot diversify away aggregate macroeconomic risk.<sup>9</sup> It also helps to ensure stationarity of the county-level income series in our empirical work.

The presumption of risk-theory theory is that there exists a stationary distribution of in-

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<sup>9</sup>As a robustness the penultimate section of the paper considers deviations of county income from gross domestic product per capita. Given our focus on wage data by county, the cross-sectional mean is a preferred normalization since it ensures a conditional mean of zero in the cross-section.

come and the purpose of risk pooling is to ensure no additional dispersion of income arises as a consequence of the idiosyncratic stochastic shocks impacting individual agents. With this theoretical benchmark in mind, it is productive to parse long-run income inequality from the transitory variation in county-level business cycles around this long-run distribution. This is readily done by subtracting the time fixed-effect from both sides and computing a variance decomposition.

$$Var(W_{it}) = \left( \frac{1}{1-\rho^2} \right) Var(\alpha_i) + \left( \frac{\sigma_i^2}{1-\rho^2} \right).$$

The first term is the cross-county variance of income that would arise in the steady-state in the absence of shocks. The second term is the time series variance around these long-run means which, of course, depends on the variance of the innovations at the county level,  $\sigma_i^2$ , and the persistence of the income process,  $\rho$ . As is standard in the risk-sharing literature, the insurance is provided against the second source of variation associated with  $\varepsilon_{it}$ . In the context of full risk-sharing, the policy would call for the social planner to disburse funds to a particular county that are equal and opposite in sign to the income shock that county experiences (relative to the aggregate economy-wide shock, which has been removed) within the period.

Even within the relative large scope of discretionary spending in the ARRA fiscal package, full risk sharing was surely not implemented. To capture a more flexible formulation within the context of risk-sharing theory, consider the following stochastic process for the ARRA disbursements:

$$G_{it}(s_{jt}) = -\lambda_\tau \varepsilon_{it}(s_{jt}) + v_{it}(s_{jt})$$

Here, the benevolent social planner would provide complete state-contingent insurance against county-specific income shocks by setting  $\lambda_\tau = 1$  and  $v_{it}(s_{jt}) = 0$ . The Laissez-Faire policy with no stimulus would be  $\lambda_\tau = 0$  and  $v_{it}(s_{jt}) = 0$ . The actual policy will lie somewhere in between. The subscript on the parameter allows an accounting for the fact that the ARRA is a transitory program with varying aggregate intensity over time as the disbursements rise and fall in magnitude with the roll-out of the program.

Integrating the ARRA policy function with the wage income process, leads to the following path of wage income inclusive of the ARRA disbursements,

$$W_{it} = \alpha_i + \rho W_{it-1} + (1 - \lambda_\tau) \varepsilon_{it}(s_{jt}) + v_{it}(s_{jt}).$$

as  $\lambda$  goes from zero to one, publicly provided risk-sharing goes from the policy prescribed by the benevolent social planner (complete risk-sharing) to helicopter drops of money that differ across quarters according to the flows of funds from the government over time. Essentially, the risk-sharing component of the policy should reduce the size of the innovation by fraction  $\lambda$ .

When the policy is active, the variance decomposition becomes,



$$\text{Var}(W_{it}) = \left( \frac{1}{1-\rho^2} \right) \text{Var}(\alpha_i) + (1-\lambda_\tau)^2 \left( \frac{\sigma_{\varepsilon_i}^2}{1-\rho^2} \right) + \sigma_{v_i}^2.$$

and when the benevolent social planner implements complete state-contingent insurance against county-specific income shocks by setting  $\lambda_\tau = 1$  and  $v_{it}(s_{jt}) = 0$  only the long-run income differences across counties is observed during the “treatment” period of the ARRA. More generally, to the extent the transfers are negatively correlated with the underlying income shocks the cyclical variation is mitigated. For example if  $\lambda_\tau = 0.2$  then 20% of the shocks are mitigated by the ARRA program. The presumption of this specification is that the dynamics of income are the same no matter the value of the policy parameter. Effectively the policy introduces a shift in the variance of the income shocks that lasts for the duration of the policy period. The underlying assumption concerning the non-systematic part of the policy is that it adds an i.i.d. error term to the total resources flowing into the county (i.e. the sum of wage income the random component of the ARRA payment).

The policy implied by this simple model may be difficult to implement in practice as it requires measurement of the exogenous income shock within the quarter in addition to measurement of the disbursement of ARRA funds in response. Thus, we also consider a situation in which the disbursements lag the shocks by a quarter. The income inclusive of ARRA disbursements in this case is:

$$W_{it} = \alpha_i + \rho W_{it-1} - \lambda_\tau \varepsilon(s_{jt-1}) + \varepsilon_{it}(s_{jt}) + v_{it}(s_{jt}).$$

While the measurement of the systematic part of the transfer is likely to differ with this specification, the expectation is that the variance decomposition will be similar to the one above unless there is a significant change in the cross-sectional variance of the underlying shocks to income, which is intractable to estimate given the short time horizon of the ARRA policy.

### 3.2 Illustrative Simulations

To understand the impact of the degree of fiscal insurance on the dispersion of income, here we stimulate our benchmark model under certain assumptions. We posit preferences as the following CRRA utility function for representative agents in each county, indexed by  $i$ ,

$$U(C_t) = \frac{C_{it}^{1-\sigma}}{1-\sigma}$$

where  $\sigma$  denotes the degree of relative risk aversion. For expositional convenience, we assume that every state occurs with same probability, such that  $\Pi(s_{jt}) = 1/S$  and the social planner is benevolent in the sense that citizens in each county receive the same welfare weight  $\omega_i = 1/N$ . We also assume that the parameter  $\alpha_i$  is *ex-ante* drawn from  $N(0, \sigma_i)$ .

Table 2: Baseline Parameterization for the Benchmark Model

| Parameters | $\sigma$ | $\rho$ | $N$ | $\sigma_i$ | $\beta$ | $\sigma_v$ | $\sigma_\varepsilon$ |
|------------|----------|--------|-----|------------|---------|------------|----------------------|
| Value      | 2        | 0.9    | 300 | 0.01       | 0.99    | 0.01       | 0.01                 |

The social planning problem can be summarized as follows. The planner maximizes

$$\sum_{t=0}^{\infty} \beta^t \sum_{i=1}^N \omega_i \sum_j^S \Pi(s_{jt}) \frac{C_{it}^{1-\sigma}}{1-\sigma}$$

subject to

$$\begin{aligned} W_{it} &= \alpha_i + \rho W_{it-1} + G_{it} + \varepsilon_{it} & \forall i = 1 \dots N \\ G_{it} &= -\lambda_\tau \varepsilon_{it-1} + v_{it} & \forall i = 1 \dots N \\ \beta^t \omega_i \Pi(s_{jt}) C_{it}^{-\sigma} &= \lambda_t & \forall i = 1 \dots N \\ \sum_{i=0}^N C_{it} &= \sum_{i=0}^N W_{it} \equiv W_t \end{aligned}$$

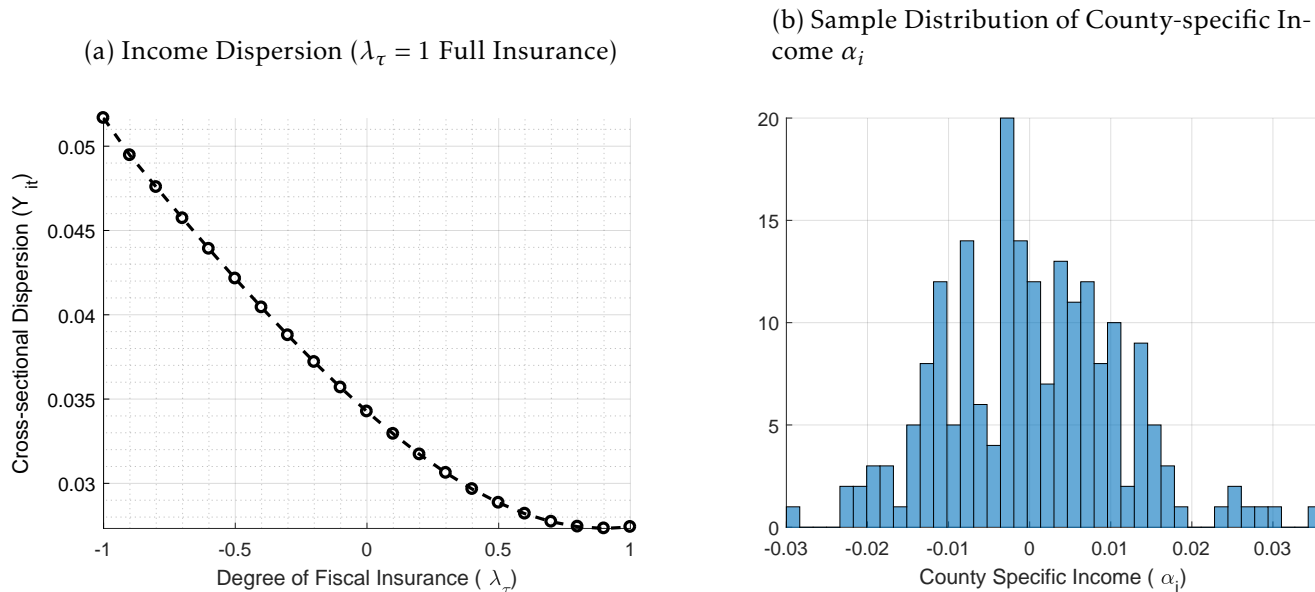
Notice that all of the aggregates are state-contingent, but the states are suppressed for notational convenience. The solution to this model involves solving a set of  $3 \times N + 1$  equations for  $3 \times N + 1$  variables  $W_{it}, G_{it}, C_{it}, \lambda_t$  for all  $i = 1 \dots N$ . We solve for the model using first order approximation with the following baseline parameterization in table 2 and simulated the model for T=2,000 periods.

Figure 6b plots the distribution of the county-specific income component  $\alpha_i$  for each of the N=300 counties used in our baseline simulation. Figure 6 plots the wage income ( $W_{it}$ ) dispersion for the simulated baseline model with N=300 counties and T=2,000 periods. One key implication of the model is that as the degree of fiscal insurance increases, income dispersion across locations decreases. Under the case that county-specific income shocks are fully insured (when  $\lambda_\tau = 1$ ), we observed the smallest income dispersion across location. On the other end, however, if income shocks are not insured (when  $\lambda_\tau = 0$ ) or further burdened by additional liabilities from the government (when  $\lambda_\tau \rightarrow -1$ ), we observe a stark increase in income dispersion across locations. We turn, now, to an empirical investigation of wage income dynamics and how they relate to the ARRA disbursements.

## 4 Results

This section begins with a summary of estimation results for a model of income dynamics that is consistent with the model described in the previous section. We use the residuals from the model of panel income dynamics as the shocks to which the ARRA responds to estimate the

Figure 6: Simulated Income Variance at the County Level



**Note:** This figure plots the income and consumption variance by the degree of fiscal insurance  $\lambda_\tau$ . We solved the model with  $3 \times N + 1$  variables and equations ( $N=300$ ) and simulated the model for 2,000 periods.

parameter  $\lambda$ , the fraction of the shock that is offset in the typical county. It is important to note that in practice not all counties receive direct ARRA transfers, so the offset is conditional on being “treated.”

Following these baseline results, consideration is given to differences in income dynamics across quartiles of the income distribution and across counties that identify as majority Democrat or Republican. Our interest in the heterogeneity in ARRA transfers across the income distribution is motivated by the possibility that the crisis may have motivated redistribution based on pre-existing income inequality which had been on the rise for many years leading up to the crisis. The Democrat and Republican partition of counties invites interesting questions related to the political economy of fiscal policy which we hope to pursue in future work.

#### 4.1 County-level Wage Income Dynamics

The aggregate U.S. business cycle has received an enormous amount of attention in the macroeconomics literature. Much less is known about the dynamics of county-level income *relative* to the national stochastic trend. This represents a natural starting point of our analysis.

The role of income persistence in assessing the welfare costs of county-level business cycles draws inspiration from work by international economists on the cross-county welfare costs of business cycles, (see, [Athanasoulis and van Wincoop \(2000\)](#) for a definitive treatment using a large cross-section of international data).

With this perspective in mind, our strategy is to divide the data into three sample periods and three county groupings. The three time periods are: (1) the entire available sample (All: 1990Q1-2015Q4), (2) the period before the Great Recession (Pre: 1990Q1-2008Q1), and (3) the period from the onset of the Great Depression and beyond (Post: 2008Q2-2015Q4).<sup>10</sup> The three county groupings are: (1) all U.S. counties, (2) counties that receive at least one dollar per capita of ARRA transfers in *at least one* quarter from 2009Q3 to 2013Q4 (Treated), and (3) counties that do not receive any ARRA money (Non-treated) in *any quarter* during the same period. Thus, there are nine different panel estimates with the standard errors clustered at the county level.

Per capita county-level wage income relative to the cross-sectional mean is modeled as a first-order auto-regression with a county-fixed effect to capture long-run county-specific income differences. Normalization to the cross-sectional mean (across counties) has two justifications here. First, it is intended to isolate the variation in county-level wage income that could be subject to risk-pooling from non-diversifiable income risk associated with the aggregate business cycle. That is, the common (across counties) movements in wage income over time. Second, the normalization helps to ensure stationarity of wage income in the context of this panel regression model.

Turning to the details, the reader is reminded that county-level wage income per capita is relative to the cross-county mean, (i.e.,  $W_t = E_i(\tilde{W}_{it})$ , where the tilde indexes the raw data) is denoted,  $W_{it}$ , leading to the following empirical model:

$$W_{it} = \rho W_{it-1} + \alpha_i + \varepsilon_{it} \quad (1)$$

where  $W_{it}$  is the logarithm of per capita wage income in county  $i$  relative to the cross-county mean,  $W_t = E_i(\tilde{W}_{it})$ .

Beginning with the results that pool all counties, the persistence over the entire sample from 1990 to 2015 is estimated to be 0.918, which translates to a half-life of about 8 quarters. The half-life before the onset of the Great Recession is about 7 quarters and the value drops to just over 1 quarter in the sample period since the Great Recession. The fact that the persistence over each sub-sample is lower than the pooled sample is suggestive of a structural break. It is interesting to contemplate the possibility that the structural break is due to the ARRA program itself.

For this reason, the persistence is estimated separately for counties that received ARRA funds and those that did not. Notice that in the period before ARRA, the estimated persistence of income in counties that subsequently received funds is 0.907 compared to 0.893 in those that do not. The similarity of persistence is reassuring both from the perspective that county income has similar persistence across the distribution of counties and in the sense that a focus

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<sup>10</sup>The Great Recession lasted from Dec. 2007 to June 2009, per NBER official recession dating.

Table 3: Estimated Income Process

|                          | All                   |                       | ARRA                 |                       | Non-ARRA              |                      |                       |                       |                      |
|--------------------------|-----------------------|-----------------------|----------------------|-----------------------|-----------------------|----------------------|-----------------------|-----------------------|----------------------|
|                          | (1)<br>All            | (2)<br>Pre            | (3)<br>Post          | (4)<br>All            | (5)<br>Pre            | (6)<br>Post          | (7)<br>All            | (8)<br>Pre            | (9)<br>Post          |
| Net Income (1-lag)       | 0.918***<br>(0.00267) | 0.904***<br>(0.00293) | 0.559***<br>(0.0231) | 0.918***<br>(0.00311) | 0.907***<br>(0.00338) | 0.527***<br>(0.0259) | 0.918***<br>(0.00491) | 0.893***<br>(0.00551) | 0.648***<br>(0.0425) |
| Obs. (N X T)             | 321,837               | 221,913               | 99,924               | 258,366               | 178,058               | 80,308               | 63,471                | 43,855                | 19,616               |
| County (N)               | 3,136                 | 3,133                 | 3,127                | 2,514                 | 2,511                 | 2,514                | 622                   | 622                   | 613                  |
| Quarters (T)             | 103                   | 71                    | 32                   | 103                   | 71                    | 32                   | 102                   | 71                    | 32                   |
| R <sup>2</sup>           | 0.855                 | 0.823                 | 0.306                | 0.857                 | 0.828                 | 0.272                | 0.851                 | 0.799                 | 0.414                |
| Cross-sectional Variance | 0.002                 | 0.003                 | 0.068                | 0.002                 | 0.003                 | 0.078                | 0.002                 | 0.004                 | 0.043                |
| Time-series Variance     | 0.010                 | 0.010                 | 0.020                | 0.010                 | 0.010                 | 0.022                | 0.010                 | 0.010                 | 0.016                |
| Total Variance           | 0.013                 | 0.014                 | 0.089                | 0.013                 | 0.013                 | 0.100                | 0.013                 | 0.014                 | 0.059                |

Standard errors in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

**Note:** We estimate the following specification  $W_{it} = \alpha_i + \rho W_{it-1} + \varepsilon_{it}$ . Here the cross-sectional and time-series variances follow the Crucini-Telmer decomposition. In particular, the cross-sectional variance is  $Var_t(E_i(\varepsilon_{it}))$  and the time-series variance is  $E_t(Var_i(\varepsilon_{it}))$ . The total variance is calculated as  $var_{it}(\varepsilon_{it})$ .

on the income shocks when studying state-contingent fiscal policy is a reasonable one.

Turning to the period following the onset of the Great Recession, counties that received ARRA funds have lower persistence (0.527) compared to those that did not (0.648). This suggests that the ARRA disbursements slightly reduced the persistence of county-specific movements of wage income (relative to the national stochastic trend) in counties that received them. Another possibility is that allowing the county-fixed effects to shift in the process of re-estimating the model over a relative short time period changes the empirical attribution of variance from the cyclical (stochastic) component to the long-run or fixed effect.

The last three rows present the variance decomposition of wage income that was developed earlier in the paper. The total variance of wage income is about 1.3 percent pooling all counties and time periods (the first column of Table 3). This is largely indistinguishable from the pre-ARRA case. Moreover, by this metric, those receiving ARRA funds are virtually indistinguishable from those that did not whether use the entire sample period or the pre-Great Recession period. However, there is a very significant increase in the total amount of county-level wage income dispersion associated with the Great Recession. That is, income both fell on average in the U.S. (the macroeconomic cycle, obviously) and also became much more unequal across counties, with the total cross-sectional variance rising from 1.4% to 8.9%. The counties that received ARRA funds experienced a much larger increase in income dispersion than those that did not, 10% versus 5.9%.

These calculations present a number of profound puzzles. If the ARRA was intended to help those most in need, it certainly did not do so in the 613 counties that failed to receive any funds at all. Since conditional on receiving funds, dispersion is almost twice as high among these counties relative to those not receiving funds it could be that the grants, loans and contracts part of the ARRA actually exacerbated income dispersion. The alternative interpretation is that somehow otherwise historically similar counties (i.e., counties that prior to the Great Recession had similar stochastic wage income processes) became very dis-similar.

Looking at the role assigned to long-run income dispersion (cross-sectional variation attributed to the fixed effects) relative to time series dispersion (stochastic shocks), much of the change is attributed to long-run wage dispersion. Before the Great Recession, between 23% and 28% of the total dispersion is estimated as arising from the fixed effects very similar across the two groups of counties (typical of the overall sample period). Of the relative increase in income dispersion across the groups, 4.1% (i.e.,  $10\% - 5.9\% = 4.1\%$ ), 3.5% is attributed to more long-run dispersion, 0.6% to cyclical effects. With the caveat that discriminating long-run and short-run sources of variation of income is challenging, particularly in short panels, we turn now to an analysis of the extent to which the temporary ARRA program offset the transitory components, the income shocks.

## 4.2 Fiscal Offset

Did the ARRA help those most in need in terms of the heterogeneous income shocks brought on during the Great Recession? To address this question, we regress the ARRA payment received in county  $i$  on the estimated income shock that county received in the prior quarter. This specification is motivated by the following thought experiment: in the third quarter of 2008, the average U.S. county experience a bad draw from the possible aggregate states of the world described by the mean of  $\varepsilon_{it}(s_{jt})$ ; however, some counties had draws well below this mean and thus should receive a larger transfer (i.e., a state-contingent payment with the state indexed by the size and sign of the shock).

With a common persistence of income recoveries across counties, the cross-sectional distribution of the impulse responses will follow:  $\rho^k \widehat{\varepsilon}_{i,08:03}$ ; where  $k$ , of course, is the number of quarters since the shock of the third quarter of 2008 and  $\widehat{\varepsilon}_{i,08:03}$  is the estimate size of the income shock experienced by county  $i$  in the third quarter of 2008. In the limit, the distribution of income across counties, will return to its stationary state as described by the estimated county-fixed effects,  $\alpha_i$ .

What the state-contingent risk sharing transfer does is mitigate the size of the shock, without materially affecting the dynamic path back to the stationary distribution of income. Thus, income dispersion is reduced relative to Laissez-Faire, but county-level income persistent is unaffected. Thus, the impulse response including the fiscal offset, will follow,  $\rho^k (1-\hat{\lambda})\widehat{\varepsilon}_{i,08:03}$  for those receiving funds and the Laissez-Faire case ( $\hat{\lambda} = 0$ ) for those not receiving funds.

The null hypothesis of full risk pooling through fiscal transfers is that the coefficient on the income shock is -1. Pooling all counties that received at least on dollar of funds over the duration of the program, the estimated fiscal offset parameter is -0.131 which means that a 100 dollar income decline is offset by about 13 dollars (see Table 4). While far from the complete risk-sharing benchmark, the estimated risk-offset is both economically and statistically significant. The lower panel of the table indicates that full insurance would result in income dispersion of 0.018 (reflecting only the long-run fixed effects), while no insurance (Laissez-Faire) would produced income dispersion of 0.051.

## 4.3 County Income Distribution

Understandably, there has been a great deal of discussion of the persistent increases in income inequality in the U.S. Our county level analysis considers the possibility that some of this income inequality is geographic and potentially affected by the Great Recession and the policy responses to it.

We start by dividing our counties into four quartiles based on their average income over the entire sample period. Figure 7 plots median wage income and median wage income adjusted for ARRA transfer to each county. The widening gap in the raw wage income data is readily

Table 4: Fiscal Insurance and the ARRA Program

Baseline Estimation

| $\hat{\lambda}_\tau$ | s.e.  | County | Total Observations |
|----------------------|-------|--------|--------------------|
| 0.131                | 0.022 | 2,514  | 27,641             |

| $\left(\frac{1}{1-\rho^2}\right) Var(\alpha_i)$ | $(1 - \lambda_\tau)^2 \left(\frac{\sigma_{\varepsilon_i}^2}{1-\rho^2}\right)$ | $Var(W_{it})$ |
|-------------------------------------------------|-------------------------------------------------------------------------------|---------------|
| 0.007                                           | 0.025                                                                         | 0.043         |

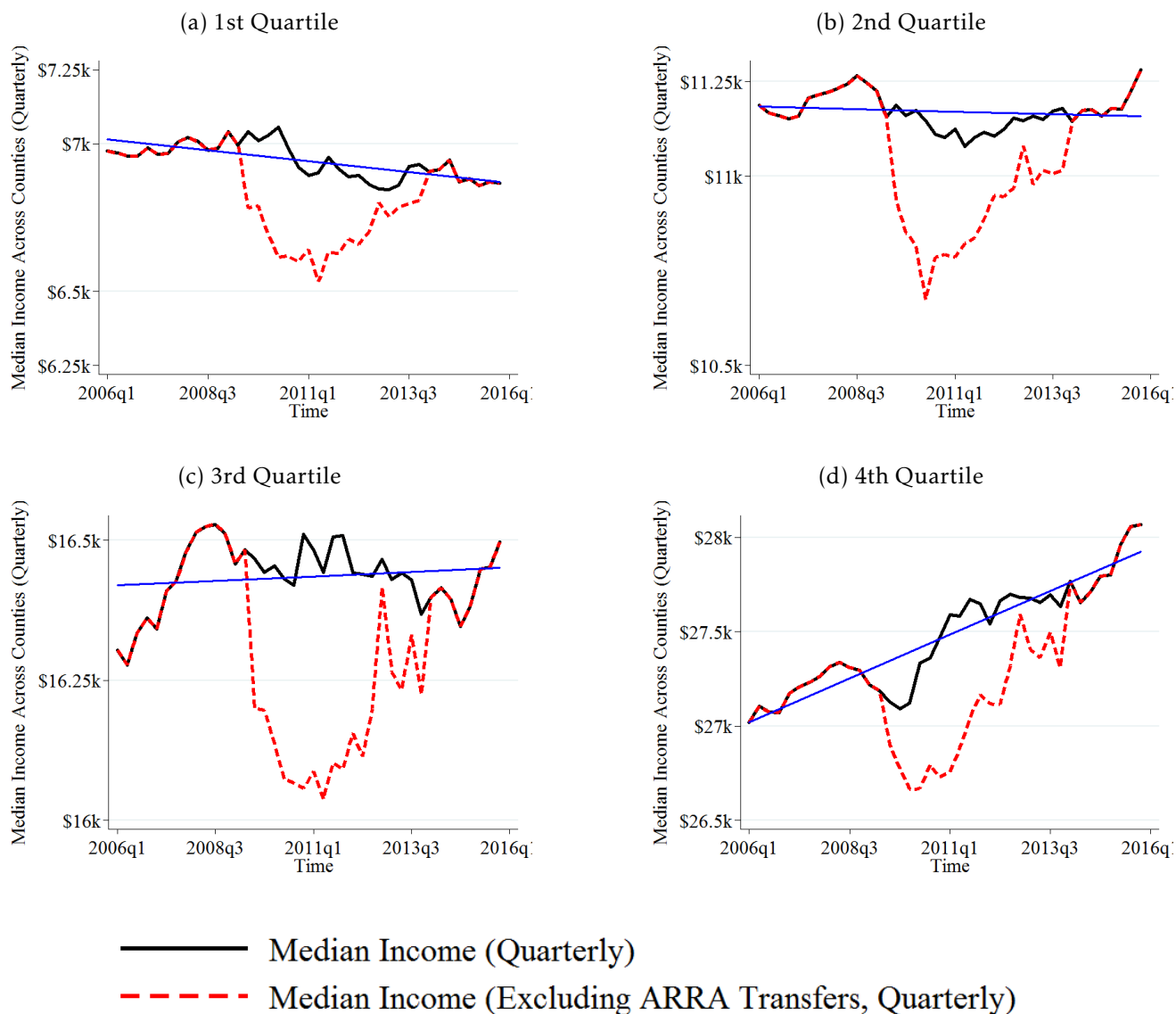
Counter-factual

| Data          | Counter-factual                  |                                  |
|---------------|----------------------------------|----------------------------------|
|               | Full Insurance                   | No Insurance                     |
| $Var(W_{it})$ | $Var(W_{it}) (\lambda_\tau = 1)$ | $Var(W_{it}) (\lambda_\tau = 0)$ |
| 0.043         | 0.018                            | 0.051                            |

evident in this income-stratified view of county-level data. The lowest income quartile group in the upper left-hand-chart indicates a negative long-term trend, the second and third quartiles are basically trendless. The fourth quartile is the engine of growth overall and, in an accounting sense, the dynamic that is generating the income inequality across these county groups.



Figure 7: Income and ARRA Transfers over the Business Cycle



**Note:** The figure plots the level of net income per capita ( $Z_{it}$ ) and the gross income per capita ( $W_{it}$ ) over the cycles. We define the level of net income per capita as the level of gross income per capita, measured by the level of total quarterly wages aggregated at the county level, minus the amount of ARRA transfers. Here we break down by quartiles of income as defined by the Total Quarterly Wage. We define the quartiles by considering the average income over the whole sample; that is, if one county belongs to one particular quartile based on the average income, it will stay under the same group throughout the analysis.

Under the assumption that the wage income includes the ARRA disbursements either directly in wage income or indirectly through spillovers, the red lines subtract the ARRA amounts from the report wage income data. This is the counterpart of Figure 1a, which reported the aggregated values of wage income and wage income net of ARRA disbursements. We see that when viewed from this perspective, it appears that most of the recessionary gap was filled for each quartile of the county-income distribution despite the heterogeneous nature of raw wage

income cycles.

### 4.3.1 Estimated Fiscal Offset by Income Quartiles

Table 5 reports the results of our analysis for counties stratified by their income levels (as well as pooled, for comparison to Table 3).

Beginning with the question of county-level business cycle persistence (relative to the aggregate), we see more persistent deviations in the tails of the distribution than in the middle. For example, the persistence is estimated to be 0.870 (0.821) when counties in the lowest (highest) income quartile are pooled compared to 0.610 (0.608) for counties in the second (third) quartile. It is important to note that total income dispersion across counties is higher among counties near the median income level than in the tails of the income distribution. For example, the total variance in wage income is 1.6% across counties in the lowest income quartile (comparable to the 2.2% in the highest income quartile), but is much higher in the second and third quartiles, 7.1% and 7.2%, respectively. Much of the difference, again, appears to be associated with the long-run sources of variation, the fixed effects.

Turning to the fiscal offset parameters, notice that they are all estimated to be negative, consistent in direction with the model of contingent fiscal policy under risk-sharing. However, the magnitudes are quite diverse across income quartiles, ranging from an estimated offset of 25.6% in the second income quartile of counties to a low of 2.3% in the highest income quartile (though this latter estimate is very imprecise).

## 4.4 County Party Affiliation

Economists have long been interested in questions surrounding the distribution of discretionary military spending in terms of the ability of members of Congress to ‘bring home the bacon.’ We consider the potential for results to skew across counties based on the party affiliation of the majority population in a given county.

While the total size of the ARRA package and broad outlines of the components are determined by legislation at the Federal level, the details of implementation involve the interactions of state and local authorities and actions of applicants for funds and the approval of those disbursements. As a result, one natural hypothesis is that disbursements may be directed on the basis of majority political affiliation of the county. We investigate this possibility by complementing our income ARRA data set with data on the political affiliations at the local level. Our starting point here is to match our ARRA data set with the publicly available data on the election results across counties by the *U.S. Census*: we focus our attention to the 2008 election, simply because the election is closest to the implementation of the ARRA program.

Table 5: Income Dynamics and Fiscal Offset by Income Quartiles

Panel A: Income Dynamics

|                          | (1)                   | (2)                   | (3)                   | (4)                   | (5)                  |
|--------------------------|-----------------------|-----------------------|-----------------------|-----------------------|----------------------|
|                          | All                   | Q1                    | Q2                    | Q3                    | Q4                   |
| Net Income (1-lag)       | 0.918***<br>(0.00267) | 0.870***<br>(0.00560) | 0.610***<br>(0.00839) | 0.608***<br>(0.00976) | 0.821***<br>(0.0142) |
| Observations             | 321,837               | 79,755                | 80,432                | 80,754                | 80,896               |
| County                   | 3,136                 | 701                   | 936                   | 884                   | 615                  |
| $R^2$                    | 0.855                 | 0.768                 | 0.378                 | 0.376                 | 0.687                |
| Cross-sectional Variance | 0.002                 | 0.006                 | 0.053                 | 0.054                 | 0.011                |
| Time-series Variance     | 0.010                 | 0.011                 | 0.018                 | 0.018                 | 0.011                |
| Total Variance           | 0.013                 | 0.016                 | 0.071                 | 0.072                 | 0.022                |

Standard errors in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

**Note:** We estimate the following specification  $W_{it} = \alpha_i + \rho W_{it-1} + \varepsilon_{it}$ . Here the cross-sectional and time-series variances follow the Crucini-Telmer decomposition. In particular, the cross-sectional variance is  $Var_t(E_i(\varepsilon_{it}))$  and the time-series variance is  $E_t(Var_i(\varepsilon_{it}))$ . The total variance is calculated as  $var_{it}(\varepsilon_{it})$ .

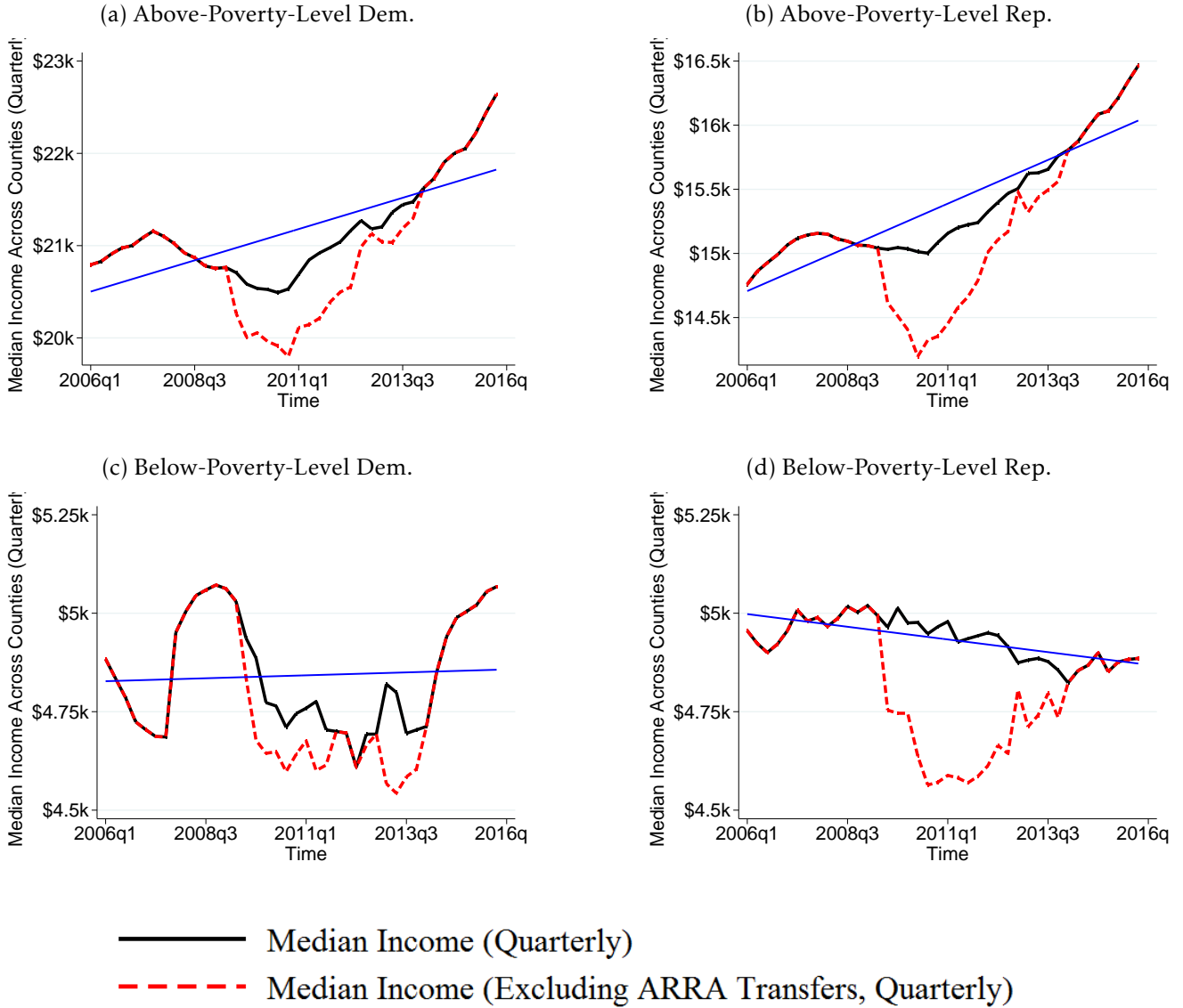
Panel B: Fiscal Offset

|                                                                               | (1)                  | (2)                 | (3)                  | (4)                  | (5)                 |
|-------------------------------------------------------------------------------|----------------------|---------------------|----------------------|----------------------|---------------------|
|                                                                               | All                  | Q1                  | Q2                   | Q3                   | Q4                  |
| Last Quarter Income                                                           | -0.131***<br>(0.022) | -0.085*<br>(0.050)  | -0.256***<br>(0.047) | -0.157***<br>(0.043) | -0.023<br>(0.039)   |
| Constant                                                                      | 5.089***<br>(0.003)  | 5.194***<br>(0.034) | 5.156***<br>(0.015)  | 4.969***<br>(0.005)  | 5.072***<br>(0.004) |
| Observations                                                                  | 27,641               | 3,745               | 5,961                | 7,332                | 10,603              |
| County                                                                        | 2,514                | 350                 | 570                  | 738                  | 857                 |
| $\left(\frac{1}{1-\rho^2}\right) Var(\alpha_i)$                               | 0.007                | 0.004               | 0.005                | 0.004                | 0.008               |
| $(1 - \lambda_\tau)^2 \left(\frac{\sigma_{\varepsilon_i}^2}{1-\rho^2}\right)$ | 0.025                | 0.037               | 0.015                | 0.016                | 0.026               |
| $Var(W_{it})$                                                                 | 0.043                | 0.056               | 0.029                | 0.028                | 0.042               |
| $Var(W_{it})$ (Full Insurance)                                                | 0.018                | 0.019               | 0.014                | 0.012                | 0.017               |
| $Var(W_{it})$ (No Insurance)                                                  | 0.051                | 0.063               | 0.041                | 0.035                | 0.043               |

Standard errors in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Figure 8: Income and ARRA Transfers: Political Affiliations and Poverty Level



**Note:** The figure plots the level of net income per capita ( $Z_{it}$ ) and the gross income per capita ( $W_{it}$ ) over the business cycle. We define the level of net income per capita as the level of gross income per capita, measured by the level of total quarterly wages aggregated at the county level, minus the amount of ARRA transfers. Here we break down by whether the county's majority voted for a Democrat candidate or a Republican candidate over the 2008 election cycle and by whether the county has at least 50 percent of the population living below the Federal poverty line, which was \$24,250 in 2015 after adjustment for changes in prices level over time.

To get a sense of how political affiliations can impact the distribution of income in our data, we stratify the counties by majority party affiliation and counties with per capita income above or below the Federal poverty line. Figure 8 plots the raw wage data (black lines) and the wage data with ARRA transfers subtracted. Again, this adjustment should be treated with caution because the wage data may or may not include (directly or indirectly) the ARRA transfers.

A few observations are worth noting. First, the medians for above poverty line counties

seem quite similar across party affiliation. And, we see that under the interpretation that wages include ARRA, the business cycle gap for the median household in these income groups is substantially mitigated. Second, the below-poverty counties are highly contrasting with the above-poverty counties both in trend and cycle. Income trends in majority poor counties appear to be flat, though possibly of opposite signs across the party affiliations. More striking is that the ARRA disbursements put the relatively impoverished Republican counties at or above their historic trend while the Democrat counties are left with a very big gap. Taken at face value, it appears that how the median county in poverty fared in getting ARRA funds is highly dependent on their party affiliation. While we do not pursue the issue here (being focused on more granular income dispersion and risk-sharing), it is interesting to consider the possible influence of this pattern on the most recent election outcome.

#### **4.4.1 Fiscal Offset by County Party Affiliation**

Once again, we conduct the same exercise as in Section 4.1, but with an additional breakdown by political affiliations in Table 6. One key insight is that fiscal offset is twice as high above the poverty line compared to below, 13.6% versus 6.9%. Stratifying by county party affiliation Republican counties below the poverty line fared the worst (6.0%) and Republican counties above the poverty line fared the best (14.1%).

## **5 Conclusion**

This paper has conducted a forensic analysis of the cross-sectional properties of an important facet of the ARRA fiscal stimulus, namely the grants, contracts and loans that can be tracked to the zip-code level. Casting the issue in terms of state-contingent fiscal risk sharing we find that for counties that received at least one dollar per capita, there was approximately a 13% offset of the income shock the median county received. So, from the perspective of cyclical risks, emphasized in the risk-sharing literature, this result is reassuring.

The estimated fiscal offsets were higher for counties toward the middle of the income distribution than those in the first or fourth quartile. It turns out that income is less persistent but subject to large innovations in this part of the income distribution, which combines to give twice the short-run or cyclical variance compared to counties in the tails of the distribution. From a risk-sharing perspective, this result also seems reassuring since larger proportions of the variance appear to be offset in counties subject to cyclical risks that were higher than the average. From a broader perspective, which would take into account the level of income or wealth, this result is not necessarily a desired one.

Results stratifying by poverty and party affiliation also indicate substantial differences in the impact of the Great Recession and the ARRA to fill the gap in median income by group, as well as income dispersion around the group means. It is somewhat early to draw conclusions

Table 6: Income Dynamics and Fiscal Offset by Political Affiliations

Panel A: Income Dynamics

|                          | Below Poverty         |                     |                      | Above Poverty         |                       |                       |
|--------------------------|-----------------------|---------------------|----------------------|-----------------------|-----------------------|-----------------------|
|                          | (1)<br>All            | (2)<br>Democrats    | (3)<br>Republicans   | (4)<br>All            | (5)<br>Democrats      | (6)<br>Republicans    |
| Net Income (1-lag)       | 0.847***<br>(0.00945) | 0.830**<br>(0.0271) | 0.850***<br>(0.0101) | 0.898***<br>(0.00345) | 0.903***<br>(0.00424) | 0.897***<br>(0.00444) |
| Observations             | 34,526                | 5,027               | 29,499               | 287,311               | 84,036                | 203,275               |
| County                   | 703                   | 108                 | 595                  | 2,433                 | 683                   | 1,750                 |
| $R^2$                    | 0.722                 | 0.698               | 0.726                | 0.820                 | 0.829                 | 0.816                 |
| Cross-sectional Variance | 0.008                 | 0.010               | 0.008                | 0.004                 | 0.003                 | 0.004                 |
| Time-series Variance     | 0.011                 | 0.011               | 0.011                | 0.010                 | 0.010                 | 0.010                 |
| Total Variance           | 0.019                 | 0.021               | 0.019                | 0.014                 | 0.014                 | 0.014                 |

Standard errors in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

**Note:** We estimate the following specification  $W_{it} = \alpha_i + \rho W_{it-1} + \varepsilon_{it}$ . Here the cross-sectional and time-series variances follow the Crucini-Telmer decomposition. In particular, the cross-sectional variance is  $Var_t(E_i(\varepsilon_{it}))$  and the time-series variance is  $E_t(Var_i(\varepsilon_{it}))$ . The total variance is calculated as  $var_{it}(\varepsilon_{it})$ .

Panel B: Fiscal Offset

|                                                                               | Below Poverty       |                     |                     | Above Poverty        |                     |                      |
|-------------------------------------------------------------------------------|---------------------|---------------------|---------------------|----------------------|---------------------|----------------------|
|                                                                               | (1)<br>All          | (2)<br>Democrats    | (3)<br>Republicans  | (4)<br>All           | (5)<br>Democrats    | (6)<br>Republicans   |
| Last Quarter Income                                                           | -0.069<br>(0.080)   | -0.103<br>(0.149)   | -0.060<br>(0.093)   | -0.136***<br>(0.024) | -0.117**<br>(0.052) | -0.141***<br>(0.027) |
| Constant                                                                      | 5.027***<br>(0.077) | 5.426***<br>(0.189) | 4.952***<br>(0.084) | 5.095***<br>(0.003)  | 5.184***<br>(0.009) | 5.058***<br>(0.002)  |
| Observations                                                                  | 1,286               | 203                 | 1,083               | 26,355               | 7,919               | 18,436               |
| County                                                                        | 135                 | 21                  | 114                 | 2,379                | 705                 | 1,674                |
| $\left(\frac{1}{1-\rho^2}\right) Var(\alpha_i)$                               | 0.008               | 0.011               | 0.007               | 0.013                | 0.015               | 0.010                |
| $(1 - \lambda_\tau)^2 \left(\frac{\sigma_{\varepsilon_i}^2}{1-\rho^2}\right)$ | 0.074               | 0.069               | 0.075               | 0.038                | 0.034               | 0.040                |
| $Var(W_{it})$                                                                 | 0.098               | 0.097               | 0.099               | 0.061                | 0.057               | 0.060                |
| Full Risk-sharing: $\lambda_\tau = 1$                                         | 0.025               | 0.028               | 0.024               | 0.023                | 0.023               | 0.021                |
| No Offset : $\lambda_\tau = 0$                                                | 0.110               | 0.114               | 0.109               | 0.074                | 0.066               | 0.075                |

Standard errors in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

from this facet of our analysis, but we hope to pursue a full political economy investigation in future extensions.

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## A Appendix: Data Sources

### A.1 Income Data

Data for the *Quarterly Census of Employment and Wages (QCEW)* are of quarterly frequency and are seasonally adjusted. Income data from this data-set are reported using the (county-level) Area-FIPS codes (by the Geography Division of the U.S. census). Since the QCEW data are based on the jobs, it is possible that individuals who hold multiple jobs are counted multiple time at the micro level. Income data for the *Quarterly Census of Employment and Wages (QCEW)* come in under four main types of measures: total quarterly wages, taxable quarterly wages, average weekly wages, and quarterly contributions. Total quarterly wages include bonuses, stock options, severance pay, profit distributions, cash value of meals and lodging, tips and other gratuities, and in some cases, deferred contributions to employee retirement plans. 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.”

**Location of ARRA Data** There are two variables that 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 as the location of the award.

**Magnitude of the ARRA transfers** In the publicly available ARRA data, there are two variables that 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 or “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.”<sup>11</sup> Here we use the latter definition for the amount of ARRA transfers and deflate by the appropriate GDP deflator.

Table A1 presents the average amount of awards for the project (award amount) and for the projects’ sub-contractors (local amounts) across all zipcodes and quarters in the original ARRA

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<sup>11</sup>Source: [www.recovery.org](http://www.recovery.org)

Table A1: Average Total Loans, Contracts, and Grants

|                                    | 2009       | 2010      | 2011        | 2012       | 2013       | All Years  |
|------------------------------------|------------|-----------|-------------|------------|------------|------------|
| Loans                              | \$ 88.49   | \$ 206.6  | \$ 471.1    | \$ 693.2   | \$ 752.2   | \$ 453.3   |
| Contracts                          | \$ 942.8   | \$1,265.7 | \$1,276.6   | \$1,237.8  | \$912.7    | \$ 1,167.6 |
| Grants                             | \$ 6,273.3 | \$7,152.2 | \$7,125.1   | \$4,971.8  | \$ 5,147.6 | \$ 6,263.0 |
| Total Award                        | \$ 7,304.6 | \$8,624.4 | \$8,872.8   | \$6,902.8  | \$ 6,812.6 | \$ 7,883.9 |
| Loans (Local/Sub-contractors)      | \$ 90.18   | \$ 214.6  | \$ 534.3    | \$ 843.4   | \$ 853.9   | \$ 519.9   |
| Contracts (Local/Sub-contractors)  | \$ 942.0   | \$1,268.3 | \$ 1,263.1  | \$1,224.9  | \$ 921.9   | \$1,163.5  |
| Grants (Local/Sub-contractors)     | \$ 6,882.5 | \$8,177.2 | \$ 8,692.6  | \$ 6,257.1 | \$6,133.8  | \$ 7,429.7 |
| Total Local Award /Sub-contractors | \$ 7,914.7 | \$9,660.1 | \$ 10,489.9 | \$ 8,325.4 | \$ 7,909.6 | \$ 9,113.1 |
| Observations                       | 336,210    |           |             |            |            |            |

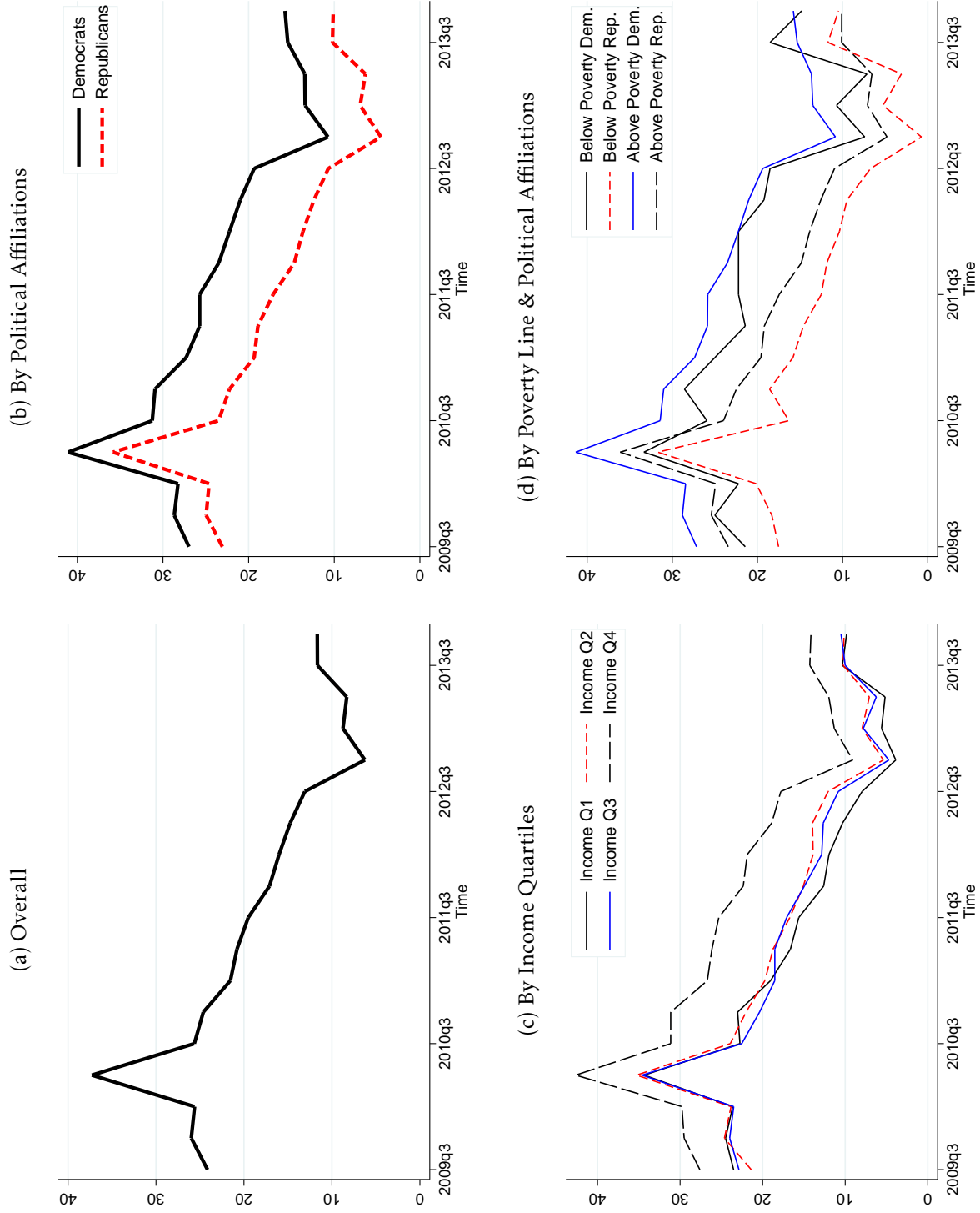
Source: In thousands of 2005 U.S. dollars per zipcode.

data by year. Averaging across all years of the program, the amount of grants awarded per county were significantly larger than the equivalent amounts for contracts and loans.

**ARRA Recipients** Figure A.1 plots the percentage of counties receiving ARRA transfers (%) over time. Here we also break the percentage of recipient counties by income quartiles and by their political affiliations. We match each county's FIPS code with their corresponding political affiliation (defined as the party with the most votes during the 2008 election season). Data for political affiliation were obtained from the *U.S. Census* at <https://www.census.gov/topics/public-sector/voting.html>

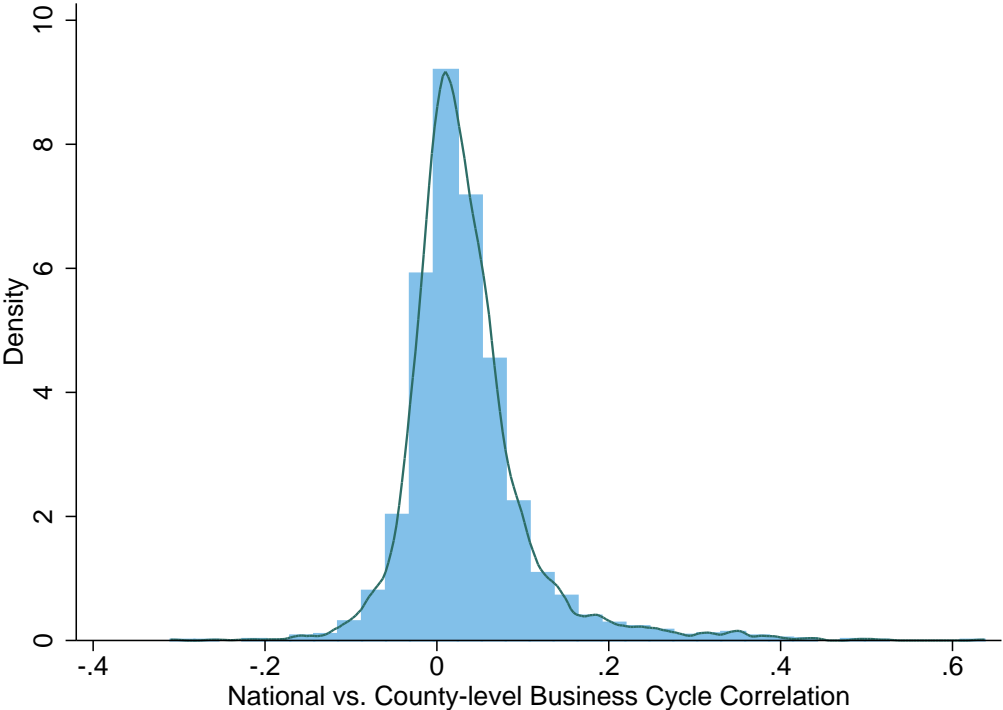
**Matching Income Data to ARRA Data** We match wage and income data from the *Quarterly Census of Employment and Wages (QCEW)* using the ARRA grants, contracts, and loans data (the recovery data). Since the location unit for the QCEW is county (as designated by the area county-level FIPS codes) and the recovery data are by zip-code, we aggregate the recovery data to the county level using a county level FIPS to zip-code by the census.

Figure A.1: Percentage of Counties Receiving ARRA Transfers (%) Over Time



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

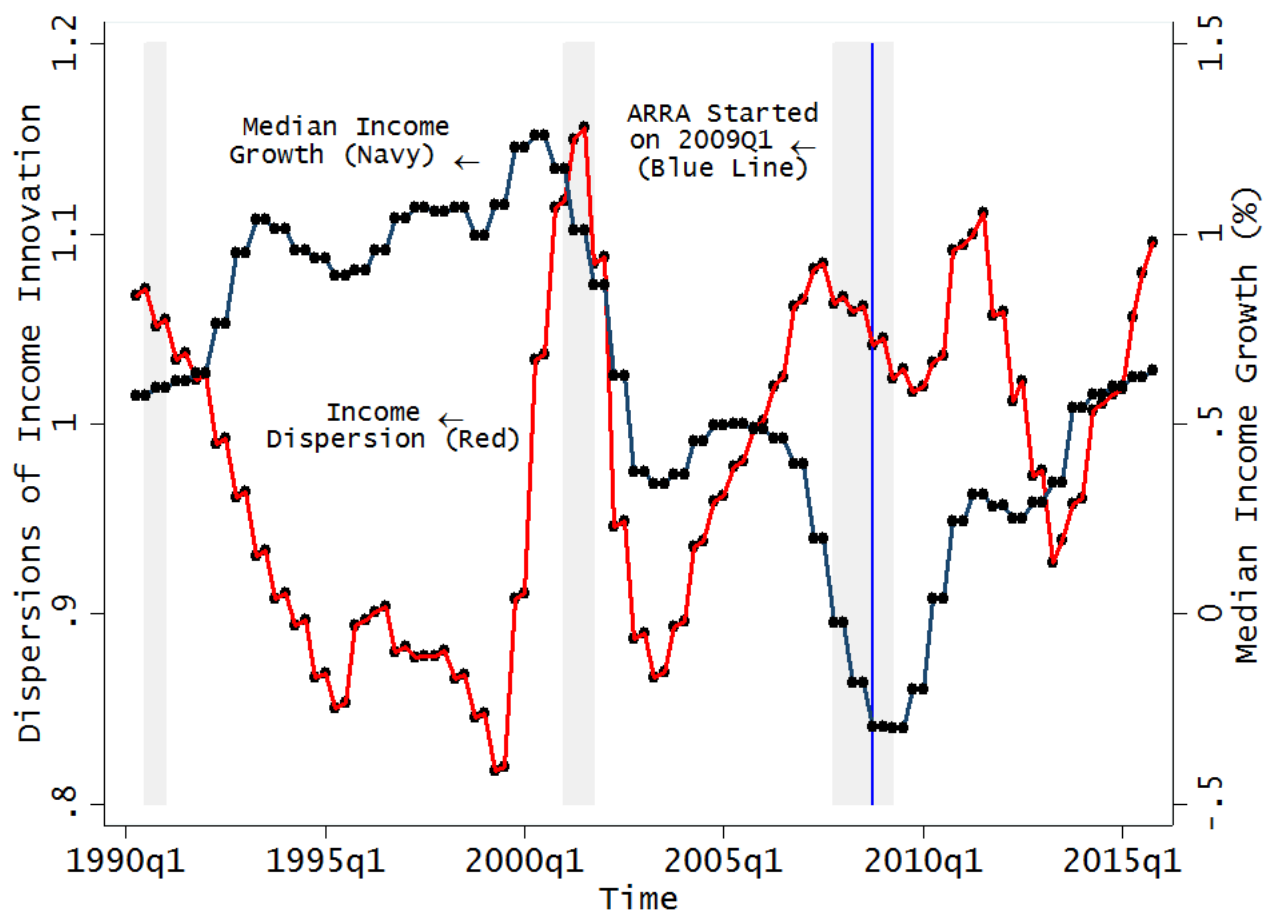
Figure A.2: County-level vs. National Business Cycle Correlations



**Note:** This figure plots the correlations between county  $i$  wage income process ( $W_{it}$ , first-differenced) and the average wage income process across all counties ( $W_t$ , first-differenced).

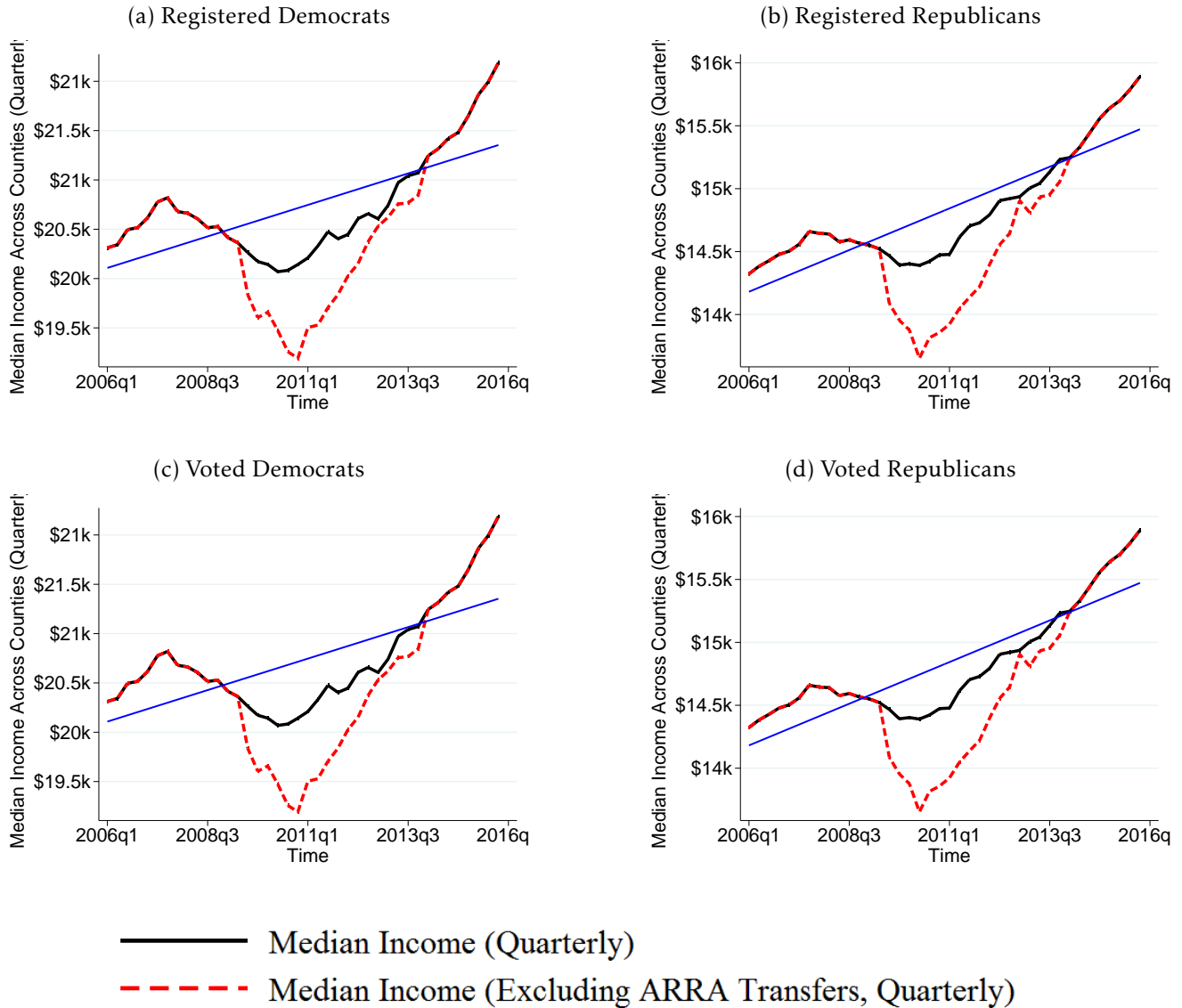
Figure A.3: Income Innovations and the ARRA Program

(a) Dispersion and Median Unexpected Income Shocks over the Cycle



**Note:** The upper figure plots the median and dispersions of income shocks across different counties. We regress an AR(1) process with log income as measured by the average total quarterly income at each county of the following form  $W_{it} = \alpha_i + \rho W_{it-1} + \varepsilon_{it}$ . We then calculate the dispersion as the standard deviation of the error terms  $\varepsilon_{it}$  over all county  $i$ .

Figure A.4: Income and ARRA Transfers: Political Affiliations



**Note:** The figure plots the level of net income per capita ( $Z_{it}$ ) and the gross income per capita ( $W_{it}$ ) over the business cycle. We define the level of net income per capita as the level of gross income per capita, measured by the level of total quarterly wages aggregated at the county level, minus the amount of ARRA transfers. Here we break down by whether the county's majority voted for a Democrat candidate or a Republican candidate over the 2008 election cycle.

## B Robustness: Labor Market Areas

In this section, we test the robustness of our main results using the *Labor Market Areas* (LMAs) from the Bureau of Labor Statistics as our unit of locality.<sup>12</sup> 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 results on fiscal insurance across different

<sup>12</sup>Retrieved from <https://www.bls.gov/lau/lmadir2015.xlsx> on Nov. 02, 2017



Table A2: Income Process and Fiscal Insurance by Quartiles (using LMAs)

|                          | (1)                   | (2)                   | (3)                   | (4)                  | (5)                  |
|--------------------------|-----------------------|-----------------------|-----------------------|----------------------|----------------------|
|                          | All                   | Q1                    | Q2                    | Q3                   | Q4                   |
| Net Income (1-lag)       | 0.907***<br>(0.00378) | 0.801***<br>(0.00929) | 0.446***<br>(0.00807) | 0.411***<br>(0.0102) | 0.732***<br>(0.0224) |
| Observations             | 228,046               | 56,355                | 57,008                | 57,250               | 57,433               |
| LMAs                     | 2,219                 | 487                   | 642                   | 629                  | 461                  |
| $R^2$                    | 0.834                 | 0.726                 | 0.380                 | 0.341                | 0.613                |
| Cross-sectional Variance | 0.002                 | 0.009                 | 0.069                 | 0.078                | 0.016                |
| Time-series Variance     | 0.011                 | 0.011                 | 0.025                 | 0.027                | 0.013                |
| Total Variance           | 0.013                 | 0.020                 | 0.094                 | 0.105                | 0.029                |

Standard errors in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ 

## Estimation of the Degree of Fiscal Insurance

|                                                                               | (1)                  | (2)                 | (3)                  | (4)                 | (5)                 |
|-------------------------------------------------------------------------------|----------------------|---------------------|----------------------|---------------------|---------------------|
|                                                                               | All                  | Q1                  | Q2                   | Q3                  | Q4                  |
| Last Quarter Income Shocks                                                    | -0.136***<br>(0.026) | -0.088<br>(0.063)   | -0.265***<br>(0.048) | -0.104**<br>(0.049) | -0.065<br>(0.044)   |
| Constant                                                                      | 5.170***<br>(0.004)  | 5.319***<br>(0.041) | 5.220***<br>(0.018)  | 5.136***<br>(0.009) | 5.098***<br>(0.005) |
| Observations                                                                  | 20,519               | 2,714               | 4,207                | 5,623               | 7,975               |
| LMAs                                                                          | 1,792                | 229                 | 415                  | 561                 | 587                 |
| $\left(\frac{1}{1-\rho^2}\right) Var(\alpha_i)$                               | 0.004                | 0.006               | 0.003                | 0.003               | 0.012               |
| $(1 - \lambda_\tau)^2 \left(\frac{\sigma_{\varepsilon_i}^2}{1-\rho^2}\right)$ | 0.018                | 0.023               | 0.006                | 0.007               | 0.016               |
| $Var(W_{it})$                                                                 | 0.033                | 0.042               | 0.014                | 0.014               | 0.037               |
| Full Risk-sharing: $\lambda_\tau = 1$                                         | 0.015                | 0.019               | 0.008                | 0.007               | 0.021               |
| No Offset : $\lambda_\tau = 0$                                                | 0.039                | 0.046               | 0.019                | 0.015               | 0.039               |

Standard errors in parentheses. Clustered at the LMAs level.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ 

income quartiles are reported in Table A2.