The Geography of Consumption and Local Economic Shocks: The Case of the Great Recession

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July 9, 2021

Abstract

We estimate across-county spending flows between firms and consumers for every county in the U.S., providing a new consumption link that has not previously been studied. We highlight the importance of this link by estimating the effect of changes in local housing net worth on consumption and employment during the 2007–2009 Great Recession. We find that the effects of the housing wealth decline crosses borders to reduce consumption and employment in a pattern consistent with our spending flows. Around 30 percent or more of effects are generated by housing wealth changes outside of the county where the firm resides.

1 Introduction

Consumers regularly travel to consume outside their home county, affecting both revenues and employment across different locations. In this paper we argue that this consumption link across geographic markets has important implications for economic measurement. Although there are rich data sources that provide detailed and nearly complete coverage of both consumption (e.g., the Economic Census(EC)) and employment (e.g., the Quarterly Census of Employment and Wages(QCEW)) for every county in the United States, they are centered around the location of the firm and not the location of the consumer. Data centered around the firm does not identify

*We would like to thank Christian Awuku-Budu, Mary Bohman, Ben Bridgman, Eva De Francisco, Lasanthi Fernando, Dennis Fixler, Aaron Flaaen, Kyle Hood, Matt Knepper, Justine Mallatt, and Scott Wentland for comments. We would also like to thank seminar participants at the Meeting of the Urban Economics Association (October, 2020), Bank of Italy and Federal Reserve Board joint conference on Nontraditional data (November, 2020), and the Winter Meetings of the Econometric Society (December, 2020). We would also like to thank Fiserv for the use of their data and the substantial work of the employees at Palantir who helped manage and work with the enormous Fiserv database, especially Albert Altarovici, Brady Fowler, and Daniel Williams. We would also like to thank Ledia Guci for some preliminary analysis of Fiserv data for purposes of measuring regional consumption. The views expressed in this paper are solely those of the authors and do not necessarily reflect the views of the U.S. Bureau of Economic Analysis or the U.S. Department of Commerce.

the primary cause of the change in revenues, which is rooted in the consumption patterns of consumers both local and afar. To study the consumption link between counties, and to fully utilize these rich data sources, we introduce a complementary new data source on spending flows between consumers and firms for all counties in the United States. We combine traditional and novel data sources to study the housing wealth decline from the 2007–2009 Great Recession and we show how firms are differentially affected by local and more distant economic shocks to consumption. This is the first paper to construct a comprehensive data set of consumption flows across counties for the entire United States, and also the first to measure the importance of shocks to consumption transmitted across geographic markets.

We construct the spending flow estimates using card transaction data from Fiserv, one of the largest card transaction intermediaries in the country, with well over $2 trillion dollars in card volume going through their system worldwide annually. Typically, when a firm uses Fiserv services, all associated debit and credit card transactions go through their systems. At a micro level, these data include information about both the location of consumers' residence as well as the physical location of firms, allowing the measurement of cross-county spending flows. The data are aggregated and anonymized across firms and consumers by county and by three-digit North American Industry Classification System (NAICS) industry codes. While there are around 4.5 million establishments underlying the data, they still represent a sample of the total establishments in the country. These card data are combined with EC data and other sources to build representative estimates of spending flows across all counties in the United States for 15 three-digit NAICS categories for the year 2015. The focus of the analysis is on brick-and-mortar stores and excludes the nonstore retail category such as e-commerce firms (e.g., Amazon and eBay).[1]

The 15 NAICS categories we study account for a total of about 79 percent of consumer

[1] Our paper is related to Dolfen et al. (2019) that uses detailed VISA data on consumer location and spending habits across locations to assess the gains in e-commerce. They find large gains from the introduction and expansion of e-commerce. In contrast, our paper focuses more explicitly on brick and mortar stores for two reasons. First, the coverage of our data set is more complete and accurate for brick-and-mortar stores. With additional data, the basic approach laid out in our paper could be adapted to e-commerce sales. Second, the analysis in our paper focuses on the period during the Great Recession when e-commerce was a much smaller share of spending. According to Dolfen et al. (2019) online sales were around 5 percent in the 2007-09 period of our study and the share was less than 7 percent in 2015. We also exclude the nonstore retail and airline categories, which are two of the industries with a highest share of e-commerce sales according to Dolfen et al. (2019).

spending nationally, excluding housing, health care, and financial services.[2] On average, we find that around 62 percent of expenditures take place in the same county in which individuals reside and that about 80 percent of spending occurs within a 100 mile radius of the home county. While these statistics show that spending typically occurs near where individuals reside, spending outside the home county still makes up a substantial share of total spending and may vary greatly depending on the local geography and industry. This turns out to be extremely important for some industries, such as accommodations, where only 12 percent of spending occurs in a person's home county, but less important for other industries, such as food and beverage stores, where over 75 percent of spending takes place in the home county.

We demonstrate the importance of these cross-border effects in two ways. First, we show how these spending flows are part of a regional accounting framework. The total consumption of individuals that reside in a county equals total final consumption sold in that county minus net exports of consumption (i.e., the total amount sold by firms to individuals outside of the county, minus total amount consumers purchase outside of the county in which they reside). We form a simple empirical test of this accounting relationship and find evidence that this relationship holds in the data and has significant explanatory power. Moreover, we show that the across-county spending flows estimated for 2015 are relevant throughout the period from 2002 to 2017. This spending flow analysis helps to validate the regional economic accounting framework and also provides a useful check on the Fiserv data.

Next, we apply the across-county consumption flows to re-examine the effects of housing wealth declines from the 2007–2009 Great Recession. In particular, we follow the well-known work of Mian et al. (2013) and Mian and Sufi (2014) to study how local changes in housing wealth affect consumption and local employment, although the focus of our paper is distinctly centered around the consumption link across markets. Our paper starts with spending estimates from official sources that are centered around the location of a firm and considers the housing wealth of all consumers, including both local consumers and those traveling from other counties, in determining the effect of housing wealth declines on firm revenue. The across-market flow estimates provide detailed information regarding the location of potential consumers across

[2]These shares were computed for the years 2006 to 2010.

counties. We find that firms are affected in proportion to the change in housing wealth of their customers, even if their customers reside in another county. While this connection is clear in theory, this is the first paper to empirically measure these across-market effects.

We find spending flows are important for obtaining the appropriate measure of the housing wealth change relevant to firms. The firms in high consumption export counties, those counties with higher levels of consumption from outside the county (e.g., Clark County, Nevada), are relatively unaffected by housing wealth changes within their own county, but are instead affected by housing wealth changes from the visiting customers' counties. Alternatively, those counties with low consumption exports are unaffected by housing wealth changes in other counties, and are only affected by housing wealth changes in their own county. As a result, ignoring spending flows across counties tends to reduce the elasticity of housing wealth changes on spending and local employment.

We find heterogeneous effects on consumption and employment depending on both the industry and the location of potential consumers. Our study is the first to show that an astonishing 30 to 40 percent of the spending and employment effects are generated by housing wealth changes outside of the county where the firm is located. Moreover, we also find that consumption and employment is significantly impacted by housing wealth changes from consumers that reside more than 100 miles away, accounting for around 13 to 29 percent of the total effect. Those industries and counties that rely more heavily on consumers that reside outside the area are disproportionately affected by the housing wealth decline, highlighting an important avenue for economic shocks to propagate across distant geographic markets. Grouping industries by the tendency to export, we find the high export share industries (e.g., accommodations and sporting events), were more heavily impacted by the housing wealth changes, relative to low export industries (e.g., grocery stores and general merchandise stores).

Our elasticity of housing wealth change to spending is 0.19, which implies a marginal propensity to consume out of housing wealth (MPCH) of 7.6 cents on the dollar, although the estimate is around 6.4 cents on the dollar if spending flows are not accounted for.[3] When employment is

[3]As discussed in the results section, the MPCH is determined by dividing the spending elasticity by the ratio of housing wealth to personal consumption.

used as the dependent variable, we find an elasticity of 0.15, which would indicate an estimate of 5.9 cents on the dollar.[4] These estimates are quite close to previous research by Mian et al. (2013) and Mian and Sufi (2014) who find estimates implying a MPCH of 7.2 cents on the dollar and an MPCH between 4.1 and 7.3 cents on the dollar based on estimates using employment.[5]

Similar to previous studies in this literature, we find that counties with the greatest drop in net housing wealth show the largest declines in consumer spending and local employment.[6]. However, we show that this effect is not isolated to county borders. Additionally, we find that not accounting for these cross-border effects leads to an underestimate of the effects of the housing net wealth shock on both spending and employment by around 19 percent and 17 percent, respectively; and a misallocation of where these effects occur of around 11 percent for both spending and employment. Although measuring these effects is not the primary goal of this paper, but instead to highlight that much of these effects, 30 to 40 percent, are occurring across county borders.

Our results are robust to a number of alternative specifications and checks. Our robustness checks include both panel regression models and instrumental variable estimates following Guren et al. (2020). We also introduce an alternative method to address endogeneity through the inclusion of commuting zone fixed effects. The inclusion of commuting zone fixed effects account for general changes in the broader labor market that might affect housing prices, while still identifying the effects of housing wealth changes that are specific to counties. We identify the effects of housing wealth changes both within and across commuting zones, demonstrating that there is important variation occurring within commonly used geographic markets. As another robustness check, we generate predicted spending flows for 2007, rather than using the observed 2015 spending flows directly, and we find that results do not change. All of these robustness checks confirm the importance of the cross-county consumption link and show that ignoring

[4]The calculation is using employment as a proxy for consumption assuming a one-to-one relationship between employment and consumption.

[5]Although we expand their analysis from 900 counties to over 3,000 counties in the United States and use alternative methods for constructing spending estimates from official sources. Rather than addressing the cross-border issue when studying spending, Mian et al. (2013) turn to an alternative card transaction data source that contains information on spending based on the location of the consumer. Our employment estimates improve on Mian and Sufi (2014) that does not address the cross-border issue when studying employment effects.

[6]See papers by Aladangady (2017), Guren et al. (2020), Mian et al. (2013), and Mian and Sufi (2014)

across-county flows tends to understate the effects of housing wealth changes.

This paper relates to a large literature that studies geographic markets for specific industries, which often focus on particular cities or regions.[7] Our paper contrasts with these papers as we study several industries across all counties in the United States. Our paper also relates to Agarwal et al. (2017) who use card transaction data to investigate spending patterns across geographic markets and for multiple industries. Similar to our work, they find consumer mobility varies substantially across industries. However, the focus of Agarwal et al. (2017) is in understanding factors that influence the spatial structure of geographic markets (e.g., how storability of goods (proxied by transaction frequency) affects firm location by industry). In contrast, our paper focuses on how observed spatial linkages in consumption have implications for the transmission and measurement of local economic shocks across areas. Finally, our paper also relates to Acemoglu et al. (2016), who highlight the importance of economic shocks across industries located within the same geographic market. In contrast, our paper demonstrates how economic shocks may propogate across distant geographic markets through an across-market linkage in consumption.

There is also a growing literature using more granular and real-time data sources on both consumption and employment to measure the effects of local economic shocks or policies (Aladangady et al. (2021), Baker et al. (2020),Chetty et al. (2020), Cox et al. (2020), and Bureau of Economic Analysis County GDP[8]). Arguably, a better understanding of the consumption link across local geographic markets will only increase in importance as additional rich data sources become available. This paper shows that for firms, the potential consumer demand at a location is more important than the consumer demand within a defined geographic area (e.g, county or commuting zone).

[7] Allcott et al. (2019) - groceries and food, Houde (2012) - gasoline stations, Davis et al. (2019) - restaurants, Davis (2006), and many papers in the health care sector, where the geography of markets is featured prominently in the literature (See Gaynor et al. (2015) for a review))

[8] https://www.bea.gov/data/gdp/gdp-county-metro-and-other-areas

2 Data

The card transaction data source used in this paper is from Fiserv, a card transaction intermediary, which processes transactions for establishments around the world, including credit, debit, and prepaid gift cards that includes all types of card transactions (e.g., Visa, MasterCard, Discover and others).[9] The unit of observation on the Fiserv system is a single transaction at a firm. Once a firm signs up for Fiserv services, typically all card transactions go through the Fiserv system. However, we do not see the data at this level of detail. Fiserv works with Palantir, which is a software company that specializes in the management and analysis of big data. Fiserv and Palantir have aggregated and anonymized transaction data to the county level in a way that provides detailed and meaningful economic information, while still protecting the identity of both firms and individuals. The data contain 4.5 million firms and millions of transactions that span all states in the United States and the District of Columbia. The data includes transactions from e-commerce (primarily captured in NAICS category 454 for non-store retailers), but the coverage for this category is relatively poor, so we exclude e-commerce firms.

For counties within the United States, the home location of each card holder is estimated based on the transaction history of the card using information on all transactions across all industries.[10] The home location algorithm is optimized based on a subset of cards within the Fiserv database, where the home location of the card holder is known. [11]

The Fiserv data we use is from 2015 and includes aggregate county-level information by three-digit NAICS industry. For every county-industry combination, the data contains an estimate of the share of revenues for establishments in that county coming from consumers residing in one of the more than 3,000 counties in the United States. For instance, this data includes information on the share of accommodation revenues (NAICS 721) in Clark County, Nevada (i.e., Las Vegas) coming from Orange County, California. The total shares across all areas add up to one. Our study focuses on 15 select three-digit industries that have good coverage in the Fiserv data.[12]

[9]Other electronic card transactions are also included, such as Electronic Benefit Transfer.

[10]See data appendix for more details.

[11]As an additional check on the home-location algorithm, we also have a version of the data based solely on those consumers for whom the home location is known. This data are also similarly aggregated and anonymized to the county level. We find the two estimates of spending flows to be quite similar.

[12]We consider flows with good coverage to be the flows with lowest number of suppressed observations which

These select industries account for 64 percent of personal consumption spending after excluding housing and financial services. They account for 79 percent of consumer spending if health care is also excluded.[13] Notably, the spending data excludes the purchase of cars, which are typically not paid for by debit or credit cards.

To protect the anonymity of firms and consumers in the Fiserv data, information on the transaction flows across geographies are suppressed in some cases. This is especially common in areas where revenues for an industry in a particular county are small.[14] Using information from the EC, we find that about 15 percent of spending is suppressed for these select industries.

For those county-industry pairs with suppressed flow information, we apply flexible models based on observable transactions in the database across areas to generate estimates of transaction flows across all areas in the country. To impute spending flows, information for those industries in which transactions are observed in a county (e.g., the category restaurants and bars (NAICS 722), where 98 percent of spending is unsuppressed), combined with information on distances traveled, revenues estimated based on the EC, and other covariates to impute the remaining spending flows. For instance, if we are missing accommodations flows in an area, but we observe flows of restaurant services, we can use information on the restaurant service flows between areas, combined with information on how far individuals typically travel to purchase accommodation services, as well as other information such as population and revenues, to impute the flows for accommodation services between two areas. We have explored a variety of flexible models to impute this missing information and selected our current specification using a holdout sample and cross-validation. We chose the method with the lowest mean squared error in our hold-out sample. Additional details of this imputation method are described in the appendix.

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

happen to be mostly retail and some services e.g. restaurants and hotels.

[13] The 15 select industries account for 41 percent of total consumption, including all consumption categories. These calculations were done for the years 2006 to 2010

[14] The specific rule is that there needs to be 10 or more firms in that three-digit NAICS, with no firm having more than a 20 percent market share. In addition to these criteria, some merchants have agreements with Fiserv to "opt out" of their data being used and their data are not included.

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 merchants that might interfere in accurately measuring changes in spending over time (E.g., a merchant 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 merchants available.

In addition to card transaction data from Fiserv, we also construct estimates of county-level spending and employment for the 15 select industries. For the employment data we use the QCEW, which is an official Bureau of Labor Statistics (BLS) data source that includes quarterly employment and wage estimates for 95 percent of jobs at the county level and by detailed NAICS industry category. The source of the QCEW is administrative data from state unemployment insurance programs. While nearly all employment is included, it excludes select areas such as proprietors and the self-employed. QCEW is the same data source used by Guren et al. (2020). In contrast to Guren et al. (2020) who focus on retail employment, we study employment for our 15 select industries. However, our version of the QCEW data includes complete coverage of all counties at the three-digit industry level from 2002 to 2017.[15]

For the spending estimates we use the Geographic Area Series of the 2002, 2007, 2012, and 2017 ECs that contains information on revenues and establishment counts by NAICS industry and county-level geographies.[16] Next, to estimate spending for all of the intercensal years, we use the QCEW growth rates to interpolate county-level growth rates by NAICS. Specifically, the annual QCEW growth rates are rescaled by the ratio of the annualized 5-year EC growth rate and the annualized 5-year QCEW growth rate. This method essentially anchors the annual growth rates in QCEW wages to match the average growth rate in the EC (see the appendix for additional details). A similar method is applied in the Bureau of Economic Analysis (BEA)

[15](Mian and Sufi, 2014) use County Business Patterns (CBP) data from Census, which also provides information on employment and earnings. The CBP data are annual and QCEW data are quarterly and there are also slight differences in coverage. Overall the two sources are similar for the industry categories studied here.

[16]A subset of counties in the EC contain suppressions at the three-digit industry level, representing about 1 to 2 percent of spending. The estimates for suppressed counties are imputed using state-level EC data and QCEW data to create estimates for all counties in the United States for these benchmark years.

regional economic accounts and private sector organizations such as Moody's and the Survey of Buying Power, as historically there is a high correlation between the growth rate in the EC and wages from the QCEW. In the appendix, we show that wage data performs quite well in predicting growth rates in revenues based on the EC years. Guren et al. (2020) also use employment data as a proxy for changes in spending, which we agree is a good proxy for our 15 industry categories. However, we view growth rates from the QCEW as distinct from our spending estimates as our spending estimates are anchored to the EC around the Great Recession for the years 2007 and 2012. This distinction appears to matter for our estimates, as we generally find higher elasticities for spending than for employment. Additional details of our county estimates of spending are outlined in the appendix.

Finally, another important data set used in our analysis is from Zillow, which contains monthly home pricing information from 1996 to January of 2020 for more than 2,000 counties.[17] The remaining counties are relatively small rural counties with relatively little economic activity. For our key analysis, we focus on the change in home prices at the end of 2006 to the beginning of 2009, which we calculate directly with the Zillow data. For the missing counties, we assume the price decline is equal to the median price decline across counties in the same state. While this is a strong assumption, these are very rural counties and this has very little effect on the estimates and allows us to examine effects of housing wealth declines across all counties.[18] The measure of housing wealth decline is calculated as

$$\Delta HNW_i = \frac{P_{h,i}^{2009} - P_{h,i}^{2006}}{P_{h,i}^{2006}}$$

where ΔHNW_i is the change in housing wealth computed by the change in housing price from December 2006 to the end of 2009, where $P_{h,i}^{t}$ is the housing price for county i in year t. The Zillow data is also used later in the paper to help form an instrumental variable for the housing wealth change following Guren et al. (2020). Details of this strategy are discussed in the robustness section of this paper.

[17] The data was downloaded from: https://www.zillow.com/research/data/. See the appendix for additional details on the Zillow data.

[18] Excluding these more rural counties that have missing data also potentially introduces systematic bias in our estimates, so we chose to use the state's median price change instead.

3 Descriptive Statistics

Table 1 shows total estimated spend in 2015 by NAICS industry, in which the total is decomposed into the percent of spending that is observed, the percent of spending that was imputed, and the percent that could not be imputed. Across-market spending flows are observed for about 86 percent of spending, therefore no additional imputation is required. About 14 percent of the flow shares are imputed using the method described in the appendix. For less than 0.1 percent of spending, it was not possible to impute the flows across areas. The amount of imputation needed varies greatly by industry. For food services and drinking places (NAICS 722) we observe 98 percent of spending flows, but we observe just 63 percent for performing arts, spectator sports, and related industries.

Table 1: Spending by Industry

	Total $Millions	% Observed	% Imputed	% Unknown
Accommodation (NAICS 721)	215,966.4	85.12	14.81	0.07
Ambulatory Health Care Services (NAICS 621)	962,415.1	95.75	4.21	0.05
Amusement, Gambling, and Recreation Industries (NAICS 713)	119,931.7	86.61	13.32	0.07
Building Material and Garden Equipment and Supplies Dealers (NAICS 444)	327,286.9	69.24	30.62	0.14
Clothing and Clothing Accessories Stores (NAICS 448)	240,989.6	95.89	4.08	0.02
Food Services and Drinking Places (NAICS 722)	678,876.9	98.31	1.67	0.01
Food and Beverage Stores (NAICS 445)	731,541.9	87.91	12.06	0.04
Furniture and Home Furnishings Stores (NAICS 442)	126,738.5	82.51	17.34	0.14
Gasoline Stations (NAICS 447)	655,703.3	83.93	16.01	0.06
General Merchandise Stores (NAICS 452)	786,300.9	67.06	32.82	0.13
Miscellaneous Store Retailers (NAICS 453)	141,851.4	95.33	4.64	0.03
Performing Arts, Spectator Sports, and Related Industries (NAICS 711)	99,503.8	63.28	36.64	0.07
Personal and Laundry Services (NAICS 812)	108,216.7	94.68	5.20	0.11
Repair and Maintenance (NAICS 811)	180,253.6	89.58	10.32	0.11
Sporting Goods, Hobby, Book, and Music Stores (NAICS 451)	107,970.7	81.92	17.99	0.09
Total	5,483,547.5	85.90	14.04	0.07

Notes: The total spending for 2015 estimates are based on our estimate of total spending by firms in each county. Additional detail regarding the 2015 spending estimates by industry are provided in the appendix. The share imputed for each NAICS category is computed as the total revenues where spending flows are not observed across all counties, divided by the total revenues across all counties. 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.

3.1 Geography of Consumption

The amount individuals travel to consume varies greatly by industry. Figure 1 shows the cumulative distribution of spending by NAICS for the first 1,000 miles away from a firm's home location, where the location within each county is based on the population centroid.[19] Categories such as food and beverage stores and health care are among those in which most consumption occurs locally. The finding that preferences for food and beverage stores (i.e., grocery stores) is highly localized relates to the literature on food deserts and local availability on consumption (Allcott et al. (2019)). In contrast, people tend to travel farther for arts and spectator sports, and accommodations. Additional details descriptive statistics of spending by distance are included in section A.3 of the appendix.

While there is considerable variation across industries, both the geography of different locations as well as the concentration of different industries and populations across the United States leads to large variation in how much consumers spend outside of the county in which they reside. Figure 2 shows the share of consumption that is consumed in a consumer's home county, with darker shades indicating that more consumption is occurring in the home county. Figure 2 shows that for most counties more than 50 percent of consumption occurs in the home county, and this is particularly true in large cities.[20] In contrast, in rural areas consumers tend to travel more to consume.

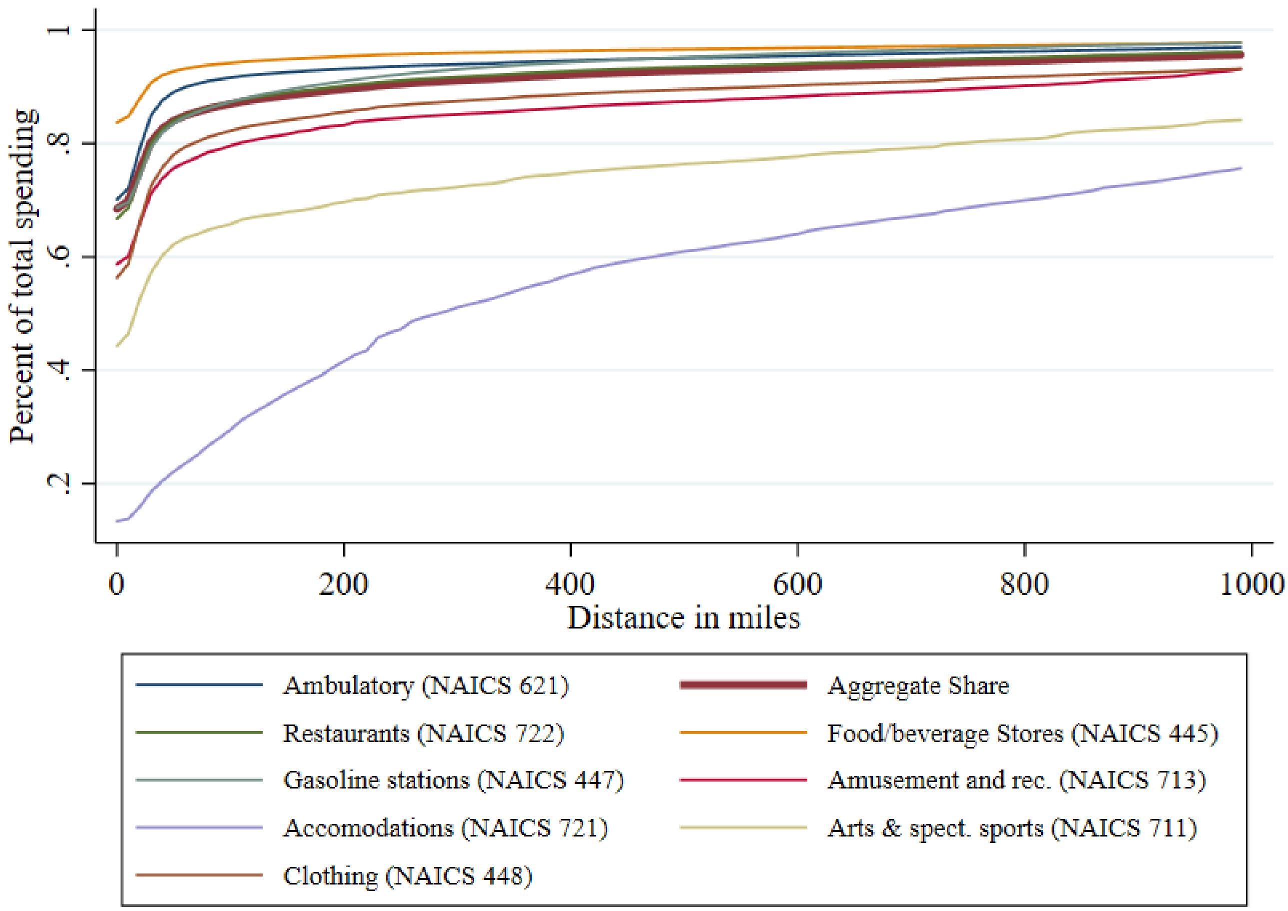
Counties may differ greatly in how much spending flows in and out of them, and the net difference may not be symmetric. We summarize the share of net flows by calculating the total exports (i.e., firm revenues from consumers outside of the county), minus imports (i.e., the total amount of revenue from consumers leaving the county), divided by the total amount of final consumption sold in the county. Figure 3 shows the distribution of net exports across the United States, both unweighted and weighted by the final consumption sold in the county. Figure 3 shows a large variation across the United States, especially for more rural counties, which are more represented in the unweighted distribution.

Next we show this distribution in the form of a map, with Figure 4 showing the distribution of net export shares across the United States with darker shades of red indicating a high net export share, while darker shades of blue indicate a higher import share. Here we see many expected patterns, including high export shares from places like Nevada and Hawaii, which are

[19] We truncated the distribution at 1,000 miles to better highlight the differences across industries.

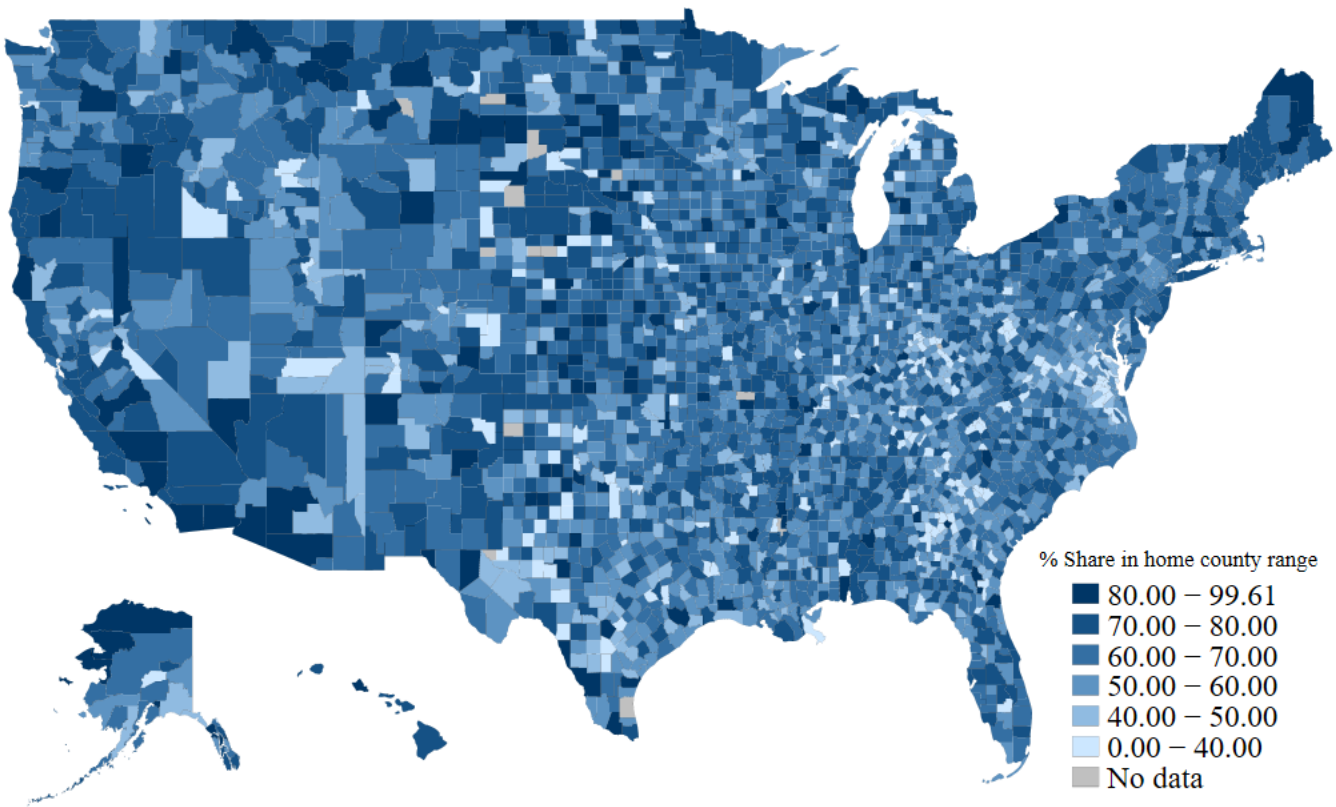
[20] We construct the same figure based on firm revenue share occurring in the home county, but it essentially shows the same pattern, in which most consumption occurs locally in more populated areas of the country.

Figure 1: Cumulative Distribution of Spending by Distance, Truncated at 1,000 Miles



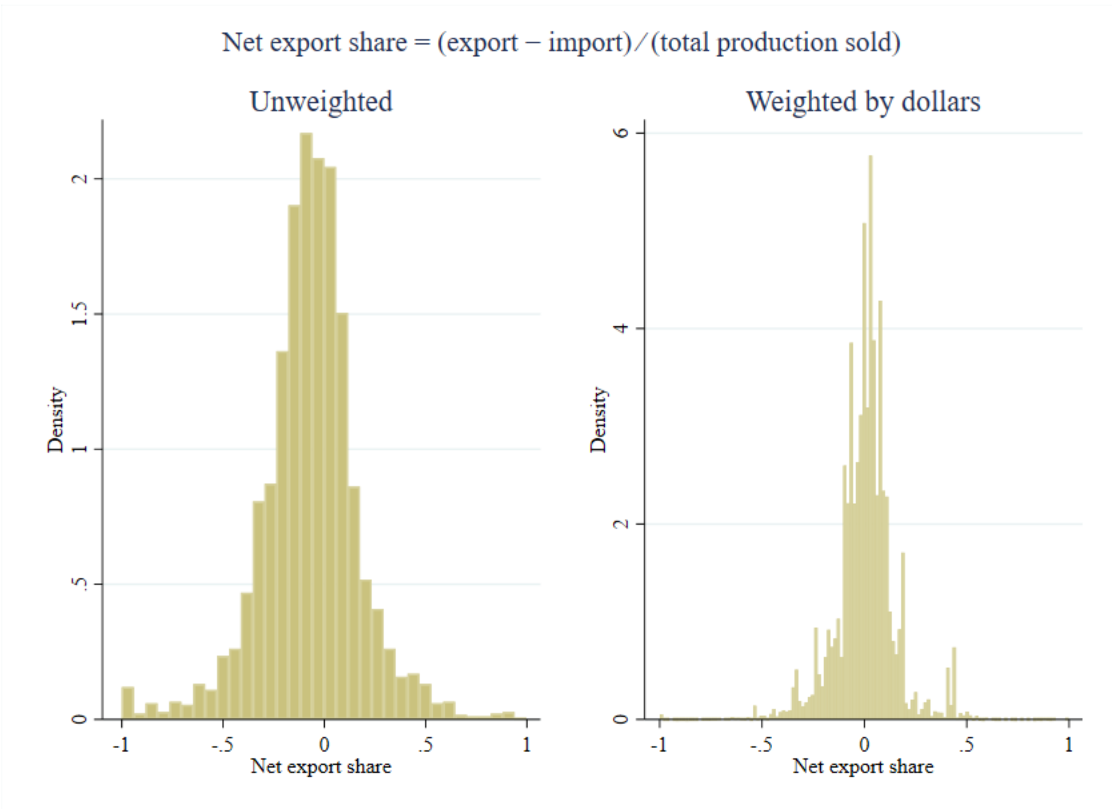
Notes: The cumulative spending is calculated for each NAICS category based on the total share of spending occurring within a distance radius of the merchants location where the location in each county is determined by the population centroid of the county. The figure shows 9 of the 15 NAICS categories in our data. Additional details by industry are in Table A3 of the appendix. Spending tends to be more local for food/beverage stores and ambulatory services, whereas for accommodations and arts and spectator sports it tends to have a greater share of revenue coming from more distant locations.

Figure 2: Share of Consumer Consumption in Home County



Notes: For each county we use all 15 NAICS categories and spending flow estimates for all counties to calculate the total spending by consumers in their home county and the total spending by consumers across all counties. We then take the ratio of home county consumption to total consumption. Darker shaded areas indicate more consumption is occurring in a consumer's home county. In general, more rural areas tend to have lighter shading as consumers tend to travel to consume, while more urban areas have darker shading.

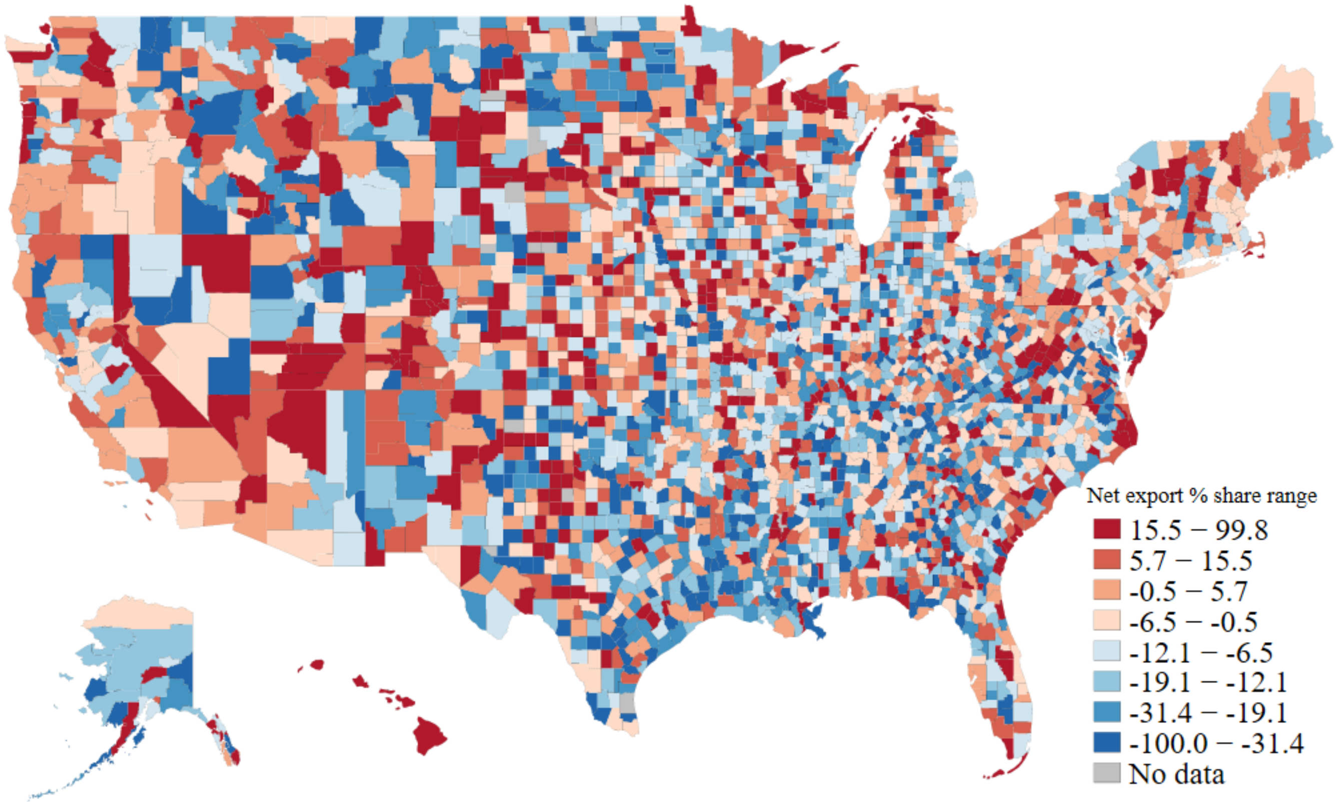
Figure 3: Distribution of Net Export Share



Notes: The net export share of each county is calculated as total exports (i.e., firm revenues from consumers outside of the county), minus imports (i.e., the total amount of revenue from consumers leaving the county), divided by the total amount of final consumption sold in the county. The distribution has been winsorized at -1 to avoid the long tail of rural counties that import most of their consumption.

Figure 4: Distribution of Net Export Share in the United States

Red – high export share Blue – high import share



Notes: The net export share of each county is calculated as total exports (i.e., firm revenues from consumers outside of the county), minus imports (i.e., the total amount of revenue from consumers leaving the county), divided by the total amount of final consumption sold in the county. Positive values indicate higher net export share and are shown in red and negative values indicate lower net export share and are shown in blue. Top tourist destinations e.g. Nevada and Hawaii with high export shares are shown in dark red, as expected. and more remote counties with high import shares are shown in dark blue.

top tourist destinations. Overall, these patterns in Figures 3 and 4 highlight the idea that counties are interconnected through consumption, indicating the potential importance of across-county consumption patterns.

4 Consumption Flow Accounting: A Simple Test of Correlation

The level of spending by consumers (i.e., consumption) that reside 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 (1).

$$\begin{aligned} \text{Household Consumption} =& \text{Final Product Sold} - \text{Export of Consumption} \\ &+ \text{Imports of Consumption} \end{aligned} \tag{1}$$

We use this basic accounting relationship to both test the validity of the data and also highlight 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 the empirical measure of consumption on the left hand side is based on an independent source. Therefore, empirically estimating this relationship provides an external validity check on the data and this accounting relationship.

Moving from left to right, 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 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 (1) 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

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

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 (1), we can estimate a simple regression model to test the accounting relationship:

$$\begin{aligned}\text{Household }\widehat{\text{Consumption}}_{j,t} =& \beta_1(\widehat{\text{Final Product Sold}}_{j,t}) - \beta_2(\text{Exports of }\widehat{\text{Consumption}}_{j,t}) \\ &+ \beta_3(\text{Imports of }\widehat{\text{Consumption}}_{j,t}) + \epsilon_{j,t}\end{aligned} \tag{2}$$

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 2002 to 2017, but with different coefficients for each year. The coefficient for each year is shown in

Figure 5. 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.

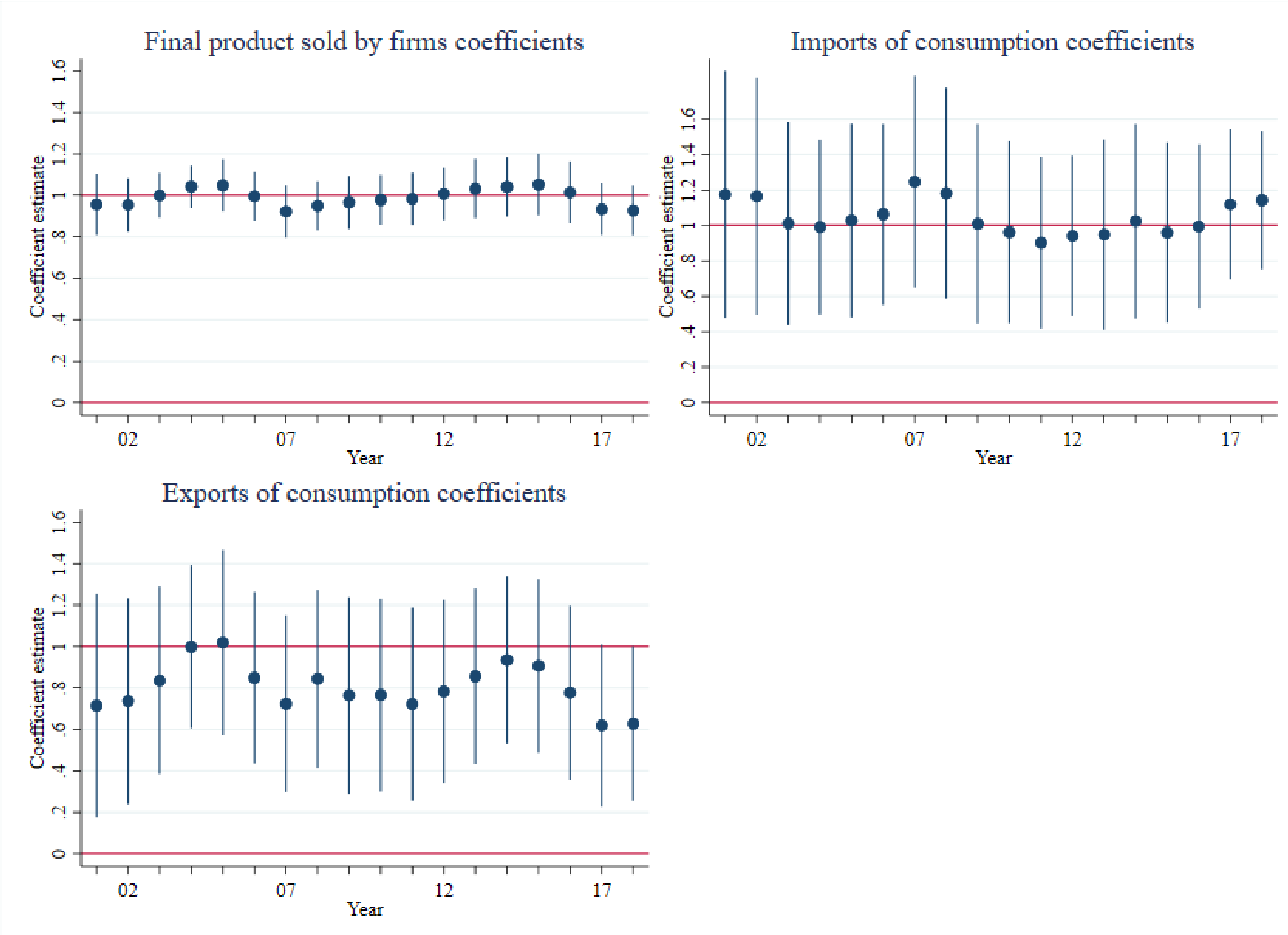
We find this strong relationship despite the possibility of measurement error entering the equation from multiple sources. In particular, there may be measurement error from assuming shares $S_{i,k,n}$ are constant across years, from the Fiserv data measurement error, or from assuming homothetic preferences across counties. 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 Great Recession. 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 Great Recession, 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 2007, rather than use observed spending flows in 2015.

5 Empirical Application: The Case of the Great Recession

In this section we re-examine the Great Recession and the effect of housing wealth on spending and employment across areas. We specifically look at the effects of the recession on aggregate spending and employment for firms. We focus on firms, rather than consumers, as the spending flow information from Fiserv is based on firm-level data, and it also allows us to analyze the different components of housing wealth shocks affecting firms. For instance, we can look at the

Figure 5: Regression Coefficients from Accounting Tests Across Years



Notes: This figure shows the coefficient estimates from the regression equation 2. 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.

effect of housing wealth changes from consumers that reside in the same county as the firm, as well as housing wealth changes from the export of consumption to consumers that reside outside the county.

Following the specification of Mian et al. (2013) and Mian and Sufi (2014), growth rates are computed as percent changes between years t and $t-2$

$$\Delta Y_{j,t} = \frac{Y_{j,t} - Y_{j,t-2}}{Y_{j,t-2}}$$

where $t = 2009$ is our main specification. The paper by Mian and Sufi (2014) focuses on the 2007 to 2009 period, but the paper by (Mian et al., 2013) focuses on the 2006 to 2009 period. Given that the Great Recession did not start until December 2007, we use 2007 as the base year for both our spending and employment analysis.

The variable $\Delta Y_{j,t}$ is either the growth rate in spending or employment. For our main specification, the 15 NAICS categories included in both the spending and employment estimates, $\Delta Y_{j,t}$, corresponds to the same NAICS categories used in the flow estimates.[21]

5.1 Weighting Housing Wealth Change by Spending Flows

Our base measure of housing wealth change for consumers residing in county i is ΔHNW_i. Assuming that consumption does not cross county borders, then the wealth change relevant for firms in county j is then ΔHNW_i where $i = j$.

The hypothesis in this paper is that the effect of the change in housing wealth is not constrained to county borders. To distribute housing wealth shocks to firms more accurately, we use an aggregate measure of consumption flow across all industries in our data based on where consumers reside. The aggregate expenditure flows are measured as the share of revenues coming from each industry, weighted by the industry spending in the county

$$S_{i,j}^{AGG} = \frac{\sum_{\forall n \in I} R_{j,n} . S_{i,j,n}}{\sum_{\forall n \in I} R_{j,n}}$$

This share, $S_{i,j}^{AGG}$, better captures the likely or potential consumers from location i for firms located in county j. For examples, if 60 percent of a firms revenue in county A comes from the home county A, $S_{i=A,A}^{AGG} = 60\%$, then we should expect changes in the wealth of those potential consumers in A to account for around 60 percent of the total effect. The remaining 40 percent

[21] As a robustness check and for comparison, we have also estimated spending, employment and spending flow estimates focusing only on the non-tradable categories, as defined by Mian et al. (2013) and Mian and Sufi (2014). We obtain estimates very similar to those shown here. Assuming our spending flow estimates are more broadly representative of spending flows more generally, we can expand the number of industry categories included in the employment and spending estimates.

would be from exports (i.e., consumption from consumers that reside outside of the county).

Taking these shares as fixed over time, the housing wealth change that is more relevant for firms in county j is then:

$$\Delta HNW_j^{FLOW} = \sum_{\forall i \in C} (\Delta HNW_i).S_{i,j}^{AGG} \tag{3}$$

Continuing with the example, suppose the local housing decline was 20 percent in the home county, A, that has 60 percent of the potential consumers, but just a 2 percent decline for counties outside of the home county, then the associated change for firms located in county A would be $\Delta HNW_A^{FLOW} = -20\% \cdot 60\% + -2\% \cdot 40\% = -12.8\%$.

This can be decomposed into two components of the housing wealth change – one measure from consumers that reside in the same county as the firm, and another measure from consumers outside of the county: $\Delta HNW_j^{FLOW} = \Delta HNW_j^{Home} + \Delta HNW_j^{Export}$. More specifically these can be measured as

$$\Delta HNW_j^{Home} = (\Delta HNW_{i=j}).S_{i=j,j}^{AGG}$$

and also a separate measure from consumers that reside outside the county

$$\Delta HNW_j^{Export} = \sum_{\forall i \neq j \in C} (\Delta HNW_i).S_{i,j}^{AGG}$$

For clarity, we calculate each of these components for the hypothetical example in Table 2.

The regression we analyze then takes the form:

$$\Delta Y_{j,t} = \beta_1 f(\Delta HNW_j, S_{i,j}^{AGG}) + \beta_2 X_{j,t} + \epsilon_{j,t} \tag{4}$$

where $f(\Delta HNW_j, S_{i,j}^{AGG})$ is a function of housing wealth changes and across-market spending flows. We examine two types of housing wealth measures: 1) those that ignore across-county consumption flows ΔHNW_j, and 2) those that use the across-county consumption flows by including ΔHNW_j^{FLOW} or by including both ΔHNW_j^{Home} and ΔHNW_j^{Export}.

As mentioned previously, the dependent variable, $\Delta Y_{j,t}$, will be either changes in spending

Table 2: Hypothetical Example County A

Home Share	60%
Export Share	40%
Home Housing Price Change	-20%
Export Housing Price Change	-2%

Calculations of ΔHNW

$$\Delta HNW_A^{FLOW} = -20\% \cdot 60\% + -2\% \cdot 40\% = -12.8\%$$
$$\Delta HNW_A^{Home} = -20\% \cdot 60\% = -12\%$$
$$\Delta HNW_A^{Export} = -2\% \cdot 40\% = -0.8\%$$

Note: The table contains hypothetical numbers to demonstrate how the housing net wealth change variable is calculated.

or employment. The first differencing in the estimation essentially makes this a difference-in-difference analysis, comparing spending and employment changes in areas that are more or less affected by housing wealth changes. The key controls included in the estimation are 2-digit industry shares in each county that account for the general growth rate of different sectors over this time period. The inclusion of industry shares mitigates the potential endogeneity concern that industry structure could be associated with changes in housing wealth.

This specification is an ordinary least squares (OLS) regression model. The advantage of the OLS model is that it directly shows the correlation in the housing wealth shock on across-county spending and employment. Arguably the spending flows help to address some of these endogeneity concerns. The housing wealth change that affects firms is not necessarily specific to the firm's county, introducing plausibly exogenous variation in housing fluctuations from potential consumers that reside outside the county in which the firm is located. However, there is still the possibility that the estimates are affected by endogenous factors. For instance, employment declines could cause a downward shift in housing prices.

We focus on the OLS estimates as our main results because they are relatively simple and the results are quite similar to three alternative identification strategies that address endogeneity. As a first strategy, we include commuting zone fixed effects. The commuting zone fixed effects serve two purposes: (1) they help control for reverse causality by capturing general changes in the labor market activity in the area; and (2) they demonstrate that not all of the important variation is happening at a broader geographic market. The next two methods involve applying both panel and instrumental variable (IV) specifications. The panel model helps to control for changes in growth specific to each county leading up to the Great Recession. The IV strategy applies the same method as Guren et al. (2020), which is described in greater detail below.

Finally, researchers may be concerned with the assumption of stable spending flow patterns across years may be violated and affect our estimates. In the appendix we describe a method of relaxing this assumption by forming a prediction of cross-county spending flows in 2007 using a flexible conditional logit model based on observable variables in 2015 (e.g., spending at firms and household income) and corresponding information from 2007. We estimate the predicted shares based on 2015 data and save the fitted values and parameter estimates. Next, we substitute the 2015 variables with the corresponding variables from 2007. Finally, using the fitted values of the model, we predict the spending shares based on the variables from 2007. These alternative spending flows are then used to weight housing price changes, as previously described.

6 Results

The first set of regression results are shown in Table 3. The first specification (1) uses the housing wealth change that is in the same county as the firm is located, which ignores spending flows. The effect of the housing wealth change on spending is positive and significant, as expected and consistent with previous work, with an elasticity of 0.16. If housing wealth declines by 10 percent, there is a 1.6 percent reduction in spending. In specification (2) we form our preferred specification that includes the weighted consumption flows, which also shows a positive and significant coefficient, but the magnitude is about 25 percent larger with an elasticity of around 0.19.

To compare this estimate to other work in the literature, we convert the elasticity of spending from changes in housing wealth (i.e., 0.16 and 0.19) to a marginal propensity to consume out of housing wealth by dividing these elasticities by the ratio of housing wealth to consumption, which we estimate to be 2.47.[22] The marginal propensity to consume based on the estimates without the flows is 6.4 cents on the dollar. Our preferred specification (2) indicates a value of 7.7 cents on the dollar, which matches closely with the estimate from Mian et al. (2013) of around 7.2 cents on the dollar. Our estimates are surprisingly similar given that many aspects of our data and analysis are distinct. For instance, our estimates are based on over 3,000 counties, while they looked at 900; we use different spending estimates based on the EC; and we adjust for consumer location using across-county spending flows.[23] These estimates are based on OLS regressions, but in our robustness section we show that these estimates correspond quite closely to our IV and panel estimates, as well as alternative specifications including commuting zone fixed effects.

We include additional specifications to demonstrate the economic importance of including spending flows. The third specification (3) presents a test of the relative importance of these two alternative measures, which includes both the net housing wealth change variable with and without the spending flow weights. The measure of the net housing wealth change that ignores the flows, appears to be statistically insignificant, while the measure of the net wealth change with the flows is positive and statistically significant. This indicates that the estimates with the associated weighted spending flows is producing a more accurate measure of the associated housing wealth shock. In other words, all of the explanatory variation loads onto the explanatory variable that includes the flows, which suggests it is the better measure. Specification (4) includes the net housing wealth effect that ignores the flows, but also includes two flow weighted measures: the home net housing wealth effect and the export net housing wealth effect. The two flow weighted estimates are again significant, but the estimates without weighted flows are insignificant. The

[22] The elasticity captures the percent change in spending from a percent change in housing prices. To arrive at a dollar change in spending from a dollar change in housing wealth, we divide the elasticity by housing wealth and multiply it by the level of consumption following Guren et al. (2020). We estimate the value of the housing spending based on the market value of owner-occupied real estate from the Flow of Funds and we estimate the value of consumption based on total personal consumption expenditures net of housing and utilities from the Bureau of Economic Analysis. We calculate the average of the consumption and housing value components over the period 2000–2019 and then form the ratio.

[23] Our results are also similar in range to Di Maggio et al. (2020) that examines the MPCH based on stock returns and find estimates of 5 cents on the dollar or more. Aladangady (2017) estimates a MPCH based on microdata of 4.7 cents for homeowners and finds no effects for renters. Based on a homeownership rate of 65 percent, this corresponds to an MPCH of 3.1 cents overall. Guren et al. (2020) find a MPCH of around 2.4 cents on the dollar looking over a longer time horizon and different geographic market. The Guren et al. (2020) estimates are also based on employment, rather than spending, which we find produces a slightly lower implied elasticity. The estimates in Guren et al. (2020) are also not directly comparable as they focused specifically on retail, while we've included additional industries.

last specification (5) is the same as specification (4), but excludes the unweighted housing wealth change. The results show positive and significant effects of changes in housing wealth on spending, whether it is from an export county or import county. The magnitude of the effect appears to be slightly higher from net housing wealth changes from exports relative to changes in net housing wealth from the home location, but we cannot reject the hypothesis that the coefficients are equal.

Table 3: Housing Wealth Change on Spending Growth

	(1) % Chg. Spend	(2) % Chg. Spend	(3) % Chg. Spend	(4) % Chg. Spend	(5) % Chg. Spend
Δ HNW (No Flow)	0.158***		-0.0888	-0.0741	
	(0.0196)		(0.0865)	(0.0830)	
Δ HNW (Total Flow)		0.191***	0.295***		
		(0.0232)	(0.101)		
Δ HNW (Home)				0.269***	0.179***
				(0.0957)	(0.0253)
Δ HNW (Export)				0.322**	0.256***
				(0.120)	(0.0793)
Observations	3063	3062	3062	3062	3062

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

Note: The table presents results from a linear regression estimate of the change in spending for 15 select industries in the county from 2007 to 2009 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 two digit industry employment share by county variables as controls.

Table 4 is the same as Table 3, but examines the effect on employment as a dependent variable rather than spending. The magnitude of the effect is smaller, with an elasticity of 0.11 in specification (1) without using spending flows. Similar to the spending estimates, the magnitude of the estimate increases with the incorporation of the spending flows in specification (2). When both measures of housing wealth change are included together in specification (3), the measure that incorporates spending flows remains significant, while the measure that excludes the spending flows is insignificant. Interestingly, employment is affected more by export housing wealth changes relative to changes in the home market (specifications (4) and (5)).

The result of our main specification (2) is similar to Mian and Sufi (2014) where the housing wealth effect on employment that they observe implies estimates of MPCH of between 4.1 and 7.3

cents on the dollar according to Guren et al. (2020), while our main estimate implies an MPCH of 5.9 cents on the dollar.

Table 4: Housing Wealth Change on Employment Growth

	(1) % Chg. Emp.	(2) % Chg. Emp.	(3) % Chg. Emp.	(4) % Chg. Emp.	(5) % Chg. Emp.
Δ HNW (No Flow)	0.119***		-0.148**	-0.133***	
	(0.0200)		(0.0575)	(0.0476)	
Δ HNW (Total Flow)		0.145***	0.318***		
		(0.0237)	(0.0805)		
Δ HNW (Home)				0.293***	0.130***
				(0.0620)	(0.0193)
Δ HNW (Export)				0.345***	0.227**
				(0.112)	(0.0903)
Observations	3109	3108	3108	3108	3108

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

Note: The table presents results from a linear regression estimate of the change in employment for 15 select industries in the county from 2007 to 2009 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 employment 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 2-digit industry employment share by county variables as controls.

6.1 Regression by Export Quartile

All of the analysis above relies on interactions of spending flows and housing wealth changes. In this section, we highlight the importance of the flows by discretely categorizing counties into export quartiles. If the consumption flows are meaningful, then we should expect the export housing wealth changes to have larger effects in the high-export quartile and to have less effect in the low-export quartile. Similarly, we should expect the home wealth change to have larger effects in those counties that export less spending. To perform this exercise, we construct a measure of average housing wealth change from consumers that reside outside of the county, and another measure for the average net wealth change from the home location.

The average net wealth shock from the home location is the average home wealth shock divided by the share of spending from the home location, which simplifies to the housing wealth change that excludes flows:

$$Average\Delta HNW_j^{Home} = \frac{\Delta HNW_j^{Home}}{S_{i=j,j}^{AGG}} = \frac{\Delta HNW_{i=j}.S_{i=j,j}^{AGG}}{S_{i=j,j}^{AGG}} = \Delta HNW_j$$

Returning to our previous example for county A, this would be the housing wealth decline in the home county, which was equal to 20 percent.

The average wealth change from outside the county is just the export housing wealth change divided by the export share:

$$Average\Delta HNW_j^{Export} = \frac{\Delta HNW_j^{Export}}{\Sigma_{\forall i\neq j\in C} S_{i,j}^{AGG}} = \frac{\Sigma_{\forall i\neq j\in C}(\Delta HNW_i).S_{i,j}^{AGG}}{\Sigma_{\forall i\neq j\in C} S_{i,j}^{AGG}}$$

In our previous example for county A, this average would be the average housing wealth decline outside of the home county, which was equal to 2 percent.

Both of these measures are simply average measures of housing wealth changes across their potential consumers, which ignore the share of consumption coming from outside or inside the county, which were both 50 percent in our example involving county A. In the county A example, if the potential consumers are primarily from the home county, say with a 90 percent share of spending, rather than 50 percent, then the home price decline of 20 percent should be more salient. However, if potential consumers are primarily from outside the home county, say a 10 percent share of spending coming from the home county, then the home price decline of 2 percent should be more salient.

The estimates for spending by export quartile are shown in Table 5. The estimates show that for higher export counties, the housing wealth changes are significantly more important. As expected, in the fourth quartile, the export coefficient is significant and also larger in magnitude, as would be expected, given that a greater share of the change in housing wealth is coming from consumption exports. The magnitude of the net housing wealth effect from exports declines for those counties in which exports are lower, as we should expect. For the highest export quartile, the home net wealth shock is statistically insignificant, but becomes statistically significant for the lowest two quartiles, in which most of the consumption occurs locally. Table 6 shows a very similar pattern, but for employment.

These estimates show that for high export counties, focusing only on local shocks to consumers can be highly misleading.

Table 5: Housing Wealth Change from Home and Export Counties on Spending Growth: By Quartile of Export Share

	(1) Quartile 4	(2) Quartile 3	(3) Quartile 2	(4) Quartile 1
Δ HNW (No Flow)	0.0266	0.0325	0.0752**	0.193***
	(0.0451)	(0.0497)	(0.0350)	(0.0444)
Average Δ HNW (Export)	0.252***	0.206***	0.137*	-0.0301
	(0.0900)	(0.0698)	(0.0707)	(0.101)
Observations	754	766	772	770

* 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 2007 to 2009 on the change in housing wealth variable. The housing wealth variable in the first row is the housing wealth change of consumers that reside in the same county as the firm, while the second variable is the average housing wealth change by potential consumers that reside outside of the county. The specifications across the columns differ based on the selected sample, with quartile 4 being those counties with the highest quartile of spending coming from outside the county and quartile 1 being the lowest quartile of spending coming from outside of the county. 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 2-digit industry employment share by county variables as controls.

6.2 Heterogeneous Effects By Industry Type and Distance

The focus of our analysis has been on overall spending and employment across the included categories in our data, but it is not necessarily the case that all industries are equally affected. This may be due to a variety of factors. The housing price decline may impact both the type of goods and services that are consumed, and also whether consumers decide to travel to consume. To examine the heterogeneity by industry, we divide our select NAICS categories into three general industry groups: (1) home industries, where consumers travel less to consume; (2) export industries, where consumers often travel to consume; and (3) intermediate industries, that fall between the other two categories. The industries that are categorized as home industries include categories such as food and beverage stores and general merchandise stores; intermediate industries include car repair and ambulatory health care; and export industries include accommodations, bars and

Table 6: Housing Wealth Change from Home and Export Counties on Employment Growth: By Quartile of Export Share

	(1) Quartile 4	(2) Quartile 3	(3) Quartile 2	(4) Quartile 1
Δ HNW (No Flow)	-0.00355	0.0514	0.0789**	0.0897***
	(0.0318)	(0.0358)	(0.0327)	(0.0212)
Average Δ HNW (Export)	0.231***	0.157***	0.0768	0.0916
	(0.0634)	(0.0481)	(0.0487)	(0.0640)
Observations	773	779	778	778

* 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 2007 to 2009 on the change in housing wealth variable. The housing wealth variable in the first row is the housing wealth change of consumers that reside in the same county as the firm, while the second variable is the average housing wealth change by potential consumers that reside outside of the county. The specifications across the columns differ based on the selected sample, with quartile 4 being those counties with the highest quartile of spending coming from outside the county and quartile 1 being the lowest quartile of spending coming from outside of the county. We exclude outliers where the absolute value of the change in employment exceeds 50 percent. Standard errors are in parentheses and are clustered by state. Estimates are weighted by 2007 population levels. All estimates include 2-digit industry employment share by county variables as controls.

restaurants, spectator sports and performing arts. Each category accounts for about a third of the total spending in our data. For each industry category, we estimate spending, employment, and consumption flows specific to those categories and estimate the effects identical to before, but specific to the selected industry group. Additional discussion regarding these categories and how they are selected is included in the appendix section A.3 and relevant descriptive statistics in Tables A3 and A4 of the appendix.

Table 7 shows effects of the housing wealth change by industry, where the first three columns ignore spending flows, and the last three columns apply the spending flows specific to each industry group. Similar estimates are shown for employment in Table 4. As before, the estimates that do not take account of flows are systematically lower than those that do account for flows, especially for the high export industries. The high export industries appear to be much more affected by the housing price change relative to either the home industries or intermediate industries, with the effect of the housing wealth decline on spending for export industries nearly double the magnitude of the other two categories. This perhaps indicates more discretionary spending for export industries. The housing wealth effect on employment is also greater for these export industries, although the magnitude of the difference across categories is smaller. In both estimates, the intermediate category industries are least affected by the housing wealth change, perhaps because they include categories such as car repair and ambulatory health care, which are consumption categories where consumers may be relatively inelastic.

Table 7: Housing Wealth Change on Spending by Industry

	(1) Home Industries	(2) Intermediate	(3) Export Industries	(4) Home Industries	(5) Intermediate	(6) Export Industries
Δ HNW (No Flow)	0.135***	0.106***	0.198***			
	(0.0276)	(0.0173)	(0.0316)			
Δ HNW (Home Ind. Flow)				0.150***		
				(0.0306)		
Δ HNW (Inter. Ind. Flow)					0.120***	
					(0.0189)	
Δ HNW (Export Ind. Flow)						0.274***
						(0.0399)
Observations	3020	2991	3053	3020	2991	3053

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

Note: The table presents results from a linear regression estimate of the change in spending in the county from 2007 to 2009 on the change in housing wealth variable. Each regression is based on spending and spending flows that are specific to the corresponding industry group. The columns provide estimates for different industry groupings, including high export industries, home industries, and intermediate industries. The first three columns ignore the consumption flow weights, while the last three columns apply the consumption flow weights that correspond to the industry grouping. We exclude outliers where the absolute value of the change in spending exceeds 50 percent. The first three columns ignore consumption flows, while the last three columns apply consumption flows specific to the industry group. Standard errors are in parentheses and are clustered by state. Estimates are weighted by 2007 population levels. All estimates include 2-digit industry employment share by county variables as controls.

Another dimension to explore the heterogeneity of these effects is based on the distance of the potential consumer population. To investigate the effect of the potential consumers' distance on the change in spending and employment, we calculate the housing wealth change for four distinct distance categories: (1) the housing wealth effect from potential consumers that reside in the same county as the firm; (2) the housing wealth effect from potential consumers that reside outside of the county, but within 100 miles of the firm's county; (3) the housing wealth effect from potential consumers that are more than 100 miles away but less than 500 miles; and (4) the housing wealth effect from potential consumers that are more than 500 miles away.[24] The results

[24]All distances are based on the population centroid of each county. The calculation is identical to before,

Table 8: Housing Wealth Change on Employment by Industry

	(1) Home Industries	(2) Intermediate	(3) Export Industries	(4) Home Industries	(5) Intermediate	(6) Export Industries
Δ HNW (No Flow)	0.128***	0.0887***	0.133***			
	(0.0211)	(0.0240)	(0.0220)			
Δ HNW (Home Ind. Flow)				0.141***		
				(0.0227)		
Δ HNW (Inter. Ind. Flow)					0.104***	
					(0.0274)	
Δ HNW (Export Ind. Flow)						0.186***
						(0.0284)
Observations	3068	3082	3075	3068	3082	3075

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

Note: The table presents results from a linear regression estimate of the change in employment in the county from 2007 to 2009 on the change in housing wealth variable. Each regression is based on employment and spending flows that are specific to the corresponding industry group. The columns provide estimates for different industry groupings, including high export industries, home industries, and intermediate industries. The first three columns ignore the consumption flow weights, while the last three columns apply the consumption flow weights that correspond to the industry grouping. We exclude outliers where the absolute value of the change in employment exceeds 50 percent. The first three columns ignore consumption flows, while the last three columns apply consumption flows specific to the industry group. Standard errors are in parentheses and are clustered by state. Estimates are weighted by 2007 population levels. All estimates include 2-digit industry employment share by county variables.

show that the wealth change of potential consumer's 100 miles or more away from the home location, have a much larger marginal effect on spending. In particular, the effects are about three times larger than the effect of a housing wealth change in the home location. This larger effect from more distant consumers may be due to two possible factors. First, travel may represent discretionary spending that is more likely to be cut as wealth declines. Second, there may be a larger multiplier effect from export, relative to spending changes from consumers that reside in the area. Without additional information it may be difficult to distinguish between these two potential explanations. For employment, we find that the distance from 100 to 500 miles has a disproportionately large effect, but find no significant effect on housing wealth changes from potential consumers more than 500 miles away.

but the export effect is broken out by distance. For example, the calculation for the housing wealth change from consumers outside the county, but less than 100 miles away is: $\Delta HNW_j^{Export \leq 100miles} = \sum_{\forall i \neq j \in C} (\Delta HNW_i) \cdot (distance_{i,j} \leq 100miles)$

Table 9: Housing Wealth Changes on Spending and Employment by Distance

	(1) Effect of Spending By Distance	(2) Effect on Employment By Distance
Δ HNW (Home)	0.176***	0.126***
	(0.0253)	(0.0176)
Δ HNW (Export: ≤ 100 Miles)	0.144	0.167**
	(0.0945)	(0.0771)
Δ HNW (Export: >100 & ≤ 500 Miles)	0.861***	0.588**
	(0.257)	(0.238)
Δ HNW (Export: >500 Miles)	0.573***	0.166
	(0.178)	(0.264)
Observations	3117	3117

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

Note: The table presents results from a linear regression estimate of the change in spending or employment for 15 select industries in the county from 2007 to 2009 on the change in housing wealth variable(s). The specifications are similar to those in Table 3 and 4, but the export housing wealth variables is broken up by distance, as described in the text. We exclude outliers where the absolute value of the change in spending or employment exceeds 50 percent. Standard errors are in parentheses and are clustered by state. Estimates are weighted by 2007 population levels. All estimates include 2-digit industry employment share by county variables as controls.

6.3 Effects Within and Across commuting zones

It has long been recognized that counties may not represent a local labor markets, as workers commute to their jobs across county borders. As an alternative to using counties, Tolbert and Sizer (1996) define commuting zones, which groups counties in a way to better capture the local labor market areas.

Therefore, one argument against analyzing economic effects at the county level is that the main economic effects could be common across a larger geography, such as a commuting zone, so that little is gained by disaggregation. Moreover, it is also possible that using a larger geographic area would have fewer imports and exports of consumption, reducing the importance of cross-county spending flows. To test whether these effects occur at a more aggregate commuting zone level, we include commuting zone fixed effects, to account for changes in a larger and commonly used geographic unit. If all of the change in spending or employment is common across commuting zones, then the inclusion of these fixed effects will eliminate the relationship between housing wealth changes and changes in spending and employment.

However, if much of the variation is county-specific, then the inclusion of commuting zone fixed effects may serve an additional important purpose. Specifically, the commuting zone fixed effects offer a unique way to control for endogeneity that might occur through reverse causality, where the decline in the labor market may cause a decline in housing prices. If changes in the labor market are reflected at the commuting zone level —geographic areas designed to capture local labor market activity —then the inclusion of commuting zones will help control for potential endogeneity.

In this section we repeat previous estimates, but with the inclusion of commuting zone fixed effects. The results are shown Table 10, with results on spending shown in columns (1) to (4) and results on employment shown in columns (5) to (7). What is interesting about these estimates is that they look nearly identical to those presented in Tables 3 and 4. Similar to previous estimates, we find that accounting for spending flows appears to increase the magnitude of the estimates of housing wealth change on spending by a large margin. Also as before, the effects from the change in housing wealth come from both the home county, and also from export counties. Dividing the housing wealth changes from exports by distance in columns (4) and (7) we still find evidence of some significant effects from housing wealth changes more than 100 miles from the home location county, showing consumption effects crossing commuting zone borders. In addition to addressing potential endogeneity, these estimates demonstrate that there is important variation occurring within more aggregate geographic markets commonly used in the literature, as we identify the effects of housing wealth changes both within and across commuting zone markets.

6.4 Robustness Checks

Although we argue that the use of spending flows helps to address potential endogeneity concerns, the above specifications could still potentially be affected by endogeneity problems, as the decline in employment could be a cause, and not a result, of the housing wealth decline. We argue that the inclusion of commuting zone fixed effects is one method of addressing this endogeneity

Table 10: Housing Wealth Changes on Spending and Employment with Commuting Zone Fixed Effects

	(1) % Chg. Spend	(2) % Chg. Spend	(3) % Chg. Spend	(4) % Chg. Spend	(5) % Chg. Emp.	(6) % Chg. Emp.	(7) % Chg. Emp.
Δ HNW (No Flow)	0.151***						
	(0.0210)						
Δ HNW (Total Flow)		0.239***			0.133***		
		(0.0298)			(0.0205)		
Δ HNW (Home)			0.239***	0.237***		0.133***	0.133***
			(0.0298)	(0.0664)		(0.0205)	(0.0315)
Δ HNW (Export)			0.326***			0.220***	
			(0.0871)			(0.0601)	
Δ HNW (Export: ≤ 100 Miles)				0.212			0.219*
				(0.190)			(0.127)
Δ HNW (Export: >100 & ≤ 500 Miles)				0.630			0.274*
				(0.416)			(0.162)
Δ HNW (Export: >500 Miles)				0.840**			0.162
				(0.414)			(0.282)
Observations	3062	3061	3061	3062	3107	3107	3108

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

Note: The table presents results from a linear regression estimate of the change in spending or employment for 15 select industries in the county from 2007 to 2009 on the change in housing wealth variable(s). The specifications are similar to those in Tables 3 and 4, but the specifications include commuting zone fixed effects. We exclude outliers where the absolute value of the change in spending or employment exceeds 50 percent. Standard errors are in parentheses and are clustered by state. Estimates are weighted by 2007 population levels. All estimates include 2-digit industry employment share by county variables. All regressions in this table include commuting zone fixed effects, which are designed to capture local labor market activity, which may help to address potential reverse causality.

concern, and we find that our results remain similar to the OLS specification. Here we explore a two additional methods to address potential endogeneity.

One alternative is to estimate a panel model, which can reduce endogeneity by controlling for local factors affecting growth leading up to the Great Recession.

$$\Delta Y_{j,t} = \beta_1 f(\Delta HNW_j, S_{i,j}^{AGG}) \cdot (t = 2009) + \beta_2 X_{j,t} + \gamma_j + \tau_t + \Delta\epsilon_{j,t} \tag{5}$$

In addition to the 2007–2009 period, the panel model includes 2005–2007 and 2003–2005. The model includes the addition of a county-specific fixed effects γ_j that captures the unique growth factors associated with a particular county. The model also includes year fixed effects, τ_t, capturing national trends in growth rates over each period. The estimates also includes controls for 2-digit industry share interacted with the year to control for economic shocks specific to industries in the county. The estimates from the panel specification on spending and employment are shown in Table 11 with estimates on the change in spending in the first three columns and estimates on the change in employment in the last three columns. The results are qualitatively similar in many respects to the simple OLS estimates. The effect of net wealth on employment and spending is positive and the net wealth effects based on the flows are larger than those excluding the flows, by around 20 percent for both spending and employment. The effect on the housing wealth change from exports is positive and significant for both spending and employment.

Table 11: Panel Regression Model of Spending and Employment

	(1) % Chg. Spend	(2) % Chg. Spend	(3) % Chg. Spend	(4) % Chg. Emp.	(5) % Chg. Emp.	(6) % Chg. Emp.
Δ HNW (No Flow)	0.171***			0.111***		
	(0.0321)			(0.0239)		
Δ HNW (Total Flow)		0.189***			0.134***	
		(0.0439)			(0.0321)	
Δ HNW (Home)			0.184***			0.107***
			(0.0505)			(0.0387)
Δ HNW (Export)			0.218			0.278***
			(0.142)			(0.0970)
Observations	12201	12198	12198	12401	12397	12397

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

Note: The table presents results from a panel model estimating the change in spending or employment for 15 select industries in the county on the change in housing wealth variable(s). The panel model includes changes in spending for the years 2003–2005, 2005–2007, and 2007–2009. The panel models include year dummies and county-specific fixed-effects to control for trends specific to each county. Standard errors are in parentheses and are clustered by state. Estimates are weighted by 2007 population levels. All estimates include 2-digit industry employment share by county variables interacted with each year of the panel to allow for distinct industry-specific shocks in each year.

Even with a panel specification, there may be concerns of endogeneity that have been raised in previous research by Mian et al. (2013), Mian and Sufi (2014), and Guren et al. (2020). For instance, the shock to income or employment could have initiated the decline in housing prices in the area. The instrument used in Mian et al. (2013) and Mian and Sufi (2014) are based on estimates from Saiz (2010), capturing the housing supply elasticity for a subset of metropolitan statistical areas, but we are attempting to capture effects for all counties in the United States. Moreover, this instrumental variable strategy has been critiqued by Guren et al. (2020) and Davidoff (2016) as potentially being correlated with other city characteristics leading to potential biases. Therefore, we follow Guren et al. (2020), which uses a history of housing price data that captures systematic differences in exposure to regional price fluctuations. The basic idea behind the instrument is to identify those regions in the country that have a particularly strong response to national or regional fluctuations in price. Therefore, the instrument is based on the general price sensitivity in the county, and not on other local factors that may be occurring directly around the Great Recession event date.

Following Guren et al. (2020), we use historical information on local area housing price responsiveness to regional price movements to estimate instruments for the level of sensitivity in local markets to regional shocks. Using Zillow data from January 1996 to January 2020, we estimate the responsiveness of county-level housing prices to regional changes in housing prices. The estimated county-specific responsiveness to regional price movements is the instrument that we apply in our estimates. The spending flow data are used to weight the instrument across different counties in a way that corresponds to the associated variable. Additional details of the formation of this instrument are included in the appendix.

Tables 12 and 13 show alternative models that include IV specifications. Specification (1) includes an IV model that excludes accounting for spending flows, along with IV models and IV panel models that account for the cross-market spending flows. The estimates are again qualitatively similar to those found using the simple regression models. We see the magnitude of the estimates show that accounting for spending flows, specification (2), exceed the estimates that do not include spending flows, specification (1). Specifications (4) and (5) apply the IV strategy to our panel estimates and we again obtain similar results.

We have also applied this instrumental variable strategy to our industry-specific estimates and estimates by distance and we obtain similar results to those reported in our OLS estimates above (see Appendix Tables A5 and A6).

Using the accounting relationship from equation (1), we argued that the consumption flows likely remained relatively stable over time. However, another potential concern for identification might arise if the spending shares changed substantially over time. As an alternative to applying the 2015 spending flows directly, in the appendix we estimate predicted spending flows in 2007 using information on income and spending by industry in 2007 and 2015. To predict 2007 shares, we first estimate the predicted shares based on 2015 data and save the fitted values and

Table 12: Instrumental Variable Regression Model for Spending

	(1) IV No Flow	(2) IV Flows	(3) IV Flows	(4) Panel IV Flows	(5) Panel IV Flows
Δ HNW (No Flow)	0.171***				
	(0.0209)				
Δ HNW (Total Flow)		0.206***		0.226***	
		(0.0242)		(0.0451)	
Δ HNW (Home)			0.203***		0.200***
			(0.0291)		(0.0520)
Δ HNW (Export)			0.221**		0.374**
			(0.102)		(0.147)
Observations	3063	3062	3062	12194	12194

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

Note: Standard errors are in parentheses and are clustered by state. Estimates are weighted by 2007 population levels. All estimates include 2-digit industry employment share by county variables. The instruments are constructed following the methodology of Guren et al. (2020) and are described in greater detail in the text and the appendix. The panel model includes changes in spending for the years 2003–2005, 2005–2007, and 2007–2009. The panel models include year dummies and county-specific fixed-effects to control for trends specific to each county. The panel model also includes 2-digit industry employment share by county variables interacted with each year of the panel to allow for distinct industry-specific shocks in each year.

parameter estimates. Next, we substitute the 2015 variables with the corresponding variables from 2007. Finally, using the fitted values of the model, we predict the spending shares based on the variables from 2007. A more detailed discussion is available in the appendix. Results using the 2007 predicted spending flows are reported in Tables A7 and A8. We find that the results using the predicted spending flows for 2007 are very close to the results using the 2015 spending flows.

As another robustness check on the estimates we re-estimate Tables 3 and 4, but include additional industry categories for our spending and employment estimates, including all non-tradable categories. The basic idea is that the spending flows may provide reasonable proxies for all economic activity between areas. We again find results very similar to those presented here. We have also estimated the model using only those non-tradable categories used in (Mian and Sufi, 2014) and obtain qualitatively similar results.

Table 13: Instrumental Variable Regression Model for Employment

	(1) IV No Flow	(2) IV Flows	(3) IV Flows	(4) Panel IV Flows	(5) Panel IV Flows
Δ HNW (No Flow)	0.121***				
	(0.0239)				
Δ HNW (Total Flow)		0.149***		0.156***	
		(0.0268)		(0.0340)	
Δ HNW (Home)			0.143***		0.130***
			(0.0263)		(0.0381)
Δ HNW (Export)			0.187**		0.307***
			(0.0938)		(0.0875)
Observations	3109	3108	3108	12396	12396

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

Note: Standard errors are in parentheses and are clustered by state. Estimates are weighted by 2007 population levels. All estimates include 2-digit industry employment share by county variables. The instruments are constructed following the methodology of Guren et al. (2020) and are described in greater detail in the text and the appendix. The panel model includes changes in spending for the years 2003–2005, 2005–2007, and 2007–2009. The panel models include year dummies and county-specific fixed-effects to control for trends specific to each county. The panel model also includes 2-digit industry employment share by county variables interacted with each year of the panel to allow for distinct industry-specific shocks in each year.

7 Economic Implications

We next evaluate the local economic effect of the change in housing wealth on spending and employment for the entire nation. We do this using estimates from specification (2) of Tables 3 and 4, which appear to produce estimates in a similar range to those based on numerous robustness checks, including the panel, IV and IV panel estimates.

Our estimates have implications regarding how firms are affected by economic shocks from both local and more distant potential consumers. We use the estimates reported in Tables 3 and 4 to measure how much of the effect on spending and employment is from potential consumers that reside in the same county and how much is from consumers that reside outside of the county. To conduct this decomposition, recall that the housing wealth variable can be decomposed into both a ”home” and ”export” component: $\Delta HNW_j^{FLOW} = \Delta HNW_j^{Home} + \Delta HNW_j^{Export}$. Next, we analyze the effect using the estimated coefficient β in specification (2) that is equal to 0.191 for spending and 0.145 for employment from Tables 3 and 4, respectively. For every county, j, we also have spending and employment levels for 2007, $Spend_{j,2007}$ and $Employment_{j,2007}$. The total spending effect across all counties in the U.S. is $\sum_{\forall jinC} \beta \cdot \Delta HNW_j^{FLOW} \cdot Spend_{j,2007}$. The home effect is $\sum_{\forall jinC} \beta \cdot \Delta HNW_j^{Home} \cdot Spend_{j,2007}$ and the export effect is $\sum_{\forall jinC} \beta \cdot \Delta HNW_j^{Export} \cdot Spend_{j,2007}$. Employment effects are calculated similarly.

We find the total effect on spending to be \$116 million, with 29 percent of the effect comes from potential consumers that reside outside of the county, and 71 percent from those consumers that reside in the same county as the firm. Performing an identical calculation for employment we find a total decline in employment of 663 thousand, again with 29 percent of the effect from outside the local market. The share of the effect outside of the local market is equal because the spending flows used are identical, and the β coefficient is assumed to be identical for both the home and export housing wealth changes. We can perform a similar calculation, but allow for the effects of housing wealth changes to be distinct for ΔHNW_j^{Home} and ΔHNW_j^{Export}, as in specification (5) in Tables 3 and 4. Using these values we find the spending effect from consumers that reside outside the local county accounts for 37 percent of the total effect and the same figure for employment is 42 percent.

We can perform similar calculations based on distance from the home location, using estimates from specification (2) in 3 and 4, where the coefficient is constrained to be the same across distances. Based on these estimates we find that around 13 percent of the effects of consumption and employment are from consumers that reside more than 100 miles from the home location. If we allow for differential effects depending on the distance of the potential consumer, as in Table 9, we find the economic effects from consumers over 100 miles away to account for over 29 percent of the spending and employment effects. All of these estimates suggest that across-market consumption link is an important determinant of local spending and employment and can span distant geographic markets.

Next, we contrast the total effects on spending and employment using the preferred specification (2) from Tables 3 and 4 with specification (1) from those same tables, which ignores spending flows. We compute the totals using the calculations previously described, but using the two distinct specifications. A summary of our estimates are reported in Table 14. As mentioned previously, when using specification (2), we find the total effect on spending and employment to be \$116 million and 663 thousand, respectively. These values indicate a decline in spending of 2.9 percent and decline in employment of 2.1 percent. The table also shows that the effects of housing wealth changes on spending and employment are understated when spending flows are ignored. The estimated decline in employment and spending, are 19 percent larger and 17 percent larger, respectively, when accounting for the across-county flows.

In addition to different effects on magnitude, there are also implications for the allocation of which firms are most affected. For instance, suppose county A has a large change in housing prices of 20 percent, but all of county A's consumption is from consumers that reside in county B. Without using the flows, the implied decline in spending and employment will entirely be attributed to county A, when they should not be. We capture the differential allocation of effects across counties by using coefficient estimates from specification (2), to normalize the magnitude of the effect, but calculate the decline in spending and employment based on the two different estimates of the housing wealth change. One estimate uses spending flows, ΔHNW_j^{FLOW}, and the second estimate ignores the spending flows, ΔHNW_j. To measure this difference, we calculate the absolute value of the difference in spending and employment, based on those two alternative measures. We then add up the absolute differences across all counties in the country. To obtain a percentage effect, we divide this total by full magnitude of the decline. For spending, the calculation is: $\frac{\sum_{\forall j \in C} \left| \beta_1 (\Delta HNW_j^{FLOW} - \Delta HNW_j) \cdot Spend_{j,2007} \right|}{\sum_{\forall j \in C} \beta_1 (\Delta HNW_j^{FLOW}) \cdot Spend_{j,2007}}$ and there is a parallel calculation for employment. We find a percent difference in allocation of over 11 percent for both employment and spending.

Even though around 30 percent of the effects on spending and employment are caused by housing wealth changes outside of the county, the effect on allocation is just 11 percent. This difference is caused by housing wealth changes that may move in similar directions. To see this, we return to the example in the last paragraph, where the change in spending for firms in county A are entirely from consumers that reside in county B. Now also suppose that county B has a change in housing prices of 20 percent. In this case, even though 100 percent of county A's consumption comes from county B, the allocation difference would be 0 since the change in housing wealth is identical across counties A and B.

Table 14: Measuring Local Economic Effects

Employment Effects (# of persons)			Spending Effects (in millions)		
		% Chg			%Chg
Total Labor in Sector	31,294,085		Total Revenues in Sectors	$3,999,576	
Labor Declined with Flows	663,075	2.1%	Spend Decline with Flows	$116,390	2.9%
Labor Declined with No Flows	555,815	1.8%	Spend Decline with No Flows	$99,308	2.5%
		%Diff			%Diff
Relative to No Flows Prediction			Relative to No Flows Prediction		
Additional Decline with Flows	107,259	19.3%	Additional Decline with Flows	$17,081	17.2%
Allocative Difference with Flows	75,779	11.4%	Allocative Difference with Flows	$13,189	11.2%

Note: The first row of this table shows the total employment and spending for these 15 industries in 2007. The second row computes the total change in employment and spending using specification (2) from Tables 3 and 4. The third row repeats the same calculation as row (2), but computes these changes based on specification (1) from Tables 3 and 4. The fourth row is computed as the second row minus the third row. The last row holds the magnitude of the effect constant and measures the difference in what counties are affected if flows are used or not. Details of this last calculation are provided in the text.

8 Conclusion

In this paper, we introduce a new data source based on card transaction data that provides estimates of cross-county spending flows for the U.S., providing a new consumption link across counties that has not previously been studied. We show net exports of consumption vary greatly across counties, and this has implications for how each county is affected by local economic shocks. We find that consumption in one county may have effects on firm revenues and employment across different geographic markets. Looking at the housing price decline from 2007 to 2009, we find that around 30 percent of the associated decline in spending and employment is caused by housing price declines from consumers that reside outside of the county. Depending on the specification used, the share of the effect coming from outside of the county could potentially be as high as 40 percent and much of the effect appears to come from geographic markets more than 100 miles away. We also find that estimates that ignore spending flows tend to understate the magnitude of the effects on both employment and spending.

The estimates in this paper establish the importance of the across-county link in consumption for local economic measurement, which has implications for policy design. The effect of local targeted policies on either firms or consumers may have broader effects outside of local markets, depending on the spending patterns of consumers.

More generally, the across-county consumption link is an important aspect of spatial economics that has received relatively little attention, likely due to data limitations Redding and Rossi-Hansberg (2017). There are many potential applications to the data constructed in this study. These data may be used to help understand the effects of local tax policies, income shocks to consumers, or policies that affect the population heterogeneously, such as the ACA. This data may also help in understanding the economic effects of the COVID-19 pandemic, where the typically stable spending flows studied here, were likely disrupted, potentially leading to large changes in spending and employment, especially for high export areas. In addition to these applications, these data may also be used to help define local consumption markets, akin to how labor markets are defined using commuting data to construct commuting zones. Across-county links in goods and factor markets have been shown to be empirically important, such as in the work by Monte et al. (2018), in which they examine labor demand shocks on employment elasticities using a general equilibrium framework. The across-county consumption link may be an important addition to this literature.

There are many potential avenues for improvements to our estimates. One area where additional work may be useful is e-commerce. This was not a limitation for our application over the 2007 to 2009 period, when e-commerce was a relatively small share of consumption, but this is an area of growing importance. Researchers may want to turn to alternative data sources to capture this aspect of spending. Also, in our work we excluded foreign spending to simplify the analysis, but it may be of particular interest in future work to better understand how foreign consumption spending can impact local markets. Finally, for our analysis we focus on a single cross-section in 2015. It may be of interest in future work to look at changes in spending flows and the determinants of across-county spending flows over time.

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A Appendix

A.1 Economic Census Receipts

The Geographic Area Series of the EC is collected every 5 years at detailed geographic and NAICS industry levels. The EC contains information on industry-level revenues which are used in this study to create measures of consumer spending. Our study focuses on county-level estimates for 15 industries that are important contributors to personal consumption expenditures, 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 **??** shows list of industries included in our analysis with their associated share of suppressed revenues to total revenues for each census year.[25] The level of these suppressions vary across industry, but in general they 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.)

A.1.1 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

[25] The rate of suppression is determined by comparing to unsuppressed national estimates.

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	1.8	3.0	2.0	2.0
444	Building Material and Garden Equipment	1.1	1.6	0.7	0.7
445	Food and Beverage Stores	1.3	1.4	0.9	0.5
447	Gasoline Stations	0.7	0.5	0.5	0.5
448	Clothing and Clothing Accessories Stores	0.7	0.5	0.9	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	11.0	10.0
453	Miscellaneous Store Retailers	7.4	8.8	9.3	10.3
621	Ambulatory Health Care Services	1.8	3.0	4.0	4.0
711	Performing Arts, Spectator Sports	3.5	3.0	10	10
713	Amusement, Gambling, and Recreation	5.1	6.5	11	15
721	Accommodation	1.0	1.2	2.8	1.3
722	Food Services and Drinking Places	1.1	1.1	1.8	1.4
811	Repair and Maintenance	0.7	1.0	1.9	1.5
812	Personal and Laundry Services	0.6	0.7	2.2	2.3

Source: Authors' calculation

Notes: 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).

annual series of 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 does 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.[26]

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 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.[27]

[26]The method used here is consistent with the method used by the BEA to create consumption estimates using EC revenues.

[27]The assumption is that if there are wages being paid in that NAICS industry there should be revenue associated with the wage 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.

A.1.2 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 five 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:

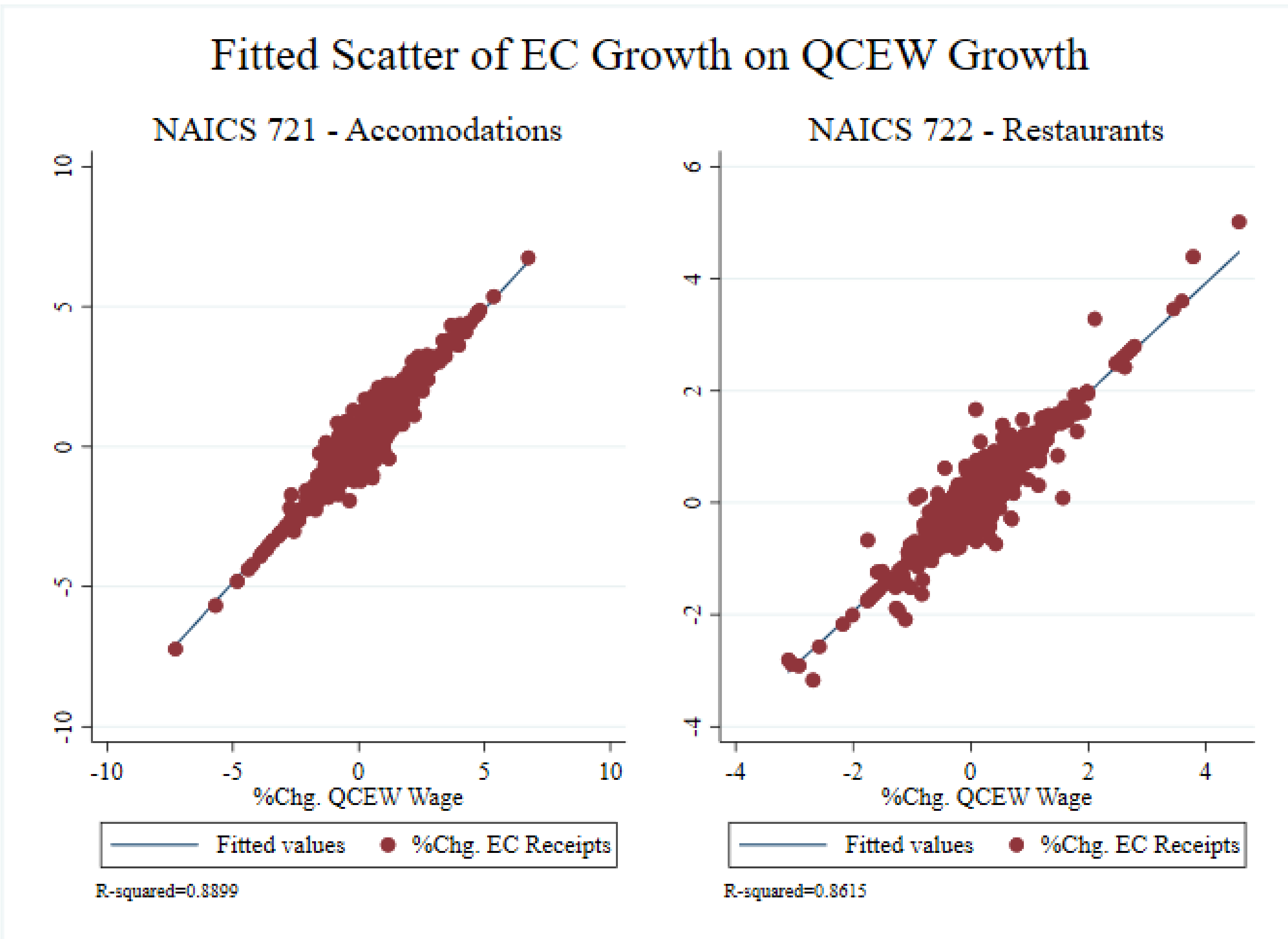
$$Revenue_{t+n} = \frac{Wage_{t+n}}{Wage_t} \cdot Revenue_t \cdot \left(\frac{Revenue_{t+n}/Wage_{t+n}}{Revenue_t/Wage_t} \right)^{(n/5)}$$

The first term $\frac{Wage_{t+n}}{Wage_t} \cdot Revenue_t$ is the estimated annual revenue based 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 five 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.

This method does quite well more generally. Table A2 shows the R^2 estimate from that same regression for many NAICS industry categories. The three-digit NAICS categories used in our analysis are highlighted in red. The R^2 for our select industries are all above 0.70, except for NAICS categories 447 (gasoline stations) and 451 (sporting goods) that 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.

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



Notes: 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.

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

Notes: 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.

A.1.3 Fiserv Data, Spending Flows and the Home Location Algorithm

The micro level data from Fiserv contains transaction level information for each firm. Fiserv data contains well over one-third of all U.S. credit card transaction spending which includes more than 4.5 million U.S. 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. As mentioned previously, the data has been aggregated and anonymized by Fiserv and

Palantir in the secure, First Data environment, and only the aggregate results are made available to end users. The engineers at Palantir 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 where the individual actually resides.

A.2 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, this accounts for about 15 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.[28]

One factor that helps with imputation is that even when spending flows are suppressed, our data provides 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 distance 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

[28]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 the model is used to predict the output values for the data in testing set.

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.

Using cross-validation, we test a variety of alternative models and examine the fit based on mean squared error and mean absolute deviation. We selected the methodology with the smallest mean squared error and mean absolute deviation based on a 5 percent holdout sample.

A.3 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 A3 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 A3 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 were 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 a "export industry" group were a relatively large share of spending is from consumers that reside away from the consumer'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 A3 shows differences in spending by industry, it is important to note that this information is weighted by spending, and this weighting will disproportionately weight those areas of the country with more spending. To show the variation across counties in the data, Table A4 shows the distribution of the share of spending in the consumers home location across counties in the U.S. Table A4 shows substantial variation in the amount that different counties

Table A3: Spending Share By Distance Weighted By Spending

	Share Home	Share Under 100 Miles	Share 100 to 500 Miles	Share 500+ Miles
Accommodation (NAICS 721)	0.132	0.161	0.311	0.396
Ambulatory Health Care Services (NAICS 621)	0.701	0.215	0.035	0.050
Amusement, Gambling, and Recreation Industries (NAICS 713)	0.589	0.208	0.077	0.127
Building Material and Garden Equipment and Supplies Dealers (NAICS 444)	0.744	0.192	0.030	0.034
Clothing and Clothing Accessories Stores (NAICS 448)	0.563	0.258	0.073	0.106
Food Services and Drinking Places (NAICS 722)	0.667	0.205	0.062	0.066
Food and Beverage Stores (NAICS 445)	0.837	0.105	0.024	0.034
Furniture and Home Furnishings Stores (NAICS 442)	0.622	0.241	0.052	0.084
Gasoline Stations (NAICS 447)	0.690	0.184	0.078	0.048
General Merchandise Stores (NAICS 452)	0.762	0.161	0.036	0.041
Miscellaneous Store Retailers (NAICS 453)	0.616	0.195	0.071	0.117
Performing Arts, Spectator Sports, and Related Industries (NAICS 711)	0.441	0.216	0.106	0.237
Personal and Laundry Services (NAICS 812)	0.737	0.173	0.036	0.054
Repair and Maintenance (NAICS 811)	0.732	0.184	0.039	0.046
Sporting Goods, Hobby, Book, and Music Stores (NAICS 451)	0.594	0.236	0.071	0.099

Notes: 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 then 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).

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.

A.4 Instrumental Variable

In this section 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 price changes over a period of time to identify the sensitivity of different areas to national or regional shocks. To do this, we estimate the following regression model:

$$HousingPriceGrowth_{i,t} = \alpha_i + \gamma_i \cdot RegionalHousingPriceGrowth_{R,t} + \beta_1 \cdot \delta y_{i,t} + \beta_2 \cdot \delta Y_{R,t} + \beta_3 \cdot X_{i,t} + \epsilon_{i,t}$$

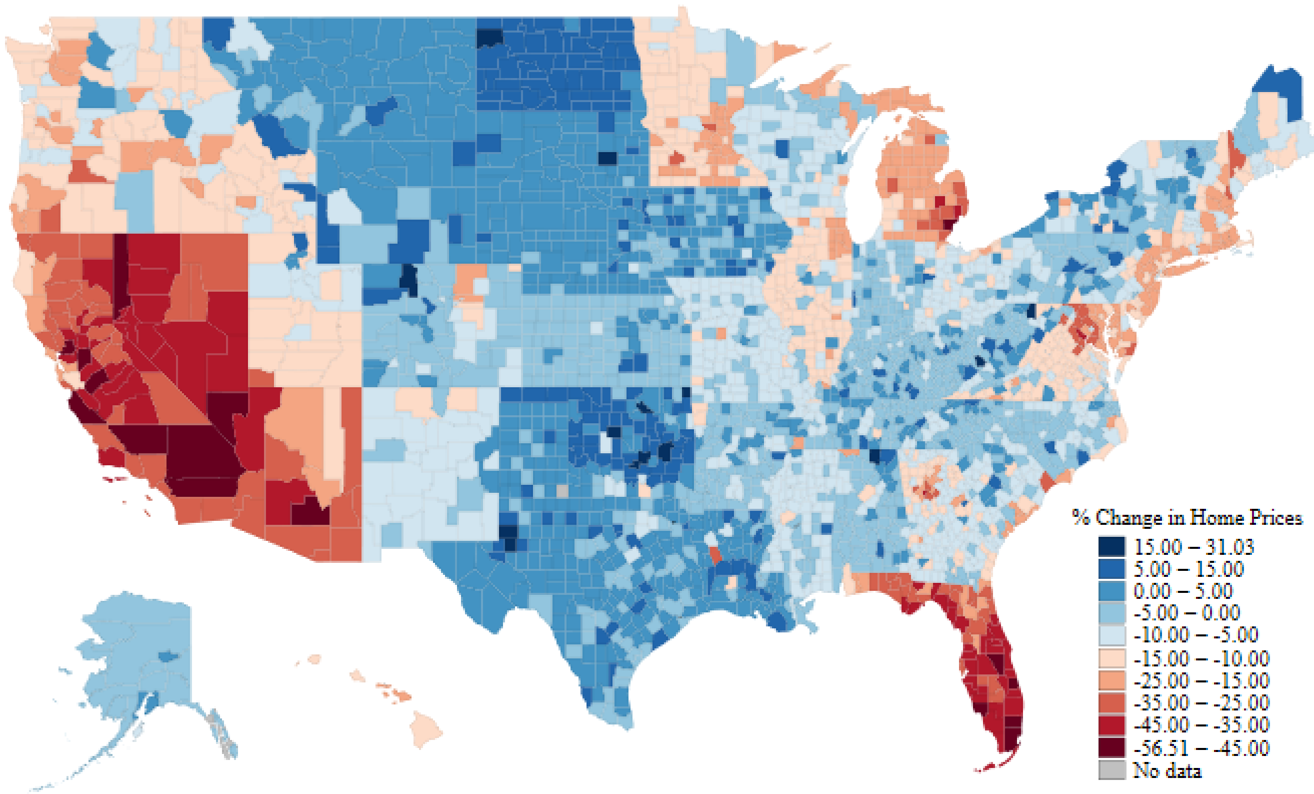
Table A4: Distribution of Spending Share From Consumers that Reside in the Same County as the Firm

	Median	10th	25th	75th	90th
Accommodation (NAICS 721)	0.088	0.029	0.049	0.135	0.185
Ambulatory Health Care Services (NAICS 621)	0.768	0.571	0.670	0.858	0.909
Amusement, Gambling, and Recreation Industries (NAICS 713)	0.639	0.385	0.520	0.730	0.812
Building Material and Garden Equipment and Supplies Dealers (NAICS 444)	0.764	0.577	0.675	0.829	0.877
Clothing and Clothing Accessories Stores (NAICS 448)	0.522	0.265	0.401	0.620	0.715
Food Services and Drinking Places (NAICS 722)	0.558	0.233	0.372	0.676	0.740
Food and Beverage Stores (NAICS 445)	0.822	0.622	0.739	0.877	0.908
Furniture and Home Furnishings Stores (NAICS 442)	0.680	0.440	0.568	0.775	0.862
Gasoline Stations (NAICS 447)	0.621	0.380	0.499	0.720	0.785
General Merchandise Stores (NAICS 452)	0.782	0.618	0.708	0.833	0.880
Miscellaneous Store Retailers (NAICS 453)	0.542	0.303	0.434	0.643	0.731
Performing Arts, Spectator Sports, and Related Industries (NAICS 711)	0.422	0.115	0.254	0.555	0.677
Personal and Laundry Services (NAICS 812)	0.747	0.534	0.656	0.815	0.878
Repair and Maintenance (NAICS 811)	0.772	0.570	0.678	0.856	0.922
Sporting Goods, Hobby, Book, and Music Stores (NAICS 451)	0.551	0.308	0.441	0.649	0.741

Notes: 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.

The model includes the average housing price growth of county i for the past two years in year t on the left-hand side of the model, $HousingPriceGrowth_{i,t}$. The right-hand side includes county-level fixed-effects α_i and a county-level coefficient on the responsiveness of regional housing price movements γ_i that is interacted with the regional housing price growth, $RegionalHousingPriceGrowth_{R,t}$. The term $\gamma_i \cdot RegionalHousingPriceGrowth_{R,t}$ is the associated instrument that we apply to the data. To avoid potential reverse causality we include a number of additional controls, including the growth in county-level receipts, $\delta y_{i,t}$, and growth in regional-level receipts, $\delta Y_{R,t}$. We also include 2-digit industry share for each county interacted with a year dummy, $X_{i,t}$, which allows for an industry-specific shock for each year. For the regional-level price change we use the median price change across all counties to account for the common movement across geographic areas. The median has a few advantages over the mean, as it does not place excess weight on highly populated counties, but it is also unaffected by outlier price changes.

Figure A2: Percent Change in Zillow Home Prices between 2006 and 2009



Notes: The estimates are based on the Zillow home value index reported on the Zillow website that is a seasonally adjusted index covering all housing types. The price change calculation is based on the home price change from December of 2006 to January of 2009.

A.5 Zillow Home Value Index

Zillow home value index (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 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 covers approximately 2000 counties within the US for December of 2006 and January of 2009. The data is available at: https://www.zillow.com/research/data/. For the missing counties, mostly rural counties, we assume the price decline is equal to the median price decline across counties in the same state. Figure A2 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.

A.6 Additional Robustness Checks

A.6.1 Additional Regressions Applying Instrumental Variable Analysis

Similar results by industry and by distance are obtained when instrumental variables are applied rather than OLS Estimates. Tables A5 and A6 repeat the results of Tables 7, 8, and 9, but apply instrumental variables. In each case, the instruments are weighted by spending share in a way that corresponds to the housing wealth variable.

Table A5: Instrumental Variable Regression Model of Spending and Employment By Industry Category

	(1) Spend Home Industries	(2) Spend Intermediate	(3) Spend Export Industries	(4) Emp. Home Industries	(5) Emp. Intermediate	(6) Emp. Export Industries
Δ HNW (Home Ind. Flow)	0.184***			0.143***		
	(0.0339)			(0.0273)		
Δ HNW (Inter. Ind. Flow)		0.0976***			0.107***	
		(0.0185)			(0.0315)	
Δ HNW (Export Ind. Flow)			0.305***			0.193***
			(0.0376)			(0.0292)
Observations	3020	2991	3053	3068	3082	3075

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

Note: Standard errors are in parentheses and are clustered by state. Estimates are weighted by 2007 population levels. All estimates include 2-digit industry employment share by county variables. The instruments are constructed following the methodology of Guren et al. (2020) and are described in greater detail in the text and the appendix.

A.6.2 Relaxing Assumption of Constant Shares

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 (1) 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 2007 to more accurately capture potential consumption at the beginning of the housing wealth decline.

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

Table A6: Instrumental Variable Regression Model of Spending and Employment By Distance

	(1) % Chg. Spending	(2) % Chg. Employment
Δ HNW (Home)	0.197***	0.134***
	(0.0302)	(0.0239)
Δ HNW (Export: ≤ 100 Miles)	0.0947	0.111
	(0.144)	(0.0881)
Δ HNW (Export: >100 & ≤ 500 Miles)	0.697***	0.606***
	(0.258)	(0.222)
Δ HNW (Export: >500 Miles)	0.333	0.137
	(0.259)	(0.263)
Observations	3117	3117

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

Note: Standard errors are in parentheses and are clustered by state. Estimates are weighted by 2007 population levels. All estimates include 2-digit industry employment share by county variables. The instruments are constructed following the methodology of Guren et al. (2020) and are described in greater detail in the text and the appendix.

across all 15 of our industries. The prediction model relies on spending information at firms that is observed in both 2015 and in 2007. We first estimate the model using the 2015 income and receipt information. Next, we substitute in the 2007 data for the 2015 covariates. Finally, using the model parameters based on 2015 estimates, we predict the spending flows using the 2007 covariates. 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 similar to the Constant Elasticity of Substitution (CES) functional form often applied in the trade literature Dubé et al. (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:

$$log(S^{2015}_{i,j,n}) - log(S^{2015}_{i=j,j,n}) = \\ g(\delta_j, distance_{i,j}, income^{2015}_i, income^{2015}_j, spend^{2015}_{i,n}, spend^{2015}_{j,n}, NAICs_n) + \gamma^{2015}_{i,j,n} \tag{7}$$

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 $\gamma^{2015}_{i,j,n}$ is the error term. Based on this functional form, the spending share for consumers coming from county i may be calculated as:[29].

$$S^{2015}_{i,j,n} = \frac{exp(g(*)^{2015} + \gamma^{2015}_{i,j,n})}{1 + \Sigma_{\forall i \in C} exp(g(*)^{2015} + \gamma^{2015}_{i,j,n})} \tag{8}$$

Equation (7) 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.[30] After running the predictions of the model for 2015 using 2015 covariates, we predict the 2007 shares. We assume that the error term does not change across years, so the error term from the 2015 prediction model is applied in the 2007 predictions. Specifically, if we let $\widehat{g(*)^{2007}}$ be the fitted values from the linear regression model, but using 2007 data, then the predicted shares for 2007 are calculated as:

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

[30]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.

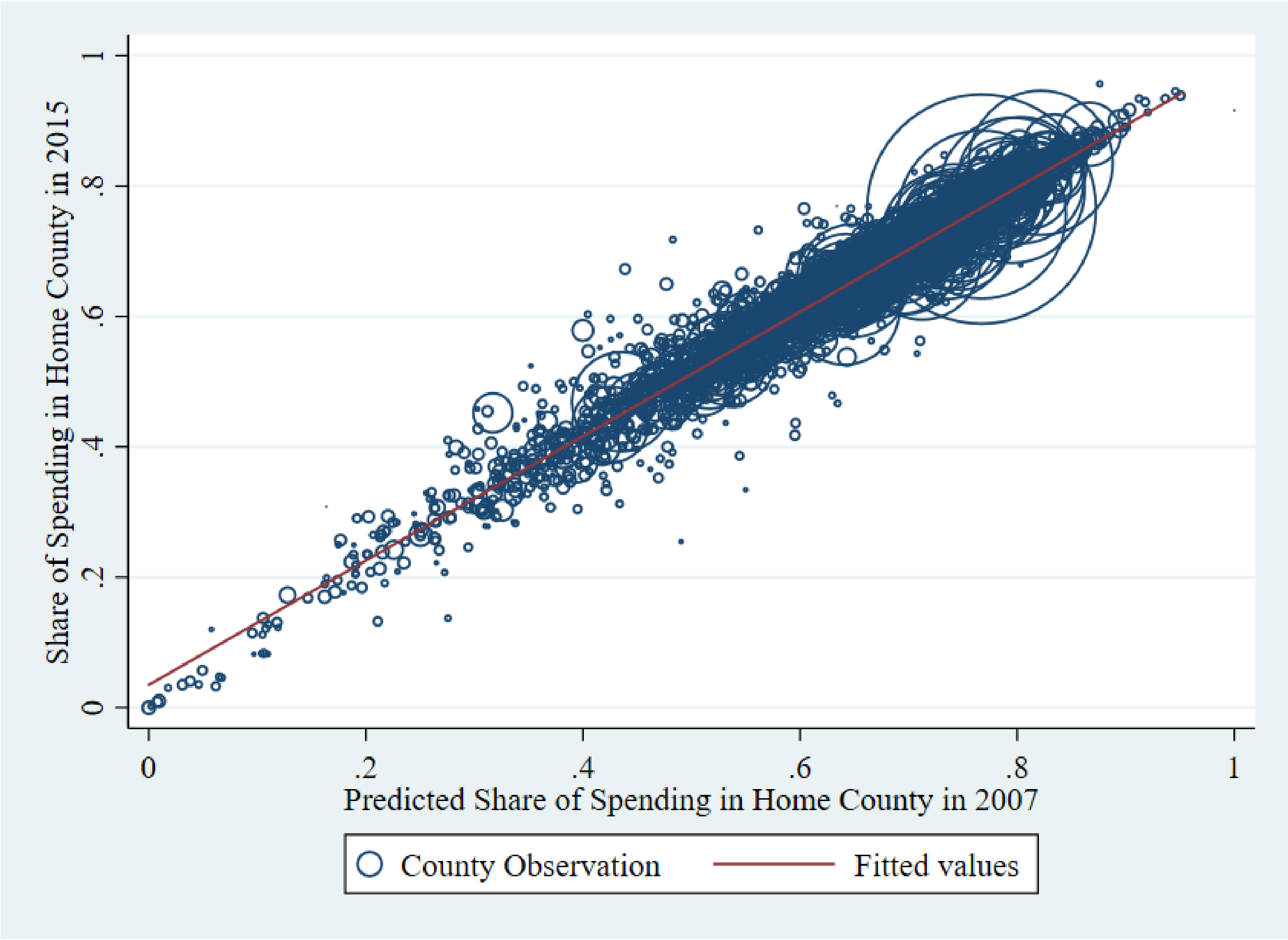
$$\widehat{S_{i,j,n}^{2007}} = \frac{exp(\widehat{g(*)^{2007}} + \widehat{\gamma_{i,j,n}^{2015}})}{1 + \Sigma_{\forall i \in C} exp(\widehat{g(*)^{2007}} + \widehat{\gamma_{i,j,n}^{2015}})} \tag{9}$$

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 A3 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 this fixed-share assumption, we calculate the housing net wealth variable applying the exact formula applied in equation (3), but using predicted shares for 2007 rather than observed shares for 2015. We then repeat the analysis from our main tables, but using the predicted flows. These results are shown in Tables A7 and A8.

Similar results may be obtained using these prediction shares along with instrumental variables rather than OLS estimates. These results show that relaxing the fixed spending share assumption does not change our results.

Figure A3: 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.

Table A7: Housing Wealth Change on Spending Growth Using 2007 Predicted Shares

	(1) % Chg. Spend	(2) % Chg. Spend	(3) % Chg. Spend	(4) % Chg. Spend	(5) % Chg. Spend
Δ HNW (No Flow)	0.158***		-0.0634	-0.0237	
	(0.0196)		(0.0856)	(0.0826)	
Δ HNW (Total 2007 Pred. Flow)		0.191***	0.265**		
		(0.0238)	(0.102)		
Δ HNW (Home Pred. 2007)				0.195*	0.166***
				(0.101)	(0.0276)
Δ HNW (Export Pred. 2007)				0.351***	0.329***
				(0.120)	(0.0772)
Observations	3063	3063	3063	3063	3063

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

Notes: The shares used in these estimates are predicted shares based on covariates from 2007 and described in greater detail in the text. Standard errors are in parentheses and are clustered by state. Estimates are weighted by 2007 population levels. All estimates include two digit industry employment share by county variables as control variables.

Table A8: Housing Wealth Change on Employment Growth Using 2007 Predicted Shares

	(1) % Chg. Emp.	(2) % Chg. Emp.	(3) % Chg. Emp.	(4) % Chg. Emp.	(5) % Chg. Emp.
Δ HNW (No Flow)	0.119***		-0.119**	-0.0960**	
	(0.0200)		(0.0525)	(0.0448)	
Δ HNW (Total 2007 Pred. Flow)		0.145***	0.284***		
		(0.0240)	(0.0755)		
Δ HNW (Home Pred. 2007)				0.244***	0.127***
				(0.0606)	(0.0195)
Δ HNW (Export Pred. 2007)				0.333***	0.246**
				(0.110)	(0.0929)
Observations	3109	3109	3109	3109	3109

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

Note: The shares used in these estimates are predicted shares based on covariates from 2007 and described in greater detail in the text of the appendix. Standard errors are in parentheses and are clustered by state. Estimates are weighted by 2007 population levels. All estimates include two digit industry employment share by county variables as control variables.