Online Appendix:
Geography of Consumption and Local Economic Shocks

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A. *Economic Census Revenue and Imputation*

The Geographic Area Series of the Economic Census (EC) is collected every 5 years at detailed geographic and NAICS industry levels. The EC contains information on industry-level revenues which we use to create measures of consumer spending. Our study focuses on county-level estimates for 15 industries that are important contributors to personal consumption expenditures, and which also have good coverage in the Fiserv database. While EC provides detailed information for many industries at the county level, there are some geography and NAICS combinations that are suppressed. We have used county-level three-digit NAICS industries for 2002, 2007, 2012 and 2017 as our benchmark years.

Table A1 lists the industries included in our analysis with their associated share of suppressed revenues to total revenues for each census year.[1] The levels of suppression vary across industry, but in general are extremely low. Industries such as gasoline stations have high coverage and only suppress 0.5 percent of all receipts. Meanwhile, industries including performing arts, and amusement and recreation had relatively higher suppression rates in early years (10 percent in 2002 and 2007) before filling out more in later years (6.5 and 3 percent, respectively in 2012 and 2017.)

Imputing Revenue for Suppressed Values in Economic Census Benchmark Years. — Overall suppression in EC years is quite low, but to obtain complete coverage across counties, we perform some imputations. To address the issue of suppression in the benchmark years, the annual series of the Quarterly Census of Employment and Wages (QCEW) is used to create full set of revenues for all county-NAICS combinations. Annual QCEW data for privately owned establishments provide information on payroll, employment, and wages, and do not contain any suppression across counties. The method used for these imputations is relatively simple and uses wage data to allocate missing revenues across counties.[2]

To impute the revenues in benchmark years, we take three steps. First, we use wages in QCEW to impute missing payroll data on EC. Second, we calculate the

[1]The rate of suppression is determined by comparing to unsuppressed national estimates.
[2]The method used here is consistent with the method used by the BEA to create consumption estimates using EC revenues.

Table A1—Share of Suppressed Receipts to Total in Selected NAICS Industries (Percentages)

NAICS	NAICS Description	2017	2012	2007	2002
442	Furniture and Home Furnishings Stores	1.9	3.5	1.2	2.0
443	Electronics and Appliance Stores	2.7	2.5	1.4	3.0
444	Building Material and Garden Equipment	1.4	2.1	0.5	0.7
445	Food and Beverage Stores	1.6	2.2	0.4	0.5
446	Health and Personal Care Stores	1.6	2.6	1.0	1.5
447	Gasoline Stations	0.9	1.1	0.3	0.5
448	Clothing and Clothing Accessories Stores	1.2	1.6	1.6	0.8
451	Sporting goods, hobby, book and music stores	2.6	4.6	2.0	2.0
452	General Merchandise Stores	5.2	8.3	11.8	10.0
453	Miscellaneous Store Retailers	7.4	8.8	9.3	10.3
541	Professional, Scientific Services	2.5	4.0	6.0	5.0
621	Ambulatory Health Care Services	1.9	3.4	4.0	4.0
711	Performing Arts, Spectator Sports	3.5	6.5	10	10
713	Amusement, Gambling, and Recreation	5.2	7.5	10	15
721	Accommodation	1.5	2.2	1.4	1.3
722	Food Services and Drinking Places	1.3	2.06	1.0	1.4
811	Repair and Maintenance	0.7	1.3	1.8	1.5
812	Personal and Laundry Services	0.6	1.1	2.8	2.3

Note: The table reports the percentage of spending that is suppressed in the Economic Census data at the county level for the years 2002, 2007, 2012 and 2017. The suppressed share is computed by comparing the national total spending by industry (which is unsuppressed) with the total of all of the unsuppressed county-level revenues by industry. For example, the table shows that 1 percent of the accommodation revenues are suppressed in 2017. North American Industry Classification (NAICS).

ratio of payroll to revenue for the non-suppressed receipts by industry. Third, we multiply the payroll data from the QCEW to the ratio of revenue to payroll by industry to impute the missing revenue for NAICS-county combinations.[3]

Imputing Revenues for Intercensal Years . — For the two benchmark years t to $t+5$, the revenues are observed $Revenue_t$ and $Revenue_{t+5}$. For the years between ECs, we interpolate revenues using annual QCEW wage data.

The interpolation adjusts revenues based on the growth rate in wages, but there is an annual adjustment to account for the divergence in growth rates between revenues and wages over the 5 years of the EC. Let t represent a benchmark year, and let $t+n$ be an intercensal year where n is between 1 and 4. The revenue in year $t+n$ is calculated as:

$$Revenue_{t+n} = \left(\frac{Wage_{t+n}}{Wage_t} \cdot Revenue_t\right) \cdot \left(\frac{Revenue_{t+n}/Wage_{t+n}}{Revenue_t/Wage_t}\right)^{(n/5)}$$

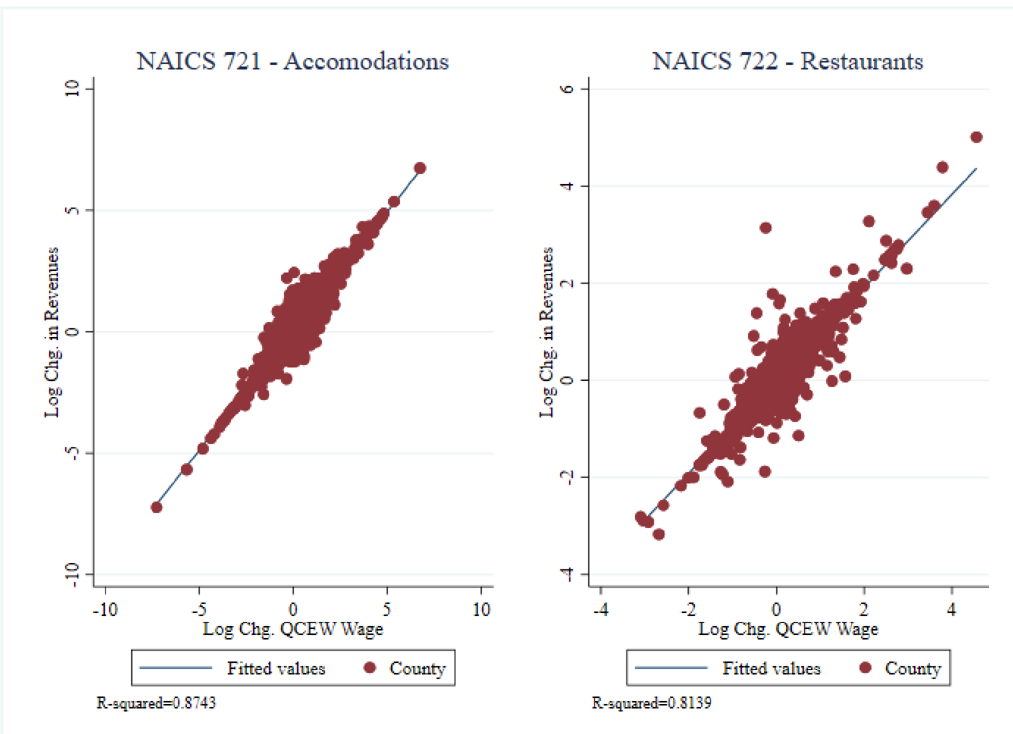
The first term, $\left(\frac{Wage_{t+n}}{Wage_t} \cdot Revenue_t\right)$, is the estimated annual revenue based

[3] The assumption is that if there are wages being paid in that NAICS industry there should be revenue associated with the wages being paid. Only if both QCEW and census receipt are missing or are zero in a location for a specific industry, it is assumed that the revenue is zero.

solely on the growth rate in wages. The second term, $\left(\frac{Revenue_{t+n}/Wage_{t+n}}{Revenue_t/Wage_t}\right)^{(n/5)}$, is the annual adjustment to better align changes in wages to predicted revenues. This first term suggests that our estimated changes in revenues may deviate from changes in wages.

While revenue growth is constrained to the growth rate in benchmark revenues, the year-to-year allocation of the 5-year revenue growth is determined by wages. To determine if applying wage data in this way is reasonable, we examine how well wages predict revenues in benchmark years. Figure A1 is the graphical representation of regressing growth rates of EC revenues in the benchmark years on QCEW wage growth rates over the same periods for accommodations (NAICS 721) and restaurants (NAICS 722). The QCEW growth rates are closely correlated with EC growth rates. The R^2 for both accommodations and restaurants is around 89 percent.

Figure A1. Growth in Spending from the EC and Wage Growth from the QCEW



Note: This figure shows a scatter plot and fitted line of the change in county spending from the Economic Census (EC) on the change in wages from the Quarterly Census of Employment and Wages (QCEW) spanning economic census years. The plot is reported for two three-digit NAICS categories, 721 and 722. The R-squared from additional fitted values is shown in Table A2.

This method does quite well more generally. Table A2 shows the R^2 performs well not only for our select industries (in red) but broadly for other NAICS industries too. The R^2 for our select industries are all above 0.70, except for NAICS categories 447 (gasoline stations) and 451 (sporting goods) which have R^2 of around 0.5. The low R^2 for 447 is likely due to gas price fluctuation. Overall, the interpolation of revenue growth using wage data appears to do quite well at approximating revenues for many industries.

Table A2—Regression Economic Census Growth Rates on the QCEW Growth Rate for Selected Industries for Census Years 2002, 2007, 2012 and 2017

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
NAICS	**441**	**442**	**443**	**444**	**445**	**446**	**447**	**448**	**451**	**452**
R^2	0.691	0.899	0.785	0.872	0.748	0.689	0.530	0.934	0.552	0.955
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
NAICS	**453**	**454**	**481**	**483**	**484**	**485**	**486**	**487**	**488**	**492**
R^2	0.835	0.490	0.674	0.667	0.775	0.915	0.855	0.976	0.879	0.867
	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)
NAICS	**493**	**511**	**512**	**515**	**517**	**518**	**519**	**521**	**522**	**523**
R^2	0.661	0.656	0.930	0.674	0.902	0.485	0.850	0.589	0.891	0.918
	(31)	(32)	(33)	(34)	(35)	(36)	(37)	(38)	(39)	(40)
NAICS	**524**	**531**	**532**	**533**	**541**	**551**	**561**	**562**	**611**	**621**
R^2	0.955	0.688	0.856	0.556	0.584	0.937	0.178	0.874	0.608	0.800
	(41)	(42)	(43)	(44)	(45)	(46)	(47)	(48)	(49)	(50)
NAICS	**622**	**623**	**624**	**711**	**712**	**713**	**721**	**722**	**811**	**812**
R^2	0.923	0.902	0.613	0.707	0.659	0.810	0.868	0.905	0.786	0.711

Note: This table demonstrates the relationship between the growth in spending estimates from the EC and the growth in wages from the QCEW. For every three-digit NAICS category we run a regression of the growth in spending from the economic census on the growth in wages over the same period. The table reports the R-squared from each regression, which are typically above 0.7 and above 0.9 for many categories. The three-digit NAICS colored in **red** are the NAICS categories used in our analysis. The wage data from the QCEW is used to interpolate spending estimates between economic census years. The high R-squared values across most categories, suggest that interpolation using wages should perform well.

B. Fiserv Data, Spending Flows and the Home Location Algorithm

The micro data from Fiserv contains transaction level information for each firm.[4] Fiserv data contains well over one-third of all United States credit card transaction spending which includes more than 4.5 million United States firm locations and dollar amounts equal to 10 percent of the total GDP of the United States. To maintain the anonymity of card holders and firms, there are a number of suppression rules. The following suppression rules are applied: (1) no series has observation within a given NAICS and geography containing fewer than ten firms, and (2) across the series, no firm makes up more than 20 percent of the transaction volume. The card transactions flows include information on hashed card number, firm ID, transaction date, and transaction amount. For each firm, the firm ID is mapped to the address and firm category code (MCC), which indicates the type of firm, which is mapped to its corresponding NAICS category.

The level of observations is a single transaction, although we do not see the data at this level of detail. The data engineers have access to detailed information on each transaction and they use this information to form a prediction of the home location (HL) for each card holder in the data, in order to construct the spending flow estimates used in our analysis. The HL algorithm uses transaction patterns to determine the most likely HL of a particular card based on all of that card's transactions across all firms. The raw data for modeling the location of the consumer consists of aggregated transaction counts for each card by three-digit NAICS categories and information on the firm zip codes. The estimated HL is formed based a subset of cards for whom the HL of the cardholder is known. HL is based on a discrete loss function and covariates that help predict the likelihood that consumers reside in different areas. Covariates include information on spending across industries in each potential location. To assess the performance of the prediction, we use a hold out sample of 30 percent to evaluate the accuracy of the algorithm. The algorithm predicts the correct county for each card around 75 percent of the time. This 75 percent estimate may be lower than the actual accuracy for two reasons: (1) the cards that have more spending are likely to have more information on the spending patterns of that cardholder, generating more accurate estimates for those cards that are economically more important; (2) the zip code reported for the known home-location may be imperfect in some instances, such as, college students living away from home. In any case, the overall spending flow patterns from the known-card holder data matches well with the patterns based on the full sample in which the HL algorithm is applied.

For our analysis we could have chosen either the known HL sample or the full predicted HL sample, as the two are quite similar. However, we chose the full predicted HL sample because it is based on more observations and can also help correct for the cases in which the zip code indicated by the card does not match

[4]Throughout this paper we use the term firm to refer to a particular establishment in a county and not the associated parent company.

where the individual actually resides.

An alternative cut of the Fiserv data has been used in research to produce timely regional estimates Aladangady et al. (2021) and timely national estimates around the pandemic Dunn et al. (2021). While the underlying source data is the same, the cleaning of the data used in Aladangady et al. (2021) and Dunn et al. (2021) is focused on providing spending estimates over time. To accomplish this goal, the methodology discussed in detail in Aladangady et al. (2021) systematically excludes firms that might interfere in accurately measuring changes in spending over time (e.g., a firm entering or leaving Fiserv's system during the sample period). In contrast, the focus of our paper is to derive accurate cross-sectional estimates of spending between consumers and firms across areas, so we include the full set of firms available.

Fiserv Coverage . — Figure A2 shows coverage of spending across states in the U.S. for the select categories. There is variation in the level of coverage across states, but we see coverage in all 50 states. The median state has a coverage rate of 8.5 percent.[5] While the geographic coverage is a potential limitation, all of the estimates are scaled to the estimated EC across all regions to capture 100 percent of spending. Scaling the Fiserv spending to the estimated EC helps to address both the differential coverage across areas, and to address the issue that some populations use card transactions more than others (e.g., high-income vs low-income populations).

The main assumption is that the observed spending flows are representative of spending flow patterns for that area, which allows us to scale estimates to the EC to produce meaningful spending flow data. An analysis of our spending flow data, through both descriptive statistics and regression analysis, suggest that the data are reasonable and match expected patterns. For instance, spending declining with distance away from the firm's location, spending varying by industry in expected ways, and more spending coming from counties with higher incomes.

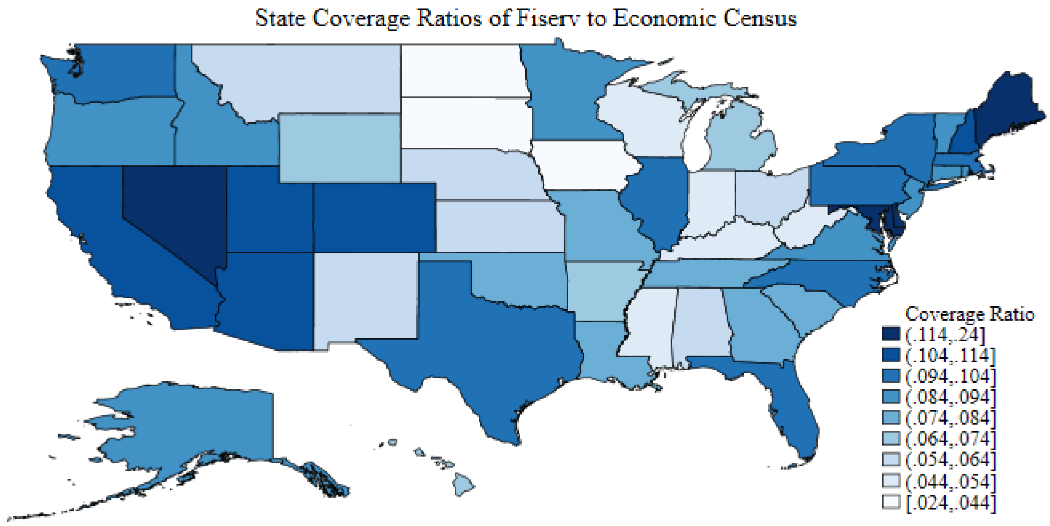
C. Estimating Final Expenditure Flows

To obtain a complete system of consumption flows for the United States, we need to estimate the consumption flows in locations where the Fiserv estimates are suppressed. Overall, imputation is needed for 14 percent of spending for our select categories. The goal of our imputation is to provide the best possible estimate for these missing expenditures. We examined a variety of flexible linear models to impute the missing spending flows, then we chose the method that performed the best based on cross-validation, a model validation technique, from a holdout sample.[6]

[5]The coverage rate is computed as the ratio of aggregate Fiserv spending over all 15 categories for each state divided by the aggregate spending total for those 15 categories estimated for 2015.

[6]The holdout method randomly divides the data into training and testing sets. To find the best model, each model is estimated using the training set only. Then we use the model to predict the output

Figure A2. Coverage Map of Fiserv Relative to the 2012 Economic Census



Note: The map shows coverage of spending across states in the U.S. for the select categories. There is variation in the level of coverage across states, but we see coverage in all 50 states. The coverage ratios are calculated relative to the 2012 Economic Census.

One factor that helps with imputation is that even when spending flows are suppressed, our data provide information regarding the set of counties where consumers are coming from, so we do not need to impute the set of potential counties. For instance, if NAICS category 448 (clothing) is suppressed in Montgomery County, Maryland, we still observe the set of counties that customers came from to purchase in 448, but we do not observe the actual spending shares across locations. To impute the share of revenues for firms in industry n and county j going to location i, we estimate a flexible linear regression model with the log share of spending on the left-hand side $log(S_{i,j,n})$. Importantly, the right-hand side of the equation includes a county-pair fixed effect, $\tau_{i,j}$, to capture economic activity occurring between two counties, using shares observed in other industries to help impute the industry share. For instance, suppose the share of a firm's revenues from a particular county for general merchandise stores is missing, but restaurants are observed. The county-pair fixed effect will capture the observed economic activity between locations in food services to help infer the amount of activity between areas for general merchandise stores. The right-hand side also includes a number of additional covariates, including revenues ($R_{j,n}$), distance ($distance_{i,j}$), population (pop_i), and industry fixed-effects ($industry_n$). The function $f()$ is specified as a flexible model that includes interactions of these variables and polynomials of distance. For instance, it includes polynomial of dis-

values for the data in testing set.

tance interacted with industry fixed effects and distance interacted with revenues and population. The model is specified as:

$$\log(S_{i,j,n}) = f(R_{j,n}, distance_{i,j}, pop_j, industry_n) + \tau_{i,j} + \epsilon_{i,j,n}. \tag{6}$$

The term $\epsilon_{i,j,n}$ is the error term. The imputed share is then calculated using the exponential of the expected value: $ImputedShare_{i,j,n} = \frac{exp(\log(\widehat{S_{i,j,n}}))}{\sum_i exp(\log(\widehat{S_{i,j,n}}))}$. For the relatively small number of areas where the county-pair fixed effects cannot be included, we use flexible linear regression models without fixed effects to impute these values.

We test a variety of alternative models and examine the fit in the holdout sample based on mean squared error. We selected the methodology with the smallest mean squared error based on a 5 percent hold-out sample.

D. Representativeness of Payment Flows

This section investigates the representativeness of the spending flow data. One particular concern with the spending flow data is that card transactions are not equally likely to be used for all demographic groups, with card transactions being used more heavily by higher income groups or groups with higher education levels (see Atlanta Fed Survey of Consumer Payment Choice, Matheny, O'Brien and Wang (2016)). This bias is particularly large for credit cards, as low-income households use this payment much less frequently. However, the Fiserv data captures all card types, including credit cards, debit cards and Electronic Benefit Transfer (i.e., cards used by Supplemental Nutrition Assistance Program (SNAP) participants), which are used by lower income populations. In other words, the Fiserv data are more representative than data sources relying only on credit cards. While we think the bias is smaller than credit card data sources, there is still a notable difference in total card transactions, as households with incomes below \$25,000 use credit or debit cards for around 33 percent of payments while households with incomes of \$25,000 or more use credit or debit between 40-50 percent of the time.

We find that this difference shows up in our data, although it is not statistically significant. To see this, we run a regression of the level of coverage as the dependent variable (i.e., ratio of Fiserv spending to EC estimates) in a regression that includes NAICS-level fixed effects and covariates for log per capita income and log population density. Also, do to suppression rules affecting coverage, we have to account for the size of the market and the probability that Fiserv will be present in the market. We include the log of total spending in the market and industry fixed effects. The results are reported in Table A3. In column (1) we find a 10 percent increase in the log per capita income leads to a 0.1 percent increase in coverage, although the effect is not statistically significant. Population density in column (2) is not correlated with coverage and column (3) includes both coverage and population density and shows no significant relationship.

Table A3—Regression of Coverage on Per Capita Income and Density

	(1) Coverage	(2) Coverage	(3) Coverage	(4) Coverage
Log(Per Capita Income)	0.0101		0.00878	0.00864
	(0.00878)		(0.00761)	(0.00754)
Log(Population Density)		0.00163	0.000847	
		(0.00186)	(0.00157)	
Observations	37213	37205	37205	37213

* p<0.10, ** p<0.05, *** p<0.01

Note: The left-hand side variable of this regression is a measure of coverage in the Fiserv data, relative to the EC. The covariates include log of per capita income and log of population density at the county level. Control variables include industry fixed effects and the log of total spending in the area based on our estimate of the EC in 2015. In column (4) we also control for state fixed effects. The controls are used to account for the presence of Fiserv as well as suppression rules that might vary with the total amount of spending in an area. Estimates are clustered at the county level.

To gauge the magnitude of the possible bias, we look at the difference between the 10th and 90th percentile per capita income levels and multiply by the coefficient 0.01 to measure the effect on coverage, which is equal to 0.06 percent relative difference in coverage. Much of the variation is potentially explained by broad regional differences in coverage (e.g., stronger Fiserv presence in certain areas), rather than income-specific effects. To see if this is the case, we run the same regression, but include state fixed effects, column (4). We still find a positive relationship between income and coverage, but the coefficient falls to 0.009, which implies that the difference in coverage is 0.5 percent between the 10th and 90th percentiles in per capita income levels. This is relative to an average coverage of 10.5 percent for the average county that reports positive coverage.

This potential bias may be greatly alleviated by scaling all of the data to the level of the EC, so that firms in both low-income and high-income areas match the EC. After this rescaling, we use the consumption flows to estimate the consumption to income ratio across areas. That is, we send the consumption to the location of the consumer and calculate the ratio of consumption to income in each county, we then report this ratio by income quartile in Table A4. If the bias toward higher income areas is high, we should expect a low consumption to income ratio in the low-income counties. In contrast, we find the share of consumption to income to be slightly larger (mean of 0.36) relative to the highest income quartile (mean 0.32).

We think these estimates of consumption to income are reasonable. Using external data from the Consumer Expenditure Survey (CEX) for 2015 and 2016, we also observe a relatively constant consumption to income ratio across geographies with different income levels. More precisely, we use spending categories comparable to our 15 select industries in the CEX data and look at the most disaggregate geographic detail available in the CEX data, the primary sampling unit (PSU), and we find a fairly constant consumption to income ratio across PSU income quartiles.

Table A4—County Consumption to Income Share by Per Capita Income Quartile

	Mean	Median	SD	N
1st Quartile	0.359	0.360	0.115	779
2nd Quartile	0.365	0.366	0.077	784
3rd Quartile	0.364	0.370	0.076	779
4th Quartile	0.328	0.321	0.137	779
Total	0.345	0.340	0.116	3,121

Note: Using data scaled to the EC for 2015, we calculate the share of consumption to income in all counties. Consumption is calculated for the select 15 industries in our data, and we "send" the consumption to the location of the consumer to form the consumption to income ratio. This table reports the share of consumption to income by per capita income quartile of the county.

Overall, the evidence in this section suggests that the representativeness of the payment flows data appear reasonable, especially after the adjustment to the EC spending levels. However, there is still the potential for bias because, conditional on a certain level of coverage, the spending flows across areas could still be affected based on consumer tendencies to use cards. For instance, coverage could be equal in all counties, but a disproportionate share of the flows could come from areas that more heavily use card transactions. For this reason, we also propose an alternative adjustment to the flows in section .F.

E. Consumption Flow Accounting

The level of spending by consumers in a county must be equal to the amount of final consumption sold, minus the export of consumption to other areas by firms in the county, plus the imports of consumption by consumers traveling to other counties to consume, as shown in equation (7):

$$\begin{aligned}\text{Household Consumption} =& \text{Final Product Sold} - \text{Export of Consumption} \\ & + \text{Imports of Consumption}\end{aligned} \tag{7}$$

We use this basic accounting relationship for two purposes. First, we use it as part of an exercise to test this accounting relationship empirically to validate the data. Second, we use the accounting formula to correct for potential biases that may exist in card transaction data, by forcing a reconciliation between the flows based on the card transaction data and independent estimates of consumption and sales across regions. The adjustment method we apply is related to a biproportional RAS method pioneered by Stone (1961) to apply to input-output matrices.

A Simple Test of Correlation. — We use the accounting relationship to both test the validity of the data, which also highlights the importance of these cross-market spending flows in understanding the consumption link across counties. To test this relationship, we first need empirical counterparts for each element. The empirical components on the right-hand side are constructed using spending flow and revenue measures, while we use an independent source for the empirical measure of consumption on the left-hand side. Therefore, empirically estimating this relationship provides an external validity check on the data and this accounting relationship.

Moving from left to right of equation (7), the first estimate that is needed is an independent measure of household consumption. Household consumption at the county level is not an official statistic that currently exists. Indeed, one motivation for working with spending flow measures is to obtain a county-level measure of consumption, potentially from the right-hand side of the accounting relationship. However, we can empirically approximate an independent value assuming that consumer preferences are homothetic at the county level. This allows us to assume a constant share of income is devoted to the goods and services in our 15 select NAICS categories. We further assume that this budget share is constant across the entire United States for a given year. With this assumption, we then look at the national budget share of consumption going to our NAICS categories, which averages to be 38 percent of income. Next, we multiply the national budget share in each year by the income in each county from the BEA to obtain an estimate of consumption in county j, $\widehat{\text{Household Consumption}}_{j,t}$.

The next necessary element for equation (7) is an estimate of $\widehat{\text{Final Product Sold}}_j$ in county j. This estimate is taken directly from our spending estimates based on the EC data where the total spending over industries n is aggregated:

$$\widehat{\text{Final Product Sold}}_j = R_j = \sum_{\forall n \in I} R_{j,n},$$

where $R_{j,n}$ is the total sold by firms in the county j for industry n and set of industries I.

The estimate of the exports of consumption is the total amount sold by firms in the county to consumers that reside outside of the county. This is calculated as:

$$\widehat{\text{Exports of Consumption}}_j = \sum_{\forall n \in I} \sum_{\forall i \in C s.t. i \neq j} R_{j,n} S_{i,j,n}$$

where $S_{i,j,n}$ is the total share of revenues for firms in industry n located in county

j selling to consumers that reside in county i. The estimated share, $S_{i,j,n}$, is based on 2015 estimates, so the implicit assumption is that these shares are constant across years in the sample.

We conduct a similar exercise to estimate dollar amount of imports coming from a county. The estimate of consumption import is the total amount consumed outside of a county by consumers that reside in county j. This amount may be estimated as:

$$\text{Imports of }\widehat{\text{Consumption}}_j = \sum_{\forall n \in I} \sum_{\forall k \in C, s.t. i=j, k \neq j} R_{k,n} S_{i,k,n}$$

After obtaining the empirical counterpart for each element of (7), we can estimate a simple regression model to test the accounting relationship:

$$\begin{aligned} \text{Household } \widehat{\text{Consumption}}_{j,t} =& \beta_1(\text{Final } \widehat{\text{Product}} \text{ Sold}_{j,t}) - \beta_2(\text{Exports of } \widehat{\text{Consumption}}_{j,t}) \\ &+ \beta_3(\text{Imports of } \widehat{\text{Consumption}}_{j,t}) + \epsilon_{j,t} \end{aligned} \tag{8}$$

If consumption flows are important, we should reject the hypothesis that they are equal to zero $\beta_2 = \beta_3 = 0$. In addition, if the accounting relationship holds, then we should not be able to reject the hypothesis $\beta_2 = \beta_3 = 1$.

The empirical test is run in a joint regression for every year and county in our data from 2001 to 2019, but with different coefficients for each year. The coefficient for each year is shown in Figure A3. Across all years we see that we can strongly reject the hypothesis that our consumption import and export measures are insignificant $\beta_2 = \beta_3 = 0$, as the estimates are significantly different from zero in each year. The import and export coefficients center around 1 across all years, and we cannot reject the hypothesis that estimates are equal to 1 in any year with a 95 percent confidence interval. In other words, we cannot reject the hypothesis that this accounting relationship holds in the data.

We find this strong relationship despite the possibility of measurement error entering the equation from multiple sources. In particular, there may be measurement error from assuming shares $S_{i,k,n}$ are constant across years, from the Fiserv data measurement error, or from assuming a fixed share of income goes to consumption across counties (i.e., the right hand side). If these measurement errors are large, this increases the likelihood of attenuating these estimates and reducing the statistical significance of the import and export variables. As we find a strong statistical relationship across years, it suggests that the assumptions (e.g., stable shares) are reasonable and the measurement error is low.

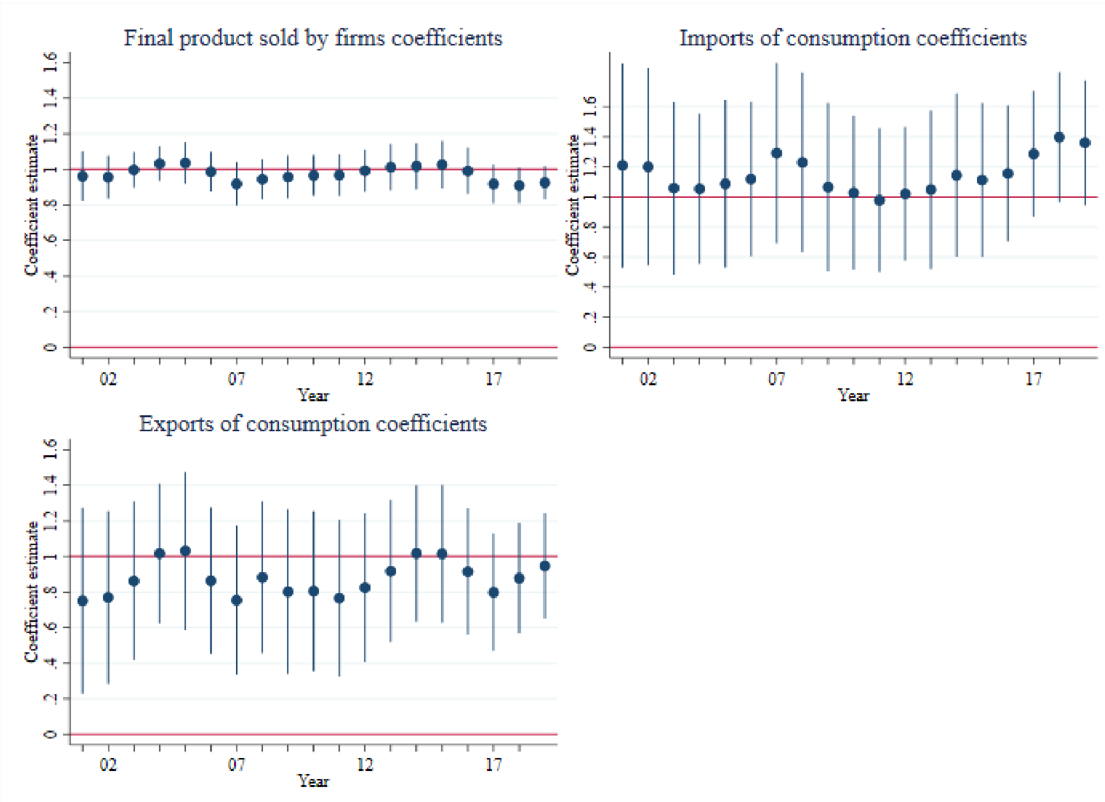
These estimates suggest that the right-hand side of the accounting relationship provides meaningful information about the components of consumption at the county level, which will be the focus of the analysis of the GR. It also suggests that the 2015 spending flows are relatively stable across years, including from 2007 to 2009.

The assumption of relatively stable shares is applied when analyzing the effects of the GR, where we apply 2015 spending flows to our estimates. Although we relax this assumption in some robustness checks where we estimate the predicted spending flows in all years, rather than use observed spending flows in 2015.

F. Adjustment for Potential Bias

After scaling the data to be representative of the EC totals to capture all of the spending for the select industries, we argue that the card transaction data provide accurate measures of spending flows. We do an external validity check

Figure A3. Regression Coefficients from Accounting Tests Across Years



Note: This figure shows the coefficient estimates from the regression equation (8). The regression is run on the full sample of counties and years with interactions of both counties and years using the income in the county in 2007 as a weight and clustering the standard errors at the state level. The upper left box shows the coefficient based on total sales by firms in the county. The upper right box shows the coefficient on imports of consumption. The lower left box shows the coefficient on exports of consumption. The blue dots represent the point estimates for the coefficient and the vertical lines represent the 95 percent confidence interval of the coefficients. Based on our regression results shown in these graphs the hypothesis that our consumption import and export measures are insignificant is strongly rejected. The import and export coefficients center around 1 across all years, therefore we cannot reject the hypothesis that the accounting relationship holds in the data.

using the accounting relationship in equation 8 and find that the accounting relationship generally holds. We also check whether there are obvious systematic biases after rescaling to the EC. For example, do we observe much larger levels of consumption, relative to income, in high-income areas, where consumers likely use card transactions more. We find no evidence of large difference by income level.

Despite all of this evidence, it is still possible for biases to enter through, for example, differences in card usage across areas. As an additional robustness check we produce an alternative set of flows to correct for any systematic bias from differences in card transaction use across areas. The basic intuition is that we can view the accounting relationship, and specifically the RHS of equation (7), as a matrix, where the rows add up to total household consumption, and the columns add up to total production. With this accounting relationship, Stone (1961) shows that knowing information on the total for the rows and columns, we can come up with a new estimate for the matrix, using the RAS biproportional smoothing methodology.

Let M be a I by J matrix where J represents all of the counties that firms sell to consumers and let I be the set of all counties where consumers reside. The element of the matrix $M_{i,j}$ represents the total amount of spending from a consumer located in county i at firms in county j. The total amount sold by firms in county, j, can be calculated by adding the rows of column j to obtain a column total. The total amount purchased by consumers located in county, i, can be calculated by adding the columns to obtain a total for each row. In our data, the elements of the matrix M are calculated by multiplying the observed spending flows across areas with our estimate of the firm spending in that location.

The main issue with this estimate of the matrix M is that the amount consumers use cards in transactions may vary across areas, and this could potentially lead to consumption levels that are either too high or two low. Using a RAS intuition, we can apply an adjustment factor to each row so that the level of consumption is closer to an independent estimate of consumption. We think that a reasonable independent estimate of consumption can be formed as a share of total income in the county, which is partly validated by the accounting test of equation (8).

For this adjustment, we treat the estimated matrix as an initial estimate, M^0, and make adjustments based on independent data on the level of consumption for each consumer i, c_i^*, where our independent measure of consumption is based on consumer income. Suppose the level of consumption for consumer i based on the matrix M^0 is c_i^0 (where c_i^0 is calculated by summing row i of M^0) then the adjustment term for that row is $\frac{c_i^*}{c_i^0}$. Each row is multiplied by this adjustment term to get a level of consumption that is consistent with our external estimate. Each component of the matrix is derived as: $M_{i,j}^1 = M_{i,j}^0 \cdot \frac{c_i^*}{c_i^0}$. This gives us a revised matrix M^1. Using this revised matrix, we can calculate revised flows, where the amount of revenue for firms located in county j will be calculated by summing the rows of M^1 for column j, so that we get $R_j^1 = \sum_{\forall i \in I} M_{i,j}^1$. The share of revenue that firm j receives from consumers residing in county i using the matrix M^1 is then $\frac{M_{i,j}^1}{R_j^1}$. We then calculate our main estimates using this adjusted matrix.

To apply this method to our data, we use the national budget share for our selected categories of 38 percent, discussed in the previous section. We multiply the national budget share of 0.38 by the county income to obtain the adjusted consumption level, c_i^*. We then apply the adjustment described in the previous paragraph to arrive at our adjusted flows. The correlation of the main flow estimates and the adjusted flows is 0.90. That is, we find the correlation in shares to be quite high, despite strong assumptions imposed by the proposed adjustment in this section. As a robustness check we estimate our main specification of housing wealth changes on spending and employment, and we find qualitatively similar results.

G. *Spending By Industry and Distance*

This section provides additional information regarding spending by industry and distance away from the home county of the firm. Table A5 shows share of spending based on the distance between the firm and the home location of the consumer weighted by spending. The first column indicates the share of spending coming from consumers that reside in the same location as the firm. The information provides similar information to that in Figure 1, but presents it in numerical form for all industries.

We use Table A5 to categorize industries into three broad industry groups based on the share of spending coming from the home location. We divide the broad industry groups so that roughly one third of spending is in each group. The first group is a "home industry" group where a large share of spending is from consumers that reside in the same county as the firm, which includes NAICS categories 445, 452, and 444. The second group is an "export industry" group where a relatively large share of spending is from consumers that reside away from the firm's home location, which includes NAICS categories 722, 442, 453, 451, 713, 448, 711, and 721. The third group is an intermediate group that falls between the other two, which includes NAICS categories 812, 811, 621, and 447.

While Table A5 shows differences in spending by industry, it is important to note that this information is weighted by spending, and this weighting will disproportionately weigh more populated areas of the United States. To show the variation across counties in the data, Table A6 shows the distribution of the share of spending in the consumers home location across counties in the U.S. The table shows substantial variation in the amount that different counties and industries rely on exports of consumption outside of the firm's county. For example, for food and drinking establishments (NAICS 722) the 10th percentile county shows just 10 percent of the revenue coming from consumers that reside in the county, while the 90th percentile shows that around 91 percent of revenues come from consumers that reside in the county.

Table A5—Spending Share By Distance Weighted By Spending

	Share Home	Share Under 100 Miles	Share 100 to 500 Miles	Share 500+ Miles
Accommodation (NAICS 721)	0.136	0.145	0.314	0.404
Ambulatory Health Care Services (NAICS 621)	0.700	0.216	0.034	0.049
Amusement, Gambling, and Recreation Industries (NAICS 713)	0.565	0.227	0.080	0.128
Building Material and Garden Equipment and Supplies Dealers (NAICS 444)	0.757	0.184	0.027	0.032
Clothing and Clothing Accessories Stores (NAICS 448)	0.565	0.257	0.072	0.106
Food Services and Drinking Places (NAICS 722)	0.670	0.203	0.062	0.066
Food and Beverage Stores (NAICS 445)	0.834	0.107	0.025	0.034
Furniture and Home Furnishings Stores (NAICS 442)	0.606	0.258	0.053	0.084
Gasoline Stations (NAICS 447)	0.694	0.182	0.077	0.047
General Merchandise Stores (NAICS 452)	0.767	0.162	0.033	0.038
Miscellaneous Store Retailers (NAICS 453)	0.616	0.196	0.071	0.117
Performing Arts, Spectator Sports, and Related Industries (NAICS 711)	0.424	0.248	0.104	0.224
Personal and Laundry Services (NAICS 812)	0.739	0.172	0.035	0.054
Repair and Maintenance (NAICS 811)	0.724	0.192	0.039	0.045
Sporting Goods, Hobby, Book, and Music Stores (NAICS 451)	0.609	0.230	0.065	0.096

Note: The table reports spending shares by industry and distance between the firm and consumer counties. The four distance categories include: (1) the share home (indicating spending share of consumers that reside in the same county as the firm); (2) share under 100 miles (indicating spending share of consumers that reside outside of firms county, but whose county's population centroid is less than or equal to 100 miles); (3) share 100 to 500 miles (indicating spending share of consumers that reside outside of firms county but whose county is more than 100 miles away, but less than or equal to 500); and (4) share 500 (indicating spending share of consumers that reside more than 500 miles from the home location of the firm).

Table A6—Distribution of Spending Share From Consumers that Reside in the Same County as the Firm

	Median	10th	25th	75th	90th
Accommodation (NAICS 721)	0.152	0.058	0.104	0.215	0.312
Ambulatory Health Care Services (NAICS 621)	0.760	0.563	0.664	0.873	0.939
Amusement, Gambling, and Recreation Industries (NAICS 713)	0.509	0.233	0.353	0.665	0.788
Building Material and Garden Equipment and Supplies Dealers (NAICS 444)	0.824	0.639	0.738	0.893	0.941
Clothing and Clothing Accessories Stores (NAICS 448)	0.590	0.359	0.482	0.703	0.852
Food Services and Drinking Places (NAICS 722)	0.633	0.409	0.527	0.712	0.769
Food and Beverage Stores (NAICS 445)	0.829	0.657	0.760	0.880	0.909
Furniture and Home Furnishings Stores (NAICS 442)	0.591	0.353	0.470	0.726	0.897
Gasoline Stations (NAICS 447)	0.651	0.442	0.545	0.736	0.795
General Merchandise Stores (NAICS 452)	0.811	0.646	0.736	0.867	0.918
Miscellaneous Store Retailers (NAICS 453)	0.617	0.353	0.492	0.723	0.820
Performing Arts, Spectator Sports, and Related Industries (NAICS 711)	0.315	0.098	0.186	0.437	0.578
Personal and Laundry Services (NAICS 812)	0.762	0.556	0.671	0.840	0.916
Repair and Maintenance (NAICS 811)	0.735	0.507	0.629	0.833	0.909
Sporting Goods, Hobby, Book, and Music Stores (NAICS 451)	0.665	0.444	0.557	0.798	0.937

Note: For each county and each industry in the data we compute the share of spending coming from consumers that reside in the same county as the firm. The table reports the distribution of that share across all counties in the data. For example, for food services and drinking places (722) the median county receives 56 percent of their spending from consumers that reside in the same county as the firm.

Predicted Shares: Relaxing Assumption of Constant Shares from 2015 . — Our main estimates assume that the location of potential demand is reflected in spending flow shares observed in 2015. The accounting test that we include from the estimates of equation (7) provides evidence that these shares are relatively stable over time. However, shifts in spending flows over time could potentially reduce the precision of the estimates. Ideally, we would use spending flows observed in each year to more accurately capture potential consumption at each period.

To relax the assumption of constant spending flows, we predict the share of revenues that a firm receives from consumers residing across all counties in the United States for the year 2015 across all 15 of our industries. The prediction model relies on spending information at firms that is observed in both 2015 and in the prediction year, for example 2007. We first estimate the model using the 2015 income, population, and revenue information. Next, we substitute in the prediction year data on income, revenues, and population (e.g., 2007 data) and apply the estimated covariates from the regression model for 2015. Finally, using the model parameters based on 2015 estimates, we predict the spending flows for the prediction year (e.g., 2007). As the goal of this model is prediction, we specify a flexible functional form, which includes the log of the income of consumers in the county, the log of receipts plus one for firms in the county for that industry, polynomials of distance, industry-specific fixed effects, and numerous interactions of these variables (e.g., distance and industry)

To form our prediction, we apply a conditional logit model that is related to the Constant Elasticity of Substitution (CES) functional form (see Dubé, Hortaçsu and Joo (2021)). For all of the markets we assume the outside good is the home county of the firm for a particular industry (e.g., for restaurants in Montgomery County, Maryland, the outside good is the share of spending going to consumers that reside in Montgomery County, Maryland.). The market shares of each industry sum to one, but the regression models for each industry are run jointly across industries to include common covariates across industries that might affect the market share. Recall that the share, $S_{i,j,n}$, is the share of spending at firms in industry n, located in county j, and sold to consumers residing in county i and the outside good share is $S_{i=j,j,n}$. The conditional logit model may be estimated using the following linear functional form based on 2015 data:

(9)
$$log(S_{i,j,n}^{2015}) - log(S_{i=j,j,n}^{2015}) = g(\delta_j, distance_{i,j}, income_i^{2015}, income_j^{2015}, spend_{i,n}^{2015}, spend_{j,n}^{2015}, NAICs_n) + \gamma_{i,j,n}^{2015}$$

The term $g()$ indicates a flexible functional form where log functional forms and interactions are applied among these different variables, where δ_j is a vector of parameters to be estimated. To simplify notation, denote the function g as $g(*)^{2015}$. The term $\gamma_{i,j,n}^{2015}$ is the error term. Based on this functional form, the spending share for consumers coming from county i may be calculated as:[7]

$$S^{2015}_{i,j,n} = \frac{exp(g(*)^{2015} + \gamma^{2015}_{i,j,n})}{1 + \Sigma_{\forall i \in C} exp(g(*)^{2015} + \gamma^{2015}_{i,j,n})} \tag{10}$$

Equation (9) is estimated using a linear regression model using population weights based on the firm's home market in 2007. For the potential set of counties, we only use those counties for which we observe some consumers purchasing in 2015.[8] After running the predictions of the model for 2015 using 2015 covariates, we use the variables from the prediction year (e.g., 2007) to predict shares in that year. We assume that the mean error term, $\gamma^{2015}_{i,j,n}$ does not change across years, so the error term from the 2015 prediction model is applied in the prediction year. For example, suppose we are predicting for the year 2007. If we let $\widehat{g(*)^{2007}}$ be the fitted values from the linear regression model using 2007 data, then the predicted shares for 2007 are calculated as:

$$\widehat{S^{2007}_{i,j,n}} = \frac{exp(\widehat{g(*)^{2007}} + \widehat{\gamma^{2015}_{i,j,n}})}{1 + \Sigma_{\forall i \in C} exp(\widehat{g(*)^{2007}} + \widehat{\gamma^{2015}_{i,j,n}})} \tag{11}$$

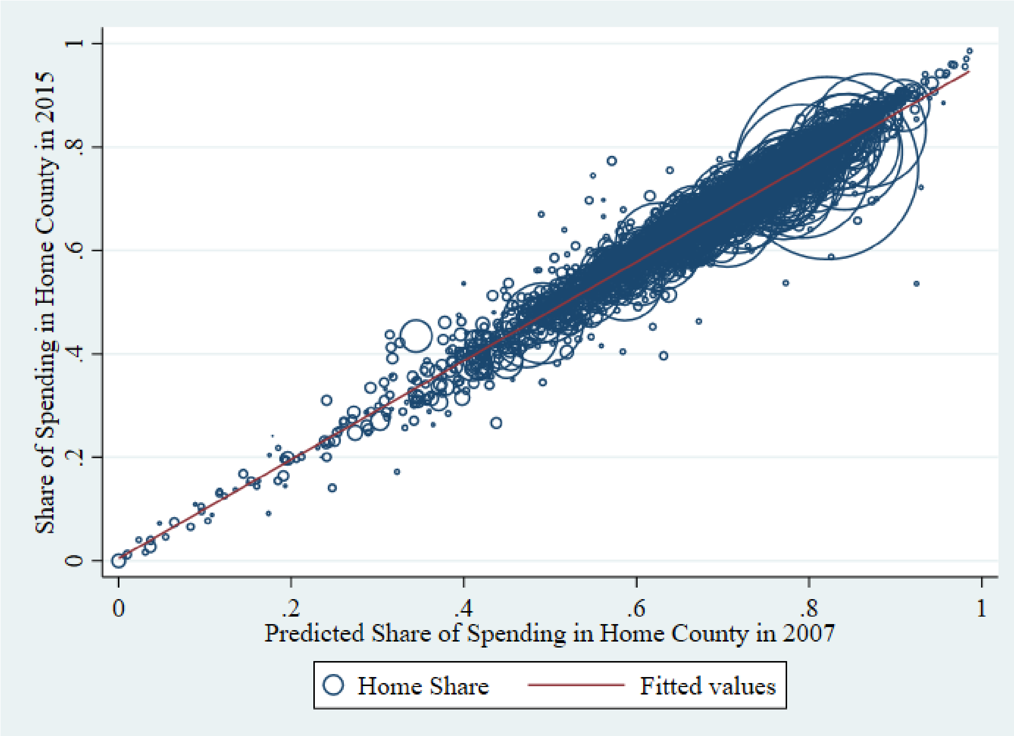
To compare the predicted 2007 shares with the 2015 shares we calculate the aggregate share of spending across all 15 industries for both the predicted 2007 shares and the 2015 shares. We aggregate over the 2007 shares using 2007 spending estimates in each county and we aggregate over the 2015 shares using the 2015 spending estimates. To compare these spending flow estimates we focus on the aggregate spending share from the home county (i.e., what share of spending is from consumers that reside in the same county as the firm). Figure A4 shows a scatter plot and fitted line of this predicted home share in 2007 on the home share observed for 2015. We find the two measures to be highly correlated and the associated regression has a regression coefficient of 0.95. This high degree of correlation is somewhat expected as many aspects of the geography are unlikely to change dramatically over this period (e.g., population, county borders, geographic features, infrastructure, etc.)

Next, to investigate the robustness of our results to the fixed-share assumption, we calculate the housing net wealth variable applying the exact formula applied in equation (2), but using predicted shares specific to the base year, rather than fixed shares for 2015. We then repeat the analysis from our main tables, but using the predicted flows. The results are reported in Tables A25 and A26.

[7] The home market share for the case where $i = j$ is: $S^{2015}_{i=j,j,n} = \frac{1}{1+\Sigma_{\forall i \in C} exp(g(*)^{2015} + \gamma^{2015}_{i,j,n})}$

[8] For example, for restaurants in Montgomery County, Maryland if we see consumers from 1,000 counties, then those 1,000 counties will enter our prediction model and others will be excluded. This will likely exclude very rural counties in the set of possible locations for many markets.

Figure A4. Regression of the Predicted Home Share of Spending in 2007 on the Observed Home Share of Spending in 2015.



Note: The scatter plot is based on the aggregate home shares across all 15 industries in 2015 and the corresponding predicted home share across all 15 industries in 2007. The red line is the fitted value, which indicates a strong positive relationship between the predicted and observed shares.

H. House Price Index Data

The main housing price data used in this project is from the Federal Housing Finance Agency (FHFA). Specifically, we use the county annual housing price index, discussed in detail in Bogin, Doerner and Larson (2019) and called the Annual House Price Indexes, Counties (Developmental Index; Not Seasonally Adjusted).[9] The county price information is based on a repeat purchase index and covers around 2700 counties over our sample period.

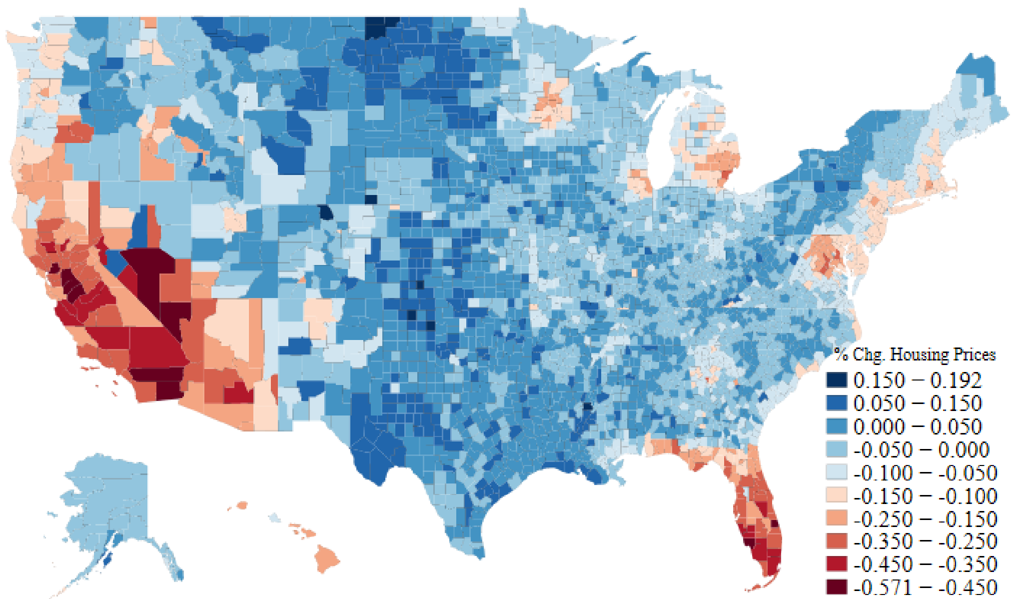
For cases where the FHFA county index is unavailable, we use the Zillow home value index (ZHVI). ZHVI is seasonally adjusted measure of typical home value and market changes across a given region and housing type. Zillow publishes ZHVI for all single-family residences, for condo or coops, for all homes

[9]The data is available at: https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index-Datasets.aspx.

with 1, 2, 3, 4 and 5 and more bedrooms, and the ZHVI per square foot. We focus on change in home prices using county-level data which cover approximately 2000 counties within the United States. The data is available at: https://www.zillow.com/research/data/. For areas where Zillow and FHFA data overlap, we find the price changes to have a correlation of 0.95. For the small number of rural counties missing price change information in FHFA and Zillow, we use the price change from other counties within the same CZ.

Using the final data set, Figure A5 shows percent change in home prices across counties in the United States between 2006 and 2009 with darker shades of red indicating larger declines in home prices, while the darker shades of blue indicate a handful of counties that experienced larger increases in home prices.

Figure A5. Percent Change in Home Prices between 2007 and 2009



Note: The estimates are based on the FHFA housing price data, which includes some imputations using Zillow home value index reported on the Zillow website.

I. *Instrumental Variable*

In the main text we outline the steps used to form the instrumental variables applied in the paper, following the work of (Guren et al., 2020). The idea is to use the history of housing wealth changes over a period of time to identify the sensitivity of different areas to national or regional shocks. As the text highlights, the constructed instrument is correlated with previous instruments used in the literature. To further highlight the strength of the instrument and to demonstrate how it compares to alternative instruments used in the literature, we estimate a first-stage regression including our main IV variable, and then include the IV variables from previous work, including Guren et al. (2020) and Saiz (2010). The estimates are reported based on the full sample from 2003 to 2019 and an additional sample that excludes the GR. We obtain similar results if we only look at the pre-GR period or post-GR period separately. The estimates are reported in Table A7 and show the main IV strategy applied in our main analysis is highly significant and correlated with housing wealth changes (column 1). The coefficient is very similar when we apply the Guren et al. (2020) instrument (column 2), which is not surprising given that the methodology for constructing the instruments is very similar. However, the estimates are different as the Guren et al. (2020) is based on a longer sample period, and uses the CBSA, rather than the county. The sample size from applying the Guren et al. (2020) IV is considerably smaller, as many counties are not included in their data. The Saiz (2010) instrument also shows strong correlation with the price change, although the coefficient is negative, since the higher the elasticity indicates lower sensitivity to regional or national shocks to housing prices. All three instruments are highly significant, even when the GR period is excluded, indicating that the instruments are not solely related to changes in price during the GR, but are more generally picking up sensitivity to regional or national shocks.

Table A7—First-Stage Regression Estimates of Housing Wealth Change on Instruments

	(1) Δ HNW (No Flow)	(2) Δ HNW (No Flow)	(3) Δ HNW (No Flow)	(4) Δ HNW (No Flow)	(5) Δ HNW (No Flow)	(6) Δ HNW (No Flow)
County-level Sensitivity Inst.	0.900***			0.799***		
	(0.0263)			(0.0261)		
Sensitivity Inst. from Guren et al.		0.936***			0.782***	
		(0.0303)			(0.0361)	
Saiz Instrument			-0.247***			-0.228***
			(0.0265)			(0.0242)
N	52876	19632	14743	46656	17322	13008
R squared	0.854	0.854	0.809	0.828	0.825	0.798
Sample	Full Sample	Full Sample	Full Sample	Excl. GR	Excl. GR	Excl. GR

* p<0.10, ** p<0.05, *** p<0.01

Note: The table presents results from a first-stage panel regression estimate of the change in housing wealth in a county on the change in the instrument. The table includes three IV variables: the first is the county-level sensitivity variable (the main IV applied in this paper), the second is the sensitivity instrument taken directly from Guren et al. (2020) and multiplied by our regional price variable, and the third is the Saiz instrument based on land unavailability. We also show these estimates for two time periods, including the full sample period (2003–2019) and excluding the GR years (i.e., excluding 2008–2009). The county-level sensitivity instrument performs similar to the Guren et al. (2020), while the Saiz instrument shows strong correlation, but is less statistically significant. Standard errors are in parentheses and are clustered by counties. Estimates are weighted by 2007 population levels. All estimates include county fixed effects, two-digit industry employment share by county interacted with year, and also region-year fixed-effects.

Recall that the main instrument is a sensitivity parameter that is constant and specific to a county, which is then interacted with regional price changes. To better understand the instrument, we regress the county-specific sensitivity parameters with numerous covariates to help understand if there are systematic factors that are correlated with this sensitivity measure. We include a number of variables, including population, per capita income, race, ethnicity and education and focus on estimates for the year 2007, given the sensitivity parameters do not change. In some specifications we also include two-digit industry employment share for the county. We also include the housing supply elasticity measure from Saiz (2010), which primarily captures physical land unavailability in an area.

The results are shown in Table A8. The first column (1) shows some correlation with the demographic variables, but these variables have little explanatory power with a reported R-squared of just 0.15. The R-squared is the same when we limit the sample to those counties where we observe the Saiz instrument (column 2). The third column adds two-digit industry shares which increases the R-squared to 0.46. Columns (4) and (5) are the same as columns (2) and (3), respectively, but the Saiz housing supply elasticity is added. The housing supply elasticity variable is highly significant and raises the R-squared substantially in both specifications. This suggests that one of the factors the sensitivity instrument seems to capture is physical land unavailability in the area.

J. Additional Industry Category Effects

Table A12 repeats the analysis in Table 8, but using employment, rather than spending. The results are qualitatively similar to those in the main text that focus on spending.

K. Additional Distance Specifications

Effects By Distance — Table A13 repeats the analysis by distance in Table A13, but uses employment rather than spending. Table A14 repeats the spending analysis by distance, but focusing only on local industries. This figure shows that local industries are not differentially affected by spending changes outside of the local area.

Table A8—Regression of Sensitivity Parameter with Demographics and Saiz Elasticity Measure

	(1) Sensitivity Inst.	(2) Sensitivity Inst.	(3) Sensitivity Inst.	(4) Sensitivity Inst.	(5) Sensitivity Inst.
Saiz Housing supply elasticity				-0.335***	-0.265***
				(0.0926)	(0.0573)
Pop. in Millions	0.0610*	0.0501*	0.0637***	0.00903	0.0257**
	(0.0323)	(0.0283)	(0.0190)	(0.0139)	(0.0125)
Per Cap. Inc. (Thousands)	5.759	7.859	5.153	1.700	0.972
	(5.905)	(7.647)	(3.403)	(4.112)	(2.577)
Share Black	0.874**	1.248***	0.601	0.727**	0.447
	(0.336)	(0.413)	(0.389)	(0.291)	(0.330)
Share Other	0.498	1.192*	1.837***	0.619	1.384***
	(0.422)	(0.704)	(0.455)	(0.597)	(0.347)
Share Hispanic	1.596	2.112*	1.186	1.431*	0.886
	(1.130)	(1.241)	(0.817)	(0.846)	(0.627)
Share High School	4.970	6.944*	5.069*	4.584*	3.685*
	(3.024)	(3.946)	(2.979)	(2.508)	(2.089)
Share College	3.432*	4.377*	2.262	2.576	1.310
	(1.966)	(2.559)	(1.787)	(1.726)	(1.247)
N	2909	868	868	868	868
R squared	0.147	0.169	0.464	0.386	0.579
2-digit Ind. Shares Included	No	No	Yes	No	Yes
Sample	Full	Saiz Sample	Saiz Sample	Saiz Sample	Saiz Sample

* p<0.10, ** p<0.05, *** p<0.01

Note: This table shows a cross-sectional regression of the county sensitivity parameters on a number of variables. The variables include population, income per capita, race, Hispanic, and education. Census-region fixed effects are also included. Additional variables include the Saiz instrument and two-digit industry share variable. As this is a cross-sectional regression, all estimates are clustered at the state level. The sensitivity parameters do not vary by year, so we only run this regression for 2007. Several of the demographic variables are from the Area Resource File: https://data.hrsa.gov/topics/health-workforce/ahrf.

Table A9—Housing Wealth Change on Employment for Local and Export Industry Category: Differential Effects During the GR, Both Home and Away

	(1) Local Industries	(2) Local Industries	(3) Local Industries	(4) Export Industries	(5) Export Industries	(6) Export Industries
Δ HNW (Flow)	0.0495**	0.0979***	0.0598**	0.0593***	0.0964***	0.0725***
	(0.0199)	(0.0197)	(0.0241)	(0.0190)	(0.0171)	(0.0221)
Δ HNW (CZ-Export)		-0.0846	-0.114		-0.0533	-0.153**
		(0.0982)	(0.112)		(0.0655)	(0.0764)
Δ HNW (Flow) · GR	0.150***		0.132***	0.119***		0.0692**
	(0.0270)		(0.0324)	(0.0232)		(0.0277)
Δ HNW (CZ-Export) · GR			0.218			0.608***
			(0.197)			(0.148)
N	52719	52719	52719	52758	52758	52758
R squared	0.227	0.228	0.228	0.333	0.333	0.333
IV Estimate	Yes	Yes	Yes	Yes	Yes	Yes

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

Note: The table presents results from panel regression and IV regression estimates of the change in employment for select local and export industries in the county from 2003 to 2019 on the change in housing wealth variables. The specifications across the columns differ by the inclusion of distinct measure of housing wealth changes and the industry category of either local or export industries. We exclude the top and bottom 50 observations with the largest changes, which is roughly 0.2 percent of the sample. Standard errors are in parentheses and are clustered by counties. Estimates are weighted by 2007 population levels. All estimates include county fixed effects, two-digit industry employment share by county interacted with year, and also region-year fixed-effects.

Table A10—Effects on Employment for Local and Export Industries Using Industry-Specific Flows: Differential Effects During the GR, Both Home and Away

	(1) Local Industries	(2) Local Industries	(3) Local Industries	(4) Export Industries	(5) Export Industries	(6) Export Industries
Δ HNW (Local Ind. Flow)	0.0460**	0.0509**	0.0495**			
	(0.0185)	(0.0204)	(0.0224)			
Δ HNW (Local Ind. Flow) · GR	0.136***	0.115***	0.122***			
	(0.0255)	(0.0289)	(0.0303)			
Δ HNW (Export Ind. Flow)				0.0663***	0.0805***	0.0785***
				(0.0199)	(0.0221)	(0.0224)
Δ HNW (Export Ind. Flow) · GR				0.126***	0.0627**	0.0636**
				(0.0255)	(0.0294)	(0.0296)
Δ HNW (Local Ind. CZ-Export)		-0.101	-0.119			0.143
		(0.126)	(0.151)			(0.118)
Δ HNW (Local Ind. CZ-Export)· GR		0.445*	0.570**			-0.0486
		(0.231)	(0.280)			(0.246)
Δ HNW (Export Ind. CZ-Export)			0.0182		-0.109**	-0.161**
			(0.0883)		(0.0514)	(0.0657)
Δ HNW (Export Ind. CZ-Export)· GR			-0.113		0.510***	0.529***
			(0.166)		(0.0996)	(0.132)
N	52719	52719	52719	52758	52758	52758
R squared	0.227	0.228	0.228	0.333	0.333	0.333
IV Estimate	Yes	Yes	Yes	Yes	Yes	Yes

* p<0.10, ** p<0.05, *** p<0.01

Note: The table presents results from panel regression and IV regression estimates of the change in employment for local and export industries in the county from 2003 to 2019 on the change in housing wealth variables. The specifications across the columns differ by the inclusion of distinct measure of housing wealth changes and industries. The housing wealth changes in this table are based on industry-specific flows. We exclude the top and bottom 50 observations with the largest changes, which is roughly 0.2 percent of the sample. Standard errors are in parentheses and are clustered by counties. Estimates are weighted by 2007 population levels. All estimates include county fixed effects, two-digit industry employment share by county interacted with year, and also region-year fixed-effects.

Table A11—Housing Wealth Change on Spending for Intermediate Industry Category: Differential Effects During the GR, Both Home and Away

	(1) Intermediate Industries	(2) Intermediate Industries	(3) Intermediate Industries
Δ HNW (Flow)	0.0334	0.0440	0.0126
	(0.0292)	(0.0274)	(0.0346)
Δ HNW (CZ-Export)		0.268	0.214
		(0.171)	(0.202)
Δ HNW (Flow) · GR	0.127***		0.103*
	(0.0436)		(0.0544)
Δ HNW (CZ-Export) · GR			0.354
			(0.326)
N	52776	52776	52776
R squared	0.272	0.273	0.272
IV Estimate	Yes	Yes	Yes

* p<0.10, ** p<0.05, *** p<0.01

Note: The table presents results from panel regression and IV regression estimates of the change in spending for select intermediate industries in the county from 2003 to 2019 on the change in housing wealth variables. The specifications across the columns differ by the inclusion of distinct measure of housing wealth changes. We exclude the top and bottom 50 observations with the largest changes, which is roughly 0.2 percent of the sample. Standard errors are in parentheses and are clustered by counties. Estimates are weighted by 2007 population levels. All estimates include county fixed effects, two-digit industry employment share by county interacted with year, and also region-year fixed-effects.

Table A12—Effects on Employment for Local Industry Category: Differential Effects During the GR, Both Home and Away

	(1) Local Industries	(2) Local Industries	(3) Local Industries	(4) Export Industries	(5) Export Industries	(6) Export Industries
Δ HNW (Flow)	0.0495**	0.0979***	0.0598**	0.0593***	0.0964***	0.0725***
	(0.0199)	(0.0197)	(0.0241)	(0.0190)	(0.0171)	(0.0221)
Δ HNW (CZ-Export)		-0.0846	-0.114		-0.0533	-0.153**
		(0.0982)	(0.112)		(0.0655)	(0.0764)
Δ HNW (Flow) · GR	0.150***		0.132***	0.119***		0.0692**
	(0.0270)		(0.0324)	(0.0232)		(0.0277)
Δ HNW (CZ-Export) · GR			0.218			0.608***
			(0.197)			(0.148)
N	52719	52719	52719	52758	52758	52758
R squared	0.227	0.228	0.228	0.333	0.333	0.333
IV Estimate	Yes	Yes	Yes	Yes	Yes	Yes

* p<0.10, ** p<0.05, *** p<0.01

Note: The table presents results from panel regression and IV regression estimates of the change in employment for select "local" industries in the county from 2003 to 2019 on the change in housing wealth variables. The specifications across the columns differ by the inclusion of distinct measure of housing wealth changes and whether IV is applied to housing wealth changes outside of the CZ. We exclude the top and bottom 50 observations with the largest changes, which is roughly 0.2 percent of the sample. Standard errors are in parentheses and are clustered by counties. Estimates are weighted by 2007 population levels. All estimates include county fixed effects, two-digit industry employment share by county interacted with year, and also region-year fixed-effects.

L. Robustness Specifications

The tables in this section perform various robustness checks on the main results presented in the paper. Most of the estimates are variations of the main results presented in Tables 6 and 7.

Consumer Share Adjustment . — The estimates in Tables A15 and A16 are the same as the main estimates, but apply an adjustment so that flows are calculated assuming that spending is a constant share of income in all counties. This corrects for potential biases in the flows, possibly caused by lower income populations using card transactions less often than high-income populations. The results are very similar to the main results.

Table A13—Employment by Distance

	(1)	(2)	(3)	(4)
	% Chg. Emp.	% Chg. Emp.	% Chg. Emp.	% Chg. Emp.
Δ HNW (Flow)	0.0655***	0.0702***	0.0311	0.0342
	(0.0182)	(0.0181)	(0.0233)	(0.0236)
Δ HNW (Export: ≤ 100 Miles)	0.0686	0.0578	0.0705	0.0644
	(0.0555)	(0.0553)	(0.0664)	(0.0672)
Δ HNW (Export: > 100 Miles)	0.0872	0.0123	-0.0400	-0.0884
	(0.0763)	(0.0757)	(0.0903)	(0.0906)
Δ HNW (Flow) · GR			0.108***	0.115***
			(0.0280)	(0.0282)
Δ HNW (Export: ≤ 100 Miles) · GR)			0.0481	0.0263
			(0.1000)	(0.103)
Δ HNW (Export: > 100 Miles) · GR)			0.771***	0.658***
			(0.156)	(0.150)
N	52874	52874	52874	52874
R squared	0.406	0.406	0.406	0.407
IV Estimate	Yes	Yes	Yes	Yes
IV Over 100 miles	No	Yes	No	Yes

* p<0.10, ** p<0.05, *** p<0.01

Note: The table presents results from a linear regression estimate of the change in spending for 15 select industries in the county from 2003 to 2019 on the change in housing wealth variable(s). The specifications across the columns differ by the inclusion of distinct measure of housing wealth changes. We exclude outliers where the absolute value of the change in spending exceeds 50 percent, although the estimates are unaffected by the exclusion of outliers. Standard errors are in parentheses and are clustered by state. Estimates are weighted by 2007 population levels. Estimates are weighted by 2007 population levels. All estimates include county fixed effects, two-digit industry employment share by county interacted with year, and also region-year fixed-effects.

Table A14—Spending by Distance for Local Industries

	(1) % Chg. Spend	(2) % Chg. Spend	(3) % Chg. Spend	(4) % Chg. Spend
Δ HNW (Flow)	0.138***	0.142***	0.125***	0.128***
	(0.0311)	(0.0311)	(0.0385)	(0.0387)
Δ HNW (Export: ≤ 100 Miles)	0.0459	0.0344	0.00102	-0.00481
	(0.116)	(0.117)	(0.125)	(0.126)
Δ HNW (Export: > 100 Miles)	0.125	0.0457	0.0643	0.0172
	(0.151)	(0.160)	(0.159)	(0.176)
Δ HNW (Flow) · GR			0.0227	0.0319
			(0.0669)	(0.0655)
Δ HNW (Export: ≤ 100 Miles) · GR)			0.320	0.291
			(0.329)	(0.330)
Δ HNW (Export: > 100 Miles) · GR)			0.357	0.199
			(0.273)	(0.298)
N	52722	52722	52722	52722
R squared	0.211	0.212	0.211	0.211
IV Estimate	Yes	Yes	Yes	Yes
IV Over 100 miles	No	Yes	No	Yes

* p<0.10, ** p<0.05, *** p<0.01

Note: The table presents results from a linear regression estimate of the change in spending for 15 select industries in the county from 2003 to 2019 on the change in housing wealth variable(s). The specifications across the columns differ by the inclusion of distinct measure of housing wealth changes. We exclude outliers where the absolute value of the change in spending exceeds 50 percent, although the estimates are unaffected by the exclusion of outliers. Standard errors are in parentheses and are clustered by state. Estimates are weighted by 2007 population levels. All estimates include county fixed effects, two-digit industry employment share by county interacted with year, and also region-year fixed-effects.

Table A15—Housing Wealth Change on Spending Growth - Consumer Share Adjustment: Differential Effects During the GR, Both Home and Away

	(1)	(2)	(3)	(4)	(5)
	% Chg. Spend	% Chg. Spend	% Chg. Spend	% Chg. Spend	% Chg. Spend
Δ HNW (Flow)	0.0799***	0.0910***	0.106***	0.0475**	0.0728***
	(0.0179)	(0.0193)	(0.0184)	(0.0233)	(0.0220)
Δ HNW (CZ-Export)		0.290***	0.138	0.320***	0.0581
		(0.0912)	(0.0983)	(0.101)	(0.108)
Δ HNW (Flow) · GR	0.143***			0.156***	0.102***
	(0.0230)			(0.0334)	(0.0300)
Δ HNW (CZ-Export) · GR				-0.0765	0.525***
				(0.203)	(0.185)
N	52875	52875	52875	52875	52875
R squared	0.342	0.342	0.343	0.340	0.342
IV Estimate	Yes	Yes	Yes	Yes	Yes
IV Outside CZ	-	No	Yes	No	Yes

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

Note: The table presents results from IV panel regression estimate of the change in employment for 15 industries from 2003 to 2019 on the change in housing wealth variables. The spending flow estimates are adjusted to account for potential biases in spending flows. Specifically, spending flows are adjusted so that all counties have a constant consumption to income ratio, based on the 2015 flow data. The specifications across the columns differ by the inclusion of distinct measure of housing wealth changes and whether IV is applied to housing wealth changes outside of the CZ. We exclude the top and bottom 50 observations with the largest changes, which is roughly 0.2 percent of the sample. Standard errors are in parentheses and are clustered by counties. Estimates are weighted by 2007 population levels. All estimates include county fixed effects, two-digit industry employment share by county interacted with year, and also region-year fixed-effects.

Table A16—Housing Wealth Change on Employment Growth - Consumer Share Adjustment: Differential Effects During the GR, Both Home and Away

	(1) % Chg. Emp.	(2) % Chg. Emp.	(3) % Chg. Emp.	(4) % Chg. Emp.	(5) % Chg. Emp.
Δ HNW (Flow)	0.0415***	0.0699***	0.0833***	0.0325*	0.0518***
	(0.0159)	(0.0153)	(0.0137)	(0.0190)	(0.0168)
Δ HNW (CZ-Export)		0.102*	-0.0376	0.0834	-0.112*
		(0.0581)	(0.0570)	(0.0652)	(0.0641)
Δ HNW (Flow) · GR	0.140***			0.122***	0.0977***
	(0.0188)			(0.0235)	(0.0193)
Δ HNW (CZ-Export) · GR				0.236**	0.492***
				(0.118)	(0.101)
N	52874	52874	52874	52874	52874
R squared	0.406	0.405	0.406	0.405	0.407
IV Estimate	Yes	Yes	Yes	Yes	Yes
IV Outside CZ	-	No	Yes	No	Yes

* p<0.10, ** p<0.05, *** p<0.01

Note: The table presents results from IV panel regression estimate of the change in employment for 15 industries from 2003 to 2019 on the change in housing wealth variables. The spending flow estimates are adjusted to account for potential biases in spending flows. Specifically, spending flows are adjusted so that all counties have a constant consumption to income ratio, based on the 2015 flow data. The specifications across the columns differ by the inclusion of distinct measure of housing wealth changes and whether IV is applied to housing wealth changes outside of the CZ. We exclude the top and bottom 50 observations with the largest changes, which is roughly 0.2 percent of the sample. Standard errors are in parentheses and are clustered by counties. Estimates are weighted by 2007 population levels. All estimates include county fixed effects, two-digit industry employment share by county interacted with year, and also region-year fixed-effects.

CZ-Wide changes in Housing Wealth. — The results in Table A17 aggregate over the housing wealth effect for the entire CZ (i.e., all counties in a CZ share the same effect from changes in housing wealth).

Table A17—Housing Wealth Change on Spending Growth - CZ-Wide Change in Housing Wealth: Differential Effects During the GR, Both Home and Away

	(1)	(2)	(3)	(4)	(5)
	% Chg. Spend	% Chg. Spend	% Chg. Spend	% Chg. Spend	% Chg. Spend
Δ CZ HNW (Flow)	0.113***	0.107***	0.132***	0.0670**	0.109***
	(0.0176)	(0.0240)	(0.0225)	(0.0293)	(0.0265)
Δ CZ HNW (CZ-Export)		0.328**	0.113	0.381**	0.0259
		(0.132)	(0.140)	(0.151)	(0.158)
Δ CZ HNW (Flow) · GR	0.116***			0.144***	0.0672
	(0.0267)			(0.0500)	(0.0424)
Δ CZ HNW (CZ-Export) · GR				-0.182	0.536**
				(0.296)	(0.263)
Observations	52875	52875	52875	52875	52875

* p<0.10, ** p<0.05, *** p<0.01

Note: The table presents results from IV panel regression estimate of the change in spending for local industries from 2003 to 2019 on the change in housing wealth variables. The housing wealth variable and associated instruments in this specification is aggregated to the level of the CZ, so that all counties within the same CZ have the same housing wealth change variable. The specifications across the columns differ by the inclusion of distinct measure of housing wealth changes and whether IV is applied to housing wealth changes outside of the CZ. We exclude the top and bottom 50 observations with the largest changes, which is roughly 0.2 percent of the sample. Standard errors are in parentheses and are clustered by counties. Estimates are weighted by 2007 population levels. All estimates include county fixed effects, two-digit industry employment share by county interacted with year, and also region-year fixed-effects.

Alternative Instruments - Sensitivity - Guren et al. (2020) . — Table A19 and A20 repeat the results, but substitute the main instrument using the instrument directly from the the paper Guren et al. (2020). For these estimates we drop those counties where the instrument from Guren et al. (2020) is not available, but their instrument covers around 90 percent of the population.[10]

The instruments in Guren et al. (2020) are constructed for the retail sector, so we limit the industry categories to the retail sector. The results are qualitatively the same to those in the main analysis, although the standard errors increase on some of the estimates.

Alternative Instruments - Land Unavailability - Saiz (2010) . — Table A21 and A22 repeat the results, but substitute the main instrument using the instru-

[10]The instrument from Guren et al. (2020) is at the CBSA-level, so we apply that instrument value to all counties within the CBSA. Since we use spending flows for the entire U.S., for those markets where the Guren et al. (2020) estimate is not available, estimate the value using our main IV approach. This only affects housing wealth changes outside of the home county.

ment directly from Saiz (2010). For these estimates we drop those counties where the instrument from Saiz (2010) is not available, but the instrument covers around 70 percent of the population.[11] These estimates are similar to those using the main sensitivity instruments applied in the paper, although the standard errors increase on some of the estimates.

Effects using Industry Categories from Mian and Sufi (2014) — Tables A23 and A24 are the same as the main estimates in the text, but use the industry categories applied in Mian and Sufi (2014), which are also similar to those in Guren et al. (2020). These categories include all the retail categories and restaurants (NAICS 722).

Predicted Share Adjustment. — The estimates in Tables A25 and A26 are the same as the main estimates, but flows are predicted specific to each year of the data. This relaxes the fixed share assumption in the main analysis. The results are qualitatively the same.

Effects of Housing Wealth Change on Employment Growth. — *Alternative Estimates Based on Export Quartile* — Table A27 repeats the analysis by export quartile in Table 5, but using employment rather than spending.

M. Implications for Employment

[11] The instrument from Saiz (2010) is at the MSA-level, so we apply that instrument value to all counties within the MSA. Since we use spending flows for the entire U.S., for those markets where the Saiz (2010) estimate is not available, we estimate the value using our main IV approach. This only affects housing wealth changes outside of the home market.

Table A18—Housing Wealth Change on Employment Growth - CZ-Wide Change in Housing Wealth: Differential Effects During the GR, Both Home and Away

	(1)	(2)	(3)	(4)	(5)
	% Chg. Emp.	% Chg. Emp.	% Chg. Emp.	% Chg. Emp.	% Chg. Emp.
Δ CZ HNW (Flow)	0.0507***	0.0664***	0.0894***	0.0259	0.0590***
	(0.0174)	(0.0194)	(0.0166)	(0.0248)	(0.0208)
Δ CZ HNW (CZ-Export)		0.190**	-0.0131	0.204**	-0.0740
		(0.0761)	(0.0705)	(0.0872)	(0.0802)
Δ CZ HNW (Flow) · GR	0.138***			0.138***	0.0988***
	(0.0210)			(0.0331)	(0.0264)
Δ CZ HNW (CZ-Export) · GR				0.0654	0.397***
				(0.166)	(0.139)
Observations	52874	52874	52874	52874	52874

* p<0.10, ** p<0.05, *** p<0.01

Note: The table presents results from a linear regression estimate of the change in employment for 15 select industries in the county from 2003 to 2019 on the change in housing wealth variable(s). The specifications across the columns differ by the inclusion of distinct measure of housing wealth changes. Housing wealth changes and associated instruments are computed by averaging over the entire CZ, so that there is one housing wealth change per CZ and per time period. We exclude outliers where the absolute value of the change in spending exceeds 50 percent. Standard errors are in parentheses and are clustered by state. Estimates are weighted by 2007 population levels. All estimates include county fixed effects, two-digit industry employment share by county interacted with year, and also region-year fixed-effects.

Table A19—Housing Wealth Change on Spending Growth - Sensitivity Instrument (Guren et al. (2020)): Differential Effects During the GR, Both Home and Away

	(1)	(2)	(3)	(4)	(5)
	% Chg. Spend	% Chg. Spend	% Chg. Spend	% Chg. Spend	% Chg. Spend
Δ HNW (Flow)	0.0944***	0.101***	0.132***	0.0452	0.0980***
	(0.0248)	(0.0274)	(0.0229)	(0.0343)	(0.0273)
Δ HNW (CZ-Export)		0.404***	0.0771	0.483***	-0.0509
		(0.132)	(0.124)	(0.151)	(0.131)
Δ HNW (Flow) · GR	0.145***			0.172***	0.0741*
	(0.0319)			(0.0475)	(0.0399)
Δ HNW (CZ-Export) · GR				-0.179	0.867***
				(0.289)	(0.255)
N	19635	19635	19635	19635	19635
R squared	0.467	0.467	0.470	0.463	0.467
IV Estimate	Yes	Yes	Yes	Yes	Yes
IV Outside CZ	-	No	Yes	No	Yes

* p<0.10, ** p<0.05, *** p<0.01

Note: The table presents results from IV panel regression estimate of the change in spending for retail industries and food service from 2003 to 2019 on the change in housing wealth variables. The IV variable in this table is taken directly from Guren et al. (2020) and multiplied by our regional price variable. The specifications across the columns differ by the inclusion of distinct measure of housing wealth changes and whether IV is applied to housing wealth changes outside of the CZ. The housing wealth change is calculated for consumers at different distances. We exclude the top and bottom 50 observations with the largest changes, which is roughly 0.2 percent of the sample. Standard errors are in parentheses and are clustered by counties. Estimates are weighted by 2007 population levels. All estimates include county fixed effects, two-digit industry employment share by county interacted with year, and also region-year fixed-effects.

Table A20—Housing Wealth Change on Employment Growth - Sensitivity Instrument (Guren et al. (2020)): Differential Effects During the GR, Both Home and Away

	(1)	(2)	(3)	(4)	(5)
	% Chg. Emp.	% Chg. Emp.	% Chg. Emp.	% Chg. Emp.	% Chg. Emp.
Δ HNW (Flow)	0.0722***	0.0793***	0.0887***	0.0761**	0.0886***
	(0.0232)	(0.0219)	(0.0188)	(0.0306)	(0.0258)
Δ HNW (CZ-Export)		0.0667	-0.0323	-0.0524	-0.176*
		(0.0856)	(0.0774)	(0.108)	(0.0916)
Δ HNW (Flow) · GR	0.0435			-0.0237	-0.0331
	(0.0304)			(0.0441)	(0.0365)
Δ HNW (CZ-Export) · GR				0.818***	0.897***
				(0.220)	(0.195)
N	19623	19623	19623	19623	19623
R squared	0.530	0.530	0.530	0.530	0.531
IV Estimate	Yes	Yes	Yes	Yes	Yes
IV Outside CZ	-	No	Yes	No	Yes

* p<0.10, ** p<0.05, *** p<0.01

Note: The table presents results from IV panel regression estimate of the change in employment for retail industries and food service from 2003 to 2019 on the change in housing wealth variables. The IV variable in this table is taken directly from Guren et al. (2020) and multiplied by our regional price variable. The specifications across the columns differ by the inclusion of distinct measure of housing wealth changes and whether IV is applied to housing wealth changes outside of the CZ. The housing wealth change is calculated for consumers at different distances. We exclude the top and bottom 50 observations with the largest changes, which is roughly 0.2 percent of the sample. Standard errors are in parentheses and are clustered by counties. Estimates are weighted by 2007 population levels. All estimates include county fixed effects, two-digit industry employment share by county interacted with year, and also region-year fixed-effects.

Table A21—Housing Wealth Change on Spending Growth - Saiz Instrument: Differential Effects During the GR, Both Home and Away

	(1) % Chg. Spend	(2) % Chg. Spend	(3) % Chg. Spend	(4) % Chg. Spend	(5) % Chg. Spend
Δ HNW (Flow)	0.107***	0.156***	0.133***	0.0927*	0.0862**
	(0.0406)	(0.0443)	(0.0364)	(0.0511)	(0.0412)
Δ HNW (CZ-Export)		0.0544	0.365*	0.214	0.293
		(0.183)	(0.205)	(0.197)	(0.215)
Δ HNW (Flow) · GR	0.207***			0.280**	0.164*
	(0.0726)			(0.111)	(0.0870)
Δ HNW (CZ-Export) · GR				-0.998*	0.500
				(0.585)	(0.510)
N	14742	14742	14742	14742	14742
R squared	0.434	0.438	0.437	0.433	0.433
IV Estimate	Yes	Yes	Yes	Yes	Yes
IV Outside CZ	-	No	Yes	No	Yes

* p<0.10, ** p<0.05, *** p<0.01

Note: The table presents results from IV panel regression estimate of the change in spending for 15 industries from 2003 to 2019 on the change in housing wealth variables. The IV variable in this table is taken directly from Saiz (2010) and interacted with the average national price change. The specifications across the columns differ by the inclusion of distinct measure of housing wealth changes and whether IV is applied to housing wealth changes outside of the CZ. The housing wealth change is calculated for consumers at different distances. We exclude the top and bottom 50 observations with the largest changes, which is roughly 0.2 percent of the sample. Standard errors are in parentheses and are clustered by counties. Estimates are weighted by 2007 population levels. All estimates include county fixed effects, two-digit industry employment share by county interacted with year, and region-year fixed-effects.

Table A22—Housing Wealth Change on Employment Growth - Saiz Instrument: Differential Effects During the GR, Both Home and Away

	(1) % Chg. Emp.	(2) % Chg. Emp.	(3) % Chg. Emp.	(4) % Chg. Emp.	(5) % Chg. Emp.
Δ HNW (Flow)	-0.0132	0.0300	0.0386	-0.0319	-0.0169
	(0.0320)	(0.0342)	(0.0268)	(0.0417)	(0.0328)
Δ HNW (CZ-Export)		0.216	0.0982	0.273*	0.0502
		(0.132)	(0.156)	(0.152)	(0.177)
Δ HNW (Flow) · GR	0.230***			0.250***	0.208***
	(0.0407)			(0.0620)	(0.0492)
Δ HNW (CZ-Export) · GR				-0.316	0.285
				(0.338)	(0.344)
N	14729	14729	14729	14729	14729
R squared	0.519	0.522	0.523	0.516	0.519
IV Estimate	Yes	Yes	Yes	Yes	Yes
IV Outside CZ	-	No	Yes	No	Yes

* p<0.10, ** p<0.05, *** p<0.01

Note: The table presents results from IV panel regression estimate of the change in employment for 15 industries from 2003 to 2019 on the change in housing wealth variables. The IV variable in this table is taken directly from Saiz (2010) and interacted with the average national price change. The specifications across the columns differ by the inclusion of distinct measure of housing wealth changes and whether IV is applied to housing wealth changes outside of the CZ. The housing wealth change is calculated for consumers at different distances. We exclude the top and bottom 50 observations with the largest changes, which is roughly 0.2 percent of the sample. Standard errors are in parentheses and are clustered by counties. Estimates are weighted by 2007 population levels. All estimates include county fixed effects, two-digit industry employment share by county interacted with year, and also region-year fixed-effects.

Table A23—Effects on Spending using Industry Categories from Mian and Sufi (2014): Differential Effects During the GR, Both Home and Away

	(1) % Chg. Spend	(2) % Chg. Spend	(3) % Chg. Spend	(4) % Chg. Spend	(5) % Chg. Spend
Δ HNW (Flow)	0.120***	0.132***	0.146***	0.0865***	0.107***
	(0.0171)	(0.0184)	(0.0175)	(0.0210)	(0.0197)
Δ HNW (CZ-Export)		0.311***	0.157*	0.360***	0.129
		(0.0929)	(0.0928)	(0.101)	(0.0973)
Δ HNW (Flow) · GR	0.148***			0.167***	0.134***
	(0.0229)			(0.0312)	(0.0274)
Δ HNW (CZ-Export) · GR				-0.179	0.206
				(0.202)	(0.175)
N	52871	52871	52871	52871	52871
R squared	0.382	0.382	0.383	0.381	0.382
IV Estimate	Yes	Yes	Yes	Yes	Yes
IV Outside CZ	-	No	Yes	No	Yes

* p<0.10, ** p<0.05, *** p<0.01

Note: The table presents results from panel regression and IV regression estimates of the change in spending for retail and restaurant industries from Mian and Sufi (2014) in the county from 2003 to 2019 on the change in housing wealth variables. The specifications across the columns differ by the inclusion of distinct measure of housing wealth changes and whether IV is applied to housing wealth changes outside of the CZ. We exclude the top and bottom 50 observations with the largest changes, which is roughly 0.2 percent of the sample. Standard errors are in parentheses and are clustered by counties. Estimates are weighted by 2007 population levels. All estimates include county fixed effects, two-digit industry employment share by county interacted with year, and also region-year fixed-effects.

Table A24—Effects on Employment using Industry Categories from Mian and Sufi (2014): Differential Effects During the GR, Both Home and Away

	(1) % Chg. Emp.	(2) % Chg. Emp.	(3) % Chg. Emp.	(4) % Chg. Emp.	(5) % Chg. Emp.
Δ HNW (Flow)	0.0882***	0.103***	0.108***	0.0943***	0.102***
	(0.0183)	(0.0162)	(0.0149)	(0.0225)	(0.0208)
Δ HNW (CZ-Export)		0.00738	-0.0463	-0.0770	-0.165**
		(0.0593)	(0.0531)	(0.0762)	(0.0680)
Δ HNW (Flow) · GR	0.0570**			0.0101	0.000163
	(0.0265)			(0.0358)	(0.0331)
Δ HNW (CZ-Export) · GR				0.587***	0.696***
				(0.174)	(0.165)
N	52872	52872	52872	52872	52872
R squared	0.427	0.427	0.428	0.428	0.428
IV Estimate	Yes	Yes	Yes	Yes	Yes
IV Outside CZ	-	No	Yes	No	Yes

* p<0.10, ** p<0.05, *** p<0.01

Note: The table presents results from panel regression and IV regression estimates of the change in spending for retail and restaurant industries from Mian and Sufi (2014) in the county from 2003 to 2019 on the change in housing wealth variables. The specifications across the columns differ by the inclusion of distinct measure of housing wealth changes and whether IV is applied to housing wealth changes outside of the CZ. We exclude the top and bottom 50 observations with the largest changes, which is roughly 0.2 percent of the sample. Standard errors are in parentheses and are clustered by counties. Estimates are weighted by 2007 population levels. All estimates include county fixed effects, two-digit industry employment share by county interacted with year, and also region-year fixed-effects.

Table A25—Housing Wealth Change on Spending Growth - Predicted Share Adjustment: Differential Effects During the GR, Both Home and Away

	(1)	(2)	(3)	(4)	(5)
	% Chg. Spend	% Chg. Spend	% Chg. Spend	% Chg. Spend	% Chg. Spend
Δ HNW (Flow Pred)	0.0779***	0.0875***	0.0997***	0.0491**	0.0698***
	(0.0172)	(0.0178)	(0.0173)	(0.0215)	(0.0205)
Δ HNW (CZ-Export Pred)		0.354***	0.192*	0.367***	0.0919
		(0.101)	(0.114)	(0.111)	(0.125)
Δ HNW (Flow Pred) · GR	0.136***			0.138***	0.0977***
	(0.0226)			(0.0317)	(0.0290)
Δ HNW (CZ-Export Pred) · GR				0.0176	0.560***
				(0.221)	(0.203)
N	52875	52875	52875	52875	52875
R squared	0.342	0.342	0.343	0.341	0.342
IV Estimate	Yes	Yes	Yes	Yes	Yes
IV Outside CZ	-	No	Yes	No	Yes

* p<0.10, ** p<0.05, *** p<0.01

Note: The table presents results from IV panel regression estimate of the change in spending for 15 industries from 2003 to 2019 on the change in housing wealth variables. The spending flow estimates are based on predicted spending flows in the base year (e.g., for the 2004–2006 change, the base year is 2003), where the methodology for predicting flows is described in appendix section .G. The specifications across the columns differ by the inclusion of distinct measure of housing wealth changes and whether IV is applied to housing wealth changes outside of the CZ. We exclude the top and bottom 50 observations with the largest changes, which is roughly 0.2 percent of the sample. Standard errors are in parentheses and are clustered by counties. Estimates are weighted by 2007 population levels. All estimates include county fixed effects, two-digit industry employment share by county interacted with year, and also region-year fixed-effects.

Table A26—Housing Wealth Change on Employment Growth - Predicted Share Adjustment: Differential Effects During the GR, Both Home and Away

	(1)	(2)	(3)	(4)	(5)
	% Chg. Emp.	% Chg. Emp.	% Chg. Emp.	% Chg. Emp.	% Chg. Emp.
Δ HNW (Flow Pred)	0.0399**	0.0624***	0.0724***	0.0262	0.0412**
	(0.0159)	(0.0157)	(0.0148)	(0.0196)	(0.0185)
Δ HNW (CZ-Export Pred)		0.181***	0.0495	0.171**	-0.0257
		(0.0678)	(0.0630)	(0.0776)	(0.0726)
Δ HNW (Flow Pred) · GR	0.135***			0.126***	0.106***
	(0.0184)			(0.0237)	(0.0213)
Δ HNW (CZ-Export Pred) · GR				0.160	0.419***
				(0.131)	(0.110)
N	52874	52874	52874	52874	52874
R squared	0.406	0.405	0.406	0.405	0.406
IV Estimate	Yes	Yes	Yes	Yes	Yes
IV Outside CZ	-	No	Yes	No	Yes

* p<0.10, ** p<0.05, *** p<0.01

Note: The table presents results from IV panel regression estimate of the change in spending for 15 industries from 2003 to 2019 on the change in housing wealth variables. The spending flow estimates are based on predicted spending flows in the base year (e.g., for the 2004–2006 change, the base year is 2004), where the methodology for predicting flows is described in appendix section .G. The specifications across the columns differ by the inclusion of distinct measure of housing wealth changes and whether IV is applied to housing wealth changes outside of the CZ. We exclude the top and bottom 50 observations with the largest changes, which is roughly 0.2 percent of the sample. Standard errors are in parentheses and are clustered by counties. Estimates are weighted by 2007 population levels. All estimates include county fixed effects, two-digit industry employment share by county interacted with year, and also region-year fixed-effects.

Table A27—Average Housing Wealth Changes on Employment Growth: Home Market and Export Market by Export Quartile

	(1)	(2)
	% Chg. Spend	% Chg. Spend
Δ HNW (No Flow) · Q4 High Export	0.102***	-0.0152
	(0.0191)	(0.0863)
Δ HNW (No Flow) · Q3 Export	0.0824***	-0.122**
	(0.0260)	(0.0606)
Δ HNW (No Flow) · Q2 Export	0.189***	0.0593
	(0.0219)	(0.0487)
Δ HNW (No Flow) · Q1 Low Export	0.161***	0.143**
	(0.0217)	(0.0644)
(Avg. Export Δ HNW) · Q4 High Export	0.0625**	0.194*
	(0.0308)	(0.101)
(Avg. Export Δ HNW) · Q3 Export	0.0612*	0.297***
	(0.0335)	(0.0785)
(Avg. Export Δ HNW) · Q2 Export	-0.0634*	0.0962
	(0.0333)	(0.0728)
(Avg. Export Δ HNW) · Q1 Low Export	-0.0235	0.00596
	(0.0312)	(0.0824)
N	52874	52874
R squared	0.336	0.330
IV Estimate	No	Yes

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

Note: Q4 is high export quartile, so more potential consumers are away from the home county; and Q1 is low export quartile, indicating more potential consumers are in the home county. The quartile indicators are interacted with the housing price changes in the home market where housing flows are ignored (i.e., ΔHNW (No FLow)) and the average housing price change for potential consumers that reside outside the home market (i.e., Avg. Export Δ HNW). The table presents results from panel regression estimates of the change in employment for 15 select industries in the county from 2003 to 2019 on the change in housing wealth variables. Column (1) shows the OLS estimates and column (2) applies instrumental variables. We exclude the top and bottom 50 observations with the largest changes, which is roughly 0.2 percent of the sample. Standard errors are in parentheses and are clustered by counties. Estimates are weighted by 2007 population levels. All estimates include county fixed effects, two-digit industry employment share by county variables interacted with year dummies, and also region-year fixed-effects.

Table A28—Decomposition the Local Geographic Effects of the GR on Employment

Total Employment in 2007 (in Thousands)	25,850		

	Chg. in Employment (in Thousands)	Percent Decline	Share Misallocation
Baseline	-631	-2.4	-
Baseline (Within CZ Effect)	-345	-1.3	-
Baseline (Outside CZ Effect)	-286	-1.1	-
Scenario 1. No Differential CZ Effect	-424	-1.6	0.190
Scenario 2. No Differential CZ, No GR Effect	-132	-0.5	0.190
Scenario 3. Only Within CZ Effect	-345	-1.3	0.324
Scenario 4. Only Within CZ Effect, No GR Effect	-115	-0.4	0.324

Note: This table reports the effects of the housing wealth change during the 2007–2009 period based on the regression estimates in Table 7 and column (5). For instance, the baseline estimate shows the total effect of the housing wealth change on employment was around 630 billion, with 344 thousand coming from changes in housing wealth within the CZ and 290 thousand coming from changes in housing wealth outside of the CZ. Scenario 1 assumes no differential effects outside the CZ; scenario 2 assumes no differential effects outside the CZ, and no differential effect from the GR; scenario 3 assumes effects are only within CZ; and scenario 4 assumes effects are only within CZ and there is no differential effect from the GR. These results highlight the importance of both the larger effects during the GR. The last column of the table also reports the level of misallocation computed as the absolute value of the share of the total effect on spending occurring in each county compared relative to the counterfactual share of spending occurring in each county. In scenario 3 and 4 about 30 percent of the total effect would be misallocated.