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THE AGGREGATE IMPLICATIONS OF REGIONAL BUSINESS CYCLES

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ABSTRACT

Making inferences about aggregate business cycles from regional variation alone is difficult because of economic channels and shocks that differ between regional and aggregate economies. However, we argue that regional business cycles contain valuable information that can help discipline models of aggregate fluctuations. We begin by documenting a strong relationship across US states between local employment and wage growth during the Great Recession. This relationship is much weaker in US aggregates. Then, we present a methodology that combines such regional and aggregate data in order to estimate a medium-scale New Keynesian DSGE model. We find that aggregate demand shocks were important drivers of aggregate employment during the Great Recession, but the wage stickiness necessary for them to account for the slow employment recovery and the modest fall in aggregate wages is inconsistent with the flexibility of wages we observe across US states. Finally, we show that our methodology yields different conclusions about the causes of aggregate employment and wage dynamics between 2007 and 2014 than either estimating our model with aggregate data alone or performing back-of-the-envelope calculations that directly extrapolate from well-identified regional elasticities.

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A data appendix is available at http://www.nber.org/data-appendix/w21956

1 Introduction

Regional business cycles during the Great Recession in the US were strikingly different than their aggregate counterpart. This is the cornerstone observation on which this paper is built. Yet, the aggregate US economy is just a collection of these regions connected by the trade of goods and services and the mobility of factors of production. We argue that their aggregation cannot be arbitrary and that regional business cycles have interesting implications for our understanding of aggregate fluctuations.

Primarily, there have been two broad types of literatures that have tried to understand the drivers of aggregate business cycles. First, researchers have used aggregate data alone – or have combined aggregate data with household/firm level data – to estimate aggregate business cycle models.[1] Second, a recent literature has emerged using plausibly exogenous regional variation to estimate local elasticities with respect to regional shocks.[2] Researchers then often extrapolate from such well-identified regional elasticities to aggregates by performing back-of-the-envelope calculations without the aid of a formal model. The first approach ignores valuable information in regional data that can help discipline key theoretical mechanisms. The second approach risks missing economic channels and shocks that are important at the aggregate level but not the regional level.

In this paper, we present a methodology that combines the strengths of both approaches by simultaneously using regional and aggregate data in order to estimate a medium-scale New Keynesian DSGE model of a monetary union. We show that exploiting regional variation allows researchers to identify key structural parameters that under certain assumptions are common between the regional and aggregate economies. These parameters are then combined with aggregate data to estimate the remaining parameters of the aggregate economy and the underlying shocks driving aggregate fluctuations. Finally, we show that when it comes to understanding the Great Recession, our procedure yields dramatically different results than if we either estimate our model solely with aggregate data or if we naively extrapolate from well-identified regional elasticities to make inferences about the drivers of aggregate business cycles.

We begin the paper by using a variety of micro data sources to document that during the Great Recession there was a sizable positive correlation between state-level wage growth and employment growth. Specifically, using cross-state variation between 2007 and 2010, we find that a 1 percent decline in employment was associated with a 0.72 percent and

[1] See, for example, Christiano et al. (2005), Smets and Wouters (2007), Justiniano et al. (2010), Christiano et al. (2014), and Linde et al. (2016).

[2] See, for example, Mian and Sufi (2011, 2014), Mian et al. (2013), Charles et al. (2016), Mehrotra and Sergeyev (2017), and Yagan (2017).

0.64 percent decline in nominal wages and real wages, respectively. This contrasts with the muted response of aggregate wages during this period despite aggregate employment falling sharply. From the aggregate time series, a 1 percent decline in employment between 2007 and 2010 was associated with a 0.1 *increase* in nominal wages and a roughly 0.3 percent decline in real wages. The fact that wages did not move much during the Great Recession has led many academics and policy makers to conclude that nominal wages must be quite rigid.[3] However, if wages were quite rigid, why was there such a strong correlation between wages and employment at the regional level? And, what does this regional evidence imply about the drivers of the aggregate Great Recession and its aftermath?

To help answer these questions, we next develop a medium-scale New Keynesian DSGE model of a monetary union where the regions aggregate to the economy as a whole. The model includes both price and nominal wage rigidities. The regions are linked through trade of intermediate inputs and can borrow and lend from each other. Interest rates are set at the union level according to a monetary policy rule. We allow for nine potential shocks in the model that may have both a regional and aggregate component.

We show that the joint behavior of wages and employment can differ between the regional and aggregate levels for two reasons. The first reason is that the relative wage and employment responses across regions to a given type of shock (e.g., a household demand shock) are theoretically different than the aggregate responses to the corresponding aggregate shock. In general, we show this implies that the "wage elasticity"—i.e., the response of log-wages (either real or nominal) to a given change in log-employment—could be larger or smaller at the aggregate versus the regional level.[4] For example, in response to a household demand shock, the regional wage elasticity can be smaller than the aggregate wage elasticity because of trade in intermediate inputs across regions and because of cross-region borrowing and lending. Also, in response to this shock, the aggregate wage elasticity may be smaller than the regional wage elasticity because the interest rate endogenously responds to aggregate shocks in a monetary union, potentially mitigating aggregate employment fluctuations, whereas it does not respond to regional shocks.

The second reason why observed aggregate and regional wage elasticities could differ is because regional and aggregate economies were hit by different types of shocks. For instance, regional shocks that shift local labor demand could be the primary driver explaining

[3]For example, in her 2014 Jackson Hole Symposium, then-Chairwomen Janel Yellen stated that "The evidence suggests that many firms face significant constraints in lowering compensation during the [Great Recession] and the earlier part of the recovery because of downward nominal wage rigidity."

[4]The concept of the "wage elasticity" matches the empirical work in the first part of the paper. Within the model, this is the impulse response of log-wages to a given shock (or set of shocks) at a particular horizon divided by the impulse response of log-employment to the same shock (or set of shocks) at the same horizon.

cross-region differences in employment and wages during the Great Recession. However, a combination of shocks that drive both labor demand and labor supply could have been important in the aggregate during this time period. In this scenario, the shocks driving labor supply may only have an aggregate component and, hence, be differenced out when considering variation across regions. If both types of shocks reduced employment but had offsetting effects on wages, we would precisely observe that wages appeared less flexible at the aggregate level relative to the regional level.

At the heart of our procedure is the fact that the Regional and Aggregate New Keynesian Wage Phillips Curves are identical under our model assumptions. Then, we show how we can exploit shocks to regional labor demand to estimate the parameters of the New Keynesian Wage Phillips Curve using regional data alone. Specifically, our methodology uses a fixed-point procedure that loops over GMM estimates of the parameters of the New Keynesian Wage Phillips Curve using regional data and the full information Bayesian estimates of the other parameters in our model using aggregate time series data.[5] Because we document that wages and employment were strongly positively correlated across regions but not in the aggregate during the Great Recession, we estimate that the slope of the New Keynesian Wage Phillips Curve and, relatedly, the frequency of wage changes, are much higher when following our methodology than when using aggregate data alone in estimation. For instance, we estimate that around three-quarters of wages adjust every year when using our methodology, similar to micro estimates of annual wage adjustments using administrative data sources (e.g., Grigsby et al. (2018)). However, when we estimate our model with only aggregate data, we find that only half of wages adjust every year, similar to estimates from Christiano et al. (2014) and Linde et al. (2016). This is one of the key findings of the paper: we estimate wages to be more flexible when incorporating regional data into our estimation than when we use aggregate data alone.

Then, we turn to using the model to explain: (1) why observed regional wage elasticities were higher than observed aggregate wage elasticities during the Great Recession as well as (2) what caused the decline in employment during Great Recession and the sluggish recovery afterwards. When using our methodology that combines regional and aggregate data in estimation, we find that differences in aggregate versus regional elasticities to household demand shocks cannot explain why aggregate wages seemed much more sticky relative to their regional counterparts. Other demand shocks hitting the aggregate economy cannot

[5] In this sense, our methodology shares features with both full- and limited- information methods used in other papers to estimate New Keynesian DSGE models. For example, see Linde et al. (2016) for a recent survey of the use of full information Bayesian methods for estimating DSGE models. See Galí et al. (2005) for an example of using GMM techniques to estimate a "hybrid" New Keynesian Price Phillips Curve.

account for this fact either.[6] Instead, we find that aggregate labor supply shocks explain why aggregate wages did not fall.[7] Because these aggregate labor supply shocks are differenced out when comparing outcomes across regions and they push wages and employment in opposite directions, they made wages seem stickier in the aggregate than across regions during the Great Recession.

Furthermore, we find that aggregate demand shocks were indeed important drivers of aggregate employment during the Great Recession, but cannot account for the slow recovery in the aftermath. Because we estimate that wages are rather flexible when using our regional evidence, the model cannot generate enough endogenous persistence following demand shocks in order to explain why employment remained depressed three to five years after the Great Recession ended. In this sense, our results complement the results in Basu and House (2017) who show that in most medium-scale DSGE models wage stickiness is essential for obtaining persistent real effects of nominal shocks. Instead, we find that negative labor supply shocks explain much of the slow recovery in employment during the 2010-2014 period.

We interpret our findings in two ways. In order for demand shocks to be the key drivers of employment and wages during the Great Recession and its aftermath, they need to generate variation in the "labor wedge" through channels other than wage and price stickiness—the only two frictions that generate such variation in our model. For example, Angeletos, Collard, and Dellas (2017) show how "confidence" shocks can manifest themselves as "labor wedge" shocks in DSGE models. Alternatively, our estimated labor supply shocks could have resulted not from a combination of demand forces and model misspecification, but instead from a form of skill mismatch following structural changes in the labor market associated with the decline in routine occupations. This interpretation is also suggested by the findings in Stock and Watson (2012), who conclude that much of the slow recovery in employment in the US after 2010 can be traced to secular shifts in labor supply.

Lastly, we show how the conclusions of our approach of combining both aggregate and regional data differ from those of other approaches designed to understand aggregate fluctuations. Had we performed back-of-the-envelope calculations extrapolating from well-identified regional employment elasticities following household demand shocks, we would have overstated the role of such shocks in accounting for the sluggishness in aggregate employment following the Great Recession. Likewise, had we estimated our model with aggregate data alone, we would have concluded that aggregate demand shocks were much more important

[6] We refer to shocks to the discount factor as household demand shocks. Furthermore, as in Smets and Wouters (2007), we refer generically to discount factor and investment efficiency shocks as "aggregate demand" because they make price inflation and employment move in the same direction

[7] We model these as shocks to households preferences for leisure, but, as is well known, they are isomorphic to a broader set of shocks to labor supply. The two cannot be distinguished given our data.

in accounting for both the persistent employment decline and the modest fall in aggregate wages during the Great Recession. However, we would have estimated a degree of wage stickiness that is inconsistent with the flexibility of wages we observed across US states.

Our paper contributes to various literatures. First, our work contributes to the recent surge in papers that have exploited regional variation to highlight mechanisms of importance to aggregate fluctuations. For example, Mian and Sufi (2011, 2014), Mian et al. (2013), and Jones et al. (2018) have exploited regional variation within the US to explore the extent to which household leverage has contributed to the Great Recession. Nakamura and Steinsson (2014) and Chodorow-Reich (2018) use sub-national US variation to inform the size of local government spending multipliers. Autor et al. (2013) and Charles et al. (2016) document the importance of structural declines in local labor demand in explaining persistent declines in both local employment and wages. We complement this literature by showing that local wages also respond to local changes in economic conditions at business cycle frequencies.

Second, our work builds on the important work of Nakamura and Steinsson (2014) which uses a structural model to show how local government multipliers can inform aggregate multipliers. In our paper, we present a methodology where regional variation can be combined with aggregate data to learn about the nature and importance of certain mechanisms for aggregate fluctuations. We show how regional data can help discipline the Calvo parameter governing the frequency of nominal wage adjustments in a New Keynesian Wage Phillips Curve. In this sense, we are part of a growing recent literature showing how regional variation can be used to discipline aggregate models. For example, Beraja et al. (2017) use regional variation to explore the time varying aggregate effects of monetary policy, Adao et al. (2018) use a structural model to map well identified estimates of the local employment effects to trade shocks to aggregate employment trends, and Acemoglu and Restrepo (2017) use a combination of cross-region variation and a model of local economies that aggregate to explore the effects of automation on aggregate employment.

Third, our paper contributes to the recent literature trying to determine the drivers of the Great Recession and its aftermath. Christiano et al. (2015) estimate a medium-scale New Keynesian model using data from the recent recession. Although their model and identification are different from ours, they also conclude that other shocks beyond demand shocks are needed to explain the joint aggregate dynamics of prices and employment during the Great Recession. Their paper abstracts from wage rigidities all together. However, they find that productivity shocks are needed to match the missing aggregate deflation during the Great Recession[8]. Del Negro et al. (2015) estimate a medium-scale New Keynesian model

[8] Likewise, Vavra (2014) and Berger and Vavra (2018) document that prices were very flexible during the Great Recession. They conclude that something demand shocks alone cannot explain the aggregate

with financial frictions and show that it matches the joint patterns of declining output and low but positive inflation during the Great Recession. Likewise, Gilchrist et al. (2017) also uses micro data to discipline their model of price setting with firm financial constraints to explore the link between financial shocks and missing disinflation during the Great Recession. All of these papers focus on explaining the missing disinflation during the Great Recession. Our paper complements this literature by focusing on why both nominal and real wages did not fall more during the Great Recession.

Finally, our paper relates to the literature studying international business cycles. Since the seminal paper by Backus et al. (1992) on the consumption correlation puzzle, a large part of this literature has focused its attention on the ability of DSGE models to account for certain facts of international business cycles. For example, Frankel and Rose (1998) shows that trade links are key to understand the correlations of business cycles across countries, while others emphasize trade costs (Obstfeld and Rogoff (2000)) and financial frictions (Kehoe and Perri (2002)) as important for understanding international business cycles. Furthermore, a separate literature has developed New Keynesian models with multiple countries (e.g., Clarida et al. (2001), Galí and Monacelli (2008) and House et al. (2017)). We borrow much of the modeling insights from this literature. However, unlike them, we are not concerned with how shocks spillover and propagate across regions or the conduct of optimal monetary policy within a monetary union. Instead, we study how regional and aggregate responses to shocks differ in a monetary union, as well as showing how regional data can be used in estimation of aggregate models in order to identify aggregate union-level shocks.

2 Creating State-Level Wage and Price Indices

2.1 State-Level Wage Index

To construct our primary nominal wage indices at the state level, we use data from the 2000 *Census* and the 2001-2014 *American Community Surveys* (*ACS*). The 2000 *Census* includes 5 percent of the US population while the 2001-2014 *ACS*'s includes around 600,000 respondents per year between 2001 and 2004 and around 2 million respondents per year between 2005 and 2014. The large coverage allows us to compute detailed labor market statistics at the state level. For each year of the *Census/ACS* data, we calculate hourly nominal wages for prime-age males. In particular, we restrict our sample to only males between the ages of 25 and 54, who live outside of group-quarters, are not in the military, and who have no self-employment income. Then, for each individual in the resulting sample,

employment dynamics given the missing aggregate disinflation.

we divide total labor income earned during the prior 12 months by a measure of annual hours worked during the prior 12 months. Total hours worked during the previous 12 month is the product of the respondent's report of total weeks worked during the prior 12 months and usual hours worked per week. Within each year, we exclude any individual with a zero wage and we further truncate the measured wage distribution at the top and bottom one percent.

Despite our restriction to prime-age males, the composition of workers on other dimensions may still differ across states and within a state over time. As a result, the changing composition of workers could explain some of the variation in nominal wages across states over time.[9] For example, if lower wage workers are more likely to exit employment during recessions, time series patterns in nominal wages will appear artificially more rigid than they actually are. To partially cleanse our wage indices from these compositional issues, we follow a procedure similar to Katz and Murphy (1992) by creating a composition-adjusted wage measure for each U.S. state and for the aggregate economy based on observables. Specifically, within each state-year pair, we segment our sample into six age bins (25-29, 30-34, etc.) and four education groupings (completed years of schooling < 12, $= 12$, between 13 and 15, and 16+). Our demographic adjusted nominal wage series is defined as follows:

$$\widetilde{Wage}_{kt} = \sum_{g=1}^{24} Share_{k\tau}^{g} \, Wage_{kt}^{g} \tag{1}$$

where $\widetilde{Wage}_{kt}$ is the demographic adjusted nominal wage series for prime age men in year t of state k, $Wage_{kt}^{g}$ is the average nominal wage for each of our 24 demographic groups g in year t of state k and $Share_{k\tau}^{g}$ is the share of each demographic group g in state k during some fixed pre-period τ. By holding the demographic shares fixed over time, all of the wage movements in our demographic adjusted nominal wage series result from changes in nominal wages within each group and not because of a compositional shift across groups. When making our *aggregate* composition adjusted nominal wage series, we follow a similar procedure as in equation (1) but omit the k's. For the *Census/ACS* data, we set $\tau = 2005$ when examining cross-state patterns during the Great Recession and set $\tau = 2000$ when examining time series patterns of aggregate wages during the 2000s.

The benefit of the *Census/ACS* data is that it is large enough to compute detailed labor market statistics at the state level. However, one drawback of the *Census/ACS* data is that it is not available at an annual frequency prior to 2000. To complement our analysis, we use data from the March Supplement of the *Current Population Survey* (*CPS*) to examine longer

[9] See, Solon, Barsky, and Parker (1994) and Basu and House (2017) for a discussion of the importance of composition bias in the evolution of aggregate wages over the business cycle.

run aggregate trends in both aggregate nominal and real wages. These longer run trends are an input into our aggregate shock decomposition procedure discussed in subsequent sections. We compute the demographic adjusted nominal wage indices using the *CPS* data analogously to the way we computed the demographic adjusted nominal wage indices within the *Census/ACS* data.[10] When comparing aggregate time series trends in demographically adjusted wages between both the ACS and CPS during the 2000s, we set $\tau = 2000$. When computing aggregate time series trends in demographically adjusted nominal wages for our aggregate time series analysis over longer periods, we set $\tau = 1975$. Unless otherwise stated, all wage measures in the paper are demographically adjusted. For the remainder of the paper, we use the *Census/ACS* data to explore regional wage variation and the *CPS* data to examine aggregate time series wage variation. However, for the 2000-2014 period, we can compare the time-series variation in aggregate wages using the *Census/ACS* data with the time series variation in aggregate wages using the *CPS* data. The two time series have a correlation of 0.98 during this period.

2.2 State-Level Price Index

2.2.1 Price Data

State-level price indices are necessary to measure state-level real wages. In order to construct state-level price indices we use the *Retail Scanner Database* collected by AC Nielsen and made available at The University of Chicago Booth School of Business.[11] The Retail Scanner data consists of weekly pricing, volume, and store environment information generated by point-of-sale systems for about 90 participating retail chains across all US markets between January 2006 and December 2013. As a result, the database includes roughly 40,000 individual stores selling, for the most part, food, drugs and mass merchandise.

For each store, the database records the weekly quantities and the average transaction

[10] A full discussion of our methodology to compute composition adjusted wages in the *Census/ACS* and the *CPS* can be found in the Online Appendix that accompanies the paper. However, we wish to highlight one difference between the measurement of wages between the two surveys. Within the *March CPS*, respondents are asked to report their earnings over the prior calendar year as opposed to over the prior 12 months. Given this, March CPS respondents in year t report their earnings from year $t-1$. Census/ACS respondents are interviewed throughout the calendar year and are asked to report their earnings over the prior 12 months. As a result, we designate the earnings of *Census/ACS* respondents in year t as being accrued in year t.

[11] The data is made available through the Marketing Data Center at the University of Chicago Booth School of Business. Information on availability and access to the data can be found at http://research.chicagobooth.edu/nielsen/. Contemporaneously, Coibion et al. (2015), Kaplan and Menzio (2015) and Stroebel and Vavra (2018) also use local scanner data/household price data to estimate that local prices vary with local economic conditions at business cycle frequencies. Our paper complements this literature by actually making price indices using the Nielsen scanner data for each state at the monthly frequency and using those price indices to estimate structural parameters of the local wage setting equation.

price for roughly 1.4 million distinct products. Each of these products is uniquely identified by a 12-digit number called Universal Product Code (UPC). To summarize, one entry in the database contains the number of units sold of a given UPC and the weighted average price of the corresponding transactions, at a given store during a given week. The database only includes items with strictly positive sales in a store-week and excludes certain products such as random-weight meat, fruits, and vegetables since they do not have a UPC assigned. Nielsen sorts the different UPCs into over one thousand narrowly defined "categories". For example, sugar can be of 5 categories: sugar granulated, sugar powdered, sugar remaining, sugar brown, and sugar substitutes. We use these categories when defining our price indices.

Finally, the geographic coverage of the database is outstanding and is one of its most attractive features. It includes stores from all states except for Alaska and Hawaii. Likewise, it covers stores from 361 Metropolitan Statistical Areas (MSA) and 2,500 counties. The data comes with both zip code and FIPS codes for the store's county, MSA, and state. Over the eight year period, the data set includes total sales across all retail establishments worth over \$1.5 trillion. In this paper, we aggregate data to the level of US states and compute state-level retail scanner data price indices. The Online Appendix shows summary statistics for the retail scanner data for years between 2006 and 2013 and for the sample as a whole.

2.2.2 A Retail Scanner Data Price Index

In order to construct state-level price indices we follow the BLS construction of the CPI as closely as possible.[12] Our retail scanner price indices are built in two stages. In the first stage, we aggregate the prices of goods within the roughly 1,000 categories described above. Each good is defined by their unique UPC. Then, we compute, for each good, the average price and total quantity sold in a given month and state. Next, we construct the quantity weighted average price for all goods in each detailed category in a given month and state. We aggregate our index to the monthly level to reduce the number of missing values.

Specifically, for each category, we compute:

$$P^{L,k}_{j,t} = P^{L,k}_{j,t-1} \times \frac{\sum_{i\in(j,k)} p_{i,t}\bar{q_{i,y}}}{\sum_{i\in(j,k)} p_{i,t-1}\bar{q_{i,y}}} \tag{2}$$

with $\{t, t-1\} \in y+1$ for all months except when $t = January$ and $t \in y+1$, $t-1 \in y$

[12]There is a large literature discussing the construction of price indices. Melser (2011) and Ivancic et al. (2011) discuss problems that arise with the construction of price indices with scanner data. In particular, if the quantity weights are updated too frequently the price index will exhibit "chain drift". This concern motivated us to follow the BLS procedure and keep the quantity weights fixed for a year when computing the first stage of our indices rather than updating the quantities every month. While we briefly outline the price index construction in this sub-section, the full details of the procedure are discussed in the Online Appendix that accompanies our paper.

when $t = January$, where $P^{L,k}_{j,t}$ is the time t chained Laspeyres-type index for category j in state k, $p_{i,t}$ is the price at time t of good i (in category j and state k), $\bar{q_{i,y}}$ is the average monthly quantity sold of good i in state k in the prior (base) year y. By fixing quantities at their prior year's level, we are holding fixed household's consumption patterns as prices change. We update the basket of goods each year and produce the chained index for each category in each state.

In the second stage of our construction we aggregate the category-level price indices into an aggregate index for each state k. The inputs are the category-level prices from the first stage (equation (2)) and the total expenditures of each category. Specifically, for each state k we compute:

$$\frac{P^k_t}{P^k_{t-1}} = \prod_{j=1}^{N} \left(\frac{P^{L,k}_{j,t}}{P^{L,k}_{j,t-1}} \right)^{\frac{S^t_{j,k} + S^{t-1}_{j,k}}{2}} \tag{3}$$

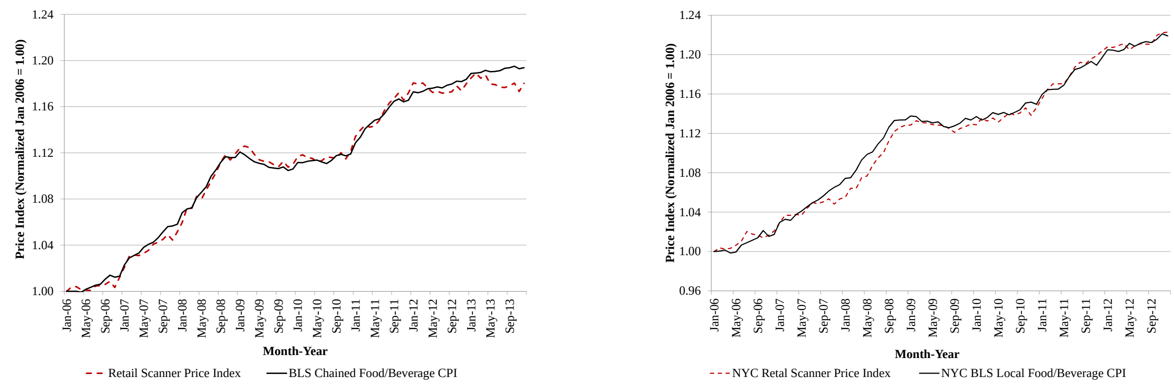
where $S^t_{j,k}$ is the share of expenditure of category j in month t in state k.

Finally, as a consistency check, we compare our retail scanner price index for the aggregate US to the BLS's CPI for food and beverages. We choose the BLS Food and Beverage CPI as a benchmark given that approximately two thirds of the goods in our database can be classified as food or drink. The top panel of Figure 1 shows that our retail scanner aggregate price index matches nearly exactly the BLS's Chained Food and Beverage CPI at the monthly level between 2006 and 2013.[13] The BLS also puts out local price indices for 27 U.S. metro areas. These price indices have a high degree of sampling variation and the BLS cautions researchers about using the metro area price indices to compute local changes in costs of living.[14] For three MSAs – NY, Chicago and LA – the BLS releases monthly price indices. For the other MSAs, the price indices are released bimonthly or semiannually. For the most part, our Nielsen Retail Price Index matches well the BLS price indices for the larger MSAs. The bottom panel of Figure 1 compares our scanner price index for the New York metro area compared to the BLS's food and beverage price index for the New York metro area. The two series track each other closely. For smaller MSAs, the BLS price indices are very noisy. Given the caution expressed by the BLS in using their local price indices, this is not surprising. However, we take it as a good sign that our scanner price index at the local level matches well the BLS price indices for similar goods for the larger MSAs.

[13]There is a slight deviation of the two indices starting in 2013. This results from a seam in when the Nielsen data was upload to the Kilts Center. When we estimate our cross-state regressions, we will exclude the 2013 data.

[14]For example, the BLS notes that: "local-area indexes are more volatile than the national or regional indexes, and BLS strongly urges users to consider adopting the national or regional CPIs for use in escalator clauses." See https://www.bls.gov/cpi/questions-and-answers.htm.

Figure 1: Nielsen Retail Scanner Price Index vs. BLS Price Index



Panel A: All U.S. | Panel B: NYC

Note: In the left panel of this figure, we compare our monthly retail scanner index for the US as a whole (dashed line) to the BLS's chained food/beverage CPI (solid line). In the right panel of this figure, we compare our monthly retail scanner index for New York City (dashed line) to the BLS's food/beverage CPI for New York City (solid line). We normalize all indices to 1 in January 2006.

Our intent is to use the state level Nielsen Retail Price Indices as a measure of state level prices. There are two concerns that one may have with such an analysis. First, at the aggregate level, food prices and prices for the broader composite CPI did not trend similarly during the Great Recession. For example, food prices fell less than the price index for the broader CPI basket between 2008 and 2010. This is not a concern for us because we are only interested in regional differences in the price indices. We never use the Nielsen Retail Price Indices to deflate aggregate variables. If the regional variation in food prices is similar to the regional variation in prices of goods in a composite consumption basket, it does not matter if the aggregate trends are different between the two series.

More substantively for us is whether the regional variation in the Nielsen Retail Price Indices does, in fact, measure well regional differences in prices for a broader consumption basket. Most goods in our Nielsen sample are produced outside a local market and are simultaneously sold to many local markets. These intermediate production costs represent the traded portion of local retail prices. If there were no additional local distribution and/or trade costs, one would expect little variation in retail prices across states; the law of one price would hold. This would be true for local variation in any tradable price index regardless of whether those tradable price indices tracked each other at aggregate levels. However, "non-tradable" costs do exist for the tradable goods in our sample, including the wages of workers in the retail establishments, the rent of the retail facility, and expenses associated with local warehousing and transportation.[15] It is these cross-region differences in non-tradable prices that constitute cross-region differences in the evolution of regional prices indices.

In the Online Appendix, we provide a simple model that allows us to extract the cross-region variation in the inflation rate for the composite consumption good using the cross-region variation we can measure using our Nielsen Retail Scanner Indices. Under a set of assumptions, the differential inflation rate across regions in the local composite consumption good is simply the differential inflation rate across regions in the Nielsen data scaled by the ratio of the non-tradable share of the composite good relative to the non-tradable share of the scanner grocery goods. Our key assumption for extracting regional variation in a broader consumption index from regional variation in our Nielsen price index is that the scaling factor is constant across states during a give time period. If this scaling factor is constant across states, the scaling factor will be absorbed into the constant term (or year dummies) in all the empirical work we do in the paper. The reason is that we run regressions that either include the level or the change in log price as a regressor or run regressions that include either the level or change in log real wages as a regressor. With our log specifications, the log of the scaling factor will be subsumed into the regression constant (or time dummies if the scaling factor varies over time). As a result, cross region variation in inflation rates generated using the Nielsen Price Index - under the assumptions outlined in the Appendix - is enough for us to identify the elasticity between real wage growth and local employment rates using cross-region data.

3 Comparing Regional v. Aggregate Patterns

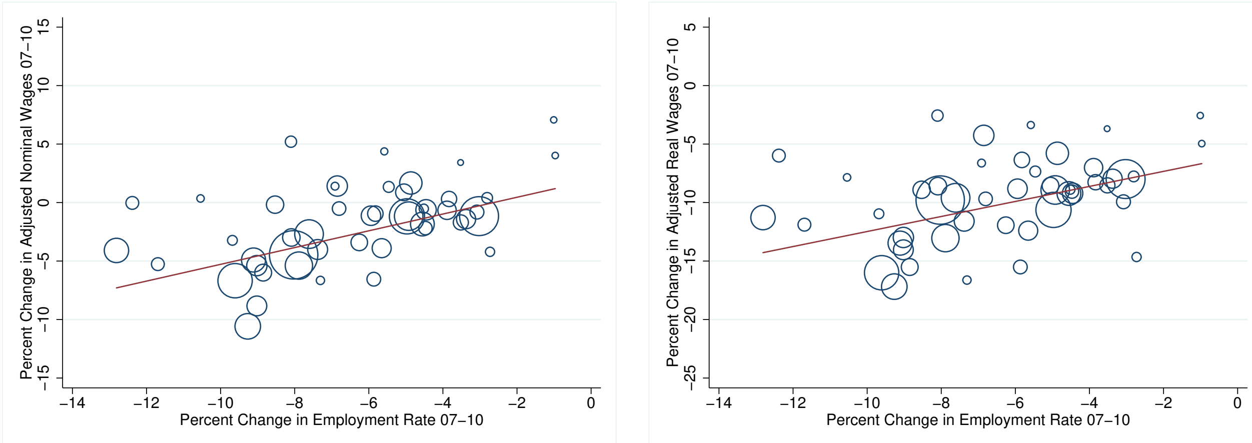
The goal of this section is to contrast the strong co-movement of wages and economic activity at the local level to the relatively weaker co-movement at the aggregate level, during the Great Recession.

3.1 Regional Patterns

The left panel of Figure 2 shows the log-change in our demographic adjusted nominal wage indices from the ACS between 2007 and 2010 across states against the log-change in the employment rate. For state employment rates, we divide state total employment by total state population. We get both state employment levels and state population levels from the U.S. Bureau of Labor Statistics (BLS). As seen from the figure, state-level nominal wage

[15] Burstein et al. (2003) document that such local costs represent more than 40 percent of retail prices in the U.S..

Figure 2: State Employment Growth vs. State Wage Growth



Panel A: Nominal Wages   Panel B: Real Wages

Note: Figure plots demographically adjusted wage growth for prime-age men during 2007-2010 vs growth in the employment rate during 2007-2010 for the cross-section of US states. Nominal wages are measured using the ACS dataset. Real wages are computed by deflating nominal wages by our Retail Scanner Price Index. State employment rates come from dividing state employment from the BLS by total state population from the BLS. Each observation is a U.S. state excluding Alaska and Hawaii. The size of the circle measures state population in 2006. Each figure includes a weighted regression line. The slopes of the regression lines are shown in Table 1.

growth was strongly and positively correlated with state-level employment growth during the 2007-2010 period. A simple linear regression through the data (weighted by the state's 2006 population) suggests that a 1 percent change in a state's employment rate was associated with a 0.72 percent change in nominal wages (standard error = 0.14). We refer to 0.72 as the cross-state nominal wage elasticity with respect to employment growth.[16]

The right panel of Figure 2 shows similar patterns for real wage variation. We compute state level demographically adjusted real wages by deflating our state level nominal wages in year t by the Retail Scanner Price Index in year t. We then compute the log change in real wages between 2007 and 2010. Again, a simple linear regression through the data (weighted by the state's 2006 population) suggests an estimated cross-state real wage elasticity of 0.64 (standard error = 0.16). Accounting for differential inflation rates across states the cross-state elasticity in nominal wages only slightly (from 0.72 to 0.64). We summarize our estimated cross-state nominal and real wage elasticities in Table 1. While adjusting for

[16]These findings are consistent with the extensive literature in labor economics and public finance showing that local labor demand shocks cause both employment and wages to vary together in the short to medium run. For example, Blanchard and Katz (1992), Autor, Dorn, and Hanson (2013) and Charles, Hurst, and Notowidigdo (2018a) all highlight that local labor demand shocks due to shifting aggregate industry trends have large effects on both local employment and local wages. Our results complement this literature by showing similar patterns at business cycle frequencies.

differences in local prices mitigates the nominal wage elasticities slightly, both the nominal and real wage elasticities we estimate using cross-region variation are large relative to the time series movements in real and nominal wages during the Great Recession. We illustrate this fact next.

Table 1: Cross-State Estimates of Wage Elasticities During the Great Recession

Wage Measure	Estimated Elasticity
Nominal Wages	0.72
	(0.14)
Real Wages	0.64
	(0.16)

Note: Table reports the simple bi-variate relationship between state employment growth between 2007 and 2010 and state demographically adjusted wage growth between 2007 and 2010. Wage data come from the ACS and are demographically adjusted as described in the text. Real wages are deflated using our Retail Scanner Price Index. Robust standard errors are in parenthesis.

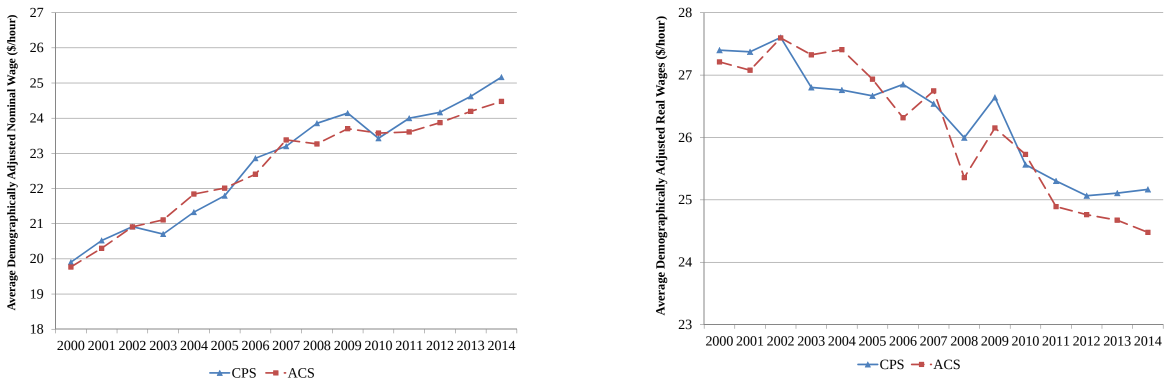
3.2 Aggregate Patterns

Figure 3 shows the time series trends in both demographically adjusted nominal wages (left panel) and real wages (right panel) for our samples of CPS and ACS respondents between 2000 and 2014. Real wages are reported in 2014 prices. To get aggregate real wages, we deflate our aggregate nominal wage series by the aggregate CPI-U for all goods.[17]

A few things are of note from Figure 3. First, the CPS and ACS demographically adjusted aggregate wage indices match each other nearly identically in both levels and trends. This gives us confidence in using the ACS data for our cross-region estimates and the CPS data for our time series analysis in subsequent sections. Second, demographically adjusted nominal wages *increased* by about 1 percent during the 2007 and 2010 periods in both datasets. Despite the employment to population ratio falling by about 8 percent nationally during the Great Recession, aggregate demographically adjusted nominal wages were rising. This pattern is at odds with the cross-region variation highlighted above. Finally, demographically adjusted real wages show little break in trend during the 2007 to 2010. In both the CPS and ACS, real wages were declining before the start of the Great Recession, declined further through the recession, and continued declining after the recession.

[17]In the Online Appendix, we compare the time series trends in our unadjusted and our demographically adjusted wage series. As predicted, adjusting for the changing composition of the workforce dampens nominal

Figure 3: Time Series Trends in Aggregate Wages ($/hour), CPS and ACS



Panel A: Nominal Wages

Panel B: Real Wages

Note: Figure shows average demographically adjusted nominal wages (left panel) and real wages (right panel) for men aged 21-55 during the 2000-2014 period. Wages are reported as $/hour. The solid line uses data from the CPS. The dashed line uses data from the ACS. Real wages are in 2014 prices and are deflated by the U.S. June CPI-U for all goods.

Table 2 creates measures of aggregate time-series wage elasticities that can be compared with the cross-region estimates in Table 1.[18] The top panel displays the aggregate nominal wage elasticity. To get this, we take the demographically adjusted nominal wage growth using aggregate data from the CPS (column 1) and ACS (column 2) between 2007 and 2010 and divides it by the aggregate percentage change in the employment rate. According to BLS, the aggregate employment to population ratio in the US fell by 7.7% between 2007 and 2010. In the aggregate time series data, there was a slight negative relationship between aggregate employment rate changes and aggregate nominal wage growth (around -0.10 in both the CPS and ACS data). As a reminder, the corresponding wage elasticity from the cross region estimates in Table 1 is 0.72. The fact that nominal wage growth did not decline despite low aggregate inflation and weak aggregate labor market conditions has led many academics and policy makers to conclude that nominal wages are quite "sticky".

The bottom panel provides an estimate of similar real wage elasticities over the same time period at the aggregate level. When computing real wage elasticities, we define the changes during the Great Recession relative to the pre-recession trend. In particular, we compute

wage growth during the Great Recession.

[18]We thank Bob Hall for giving us the idea for this table. We base it on the analysis he did as part of his discussion of our paper at the 2015 NBER summer EFG program meeting. In his discussion, he stressed the importance of controlling for past trends in real wages given that real wages have been steadily declining for many years prior to the start of the Great Recession.

Table 2: Time Series Estimates of Wage Elasticities During the Great Recession

	CPS Data	ACS Data
	Panel A: Nominal Wages	
Actual Wage Growth, 2007-2010	1.0 percent	0.8 percent
Nominal Wage Elasticity, 2007-2010	-0.13	-0.10
	Panel B: De-Trended Real Wages	
Actual Wage Growth, 2007-2010	-3.7 percent	-3.9 percent
Predicted Wage Growth, 2007-2010	-1.4 percent	-1.0 percent
Deviation from Predicted Growth, 2007-2010	-2.4 percent	-2.9 percent
Real Wage Elasticity, 2007-2010	0.31	0.38

Note: Table computes the aggregate wage elasticity to a one percent change in the employment rate. During the 2007-2010 period, the aggregate employment rate fell by 7.7 percent. The first column shows demographically adjusted wage data from the CPS while the second column shows demographically adjusted wage data from the ACS. Panel A shows actual nominal wage growth during the 2007-2010 period. Panel B shows de-trended real wage growth during the 2007-2010. Real wages are de-trended using observed wage growth during the 2000-2007 period.

the annual growth rate in demographically adjusted real wages between 2000 and 2007 and then linearly extrapolate the growth rate between 2007 and 2010. Real wages fell between 2007 and 2010 by 2.4% in the CPS and 2.9% in the ACS relative to trend. Given that the aggregate employment to population rate fell by 7.7%, the aggregate elasticity of real wages with respect to employment changes was 0.31 in the CPS and 0.38 in the ACS. Note, these numbers are about half the magnitudes estimated from the cross-region estimates.

3.3 Robustness

In this subsection, we explore two additional robustness specifications for our key result that the relationship between wage growth and employment growth during the Great Recession was much stronger using cross-state variation than using time series variation.

As discussed above, our demographic adjustments partially account for the changing selection of the workforce, based on observables, as economic conditions deteriorate. However, selection based on unobservables can still bias our estimates. We now discuss two sets of results that suggest changing selection on unobservables are not significantly affecting our conclusions. First, we note that while controlling for observable dimensions of selection (age and education) does affect the level of wage changes in both the times series and the cross section, our demographic adjustments do not affect our estimates of the *differential* patterns between the time series and the cross section. To the extent to which the changing selection of workers biases our results, the bias is similar between both the cross-region and time series estimates. Regardless of whether or not we adjust for changing composition based on observables, our estimates of cross-state wage elasticities during the Great Recession are always higher than our time series estimates. While it is hard to say how our results would change if we were able to control for unobservable selection, we find it reassuring that the main takeaway from the paper is not altered by controlling for selection based on observables.

To further explore the extent to which selection based on unobservables are biasing our results, we exploit the panel nature of the CPS. Given the CPS structure, we have multiple March Supplement earnings reports for a portion of our sample. Specifically, during the 2007-2010 period, we examine the wages of workers in $t-1$ who subsequently were not working in period t. At what point in the period $t-1$ wage distribution were these non-working individuals in period t drawn? To answer this question, we condition on the worker's age and education given that we use these for our demographic corrections. If these workers were drawn from around the median of the conditional distribution, then selection issues on unobservables are likely not important with respect to biasing our wage change measures during the Great Recession. If these individuals were drawn from the bottom part of the distribution, then our estimated conditional wage change measures during the Great Recession will be biased *upwards*. During the 2007-2010 period, we find that individuals who are not working in t but did work in $t-1$ were, on average, drawn from about the 40th percentile of the $t-1$ wage distribution (conditional on age and education). Given that this is close to the median, it suggests that selection on unobservables is likely not substantively biasing our estimates of wage changes. Moreover, to the extent that a bias exists, it suggests that our estimates of wage flexibility from the cross-region regressions is actually a *lower bound* on the true extent of wage flexibility during the Great Recession. If we were able to control for selection perfectly, wages would look even more flexible based on our cross-region variation.

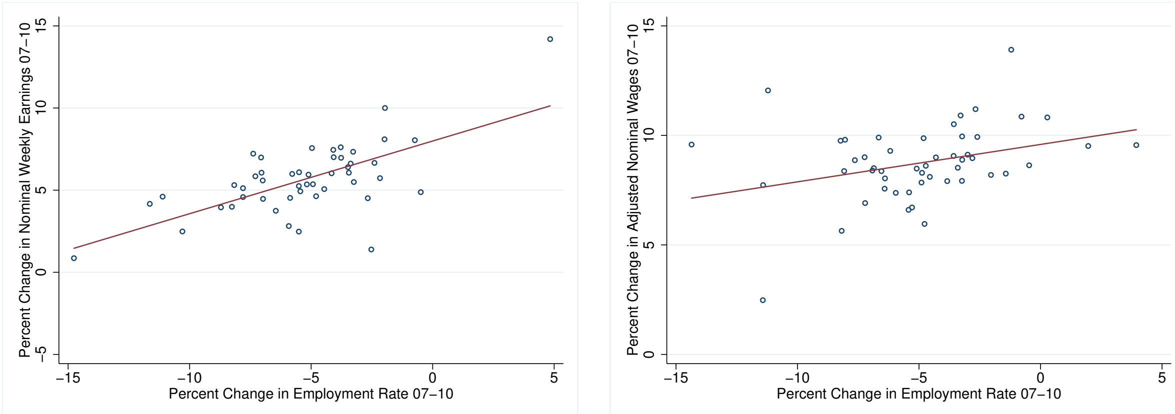
As a separate robustness exercise, we explore the extent to which the patterns we document in Figure 2 also show up in other wage series. While there are no government data sets that produce broad based composition adjusted wage series at the local level, the Bureau of Labor Statistics's (BLS's) *Quarterly Census of Employment and Wages* (QEW) collects firm level data on employment counts and total payroll at local levels. Likewise, the BLS's *Occupational Employment Survey* (OES) is a biannual survey of establishments designed to produce estimates of employment and wages for specific occupations. The *QEW* produces aggregate time series data on weekly earnings and employment while the *OES* produces time series data on average hourly earnings and employment. Additionally, both surveys report comparable statistics for each state. The *QEW* has the advantage of being from administrative data while the *OES* has the advantage of being a large survey of employers. However, neither survey controls for changes in composition. Despite this major limitation, we feel it is useful to explore patterns in these alternate data sources to examine the robustness of our results using the *CPS* and *ACS*.

In terms of time series patterns, nominal weekly earnings in the *QEW* grew by 8.7 percent between 2007 and 2010. Similarly, average nominal hourly wages in the *OES* grew by 5.0 percent during the same period. These growth rates in nominal earnings and nominal wages are much higher than the composition adjusted nominal wage growth in both the CPS and ACS during the same time period documented above. But, the qualitative patterns are similar in that nominal wages/earnings grew during the Great Recession despite sharp declines in employment. While the aggregate time series patterns suggest sizable *negative* relationships between wage growth in these other data sources and aggregate employment trends, the cross-region patterns mimic the results from the *ACS*. Figure 4 illustrates the cross-state relationship between nominal weekly earnings growth and employment growth between 2007 and 2010 in the *QEW* (left panel) and nominal average hourly wages between 2007 and 2010 from the *OES* (right panel). States that experienced larger relative declines in employment rates also experienced larger relative decline in nominal earnings or nominal wages as measured in other government data sources. While we are more confident making wage measures using the underlying micro data from the CPS and ACS, we find it encouraging that the broad contrast between time series wage patterns and cross-state wage patterns during the Great Recession show up in other data sources.

3.4 Summary and Discussion

To summarize, our main empirical finding comes from comparing the cross-state wage elasticities with the aggregate wage elasticities. The response of wages to changes in employment were *much* stronger at the state level during the Great Recession than at the aggregate level. For example, the local real wage elasticity with respect to employment changes was nearly twice as big in household data sets as the aggregate elasticity (0.64 vs. 0.31). It is this difference in the relationship between wages and employment at the local level and at the aggregate level what forms the basis of the remainder of this paper. Why did local wages adjust so much when local employment conditions deteriorated during the Great Recession while aggregate wages hardly responded at all despite a sharp deterioration in

Figure 4: Cross Region Variation in Nominal Earnings/Wages During the Great Recession, QEW and OES



Panel A: QEW Data

Panel B: OES Data

Note: Left panel shows the relationship between state nominal weekly earnings growth between 2007 and 2010 and state employment growth between 2007 and 2010 using data from the QEW. The right panel shows the relationship between state average hourly wage growth between 2007 and 2010 and state employment growth between 2007 and 2010 using data from the OES. Employment growth in both panels is measured within each survey. Each panel includes a simple linear regression (unweighted) of the cross-state relationship between nominal wage/earnings growth and employment growth. The coefficients for the regression lines in the top and bottom panels, respectively, are 0.44 (s.e. = 0.07) and 0.30 (s.e. = 0.08).

aggregate employment conditions? Can aggregate wages be sticky when local wages adjust so much? What do these patterns imply for our understanding of the Great Recession and its aftermath? We turn to answering these questions next.

4 A Monetary Union Model

In this section, we present a medium-scale, New Keynesian DSGE model of a monetary union. The model is based on the influential papers by Justiniano et al. (2010) , Christiano et al. (2014), and Linde et al. (2016) but extended to include multiple regions. We have two goals in mind: (1) to explain how and why aggregate and local wage and employment responses might differ following a given shock, and (2) to identify shocks driving aggregate business cycles. In Section 5, we develop a methodology that combines regional and aggregate data in order to estimate the model, thereby allowing us to compute such elasticities and perform shock decompositions.

Formally, our model economy is composed of many islands (indexed by k) inhabited by infinitely lived households and firms in two distinct sectors that produce a final consumption goods and intermediates that go into its production. There are only two assets in the economy: non-tradable physical capital and a tradable one-period nominal bond in zero net supply where the nominal interest rate is set by a monetary authority at the union level. We assume intermediate goods can be traded across islands but the final consumption good is non-tradable. In particular, the final consumption good is an island-aggregate of several retailers producing differentiated varieties. Finally, we assume labor is mobile across sectors but not across islands.[19] Throughout we assume that parameters governing preferences and production are identical across islands and that islands only differ, potentially, in the shocks that hit them.

4.1 Firms

Final consumption good producer A competitive firm in island k transforms a continuum of varieties i into a homogeneous final good via a CES aggregator. The profit-maximization problem is:

$$\max_{\{Y_{kt}(i)\}_i} P_{kt}Y_{kt} - \int_0^1 P_{kt}(i)Y_{kt}(i)di \qquad \text{s.t.} \qquad Y_{kt} = \left[\int_0^1 Y_{kt}(i)^{\frac{1}{\lambda^p_{kt}}} di\right]^{\lambda^p_{kt}}$$

where P_{kt} and Y_{kt} are the price and the quantity of the final good; $P_{kt}(i)$ and $Y_{kt}(i)$ are the price and quantity of variety i, and $\lambda^p_{kt} > 1$ is the desired gross markup of the sellers of the varieties, which follows an exogenous stochastic process. Profit maximization yields the iso-elastic demand function:

$$Y_{kt}(i) = Y_{kt}\left[\frac{P_{kt}(i)}{P_{kt}}\right]^{\frac{\lambda^p_{kt}}{1-\lambda^p_{kt}}} \tag{4}$$

The zero profit condition implies that the price index satisfies:

$$P_{kt} = \left[\int_0^1 P_{kt}(i)^{\frac{1}{1-\lambda^p_{kt}}} di\right]^{1-\lambda^p_{kt}} \tag{5}$$

Intermediate good producer The only commodity traded across islands is an intermediate good, x, produced by competitive firms. The representative producer of island k operates a constant-return technology in local labor N^x_{kt} and capital K^x_{kt} and solves the profit maximization problem:

$$\max_{N^x_{kt},K^x_{kt}} P^x_t A^x_{kt}(K^x_{kt})^{\alpha_x}(N^x_{kt})^{1-\alpha_x} - W_{kt}N^x_{kt} - R^K_{kt}K^x_{kt}$$

[19] We explore the issue of labor mobility during the Great Recession when we take the model to the data (see Section 5.3). However, this assumption will produce in the model wage dispersion across regions, which we observe in the data.

where P_t^x is the price of the intermediate good (equalized across islands because of the law-of-one-price), W_{kt} is the local nominal wage, R_{kt}^K is the nominal rental rate of capital, and A_{kt}^x is an exogenous stochastic process for productivity. the first order conditions are:

$$W_{kt} = (1-\alpha_x)P_t^x A_{kt}^x (K_{kt}^x)^{\alpha_x}(N_{kt}^x)^{-\alpha_x} \tag{6}$$

$$R_{kt}^K = \alpha_x P_t^x A_{kt}^x (K_{kt}^x)^{\alpha_x - 1}(N_{kt}^x)^{1-\alpha_x} \tag{7}$$

Retailers A variety i is produced by a monopolistically competitive retailer in island k using effective capital K_{kt}, labor N_{kt}^y, and intermediate goods X_{kt}. The production function is:

$$Y_{kt}(i) = K_{kt}(i)^{\alpha_1} X_{kt}(i)^{\alpha_2} \left(\Psi_t A_{kt}^y N_{kt}^y(i)\right)^{1-\alpha_1-\alpha_2} - \Psi_t F \tag{8}$$

where F is fixed cost of operating the technology that is common across islands, and A_{kt}^y is the stationary component of local productivity, and Ψ_t is a non-stationary stochastic process that affects both labor productivity and the fixed cost. Cost minimization implies that—conditional on producing—the nominal marginal cost is:

$$MC_{kt} = \left(\frac{1}{\Psi_t A_{kt}^y}\right)^{1-\alpha_1-\alpha_2} \left(\frac{R_{kt}^K}{\alpha_1}\right)^{\alpha_1} \left(\frac{P_t^x}{\alpha_2}\right)^{\alpha_2} \left(\frac{W_{kt}}{1-\alpha_1-\alpha_2}\right)^{1-\alpha_1-\alpha_2}, \tag{9}$$

Finally, we assume that retailers are subject to a Calvo-style friction and can only change their prices infrequently. In each period, only a fraction ξ_p of retailers can re-optimize their price, but the rest of the prices also change according to a backward-looking indexation rule. The profit maximization problem is:

$$\max_{P_{kt}(i), \{Y_{kt+s}(i)\}_{s=0}^{\infty}} \mathbb{E}_t \left\{ \sum_{s=0}^{\infty} (\beta\xi_p)^s M_{kt+s} Y_{kt+s}(i) \left[P_{kt}(i)\Gamma_{kt,t+s}^p - MC_{kt+s}\right] \right\}$$

$$\text{s.t. } Y_{kt+s}(i) = Y_{kt+s} \left[\frac{P_{kt}(i)\Gamma_{kt,t+s}^p}{P_{kt+s}}\right]^{\frac{\lambda_t^p}{1-\lambda_t^p}} \qquad \forall s$$

where $M_{kt,t+s}$ is the pricing kernel coming from the households, and the indexation term is defined as:

$$\Gamma_{kt,t+s}^p \equiv \prod_{l=1}^{s} \left(\pi_{kt+l-1}^{\iota_p} \pi^{1-\iota_p}\right).$$

where π_{kt} is the inflation rate in island k at time t, π is inflation target set by the monetary authority and ι_p governs the indexation.

4.2 Households and labor markets

Households Each island is populated by a representative household. Households have a continuum of members who specialize in a different labor service indexed by $j \in [0,1]$. Labor services $N_{kt}(j)$ are imperfect substitutes, giving workers some monopoly power to set wages. Analogously to the goods market, only a fraction $1-\xi_w$ of wages can be re-set in each period. This friction introduces idiosyncratic labor income risk, but we assume that the household provides full insurance against this risk.[20]

Households can save in a tradable one-period nominal bond B_{kt} (which pays an aggregate interest rate R_t that is common across regions) or in a non-tradable physical capital $\bar{K}_{kt}$. They decide their consumption C_{kt}, investment I_{kt} and utilization rate u_{kt} of capital, and savings in bonds $B_{kt} - B_{kt-1}$. However, households do not choose their labor supply directly and instead delegate this decision to a labor union. Furthermore, they receive lump-sum transfers in the form of profit of local firms Π_{kt} and government transfers T_{kt}.

The household problem is choosing $\{C_{kt}, \bar{K}_{kt}, I_{kt}, B_{kt}, u_{kt}\}_{t=0}^{\infty}$ to maximize:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^s b_{kt+s} \phi_{kt+s} \left[\log(C_{kt} - h\bar{C}_{kt-1}) - \varphi_{kt} \int_0^1 \frac{N_{kt}(j)^{1+\nu}}{1+\nu} dj \right]$$

subject to the sequential budget constraint and investment technology

$$\begin{aligned} P_{kt}\left(C_{kt} + I_{kt}\right) + B_{kt} &= R_{t-1}B_{kt-1} + \int_0^1 W_{kt}(j) N_{kt}(j) dj \\ &\quad + \left[R^K_{kt} u_{kt} - P_{kt} a(u_{kt})\right] \bar{K}_{kt-1} + \Pi_{kt} + T_{kt} \\ \bar{K}_{kt} &= (1-\delta)\bar{K}_{kt-1} + \mu_{kt}\left(1 - S\left(\frac{I_{kt}}{I_{kt-1}}\right)\right) I_{kt} \end{aligned}$$

where $a(u_{kt})$ is a capital utilization cost and $S\left(\frac{I_{kt}}{I_{kt-1}}\right)$ is a convex investment-adjustment-cost. Furthermore, we allow for shocks to the marginal efficiency of investment μ_{kt}, discount factor b_{kt}, and leisure preference φ_{kt}. Throughout, we will refer to shocks to φ_{kt} as "labor supply" shocks. Also, we denote by ϕ_{kt} the endogenous discount factor, which is treated as exogenous by households. As in Schmitt-Grohé and Uribe (2003), such model addition ensures the existence of a stationary distribution of bonds across islands. h denotes the habit in household consumption decisions. Finally, given a lagrange multiplier associated with the sequential budget constraint Λ_{kt+s}, the pricing kernel used by the retailers to discount future

[20] Justiniano et al. (2010) assume that households themselves are indexed by j, but can trade in a complete set of Arrow-Debreu securities, which makes them ex-post identical despite the Calvo shocks. The large-family assumption achieves the same.

profits is defined as:

$$M_{kt+s} = b_{kt+s}\varphi_{kt+s}\Lambda_{kt+s} \tag{10}$$

Labor Markets We assume the existence of a labor agency that buys all forms of specialized labor from the labor union and transforms them into homogeneous labor services, which it sells on a competitive market for price W_{kt}. Its profit maximization problem is:

$$\max_{\{N_{kt}(j)\}_j} W_{kt}N_{kt} - \int_0^1 W_{kt}(j)N_{kt}(j)dj \qquad \text{s.t.} \quad N_{kt} = \left[\int_0^1 N_{kt}(j)^{\frac{1}{\lambda_w}} dj\right]^{\lambda_w}$$

Analogously to the case of the final good producer, the demand for specialized labor is

$$N_{kt}(j) = N_{kt}\left[\frac{W_{kt}(j)}{W_{kt}}\right]^{\frac{\lambda_w}{1-\lambda_w}}, \tag{11}$$

where $\lambda_w > 1$ is the desired gross markup of the sellers of the specialized labor services. The wage index is

$$W_{kt} = \left[\int_0^1 W_{kt}(j)^{\frac{1}{1-\lambda_w}} dj\right]^{1-\lambda_w} \tag{12}$$

As mentioned, each worker of type j is represented by a labor union that sets the wage (locally) in order to maximize worker utility subject to it constraints. However, it can only adjust wages infrequently with the frequency being governed by the Calvo parameter ξ_w. Wages, however, can also evolve according to a pre-determined indexation rule. Taking the consumption of households as given, it solves:

$$\max_{W_{kt}(j),\{N_{kt+s}(j)\}_{s=0}^{\infty}} \mathbb{E}_t\left\{\sum_{s=0}^{\infty}(\beta\xi_w)^s\left[-b_{kt+s}\phi_{kt+s}\varphi_{kt+s}\frac{N_{kt+s}^{1+\nu}(j)}{1+\nu} + \Lambda_{kt+s}\Gamma^w_{kt,t+s}W_{kt}(j)N_{kt+s}(j)\right]\right\}$$

$$\text{s.t. } N_{kt+s}(j) = N_{kt+s}\left[\frac{W_{kt}(j)\Gamma^w_{kt,t+s}}{W_{kt+s}}\right]^{\frac{\lambda_w}{1-\lambda_w}} \qquad \forall s$$

where the indexation term is defined as

$$\Gamma^w_{kt,t+s} \equiv \prod_{l=1}^{s}\left[\pi_{kt+l-1}^{\iota_w}\pi^{1-\iota_w}\gamma\right]$$

4.3 Government policy and resource constraints

Fiscal policy Public spending is a time-varying, exogenous fraction of island-level output

$$G_{kt} = \left(1 - \frac{1}{\epsilon^g_{kt}}\right)Y_{kt}. \tag{13}$$

The role of this shock is to soak up variation in measured GDP due to changes in net exports as well as government spending when the model is fit to the data. Also, federal transfers T_{kt} are exogenous and potentially different for each region in each period. For our purposes, there will be no need to specify them.

Monetary policy is set by a central authority and hence is common for all islands. Specifically, it takes the form of a Taylor rule

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{\rho_R} \left[\left(\frac{\pi_t}{\pi}\right)^{\varphi_\pi} \left(\frac{GDP_t}{GDP_{t-1}}\right)^{\varphi_X}\right]^{1-\rho_R} \eta_t, \tag{14}$$

where GDP_t is aggregate GDP defined as

$$GDP_t = \sum_k \left[C_{kt} + I_{kt} + G_{kt}\right] \tag{15}$$

and η_t is a monetary policy shock.

4.4 Shocks

The economy as a whole is perturbed by 9 exogenous shocks. Most exogenous processes are assumed to be AR(1) with innovations having an aggregate as well as a local component. The exceptions are monetary policy and the three technology shocks. First, monetary policy is set at the level of the monetary union and thus exogenous disturbances are purely aggregate. Second, fitting non-stationary aggregate data requires that it is the growth rate—and not the level—of technology that follows an AR(1) process. Since transitory growth-rate shocks induce permanent changes in levels, they have to be the same for all islands, otherwise they diverge almost surely. Third, tradable and retail technologies have to stay in the same order of magnitude to keep relative prices bounded. These considerations lead us to model Ψ_t as purely aggregate with innovations to its growth rate, and to center the island-level transitory productivity shocks around it. Finally, we assume that (i) local innovations sum to zero in all periods and (ii) both aggregate and local innovations are normally distributed with zero mean and constant variance. See Appendix A for a formal description of the exogenous processes.

4.5 Equilibrium

An equilibrium is quantities $\{Y_{kt}, C_{kt}, I_{kt}, G_{kt}, K_{kt}, \bar{K}_{kt}, u_{kt}, N_{kt}, N^x_{kt}, N^y_{kt}, X_{kt}, B_{kt}, D_{kt}\}$ and prices $\{P_{kt}, P^x_{kt}, W_{kt}, R^K_{kt}, R_t\}$ for each island k and time t such that, given the exogenous processes and government policies, all agents are optimizing and all markets clear. In particular, the final-good and labor markets clear island-by-island. Formally,

$$Y_{kt} = C_{kt} + I_{kt} + G_{kt} + a(u_{kt})\bar{K}_{kt}, \tag{16}$$

$$N_{kt} = N^x_{kt} + N^y_{kt} \tag{17}$$

The tradable-good and bond markets clear in the aggregate

$$\sum_k X_{kt} = \sum_k A^x_{kt} N^x_{kt} \tag{18}$$

$$D_t + \sum_k B_{kt} = 0 \tag{19}$$

Finally, the island resource constraint is:

$$B_{kt} = R_{t-1} B_{kt-1} + P^x_t (A^x_{kt} N^x_{kt} - X_{kt}) + T_{kt} \tag{20}$$

And, letting D_t denote federal debt, the budget constraint of the federal government is:

$$D_t = R_{t-1} D_{t-1} + \sum_k \left[P_{kt} G_{kt} + T_{kt} \right] \tag{21}$$

4.6 Aggregation

This subsection derives aggregation results and expressions for the Aggregate and Regional New Keynesian Wage Phillips curve in a log-linearized economy. We will use these results heavily both in the next section, to show how aggregate and regional elasticities might differ, as well as later on when developing our methodology that combines aggregate and regional data in estimation.

First, we log-linearize the model around the unique balanced-growth path. Lemma 1 shows that the log-linearized economy aggregates up to a representative economy where, to a first order approximation, all aggregate variables are independent of any cross-regional considerations. This implies that, as far as aggregates are concerned, our model's implications are identical to canonical DSGE models that do not model regions directly and, instead, simply pose the existence of a representative aggregate economy that is driven by aggregate shocks alone.[21]

[21] The model we presented has many islands subject to idiosyncratic shocks that cannot be fully hedged because asset markets are incomplete. By log-linearizing the equilibrium, we gain in tractability but ignore these considerations and the aggregate consequences of heterogeneity. The approximation will be good as long as the underlying volatility of the idiosyncratic shocks is not too large. If our unit of study was an individual, as for example in the precautionary savings literature with incomplete markets, the use of linear approximations would likely not be appropriate. However, since our unit of study is an island the size of a

Second, Lemma 2 shows that island economies in log-deviations from the aggregate economy behave to a first order approximation as if they were a collection of independent small-open-economies driven by purely idiosyncratic shocks. Again, this implies that we can study variation in regional outcomes without considering aggregates.

There are two key assumption behind these results. The first is that all islands are identical with respect to their underlying parameters. The second is that the joint distribution of island-specific shocks is such that their cross-sectional sum is zero. If the number of islands is large, this holds in the limit because of the law of large numbers.

Lemma 1. *Aggregate variables in the log-linearized economy behave as if the economy had a single island, with only a non-tradable sector where firms produced with technology* $(K_t)^{\alpha_1+\alpha_2\alpha_x}(\Psi_t N_t)^{1-\alpha_1+\alpha_2\alpha_x} - \Psi_t F$, *which was hit by aggregate shocks driving AR(1) processes* $\{\lambda_t^p, z_t, b_t, \mu_t, \varphi_t, \epsilon_t^g, \eta_t\}$.

Lemma 2. *Island variables in log-deviations from aggregates behave as if each island was an independent small-open-economy, facing fixed nominal interest rate and price of tradable goods, which was hit by island shocks driving AR(1) processes* $\{\lambda_{kt}^p, A_{kt}^x, A_{kt}^y, b_{kt}, \mu_{kt}, \varphi_{kt}, \epsilon_{kt}^g\}$.

Proof. See Appendix A for a proof of Lemma 1 and 2. □

Following these lemmas, we can write the Regional New Keynesian Wage Phillips Curve as:

$$\tilde{\pi}_{kt}^w = \beta \mathbb{E}_t\left[\tilde{\pi}_{kt+1}^w\right] + \kappa_w \nu \tilde{n}_{kt} - \kappa_w \tilde{w}_{kt} + \iota_w(\tilde{\pi}_{kt-1} - \beta\tilde{\pi}_{kt}) + \frac{\kappa_w}{1-h}(\tilde{c}_{kt} - h\tilde{c}_{kt-1}) + \tilde{\varphi}_{kt} \quad (22)$$

where lowercase variables with " ˜ " represent island variables in log-deviations from aggregates with n, c, π^w, w and π representing employment, consumption, nominal wage growth, real wages in terms of the non-tradable good and the inflation rate, respectively. As a reminder, $\tilde{\varphi}_{kt}$ is the labor supply shock, $\frac{1}{\nu}$ is the Frisch elasticity of labor supply, ι_w parameterizes the degree of wage indexation, and h parameterizes the degree of habit formation.

Furthermore, the slope of Regional New Keynesian Phillip's curve is:

$$\kappa_w \equiv \frac{(1-\beta\xi_w)(1-\xi_w)}{\xi_w}\frac{\lambda_w - 1}{\lambda_w(1+\nu)-1} \quad (23)$$

U.S. state, we believe this is not too egregious of an assumption. The volatilities of key economic variables of interest at the state or country level are orders of magnitude smaller than the corresponding variables at the individual level.

where $1-\xi_w$ is the fraction of wages that re-set every period and λ_w is the desired gross wage-markup of the sellers of the specialized labor services. Thus, fixing other parameters, a lower value of κ_w implies a larger degree of wage stickiness.

Analogously, the Aggregate New Keynesian Wage Phillips Curve is:

$$\hat{\pi}_t^w = \beta \mathbb{E}_t \left[\hat{\pi}_{t+1}^w\right] + \kappa_w \nu \hat{n}_t - \kappa_w \hat{w}_t + \iota_w (\hat{\pi}_{t-1} - \beta \hat{\pi}_t) + \frac{\kappa_w}{1-h}(\hat{c}_t - h\hat{c}_{t-1}) + \hat{\varphi}_t \tag{24}$$

where lowercase variables with " ˆ " represent aggregate variables in log-deviations from the balanced growth path.

Of particular note is the fact that the Regional New Keynesian Phillips Curve shares identical parameters with the Aggregate New Keynesian Phillips Curve. Furthermore, the variables associated with such parameters are the regional counterparts to the aggregate ones. Section 5 shows how to leverage this property of the equilibrium for estimating the model using a combination of regional and aggregate data.

4.7 Aggregate vs. Regional Responses to Shocks

Having described the full model, we now explore the main economic channels that may cause aggregate and regional responses to shocks to differ. While Section 6 presents quantitative results along these lines, in this section we provide a more qualitative analysis. We highlight three such channels: (1) monetary policy only affects aggregates in a monetary union, (2) regional labor demand in the non-tradable sector is more elastic than aggregate labor demand because local purchases of imported intermediates can be adjusted, and (3) local economies can save and borrow, running current account deficits, but the aggregate economy cannot because it is closed and bonds are in zero net supply.[22]

To make the analysis as transparent as possible, we consider a simplified version of our model where we can obtain intuitive, closed-form expressions at both the aggregate and regional level for: the employment response to a discount factor shock on impact $\frac{dn_0}{db_0}$ and the reduced-form, real wage elasticity following a discount factor shock on impact $\frac{dw_0}{dn_0}$. It is worth noting that this theoretical wage elasticity is closely related to the empirical elasticities we estimated in Tables 1 and 2.

Specifically, we consider a version of our model: without capital, habit formation, indexation, or fixed costs; where we set steady state inflation to zero; where islands are endowed with a constant amount of the tradable good every period instead of producing it; where the

[22] Beraja (2018) highlights yet another important difference: in a fiscal union, the federal tax-and-transfer system redistributes resources across regions in a way that stabilizes regional business cycles. This channel is absent in the aggregate closed-economy.

nominal interest rate rule depends on current output alone; and where government spending is constant at its steady-state level. Furthermore, we assume that prices are perfectly rigid.

Appendix A.7 derives the aggregate and regional employment responses and wage elasticities below:

$$\frac{d\hat{n}_0}{d\hat{b}_0} = \frac{1}{1-\alpha}\frac{1-\rho_b}{1-\rho_b+\varphi_y} \qquad \frac{d\hat{w}_0}{d\hat{n}_0} = \frac{\kappa_w(1-\alpha+\nu)}{1-\beta(1-a_{ww}-\rho_b)+\kappa_w}$$

$$\frac{d\tilde{n}_{k0}}{d\tilde{b}_{k0}} = \frac{1-\rho_b}{1-\rho_b+\frac{1}{\beta}-a_{\tilde{\mathcal{B}}\tilde{\mathcal{B}}}} \qquad \frac{d\tilde{w}_{k0}}{d\tilde{n}_{k0}} = \frac{\kappa_w(1+\nu)}{1-\beta(1-a_{ww}-\rho_b)+\kappa_w}\frac{1+\beta(1-a_{ww})+\kappa_w-\frac{1}{\beta}}{1+\beta(1-a_{ww})+\kappa_w-a_{\tilde{\mathcal{B}}\tilde{\mathcal{B}}}}$$

where a_{ww} and $a_{\tilde{\mathcal{B}}\tilde{\mathcal{B}}}$ are the corresponding eigenvalues associated with the effects of past wages on current wages and past accumulated bonds on current bonds.[23]

As seen from above, the employment response to a discount factor shock on impact and the corresponding wage elasticities differ markedly between the aggregate and regional economies. For example, the endogenous response of the nominal interest rate rule φ_y reduces the aggregate employment impact response because the monetary authority can lower interest rates to partially offset such the discount factor shock. The parameters of the interest rate rule are entirely absent in the expression for the regional employment response because, in a monetary union, there is a common nominal interest rate across regions. This suggests that in periods where the economy is at the zero lower bound, aggregate and regional employment responses to a discount factor shock are more similar, a point also made in Nakamura and Steinsson (2014) with respect to government spending multipliers. However, in this simplified model with fixed prices, monetary policy does not affect either aggregate or regional wage elasticities.

Furthermore, since island level economies in deviations from the aggregate are small open economies, there are two related extra margins of adjustment that are absent in the aggregate closed economy. First, the possibility to substitute labor for intermediate goods in the production of final consumption goods at the regional level ($\alpha > 0$) provides regions another margin of substitution relative to the aggregate economy. This increases the aggregate employment response relative to the regional response with respect to discount factor shocks because, for an equivalent increase in current consumption demand induced by the shock, local employment needs to increase one-for-one in equilibrium while aggregate employment needs to increase by $\frac{1}{1-\alpha}$ times the consumption increase. Conversely, it decreases the aggregate wage elasticity relative to the regional one. Second, and relatedly, the possibility to transfer resources intertemporally through savings at the gross real interest rate $\frac{1}{\beta}$ decreases

[23] They are the solutions that are inside the unit circle to $0 = \beta(a_{ww})^2 - (1+\beta+\kappa_w)a_{ww} + 1$ and $0 = (1-\beta a_{\tilde{\mathcal{B}}\tilde{\mathcal{B}}})(1-a_{\tilde{\mathcal{B}}\tilde{\mathcal{B}}}) - \frac{\beta p^x x}{\mathcal{B}}\phi_0$

both the regional employment response and the wage elasticity relative to their aggregate counterparts, since $\frac{1}{\beta} > a_{\tilde{\mathcal{B}}\tilde{\mathcal{B}}}$.

We conclude that, even in this simple model where all regions are identical along the balanced-growth path, differences in economic channels that operate at the regional but not aggregate level can make both the aggregate employment response and reduced-from wage elasticity to an aggregate discount factor shock be either greater or smaller than their regional counterparts. Similar findings hold for other shocks as well. Also, adding further heterogeneity across regions (e.g., size, industrial composition, etc.) would likely exacerbate the differences between regional and aggregate employment responses and wage elasticities even more. These results point to one potential reason to explain the results in Section 3.2: economic forces can cause a wedge between regional and aggregate wage elasticities even if both regional and aggregate economies experience the same types of shocks.

5 Estimation: regional and aggregate data combined

In this section, we develop a methodology to estimate our model combining regional and aggregate data. Because this allows us to identify aggregate shocks driving business cycles, it links particular regional patterns to particular aggregate shock decompositions. Specifically, we use the regional evidence from the previous sections in order to discipline key parameters governing the degree of wage stickiness in the aggregate. When combined with aggregate time-series data, this allows us to estimate the full model, identify the aggregate shocks of interest, and quantitatively evaluate their relative importance as drivers of aggregate business cycles. Furthermore, it allows us to assess why the aggregate relationship between wages and employment during the Great Recession was weak while it was strong at the regional level, as seen from cross region variation.

The starting point of the methodology are the Regional and Aggregate New Keynesian Wage Phillips Curve, i.e., equations (22) and (24). As we showed in Section 4.6, the first crucial implication of our modeling assumptions is that the parameters in both New Keynesian Wage Phillips Curves are identical. We let $\Theta \equiv \{\beta, \nu, \iota_w, h, \lambda_w\}$ be a vector of all such parameters other than the Calvo wage adjustment parameter ξ_w. Furthermore, Lemma 1 showed that the aggregate log-linearized equilibrium behaved as if there was a representative closed economy. Since ξ_w does not directly enter in any of the rest of the equations describing the aggregate log-linearized equilibrium, we can write such system (compactly) as:

$$A(\Theta, \Sigma)\mathbb{E}_t [X_{t+1}] + B(\Theta, \Sigma)X_t + C(\Theta, \Sigma)X_{t-1} = 0 \tag{25}$$

where X_t is a vector of both endogenous and exogenous variables and $A(\Theta, \Sigma), B(\Theta, \Sigma), C(\Theta, \Sigma)$ are matrices that depend on Θ as well as a vector of all other parameters in the model (e.g., labor shares, capital adjustment costs, etc.) that we denote by Σ.

Then, we present a fixed-point strategy in order to estimate the model combining regional and aggregate data. The following algorithm describes it:

1. Estimate (24) and (25) using aggregate data only. Obtain estimates Θ^0, Σ^0 and ξ_w^0.

2. Fixing Θ^0, estimate (22) using regional data only. Obtain a new estimate ξ_w^1.

3. Given ξ_w^1, estimate (24) and (25) using aggregate data only. Obtain new estimates Θ^1, Σ^1.

4. Go back to 2. and iterate until convergence. Obtain estimates $\hat{\Theta}, \hat{\Sigma}, \hat{\xi}_w$.

5. Given $\hat{\Theta}, \hat{\Sigma}, \hat{\xi}_w$ and aggregate data, use (24) and (25) to identify all aggregate shocks.

A number of comments are in order. Regarding steps (1), (3), and (5), we use full-information Bayesian estimation techniques in the tradition of Linde et al. (2016), Christiano et al. (2014) and Justiniano et al. (2010). We follow their choices as closely as possible while ensuring consistency with our state-level data and regressions. The details of these steps as well as the time series data used for the estimation are described in Appendix A.8. However, a crucial difference with this literature is that ξ_w is not jointly estimated with Θ, Σ. Regarding step (2), beyond the Regional New Keynesian Phillips Curve, our methodology does not use any other equations describing the regional equilibrium for estimation. Instead, it just uses the regional data to estimate ξ_w since we fix all other parameters when estimating the Regional New Keynesian Phillips Curve.[24] We do this for three reasons. First, the regional evidence we presented in Section 3 is arguably informative about the degree of wage stickiness in the economy but less so, for example, about capital adjustment costs. Second, from a conceptual perspective, we want to focus on the implications of regional business cycles for wage stickiness and, as a result, on our understanding of the drivers of aggregate business cycles. Simultaneously estimating, for example, the capital adjustment cost from regional data, makes this link less transparent and the main results in the next sections harder to interpret. Third, from an econometrics perspective, in order to obtain unbiased estimates of all the parameters in the Regional New Keynesian Phillips Curve, we would need several different instruments that are orthogonal to the labor supply shock at time t

[24] Section 5.2 describes this estimation step in detail. It is in the same spirit of the limited- information methods used in, for instance, Galí et al. (2005) when estimating a “hybrid” New Keynesian Price Phillips Curve.

and expectational errors of wage inflation at time $t+1$. In practice, these many credible instruments are hard to come by. However, going forward, other researchers may use our procedure of combining regional and aggregate data to discipline other parameters if they find suitable regional variation.

5.1 Benchmark Parameterization

There are five parameters embedded in Θ that show up in the estimation of (22) and (24): β, ν, ι_w, h and λ_w. As discussed above, we are interested in recovering ξ_w using regional data. Note, as seen by equation (23), the Calvo parameter of wage adjustment (ξ_w) is a key component determining κ_w. Estimating κ_w provides us with a way to recover ξ_w, given other parameters. In terms of parameterizing Θ, we set β, ν, ι_w and λ_w. We then use our fixed point procedure to estimate h and ξ_w.

We set β equal to 0.9948. There is a large empirical literature estimating $\frac{1}{\nu}$ which is the Frisch elasticity of labor supply. Estimates from the micro literature find that the combined extensive-margin and intensive-margin uncompensated labor supply elasticities in range of 1 ($\nu = 1$).[25] Macro estimates identified off of business cycle variation estimate uncompensated elasticities above 2 (ν below 0.5).[26] Additionally, the Frisch is often imprecisely estimated in New Keynesian DSGE models. Given this, we do not estimate ν and instead set it in both our aggregate and cross-region estimation to estimates from the literature. For our benchmark estimation, we set $\nu = 1$. However, in our robustness analysis, we explore the sensitivity of our results to alternate estimates for ν such as $\nu = 0.5$ or $\nu = 2$. ι_w governs the extent of wage indexation embedded in wage contracts. If $\iota_w = 0$, there is no wage indexation. As we show later, the exact value of ι_w does not affect our estimates of ξ_w. Given this, we assume $\iota_w = 0$ in our benchmark estimation. However, we also perform a robustness specification where we estimate ι_w directly from the regional data. Finally, we follow Linde et al. (2016) and set $\lambda_w = 1.2$.

Table 3 summarizes the parameters that we keep fixed throughout. These include the aforementioned parameters in the New Keynesian Wage Phillips Curve as well as the depreciation rate, the long-run inflation rate, the steady state government spending share, and the output growth rate.

[25] Prominent estimates of the intensive margin Frisch include 0.71 from Pistaferri (2003) and 0.54 from (Chetty et al., 2011). (Chetty et al., 2011) also surveyed several quasi-experimental estimates of the extensive-margin Frisch and find an estimate of 0.32. Several authors have produced structural estimates of the extensive margin Frisch in the range of 0.4 to 0.7 (Gourio and Noua (2009), Mustre-del Ro (2015), and Park (2017)). Based on this literature we treat the combined Frisch, reflecting both the intensive and extensive responses, to be in the neighborhood of 1. This is consistent with the recent work of Christiano et al. (2014) who also exogenously set the Frisch to 1 when estimating their medium-scale DSGE model.

[26] See, for example, King and Rebelo (2000)

Table 3: Fixed parameters, annual frequency

Wage Phillips Curve Fixed Parameters		
β	discount factor	0.9948
ν	inverse Frisch elasticity	1
λ_w	wage markup	1.2
ι_w	wage indexation	0
Other Fixed Parameters		
δ	depreciation rate	0.1
Π	ss gross inflation	1.028
g	ss gov't spending share	0.2
γ	growth rate	2

While β, ν, λ_w and ι_w will be held fixed in both the steps in the estimation algorithm corresponding to the aggregate and cross-region estimation, that is not the case with h and ξ_w. We estimate the degree of habit formation in the aggregate estimation step jointly with all other parameters. But, our aggregate estimate of h is also affected by the amount of wage stickiness ξ_w in the economy. Additionally, as seen in (22), our cross-region estimates of ξ_w are determined, in part, by h. Thus, our fixed-point strategy effectively loops over h and ξ_w until convergence.

Table 4 shows all estimated parameters. Our choices for the priors follow Christiano et al. (2014) as closely as possible, subject to the necessary frequency conversions from quarterly to annual. The column "Posterior Benchmark" refers to our benchmark estimation results from the fixed-point estimation strategy that combines regional and aggregate data. Furthermore, in the next section, we will compare several quantitative implications of our model when parameterized with our benchmark estimates to those that we would have obtained had we estimated the model with aggregate data alone. These estimates are shown in the column "Posterior Aggregate Data." The key difference between the estimation strategies is that, in the later, we do not impose that the Calvo wage adjustment parameter ξ_w needs to be consistent with the regional patterns during the Great Recession. Instead, we simply estimate ξ_w jointly with all the other parameters in the model using aggregate time-series data alone, as is the standard in the literature estimating New Keynesian DSGE models.

Our fixed-point procedure converges on a value of ξ_w equal to 0.24 . This implies that 76 percent of wages adjust during a given year. This number is very similar to recent micro estimates of annual wage adjustments using administrative data sources.[27] Had we estimated the model with aggregate data alone, we would have found that ξ_w equals 0.49.

[27]See, for example, Grigsby et al. (2018).

Table 4: Model priors and posteriors

		Prior			Posterior			
					Benchmark		Aggregate data	
		Dist	Mean	SD	Mean	SD	Mean	SD
	Wage Phillips Curve							
ξ_w	Calvo wages	B	0.32	0.20	0.24	N/A	0.49	0.09
h	habit parameter	B	0.50	0.10	0.48	0.07	0.62	0.08
	Others							
α	capital share	N	0.40	0.05	0.12	0.01	0.12	0.01
ι_p	price indexation	B	0.50	0.15	0.28	0.11	0.29	0.11
λ_p	SS price markup	N	1.20	0.10	1.04	0.07	1.05	0.07
ξ_p	Calvo prices	B	0.32	0.20	0.61	0.06	0.67	0.05
χ	capital util. cost	N	1.00	1.00	1.55	0.72	1.36	0.71
S''	capital adjust. cost	N	5.00	3.00	2.99	1.23	3.16	1.14
ϕ_π	reaction infation	N	1.50	0.25	1.62	0.15	1.51	0.14
ϕ_X	reaction GDP growth	N	0.25	0.10	0.46	0.08	0.46	0.09
ρ_R	int. rate smoothing	B	0.50	0.20	0.37	0.09	0.39	0.08
ρ_η	monetary policy	B	0.50	0.20	0.43	0.14	0.41	0.12
ρ_z	TFP growth	B	0.50	0.20	0.16	0.08	0.17	0.08
ρ_g	gov't spending	B	0.50	0.20	0.61	0.13	0.61	0.13
ρ_μ	investment	B	0.50	0.20	0.68	0.10	0.69	0.10
ρ_{λ_p}	price markup	B	0.50	0.20	0.67	0.12	0.57	0.14
ρ_φ	labor supply	B	0.50	0.20	0.71	0.10	0.59	0.11
ρ_b	discount factor	B	0.50	0.20	0.70	0.07	0.70	0.08
$100\sigma_\eta$	monetary policy	IG	2.33	3.31	1.22	0.18	1.17	0.16
$100\sigma_z$	TFP growth	IG	0.80	1.32	2.17	0.25	2.17	0.26
$100\sigma_g$	gov't spending	IG	0.80	1.32	0.50	0.07	0.49	0.06
$100\sigma_\mu$	investment	IG	0.80	1.32	14.77	5.29	14.50	4.79
$100\sigma_{\lambda_p}$	price markup	IG	0.80	1.32	0.94	0.26	0.90	0.21
$100\sigma_\varphi$	labor supply	IG	0.80	1.32	1.95	0.31	1.15	0.28
$100\sigma_b$	discount factor	IG	0.80	1.32	0.67	0.14	0.52	0.12
Log marginal likelihood					-592		-589	

Note: N stands for Normal; B for Beta; IG for Inverse-Gamma distribution.
Metropolis-Hastings: 2 chains with 120,000 draws, first 24,000 were discarded.
Log marginal likelihood calculated as Modified Harmonic Mean
"Benchmark" corresponds to the fixed-point estimation using aggregate and regional data combined. "Aggregate data" corresponds to the estimation using aggregate data only.

This is consistent with other recent estimates that use aggregate data alone to estimate their medium-scale New Keynesian models. See, for example, Christiano et al. (2014) and Linde et al. (2016). Section 5.4 further comments on the differences between the two estimation strategies. Moreover, the subsequent section discusses in detail the step in the inner loop that uses regional data to estimate ξ_w for a given h.

5.2 Estimating the Wage Phillips Curve using Regional Data

In this sub-section, we discuss how we estimate the degree of wage stickiness using cross region variation during the Great Recession. This is step (2) in the inner loop of our fixed-point algorithm. In particular, we estimate equation (22) using state level data to uncover ξ_w. Our estimates of κ_w can be mapped to estimates of ξ_w given assumptions on λ_w, ν and β.

Because the nominal wage, $\tilde{W}_{kt}$, and the local price level, $\tilde{p}_{kt}$ are stationary in log-deviations from the aggregate, we re-write equation (22) in levels as opposed to growth rates as:

$$\tilde{W}_{kt} = \alpha_0 + \alpha_1 \tilde{W}_{kt+1} + \alpha_2 M\tilde{R}S_{kt} + \alpha_3 \tilde{W}_{kt-1} + \tilde{\varphi}_{kt} + \tilde{\varepsilon}_{kt+1} \tag{26}$$

where $\tilde{\varepsilon}_{kt+1}$ is the expectational error of $E\left[\tilde{\pi}^w_{kt+1}\right] - \tilde{\pi}^w_{kt+1}$ and $\tilde{\varphi}_{kt}$ is the local level labor supply shock, $M\tilde{R}S_{kt}$ is the marginal rate of substitution defined as $\tilde{p}_{kt} + \nu \tilde{n}_{kt} + \frac{1}{1-h}(\tilde{c}_{kt} - h\tilde{c}_{kt-1})$, $\alpha_1 = \frac{\beta}{1+\beta+\kappa_w}$, $\alpha_2 = \frac{\kappa_w}{1+\beta+\kappa_w}$, and $\alpha_3 = \frac{1}{1+\beta+\kappa_w}$.

In practice, when estimating (26), we compute all state level variables in log deviations from their value in 2005. This removes any persistent differences in their initial levels across states. Furthermore, instead of expressing the regional variables as log deviations from the aggregate directly, we include a vector of time fixed effects in the regression. For $\tilde{W}_{kt}$, we use our demographically adjusted state level nominal wage measures introduced in Section 2. When computing $M\tilde{R}S_{kt}$, we use our state level scanner prices calculated from the Nielsen Retail Scanner Database for $\tilde{p}_{kt}$. Our measure of $\tilde{n}_{kt}$ is the log employment rate in state k during year t. To compute the state employment rate, we download both state level employment and state level population directly from the U.S. Bureau of Labor Statistics website. Our measure of consumption $\tilde{c}_{kt}$ comes from the U.S. Bureau of Economic Analysis. We convert the nominal series to a real series by deflating by our state level price indices. A full discussion of the data sources for all state level variables used in this regression can be found in the Online Appendix that accompanies the paper. We estimate (26) using $t = 2007$, 2008, 2009, 2010, and 2011. We start in 2007 because our price data begins in 2006 and we need lagged prices to deflate $\tilde{c}_{kt-1}$. Our regressions exclude Alaska and Hawaii because we have no price information for these states. As a result, our base regression includes 240 state-year pairs. Moreover, theory implies that $\alpha_1 + \alpha_2 + \alpha_3 = 1$ and $\alpha_1 = \beta\alpha_3$. We impose these constraints when estimating (26). Our estimate of κ_w comes from taking the ratio of

α_2 to α_3.

There are a few challenges to estimating (26) via OLS. First, $\tilde{W}_{kt+1}$, by definition, is correlated with the expectation error, $\tilde{\varepsilon}_{kt+1}$, and the local labor supply shock, $\tilde{\varphi}_{kt}$. To solve this potential issue, we instrument for future wages using lagged employment ($\tilde{n}_{k,t-1}$) as well as lagged (log) real per capita GDP. We download the per capita real GDP measures directly from the U.S. Bureau of Economic Analysis website.[28] These $t-1$ variables are uncorrelated with both the expectation error in t as well as period t innovations to local labor supply shocks. Conditional on $M\tilde{R}S_{kt}$ and $\tilde{W}_{kt-1}$, lagged employment and lagged real GDP are predictive of $\tilde{W}_{kt+1}$ with an F-test of joint significance of the instruments equal to 9.9. In all specifications, we use our predicted measure of future wages as a regressor and bootstrap the standard errors to account for the first stage prediction.

A second potential concern of our estimation of (26) is that $M\tilde{R}S_{kt}$ is potentially correlated with $\tilde{\varphi}_{kt}$ given it is a function of $\tilde{n}_{kt}$. In a world where local labor supply shocks exist, changes in employment can occur holding wages fixed. Note, estimating (26) via OLS will bias our estimate of κ_w *downward* which will bias our estimates of ξ_w *upward* implying *greater* wage stickiness. Therefore, estimating (26) via OLS will give us an *lower bound* on the estimated amount of wage flexibility implied by cross-region variation. As discussed above, we find much lower wage stickiness in our cross-region regressions relative to what is implied from aggregate data even in our OLS regression. However, to better identify κ_w we instrument for the $M\tilde{R}S_{kt}$ using measures of local house price growth. Following the work of many recent papers, including Mian and Sufi (2014), we use log local house prices as an instrument for $M\tilde{R}S_{kt}$.[29] The identifying assumption is that local house price variation during this period is orthogonal to movements in local labor supply shocks. This is a likely valid assumption for preference based labor supply shifters.[30] When we instrument for both $\tilde{W}_{kt+1}$ and $M\tilde{R}S_{kt}$ using lagged log employment rates, lagged log GDP and contemporaneous log house prices, the F-stat on the lagged log employment rate and lagged log GDP in predicting $\tilde{w}_{kt+1}$ was 18.9 and the F-stat of contemporaneous log house price changes in

[28] As with all of our other state level economic variables, we create an state specific index for real log per-capita GDP with a value of 1 in 2005. All subsequent years are log deviations from 2005.

[29] Our housing data comes from the Federal Housing Finance Authority (FHFA). The FHFA produces nominal state level price indices for all states.

[30] $\tilde{\varphi}_{kt}$ could also proxy for differences in government policy across locations that could discourage labor supply. One potential policy would be extended unemployment insurance. Essentially all states increased the duration of their unemployment benefits substantively during the recession with most states increasing to 99 weeks. Other programs like SNAP, HAMP and HARP were expanded nationally but interacted with local economic conditions. Given that many of these policies (extended unemployment insurance, SNAP, HAMP and HARP) were implemented after 2009, we performed a robustness exercise of only restricting our sample to only include 2007-2009 data when instrumenting MRS with house price changes. Our point estimate for κ_w was nearly identical in this robustness specification. This is consistent with these policies having only a modest effect on individual labor supply behavior within a region.

predicting $\tilde{MRS}_{kt}$ was 41.9.

Table 5 shows our base specification estimates of (26) using cross-state variation. Column 1 shows our results when we instrument for only W_{kt+1} while column 2 shows our results when we instrument for both $\tilde{W}_{kt+1}$ and $\tilde{MRS}_{kt}$. The table shows our estimates of α_2 and α_3. We do not report α_1 since it is constrained to be equal to $\beta\alpha_3$. Our coefficient of interest is κ_w which is the ratio of α_2 to α_3. Bootstrapped standard errors clustered at the state level are shown in parenthesis.

Table 5: Estimates of κ_w from Cross State Variation 2007-2011, Base Specification

	(1)	(2)
$\hat{\alpha}_2$	0.08	0.15
	(0.03)	(0.05)
$\hat{\alpha}_3$	0.46	0.43
	(0.02)	(0.03)
$\hat{\kappa}_w$	0.18	0.35
	(0.08)	(0.15)
$\hat{\xi}_w$	0.35	0.24
Instrument for $\tilde{w}_{kt+1}$	Yes	Yes
Instrument for $\tilde{MRS}_{kt}$	No	Yes
Year Fixed Effects	Yes	Yes
Sample Size	240	240

Note: Table shows the coefficients from estimating (26). Equation estimated imposing $\alpha_1 = \beta\alpha_3$ and $\alpha_1 + \alpha_2 + \alpha_3 = 1$. Each observation is a state-year pair. $\kappa_w = \alpha_2/\alpha_3$. In both columns, we instrument for $\tilde{W}_{kt+1}$ using $\tilde{n}_{kt-1}$ and lagged log of state real GDP per capita. In column 2, we also instrument for $\tilde{MRS}_{kt}$ using contemporaneous log house prices as an additional instrument. All standard errors (in parenthesis) are bootstrapped to account for the two stage procedure. Standard errors are also clustered at the state level. See text for additional details. When computing $\hat{\xi}_w$, we set λ_w to a value of 1.2. When computing $\tilde{MRS}_{kt}$ we set $h = 0.48$ as determined by our fixed point procedure.

When ignoring the fact that $\tilde{MRS}_{kt}$ and $\tilde{\varphi}_{kt}$ are potentially correlated (column 1), our estimate of κ_w is 0.18 (standard error = 0.08). As noted above, we expect this specification to be a lower bound on the estimate of κ_w (and an upper bound on wage stickiness) given that local labor supply shifts could cause movements in employment with no corresponding fall in wages. In column 2, we instrument for $\tilde{MRS}_{kt}$ with local house price variation. As seen from column 2, instrumenting for $\tilde{MRS}_{kt}$ causes our estimates of α_2 and consequently κ_w to increase to 0.35 (standard error = 0.15). Our results in column 2 will be our benchmark estimate throughout the paper. Using equation (23) we can infer ξ_w from κ_w given our parameterization of β and ν and λ_w. Our preferred estimate of ξ_w estimated from the cross state variation is 0.24 suggesting that 76 percent of wages adjust during a given year.

When estimating (26), we impose that $\alpha_1 = \beta\alpha_3$, with $\beta = 0.9948$, and that $\alpha_1+\alpha_2+\alpha_3 = 1$. If we ran the regression without imposing the first constraint, we cannot reject that $\beta = 0.9948$ (i.e, $\alpha_1 = 0.9948\alpha_3$). Likewise, we cannot reject that the three coefficients sum to 1. For example, if we estimated the results in column 2 of Table 5 without imposing the constraints, $\alpha_1 = 0.65$ (standard error = 0.36), $\alpha_2 = 0.05$ (standard error 0.18), and $\alpha_3 = 0.30$ (standard error = 0.19). The three coefficients sum to about 1 (as predicted by theory) and α_1 is not statistically different from α_3. We wish to note that imposing the constraint that $\alpha_1 = 0.9948\alpha_3$ does increase the precision of our base estimates as seen in Table 5.

5.3 Robustness of Regional Estimates

Table 6 shows additional robustness specifications for our estimates of κ_w and ξ_w to alternate parameterizations. Row 1 of the table reproduces our results in column 2 of Table 5. All other rows show estimates for alternative values of ν, h, and ι_w. For the alternative estimates, we use the same specification as in column 2 of Table 5. Specifically, rows 2 and 3 show our estimates for alternate values of h while rows 4 and 5 show our estimates for alternate values of ν. Changing the habit parameter across the range of estimates in the literature have no effect on our estimates of wage stickiness. While our estimates of κ_w change with different values of ν, our estimates of ξ_w are relatively stable. The reason for this is that ν also effects the mapping of κ_w to ξ_w. Across the various values of ν, our estimates of ξ_w only varies slightly from 0.24 to 0.3.

In the last row of the table, we explore the robustness of our results to relaxing our assumption that $\iota_w = 0$. To do this, we estimate a equation (26) but still imposing that $\beta = 0.9948$, $\nu = 1$ and $h = 0.48$. Under these assumptions, the last term in the equation is $-(P_{kt-2} + P_{kt})$. The coefficient on this term is informative about ι_w. When we do this robustness specification, our estimates of α_2 and α_3 are essentially unchanged leaving our estimate of κ_w unchanged. Our estimate of ι_w is close to zero, but with a large standard error. This could be a result of potential measurement error in our state level price indices or it could be because ι_w is in fact zero.

In the Online Appendix accompanying the paper, we perform a further set of robustness exercises with respect to our estimates of κ_w and ξ_w using regional data. In particular,

Table 6: Estimates of κ_w and ξ_w from Cross State Variation 2007-2011, Robustness Specifications

	Estimate of κ_w	Estimate of ξ_w
Base Estimates	0.35	0.24
	(0.15)	
Robustness 1: $h = 0.3$	0.35	0.24
	(0.16)	
Robustness 2: $h = 0.6$	0.33	0.24
	(0.15)	
Robustness 3: $\nu = 1.5$	0.19	0.27
	(0.08)	
Robustness 4: $\nu = 0.5$	0.41	0.30
	(0.25)	
Robustness 5: Estimate ι_w	0.34	0.24
	(0.16)	

Note: Table shows the coefficients from estimating (26) under alternate parameter assumptions. Equation estimated imposing $\alpha_1 = 0.99\ \alpha_3$ and $\alpha_1 + \alpha_2 + \alpha_3 = 1$. Each observation is a state-year pair. $\kappa_w = \alpha_2/\alpha_3$. The specification is analogous to column (2) in Table 5. All standard errors (in parenthesis) are bootstrapped to account for the two stage procedure. Standard errors are also clustered at the state level. Row 1 redisplays our estimates under our base parameterization shown in column 2 of Table 5. Rows 2 and 3 holds our base parameterization of β, ν and ι fixed but varies h. Rows 4 and 5 holds our base parameterization of β, h and ι fixed but varies ν. In the last row, we hold our base parameterization of β, h and ν fixed but allows ι_w to be estimated from the data. See text for additional details. To compute our estimate of ξ_w, we set λ_w to a value of 1.2.

we explore whether differences in the industrial composition across states could be biasing our estimates. For example, industries that are unionized may have different wage setting patterns than non-unionized states. To assess the extent that such concerns could be biasing our state level estimates, we performed two additional analyses. First, we explicitly controlled for the states 2006 manufacturing share when estimating (26). Second, we excluded the top one-quarter of states with the highest 2006 manufacturing share from our estimating sample. In both robustness exercises, our estimates of κ_w and ξ_w were nearly identical to those reported in Table 5

Finally, before concluding this section, it is worth discussing the "no cross-state migration" assumption that we have imposed throughout. Migration is only a potential problem for our estimates of κ_w and ξ_w if migration is selected. If in states where economic conditions deteriorate, high wage workers move out, this will put downward pressure on observed state level wages even if everyone's individual wage is sticky. Two things make us confident that this is not substantively biasing our results. First, as discussed in Section 2, our wage measures are demographically adjusted. To the extent that migration is correlated with observables like age and education, such selection issues are already purged from our wage measures. Second, using data from the 2010 American Community Survey, we compute migration flows to and from each state and, then, construct a net-migration rate for each state. As documented by others, we find that the net migration rate was very low during the Great Recession (see, for example, Yagan (2017)). The fact that the net migration rate across states was low during the Great Recession suggests that if selected migration takes place, it is likely not biasing our estimates in a meaningful way.

5.4 Comparison of Regional and Aggregate Estimates

In this section, we ask: what are the implications of using regional and aggregate data combined for our parameters estimates? In Table 4 we showed the parameter estimates under both approaches. The last line shows that the log-likelihood is almost identical under both approaches. However, we find a number of differences. First, the degree of wage stickiness is much larger when estimating the model with aggregate data alone. The posterior mode of ξ_w increases to 0.49 from 0.24. This means that, when using aggregate data alone, we estimate that 49 percent of wages do not change every year, as opposed to 24 percent when estimating the model with regional and aggregate data combined. As a comparison, Christiano, Motto, and Rostagno (2014) estimate an annual ξ_w of 0.41 and Linde, Smets, and Wouters (2016) estimate an annual ξ_w of 0.47.[31] Second, the standard deviation of the labor supply shock σ_φ decreases to 1.15 from 1.95 and the persistence ρ_φ decreases to 0.59 from 0.71. Because wage stickiness is one of the main model features generating endogenous persistence and amplification in response to shocks, when wages are estimated to be more flexible, our model requires more volatile and persistent labor supply shocks in order to match the same aggregate time-series wage data. Among other things, the following section explores how such differences affect the quantitative implications of our model.

[31] Because they use quarterly data, they report a quarterly ξ_w of 0.81 and 0.83, respectively. The implied annual ξ_w is $(0.81)^4 = 0.41$ and $(0.83)^4 = 0.47$.

6 Aggregate Implications of Regional Business Cycles

The facts we presented in the first part of the paper are puzzling. Aggregate wages did not fall much during the Great Recession. However, local wages declined more in states where employment decreased more. Why did aggregate wages respond so little to the decline in economic activity during the Great Recession while the correlation was much larger across states? What can we learn from such regional patterns about the causes of the Great Recession and its aftermath?

When tackling these questions, we compare the results following our proposed methodology in Section 5—which combines regional and aggregate data—with two alternative leading approaches in the literature. In the first alternative approach, we instead use our model estimated with aggregate time-series data alone. This approach is consistent with the standard approach used to estimate medium-scale New Keynesian DSGE models. In the second alternative approach, we abstract from our model entirely. Instead, we perform back-of-the-envelope calculations that extrapolate from well-identified regional responses to household demand shocks to the aggregate responses of interest. This approach is very much in the spirit of empirical papers using variation across regions in order to make inferences about aggregates directly. For example, many papers have used cross-region variation in the exposure to housing or banking shocks during the Great Recession to assess the effects on local employment (Mian et al. (2013) and Giroud and Mueller (2015)). These estimates have then been used by some to make predictions about the causes of aggregate employment declines during this period.

The goal of these comparisons is to highlight that: (1) by focusing on aggregate data alone, existing models have ignored information in regional data that can help discipline their main mechanisms, and (2) by focusing on regional data alone, back-of-the-envelope calculations that make inferences about aggregates without the aid of a formal model may miss economic channels and shocks that are important at the aggregate but not regional level.

6.1 Why do aggregate wages look sticky?

Many authors have emphasized how changes in household demand following declines in housing wealth or a tightening of borrowing constraints were important drivers of regional business cycles during the Great Recession.[32] Within our model, discount factor shocks can be interpreted as a proxy for such household demand shocks.[33] Thus, as we discussed in

[32] See Mian and Sufi (2014) for an important contribution along these lines.

[33] See Werning (2015) for a formalization of this point.

Section 4.7, one potential explanation for the difference between aggregate time series and cross-state patterns is that household demand shocks (i.e., discount factor shocks) were the main drivers of both regional and aggregate employment and wages during the Great Recession, but the wage elasticity to this shock is smaller in the aggregate because of economic mechanisms that operate at either the aggregate or the regional level but not both. Alternatively, the differences could be explained by other shocks also being important drivers of aggregate, but not regional, employment and wage growth. For instance, if household demand shocks decreased both regional and aggregate labor demand during the Great Recession but labor supply shocks were only important in the aggregate, then because such shocks reduce employment but put upward pressure on wages, we would precisely observe that wages seemed less flexible at the aggregate than the regional level during the late 2000s. Because of our empirical findings and these theoretical differences, we use the reduced-form elasticity of real wages with respect to employment, $\frac{dlog(w)}{dlog(n)}$, as a useful statistic for discriminating across potential causes of the Great Recession as well as a diagnostic tool for distinguishing between models of business cycles.[34]

Similar in spirit to Mian and Sufi (2014), we begin by using plausibly exogenous house price changes across regions in order to estimate the regional wage elasticity $\frac{dlog(w^{reg})}{dlog(n^{reg})}$ to a regional household demand shock. This is the empirical analog to the theoretical wage elasticity $\frac{d\tilde{w}}{d\tilde{n}}$ we derived in Section 4.7. In particular, using the same state-level data underlying Table 5, we regress the log-change in real wages between 2007 and 2010 on the log-change in employment during this time period, where we instrument the later with the log-change in house prices between 2007 and 2010. We obtain a 3-year elasticity of 0.78 (0.30). This is very close to the unconditional elasticity of 0.64 we reported in Table 1, which is consistent with the observation that regional differences in employment and wages were by and large driven by household demand shocks (which are proxied by discount factor shocks in our framework).

Next, in our model, we compute the aggregate wage elasticity $\frac{dlog(w^{agg})}{dlog(n^{agg})}$ to an aggregate discount factor shock during the 2007-2010 period. This is analogous to the theoretical wage elasticity $\frac{d\hat{w}}{d\hat{n}}$ in the simplified model from Section 4.7. Because we do not have plausibly exogenous time-series variation in aggregate household demand during the Great Recession, we cannot estimate $\frac{dlog(w^{agg})}{dlog(n^{agg})}$ directly from the data as we did for the regional elasticity. Instead, we use our estimated model to compute the impulse responses of real wages and employment to a discount factor shock in 2007 that induces changes in aggregate household demand. As we have mentioned, such discount factor shock is the closest theoretical analog

[34] See Nakamura and Steinsson (2017) for a related discussion on how both well-identified moments and portable statistics are helpful to discriminate across models.

to the changes in regional household demand we used to estimate $\frac{dlog(w^{reg})}{dlog(n^{reg})}$. Computing the impulse responses at a 3 year horizon, we find an aggregate elasticity $\frac{dlog(w^{agg})}{dlog(n^{agg})}$ of 1.17 for our benchmark parameterization that combines regional and aggregate data in estimation.

Because the aggregate real wage elasticity in response to a household demand shock is actually larger than the regional one (1.17 v 0.78), economic mechanisms that differentially operate between the aggregate and regional levels cannot alone explain the relative stickiness of aggregate wages that we observed during the Great Recession. As we showed in Section 4.7, such economic mechanisms could have decreased this elasticity in theory—thus explaining the lack of flexibility of aggregate wages. However, we find that the opposite is true given our benchmark parameter estimates.[35] Had we used the alternative parameterization that uses aggregate data alone in our model estimation, we would have found that the aggregate real wage elasticity in response to a household demand shock was 0.36. This is very close to the observed aggregate real wage elasticity of 0.31 for the Great Recession shown in Table 2. Thus, we would have erroneously concluded that differences between the regional and aggregate real wage elasticities in response to a household demand shock could potentially resolve why aggregate wages look relatively sticky. However, the aggregate wage stickiness estimated using only aggregate data is inconsistent with the cross-region relationship between real wage growth and employment growth observed during the Great Recession.

Given that differences in wage elasticities in response to regional versus aggregate household demand shocks cannot explain the differential aggregate and regional wage patterns during the Great Recession, it must be that the set of shocks experienced by the aggregate economy during the Great Recession differed from their regional counterparts. However, these set of aggregate shocks get differenced out when exploiting cross-region variation. In order to see which other shocks can account for the observed aggregate wage stickiness, we feed the aggregate model with the estimated shocks during the 2007 to 2010 time period assuming the economy was on a balanced-growth path prior to 2007. We then compute the predicted log-change in real wages divided by the log-change in employment between 2007 and 2010 for each of the shocks or set of shocks we examine. Table 7 shows the results for our benchmark model as well as for the alternative parameterization that uses aggregate data alone in estimation.

The results suggest that labor supply shocks were an important factor explaining why aggregate real wages did not fall during the Great Recession. Specifically, Table 7 shows that, when we feed the model with only the discount factor shock (b) realizations, the

[35] For example, one such mechanism is monetary policy. Intuitively, because monetary policy endogenously responds to changes in demand, it stabilizes employment. As a result, the elasticity of wages to employment in the aggregate is larger than at the regional level. The large monetary policy actions taken by the U.S. Federal Reserve during the Great Recession likely helped to stabilize aggregate employment.

Table 7: Predicted $\frac{dlog(w^{agg})}{dlog(n^{agg})}$ during the Great Recession in Response to Various Shocks

	Shocks		
	b	b and μ	b, μ, and φ
Benchmark	0.97	0.83	0.31
Aggregate data alone	0.41	0.41	0.25

Note: The column first column corresponds to feeding the model with only the 2008, 2009, and 2010 realizations of the discount factor shock (b). The second column feeds the realizations of both the discount factor and investment efficiency shocks (b, μ). The final column feeds the realizations of the discount factor shock, the investment efficiency shock and the labor supply shock (b, μ, φ). The first row labeled "Benchmark" uses the parameterization and shocks when estimating the model with both regional and aggregate data. The second row labeled "Aggregate data only" uses the parameterization and shocks when only using aggregate data for estimation.

cumulative aggregate real wage elasticity between 2007 and 2010 is 0.97 under our benchmark parameterization. This is somewhat smaller than 1.16—i.e., the theoretical elasticity we computed above after a one-time discount factor shock—and closer to the regional elasticity of 0.78. But it is still much larger than 0.31—i.e., the aggregate elasticity we empirically estimated for the Great Recession shown in Table 2. When we feed the realizations of the discount factor and investment efficiency shocks combined (b and μ), the elasticity decreases slightly to 0.83. Yet, these combined "demand shocks" still cannot account for the observed stickiness of aggregate wages.[36] However, when we feed the benchmark model a combination of the discount factor shock, the investment efficiency shock *and* the labor supply shock (φ), the elasticity decreases considerably to 0.31. The combination of these three shocks using our benchmark model coincides nearly exactly with our observed elasticity for the Great Recession (as shown in Table 2).

Furthermore, Table 7 also shows that, had we estimated the model with aggregate data alone, we would have found that household demand shocks alone would have nearly matched our empirical estimates of the aggregate wage elasticity during the Great Recession. In other words, the model estimated with only aggregate data implies that labor supply shocks are not necessary to explain the aggregate relationship between wages and employment during the Great Recession. The reason for this is that under our parameterization with aggregate data alone the degree of wage stickiness is estimated to be much higher than under our base parameterization.

We conclude that aggregate wages looked much more sticky relative to their regional

[36] As in Smets and Wouters (2007), we refer to these shocks as "demand" because they cause both employment and price inflation to move in the same direction.

counterparts during the Great Recession because of labor supply shocks that hit the aggregate economy. Since these labor supply shocks push wages and employment in opposite directions and are differenced out when comparing outcomes across regions in our regional regressions, they reduced the observed aggregate wage elasticities relative to the observed regional wage elasticities during the Great Recession.

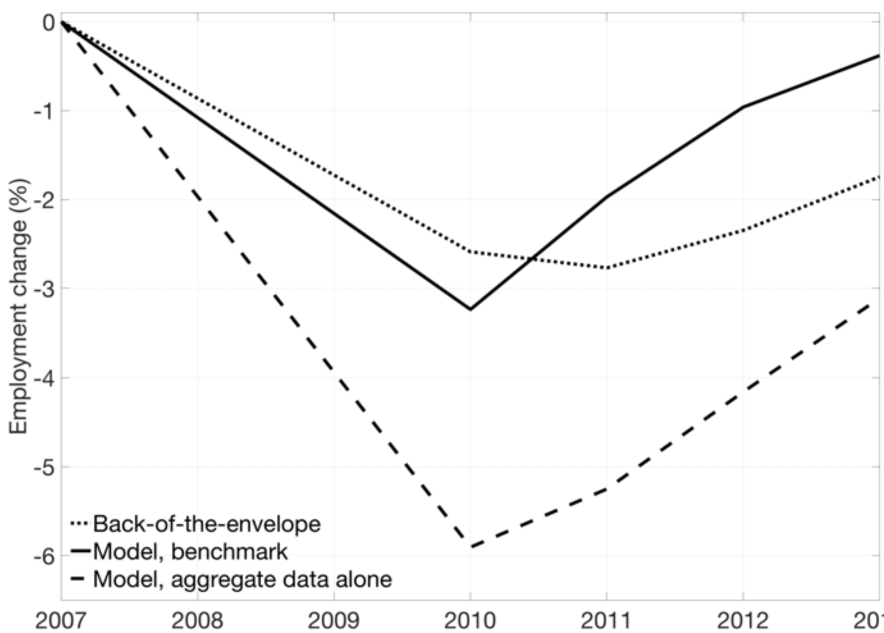
6.2 What explains the employment decline and slow recovery?

In this section, we begin by focusing on how household demand shocks contributed to the employment decline between 2007 and 2010 as well as the slow recovery afterwards. Then, motivated by the results from the previous section, we perform a model-based shock decomposition in order to understand which other shocks were also important drivers of employment during the Great Recession and its aftermath.

Following our three alternative approaches, Figure 5 compares the employment response at several horizons to household demand shocks that occurred between 2007 and 2010. As explained before, we interpret discount factor shocks as the closest model analog to changes in household demand. Then, the solid and dashed lines show, respectively, the model implied responses to discount factor shocks when using either our benchmark parameterization (i.e., combining regional and aggregate data in estimation) or the alternative parameterization that uses aggregate data alone in estimation. Specifically, we compute the predicted log-change in employment at several horizons when we feed the model with the estimated discount factor shocks between 2007 and 2010 alone, assuming the economy was in a balanced-growth path in 2007. The dotted line shows the back-of-the-envelope calculation when extrapolating from estimated regional responses. Using the same state-level data underlying Table 5, we first regress the log-change in employment from 2007 at different yearly horizons on the log-change in house prices between 2007 and 2010. Under the assumption that such house price changes are exogenous and correlated with changes in household demand, this gives estimates of the reduced-form regional employment response at different horizons to the combined household demand shocks that occurred between 2007 and 2010.[37] This regional response is the empirical analog to the theoretical response $\frac{d\tilde{n}}{d\tilde{b}}$ in Section 4.7. Then, in order to compute the aggregate employment response to household demand shocks, we

[37]House prices are not exogenously determined. However, there is growing evidence that house price movements during the 2000s were driven by either shifts in mortgage lender technology (Favilukis et al. (2017)) or shifts in beliefs about preferences for housing itself (Kaplan et al. (2017)). As house prices change, it can generate both wealth effects and liquidity effects that can drive household demand (Berger et al. (2018) and Mian and Sufi (2014)). The housing price movements therefore can serve as a proxy for shifts in expectations that can drive local consumption and employment through local household demand channels.

Figure 5: Employment Response to 2007-2010 Household Demand shocks



Note: "Model, benchmark" shows the employment response when feeding the model with the 2007-2010 discount factor shocks, under the benchmark parameterization that combines regional and aggregate data in estimation. "Model, aggregate data alone" uses the alternative parameterization when we estimate the model with aggregate data only. For "Back-of-the-envelope", we first compute the regional employment elasticity at different horizons to regional house price changes that occurred between 2007-2010. Then, we multiply these elasticities with the aggregate house price changes between 2007-2010.

simply multiply these regional responses by the aggregate decline in house prices between 2007 and 2010 of 30 percent.[38]

Between 2007 and 2010, we find a similar employment response to household demand shocks when we use our model under the benchmark parameterization or the back-of-the-envelope calculation. Employment falls between 2.5 and 3.5 percent under both approaches between 2007 and 2010. This is also very similar in magnitude to the employment response implied by the regional elasticities to a housing net worth shock in Mian and Sufi (2014).[39] However, had we used aggregate data alone in estimation, we would have predicted an employment decline of approximately 6 percent between 2007 and 2010, assigning a much

[38] To compute the change in house prices, we use the S&P/Case-Shiller 20-City Composite Home Price Index, Seasonally adjusted (SPCS20RSA) from https://fred.stlouisfed.org/series/SPCS20RSA.

[39] Mian and Sufi (2014) report a non-tradable employment elasticity to housing net worth between 0.2 and 0.4 between 2007 and 2009 (depending on their specification). In order to perform a back-of-the-envelope calculation, we can simply multiply these elasticities by their reported average housing net worth decline of 9.5 percent. This results in a predicted employment decline between 2 and 3.5 percent.

bigger role to household demand shocks in explaining the employment decline during the Great Recession.

Furthermore, under our benchmark parameterization, we find that employment should have essentially recovered by 2012 had the economy been hit by discount factor shocks alone. This is far from the case when either performing our back-of-the-envelope calculation or when using our model estimated with aggregate data alone. For example, the back-of-the-envelope calculation implies that by 2013 aggregate employment should have still been depressed by about 2 percent compared to its long-run level as a result of household demand shocks.

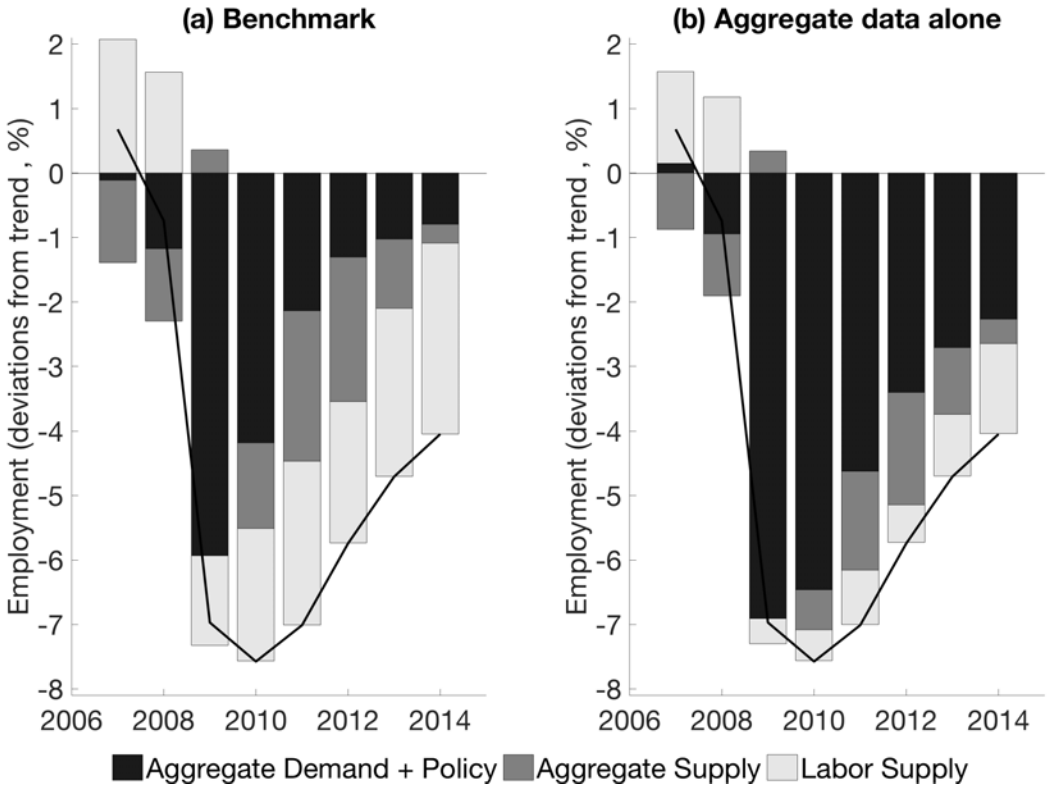
Taken together, we conclude that the combination of economic mechanisms that operate at the aggregate but not regional level does not generate quantitatively large differences in the employment response to household demand shocks at short horizons when our model is estimated using regional and aggregate data combined. However, at longer horizons, such mechanisms make extrapolating directly from regional employment elasticities more problematic.

Next, we ask which shocks can account for the employment decline between 2007 and 2010 as well as the slow recovery afterwards. In order to do so, we perform a historical shock decomposition and report the contributions of each group of shocks to the observed employment changes. Figure 6 shows the results. The solid line is the actual data. The black bars are computed by feeding the model with a combination of demand shocks (i.e., discount factor and investment efficiency shocks) and the policy shocks (i.e., monetary and government spending shocks). As mentioned, we call the combination of discount factor and investment efficiency shocks "aggregate demand" because they cause inflation and employment to move in the same direction.[40] The dark grey bars are computed by feeding the model with the "aggregate supply" shocks (i.e., productivity and price markups). Finally, the light grey bars are computed by feeding the labor supply shock alone.

We find that, under our benchmark parameterization (left panel), the combination of aggregate demand and policy shocks can account for much of the employment decline between 2007 and 2009. The same is true had we estimated the model with aggregate data alone (right panel). Thus, under both parameterizations, these shocks explain a significant portion of the employment decline during the early portions of the Great Recession. However, the differences between the two parameterizations are much starker regarding the slow recovery of employment after 2010. Under our benchmark parameterization, we find that had the economy only been hit by aggregate demand and policy shocks, employment would have recovered much faster in the aftermath of the Great Recession. Instead, it is the combination of aggregate supply and labor supply shocks that account for the slow recovery. By 2012, it is

[40] We borrow this terminology from Smets and Wouters (2007).

Figure 6: Employment shock decomposition



Note: Bars are computed by feeding the model with groups of shocks, one at a time. Combined, they add up to the data (i.e., the solid line). "Aggregate Demand + Policy" feeds the discount factor, the investment efficiency, monetary policy, and government spending shocks. "Aggregate Supply" feeds the price markup and productivity shocks. "Labor Supply" feeds the labor supply shocks alone. Panel (a) corresponds to our benchmark estimation that combines regional and aggregate data. Panel (b) uses aggregate data alone in estimation instead.

primarily the labor supply shocks that are explaining the sluggish employment recovery in the U.S. under our base parameterization. However, had we estimated the model with aggregate data alone, we would have found that aggregate demand and policy shocks significantly contributed to the observed persistence in employment decline.[41]

6.3 Discussion

To summarize, we find that a combination of aggregate demand and policy shocks were the main drivers of aggregate employment during the early parts of the Great Recession, but the wage stickiness necessary for them to account for the slow employment recovery through 2014 in our model is inconsistent with the flexibility of wages we observe across US

[41]These differences echo the point made by Basu and House (2017) that, in most medium-scale DSGE models, wage stickiness is essential for obtaining persistent real effects of nominal shocks.

states. Relatedly, directly extrapolating from regional to aggregate employment responses to household demand shock overstates their contribution to the persistent employment decline following the Great Recession. Moreover, the full set of results highlighted above suggests that labor supply shocks are needed to explain the observed differences between aggregate and regional wage elasticities, as well as much of the slow employment recovery after the Great Recession. We offer two possible interpretations in light of other existing research.

First, because our model generates wage elasticities that are counterfactually high in response to aggregate demand shocks alone, if demand forces where indeed key drivers of both employment and wages between 2007 and 2014, they ought to generate variation in the measured "labor wedge" through channels other than wage or price stickiness. For example, Angeletos, Collard, and Dellas (2017) shows how "confidence" shocks can manifest themselves as "labor wedge" shocks in a DSGE model.

Second, there is a growing literature among both labor and macro economists suggesting that structural forces contributed to aggregate employment declines observed during the Great Recession.[42] The secular decline of low skilled primarily manufacturing jobs that occurred during the 2000s may have resulted in skill mismatch in the aggregate economy that manifested itself as an increasing labor wedge. As low skilled jobs are eliminated, employment falls for low skilled workers. If these workers do not have the skills necessary to fill the jobs created in the economy, wage pressure on existing jobs will be muted. The large employment declines with mitigated downward wage pressure can look like a negative labor supply shock in aggregate data. Both Charles et al. (2018a) and Charles, Hurst, and Schwartz (2018b) use reduced form estimates to conclude that between 30 and 40 percent of the employment decline in the U.S. from prior to the Great Recession through 2014 can be attributed to declines in the manufacturing sector. Charles et al. (2016) uses detailed micro data to conclude that the housing boom masked some of these structural forces prior to the Great Recession in aggregate data making it appear that these structural forces were a "shock" that started at the onset of the Great Recession. The labor supply shock we identify in our model can potentially be proxying for these structural skill mismatch forces identified in the literature. Interpreted through that lens, our findings suggest that a combination of both business cycle and structural forces may have contributed to the sharp decline in employment during the Great Recession and can explain why employment rates for prime age workers remain low through 2014. While cyclical demand forces explained much of the employment decline in the early part of the recession, it is these structural forces which manifested themselves as a labor supply shock that potentially explains why employment

[42]See, for example, Charles, Hurst, and Notowidigdo (2016), and Charles, Hurst, and Schwartz (2018b)).

remained persistently low during the recovery.[43]

Finally, we performed a number of robustness exercises to explore the sensitivity of our main quantitative results. In particular, we re-estimate our model using each alternative parameterization of habits h, Frisch elasticity ν, and indexation ι_w from Table 6. Also, we consider setting $\lambda_w = 1.5$, another common estimate in the literature. We do so both using our methodology that combines regional and aggregate data, as well as the alternative procedure that uses aggregate data alone. All of our main findings described in the previous sections remain essentially unchanged.

7 Conclusion

In this paper, we have argued that regional business cycles have interesting implications for our understanding of aggregate business cycles, but that drawing such inferences cannot be done by naively extrapolating from regional variation alone without the aid of a formal model. Then, we have presented a methodology that combines both regional and aggregate data in order to estimate a medium-scale New Keynesian DSGE model of a monetary union.

Most of the literature estimates aggregate business cycle models without exploiting regional data. In doing so, they have ignored valuable information in regional business cycles that can help discipline theoretical mechanisms that shape aggregate business cycles. In particular, we have shown that the wage stickiness needed for aggregate demand shocks to jointly explain the behavior of aggregate employment and wages during the Great Recession and its aftermath is inconsistent with the flexibility of wages we estimate using cross-region variation. Instead, we find that something akin to aggregate labor supply shocks —which get differenced when exploiting cross-region variation—are needed to both explain the slow recovery in employment as well as why aggregate wages fell little despite the large decline in aggregate employment.

A separate strand of literature naively extrapolates from well- identified regional elasticities to learn about the drivers of aggregate business cycles. We have also shown that this approach misses economic channels and shocks that differ between regional and aggregate economies.

Given the wealth of regional data available to researchers that indeed allows for more

[43] The literature has also highlighted two other factors that could appear as increased labor supply shocks during the Great Recession. First, Aguiar et al. (2018) show how increased leisure technology shifted the labor supply curve for individuals during the 2000s. However, they estimate that such a change while potentially important for young men had only a very small effect on total prime age employment rates during the 2007-2014 period. Mulligan (2012) discussed the importance of increased government transfers at the aggregate level in reducing labor supply.

credible identification, we show how combining regional and aggregate data can help discipline key structural parameters. These structural parameters can then be embedded in models of the aggregate economy to perform quantitative exercises. As such, we hope this paper provides a bridge between researchers estimating structural models and those using regional variation to estimate reduced-form responses to shocks, further improving our understanding of the causes of aggregate fluctuations as well as the consequences of fiscal and monetary policy.

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Appendix A Model and Estimation

We begin this section by stating all equations describing the non-linear equilibrium in our economy. Then, we derive the log-linearized equations describing the log-linearized equilibrium. Next, we prove the Lemmas 1 and 2. We then derive the aggregate and regional shock elasticities described in section 4.7. Finally, we discuss our Bayesian estimation procedure along with the aggregate data we use to estimate the model.

Appendix A.1 Shocks

1. Retail markup shock:

$$\log \lambda^p_{kt} = \rho_p \log \lambda^p_{kt-1} + u^p_t + v^p_{kt}, \tag{A1}$$
$$u^p_t \sim N(0, \sigma^2_p), \quad v^p_{kt} \sim N(0, \tilde{\sigma}^2_p). \tag{A2}$$

2. Neutral technology shock:

$$z_t \equiv \Psi_t / \Psi_{t-1}, \tag{A3}$$
$$\log z_t = (1-\rho_z)\log\gamma + \rho_z \log z_{t-1} + u^z_t, \tag{A4}$$
$$u^z_t \sim N(0, \sigma^2_z) \tag{A5}$$

3. Tradable technology shock:

$$\log A^x_{kt} = (1-\rho_x)\log\Psi_t + \rho_x \log A^x_{kt-1} + v^x_{kt}, \tag{A6}$$
$$v^x_{kt} \sim N(0, \tilde{\sigma}^2_x). \tag{A7}$$

4. Retail technology shock:

$$\log A^y_{kt} = (1-\rho_y)\log\Psi_t + \rho_y \log A^y_{kt-1} + v^y_{kt}, \tag{A8}$$
$$v^y_{kt} \sim N(0, \tilde{\sigma}^2_y). \tag{A9}$$

5. Demand shock:

$$\log b_{kt} = \rho_b \log b_{kt-1} + u_t^b + v_{kt}^b \tag{A10}$$

$$u_t^b \sim N(0, \sigma_b^2), \quad v_{kt}^b \sim N(0, \tilde{\sigma}_b^2); \tag{A11}$$

6. Marginal efficiency of investment shock:

$$\log \mu_{kt} = \rho_\mu \log \mu_{kt-1} + u_t^\mu + v_{kt}^\mu \tag{A12}$$

$$u_t^\mu \sim N(0, \sigma_\mu^2), \quad v_{kt}^\mu \sim N(0, \tilde{\sigma}_\mu^2); \tag{A13}$$

7. Labor supply shock:

$$\log \varphi_{kt} = \rho_\varphi \log \varphi_{kt-1} + u_t^\varphi + v_{kt}^\varphi \tag{A14}$$

$$u_t^\varphi \sim N(0, \sigma_\varphi^2), \quad v_{kt}^\varphi \sim N(0, \tilde{\sigma}_\varphi^2). \tag{A15}$$

8. Government spending shock:

$$\log \epsilon_{kt}^g = \rho_g \log \epsilon_{kt-1}^g + u_t^g + v_{kt}^g, \tag{A16}$$

$$u_t^g \sim N(0, \sigma_g^2), v_{kt}^g \sim N(0, \tilde{\sigma}_g^2). \tag{A17}$$

9. Monetary Policy shock:

$$\log \eta_t = \rho_\eta \log \eta_{t-1} + u_t^\eta \tag{A18}$$

$$u_t^\eta \sim N(0, \sigma_\eta^2). \tag{A19}$$

Appendix A.2 Detrending

There are two sources of non-stationarity: retailer technology and inflation. We can construct stationary variables as follows

- Stationary variables:

$$N_{kt}, \quad N_{kt}^x, \quad N_{kt}^y, \quad u_{kt}, \quad q_{kt}, \quad R_t. \tag{A20}$$

- Scaled by technology:

$$y_{kt} = \frac{Y_{kt}}{\Psi_t}, \quad c_{kt} = \frac{C_{kt}}{\Psi_t}, \quad i_{kt} = \frac{I_{kt}}{\Psi_t}, \quad k_{kt} = \frac{K_{kt}}{\Psi_t}, \quad k^x_{kt} = \frac{K^x_{kt}}{\Psi_t}, \quad k^y_{kt} = \frac{K^y_{kt}}{\Psi_t}, \quad \bar{k}_{kt} = \frac{\bar{K}_{kt}}{\Psi_t},$$
$$x_{kt} = \frac{X_{kt}}{\Psi_t}, \quad gdp_t = \frac{GDP_t}{\Psi_t}. \quad g_{kt} = \frac{G_{kt}}{\Psi_t} \quad a^x_{kt} = \frac{A^x_{kt}}{\Psi_t}, \tag{A21}$$

- Scaled by price level:

$$p^x_{kt} = \frac{P^x_t}{P_{kt}} \quad r^K_{kt} = \frac{R^K_{kt}}{P_{kt}}, \quad mc_{kt} = \frac{MC_{kt}}{P_{kt}}, \quad \pi_{kt} = \frac{P_{kt}}{P_{kt-1}},$$
$$\tilde{p}_{kt} = \frac{\tilde{P}_{kt}}{P_{kt}}, \quad \tilde{\Gamma}^p_{kt,t+s} = \Gamma^p_{kt,t+s}\frac{P_{kt}}{P_{kt+s}}. \tag{A22}$$

- Scaled by technology and price level:

$$\tau_{kt} = \frac{T_{kt}}{\Psi_t P_{kt}}, \quad D_{kt} = \frac{D_{kt}}{\Psi_t P_{kt}}, \quad \lambda_{kt} = \Psi_t P_{kt} \Lambda_{kt}, \quad \mathcal{B}_{kt} = \frac{B_{kt}}{\Psi_t P_{kt}},$$
$$w_{kt} = \frac{W_{kt}}{\Psi_t P_{kt}}, \quad \pi^w_{kt} = \frac{W_{kt}}{W_{kt-1}}, \tilde{w}_{kt} = \frac{\tilde{W}_{kt}}{W_{kt}}, \quad \tilde{\Gamma}^w_{kt,t+s} = \Gamma^w_{kt,t+s}\frac{P_{kt}\Psi_t}{P_{kt+s}A^y_{t+s}}. \tag{A23}$$

Appendix A.3 Non-linear equilibrium conditions

- Marginal utility of consumption:

$$\lambda_{kt} = \frac{b_{kt}\phi_{kt}}{c_{kt} - hc_{kt-1}} \tag{A24}$$

- Euler equation for bonds:

$$\lambda_{kt} = \beta \mathbb{E}_t \left[\frac{\lambda_{kt+1}}{z_{t+1}} \frac{R_t}{\pi_{kt+1}} \right] \tag{A25}$$

- Capital utilization:

$$r^K_{kt} = a'(u_{kt}) = \zeta u^{\chi}_{kt} \tag{A26}$$

- Tobin's Q: (Euler equation for capital):

$$\lambda_{kt} = \beta \mathbb{E}_t \left\{ \frac{\lambda_{kt+1}}{z_{t+1}} \frac{r^K_{kt+1} u_{kt+1} - a(u_{kt+1}) + (1-\delta) q_{kt+1}}{q_{kt}} \right\} \tag{A27}$$

- Investment:

$$\lambda_{kt} = q_{kt}\lambda_{kt}\mu_{kt}\left[1 - S\left(\frac{i_{kt}z_t}{i_{t-1}}\right) - \frac{i_{kt}z_t}{i_{kt-1}}S'\left(\frac{i_{kt}z_t}{i_{t-1}}\right)\right] + \beta\mathbb{E}_t\left[\frac{\lambda_{kt+1}}{z_{t+1}}q_{kt+1}\mu_{kt+1}\left(\frac{i_{kt+1}z_{t+1}}{i_{kt}}\right)^2 S'\left(\frac{i_{kt+1}z_{t+1}}{i_{kt}}\right)\right] \tag{A28}$$

- Wage setting:

$$\mathbb{E}_t\sum_{s=0}^{\infty}(\beta\xi_w)^s N_{kt+s}(j)\left[b_{kt+s}\phi_{kt+s}\varphi_{kt+s}N_{kt+s}(j)^{\nu}\lambda_w - \lambda_{kt+s}\tilde{\Gamma}^w_{kt,t+s}w_{kt}\tilde{w}_{kt}(j)\right] = 0, \tag{A29}$$

- Wage law of motion:

$$1 = (1-\xi_w)\tilde{w}_{kt}^{\frac{1}{1-\lambda_w}} + \xi_w\left(\tilde{\Gamma}^w_{kt-1,t}\right)^{\frac{1}{1-\lambda_w}} \tag{A30}$$

- Wage inflation:

$$\pi^w_{kt} = \frac{w_{kt}z_t\pi_{kt}}{w_{kt-1}} \tag{A31}$$

- Price setting:

$$\mathbb{E}_t\sum_{s=0}^{\infty}(\beta\xi_p)^s\lambda_{kt+s}y_{kt+s}(i)\left[\tilde{p}_{kt}(i) - \lambda^p_{kt+s}mc_{kt+s}\right] = 0 \tag{A32}$$

- Price law of motion:

$$1 = (1-\xi_p)\tilde{p}_{kt}^{\frac{1}{1-\lambda^p}} + \xi_p\left(\tilde{\Gamma}^p_{t-1,t}\right)^{\frac{1}{1-\lambda^p}} \tag{A33}$$

- Cost minimization:

$$\frac{k_{kt}(i)}{N^y_{kt}(i)} = \frac{\alpha_1}{1-\alpha_1-\alpha_2}\frac{w_{kt}}{r^K_{kt}}, \tag{A34}$$

$$\frac{k_{kt}(i)}{x_{kt}(i)} = \frac{\alpha_1}{\alpha_2}\frac{p^x_{kt}}{r^K_{kt}} \tag{A35}$$

- Marginal cost:

$$mc_{kt} = \left(\frac{r^K_{kt}}{\alpha_1}\right)^{\alpha_1}\left(\frac{p^x_{kt}}{\alpha_2}\right)^{\alpha_2}\left(\frac{w_{kt}}{1-\alpha_1-\alpha_2}\right)^{1-\alpha_1-\alpha_2} \tag{A36}$$

- Tradable production:

$$w_{kt} = (1-\alpha_x) p_{kt}^x (a_{kt}^x)^{1-\alpha_x} (k_{kt}^x)^{\alpha_x} (N_{kt}^x)^{-\alpha_x} \tag{A37}$$

$$R_{kt}^K = \alpha_x p_{kt}^x (a_{kt}^x)^{1-\alpha_x} (k_{kt}^x)^{\alpha_x - 1} (N_{kt}^x)^{1-\alpha_x} \tag{A38}$$

- Effective capital:

$$k_{kt} = \frac{u_{kt}\bar{k}_{kt-1}}{z_t} \tag{A39}$$

- Physical capital law of motion:

$$\bar{k}_{kt} = \frac{(1-\delta)\bar{k}_{kt-1}}{z_t} + \mu_{kt}\left[1 - S\left(\frac{i_{kt}z_t}{i_{kt-1}}\right)\right] i_{kt} \tag{A40}$$

- Production function: (ignoring price and wage dispersion)

$$y_{kt} = (k_{kt}^y)^{\alpha_1} x_{kt}^{\alpha_2} \left(N_{kt}^y\right)^{1-\alpha_1-\alpha_2} - F \tag{A41}$$

- Taylor rule:

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{\rho_R} \left[\left(\frac{\pi_t}{\pi}\right)^{\phi_\pi} \left(\frac{gdp_t/gdp_{t-1}z_t}{\gamma}\right)^{\phi_X}\right]^{1-\rho_R} \eta_t \tag{A42}$$

- Government spending:

$$g_{kt} = \left(1 - \frac{1}{\epsilon_{kt}^g}\right) y_{kt} \tag{A43}$$

- GDP identity:

$$gdp_t = c_t + i_t + g_t \tag{A44}$$

- Goods market clearing:

$$y_{kt} = c_{kt} + i_{kt} + g_{kt} + \frac{a(u_{kt})\bar{k}_{kt-1}}{z_t} \tag{A45}$$

- Labor market clearing:

$$N_{kt} = N_{kt}^x + N_{kt}^y \tag{A46}$$

- Capital market clearing:

$$k_{kt} = k_{kt}^x + k_{kt}^y \tag{A47}$$

- Tradable good market clearing:

$$\sum_k x_{kt} = \sum_k (k^x_{kt})^{\alpha_x} \left(a^x_{kt} N^x_{kt}\right)^{1-\alpha_x} \tag{A48}$$

- Island resource constraint (balance of payments):

$$\mathcal{B}_{kt} - \frac{R_{t-1}}{\pi_{kt} z_t} \mathcal{B}_{kt-1} = p^x_{kt} \left[(k^x_{kt})^{\alpha_x} \left(a^x_{kt} N^x_{kt}\right)^{1-\alpha_x} - x_{kt} \right] + \tau_{kt} + g_{kt} \tag{A49}$$

- Budget constraint of federal government:

$$\mathcal{D}_{kt} - \frac{R_{t-1}}{\pi_{kt} z_t} \mathcal{D}_{t-1} = \sum_k \left[g_{kt} + \tau_{kt} \right] \tag{A50}$$

Appendix A.4 Log-linearized equilibrium conditions

Lowercase variables with " ˆ " denote log-deviations from the balanced-growth path.

- Marginal utility of consumption:

$$\hat{\lambda}_{kt} = \hat{b}_{kt} + \hat{\phi}_{kt} + \frac{h}{1-h} \hat{c}_{kt-1} - \frac{1}{1-h} \hat{c}_{kt} \tag{A51}$$

- Euler equation for bonds:

$$\hat{\lambda}_{kt} = \hat{R}_t + \mathbb{E}_t \left[\hat{\lambda}_{kt+1} - \hat{z}_{t+1} - \hat{\pi}_{kt+1} \right] \tag{A52}$$

- Capital utilization:

$$\hat{r}^K_{kt} = \chi \hat{u}_{kt} \tag{A53}$$

- Tobin's Q: (Euler equation for capital):

$$\hat{q}_{kt} = \frac{\beta(1-\delta)}{\gamma} \mathbb{E}_t \left[\hat{q}_{kt+1} \right] + \left(1 - \frac{\beta(1-\delta)}{\gamma} \right) \mathbb{E}_t \left[\hat{r}^k_{kt+1} \right] - \mathbb{E}_t \left[\hat{R}_t - \hat{\pi}_{kt+1} \right] \tag{A54}$$

- Investment:

$$0 = \hat{q}_{kt} + \hat{\mu}_{kt} - \gamma^2 S'' \left[\hat{i}_{kt} - \hat{i}_{kt-1} + \hat{z}_t \right] + \beta \gamma^2 S'' \mathbb{E}_t \left[\hat{i}_{kt+1} - \hat{i}_{kt} + \hat{z}_{t+1} \right] \tag{A55}$$

- New Keynesian Wage Phillips Curve (NKWPC):

$$\hat{w}_{kt} = \frac{\beta}{\kappa_w}\mathbb{E}_t\left[\hat{\pi}^w_{kt+1} - \iota_w\hat{\pi}_{kt}\right] - \frac{1}{\kappa_w}\left(\hat{\pi}^w_{kt} - \iota_w\hat{\pi}_{kt-1}\right) + \frac{1}{1-h}\left(\hat{c}_{kt} - h\hat{c}_{kt-1}\right) + \nu\hat{n}_{kt} + \hat{\varphi}_{kt}, \tag{A56}$$

where $\kappa_w = \frac{(1-\beta\xi_w)(1-\xi_w)}{\xi_w}\frac{\lambda_w-1}{\lambda_w(1+\nu)-1}$ is the slope of the NKWPC.

- Wage inflation:

$$\hat{\pi}^w_{kt} = \hat{w}_{kt} + \hat{z}_t + \hat{\pi}_{kt} - \hat{w}_{kt-1} \tag{A57}$$

- Price setting:

$$\hat{\pi}_{kt} - \iota_p\hat{\pi}_{kt-1} = \beta\mathbb{E}_t\left[\hat{\pi}_{kt+1} - \iota_p\hat{\pi}_{kt}\right] + \kappa_p\left(\widehat{mc}_{kt} + \hat{\lambda}^p_{kt}\right) \tag{A58}$$

where $\kappa_p = \frac{(1-\xi_p\beta)(1-\xi_p)}{\xi_p}$ is the slope of the NKPC.

- Cost minimization:

$$\hat{k}^y_{kt} - \hat{N}^y_{kt} = \hat{w}_{kt} - \hat{r}^K_{kt} \tag{A59}$$

$$\hat{k}^y_{kt} - \hat{x}_{kt} = \hat{p}^x_{kt} - \hat{r}^K_{kt} \tag{A60}$$

- Marginal cost:

$$\widehat{mc}_{kt} = \alpha_1\hat{r}^K_{kt} + \alpha_2\hat{p}^x_{kt} + (1-\alpha_1-\alpha_2)\hat{w}_{kt} \tag{A61}$$

- Tradable production:

$$\hat{w}_{kt} = \hat{p}^x_{kt} + (1-\alpha_x)\hat{a}^x_{kt} + \alpha_x\left[\hat{k}^x_{kt} - \hat{n}^x_{kt}\right] \tag{A62}$$

$$\hat{r}^K_{kt} = \hat{p}^x_{kt} + (1-\alpha_x)a^x_{kt} + (1-\alpha_x)\left[\hat{n}^x_{kt} - \hat{k}^x_{kt}\right] \tag{A63}$$

- Effective capital:

$$\hat{k}_{kt} = \hat{u}_{kt} + \hat{\bar{k}}_{kt-1} - \hat{z}_t \tag{A64}$$

- Physical capital law of motion:

$$\hat{\bar{k}}_{kt} = \frac{1-\delta}{\gamma}\left[\hat{\bar{k}}_{kt-1} - \hat{z}_t\right] + \left(1 - \frac{1-\delta}{\gamma}\right)\left[\hat{\mu}_{kt} + \hat{i}_{kt}\right] \tag{A65}$$

- Production function:

$$\hat{y}_{kt} = \frac{y+F}{y}\left[\alpha_1\hat{k}^y_{kt} + \alpha_2\hat{x}_{kt} + (1-\alpha_1-\alpha_2)\hat{n}^y_{kt}\right] \tag{A66}$$

- Taylor rule:

$$\hat{R}_t = \rho_R \hat{R}_{t-1} + (1-\rho_R)\left[\phi_\pi \hat{\pi}_t + \phi_X\left(\widehat{gdp}_t - \widehat{gdp}_{t-1} + \hat{z}_t\right)\right] + \hat{\eta}_t \tag{A67}$$

- Government spending:

$$\hat{g}_{kt} = \hat{y}_{kt} + \frac{1-g}{g}\hat{\epsilon}^g_{kt} \tag{A68}$$

- GDP identity:

$$\widehat{gdp}_t = \hat{y}_t - \frac{r^k k}{y}\hat{u}_t \tag{A69}$$

- Goods market clearing:

$$\hat{y}_{kt} = \frac{c}{y}\hat{c}_{kt} + \frac{i}{y}\hat{i}_{kt} + \frac{g}{y}\hat{g}_{kt} + \frac{r^k k}{y}\hat{u}_{kt} \tag{A70}$$

- Labor market clearing:

$$\hat{N}_{kt} = \frac{N^x}{L}\hat{N}^x_{kt} + \frac{N^y}{L}\hat{N}^y_{kt} \tag{A71}$$

- Capital market clearing:

$$\hat{k}_{kt} = \frac{k^x}{k}\hat{k}^x_{kt} + \frac{k^y}{k}\hat{k}^y_{kt} \tag{A72}$$

- Tradable good market clearing:

$$\sum_k \hat{x}_{kt} = \sum_k \alpha_x \hat{k}^x_{kt} + (1-\alpha_x)\left[\hat{a}^x_{kt} + \hat{n}^x_{kt}\right] \tag{A73}$$

- Island resource constraint (balance of payments):

$$\begin{aligned} \hat{\mathcal{B}}_{kt} - \beta^{-1}\left[\hat{\mathcal{B}}_{kt-1} + \hat{R}_{t-1} - \hat{\pi}_{kt} - \hat{z}_t\right] = \\ \frac{p^x (k^x)^{\alpha_x}(N^x)^{1-\alpha_x}}{\mathcal{B}}\left\{\alpha_x \hat{k}^x_{kt} + (1-\alpha_x)\left[\hat{a}^x_{kt} + \hat{n}^x_{kt}\right] - \hat{x}_{kt}\right\} + \frac{g}{\mathcal{B}}\hat{g}_{kt} + \frac{\tau}{\mathcal{B}}\hat{\tau}_{kt} \end{aligned} \tag{A74}$$

- Budget constraint of federal government:

$$\hat{\mathcal{D}}_t - \beta^{-1}\left[\hat{\mathcal{D}}_{t-1} + \hat{R}_{t-1} - \hat{\pi}_t - \hat{z}_t\right] = \sum_k \left[\frac{g}{\mathcal{D}}\hat{g}_{kt} + \frac{\tau}{\mathcal{D}}\hat{\tau}_{kt}\right] \tag{A75}$$

- Price of tradables:

$$\hat{\pi}^x_t = \hat{\pi}_{kt} + \hat{p}^x_{kt} - \hat{p}^x_{kt-1} \tag{A76}$$

Appendix A.5 Proof of Lemma 1

The proof proceeds as follows. First, we aggregate the economy by adding up all log-linearized model equations over k. Since this amounts to dropping the island subscripts, we will not write them out explicitly. Second, we show that, in the aggregate log-linearized economy, the tradable and non-tradable sectors collapse to one sector using Cobb-Douglas technology in labor and capital. This result is established in claims 1–4. Third, assuming that the endogenous discount factor only depends on island level bonds in log-deviations from the aggregate, it disappears from the system of equation characterizing aggregate variables while achieving stationary of island level economies. Finally, we show that the sum of all island-level household bond holdings aggregates up to the federal debt.

- Claim 1: $\hat{n}_t^x = \hat{n}_t^y = \hat{n}_t$.

  Note that the tradable shock has no aggregate component, and thus $a_t^x = 0$. This implies that (A73) becomes $\hat{x}_t = \alpha_x \hat{k}_t^x + (1-\alpha_x)\hat{n}_t^x$, and (A62) becomes $\hat{w}_t - \hat{p}_t^x = \alpha_x(\hat{k}_t^x - \hat{N}_t^x)$. Next, subtract (A60) from (A59) to get $\hat{x}_t - \hat{n}_t^y = \hat{w}_t - \hat{p}_t^x$. These three equations can hold together iff $\hat{n}_t^x = \hat{n}_t^y$. Finally, (A71) implies that they equal $\hat{n}_t$.

- Claim 2: $\hat{k}_t^y = \hat{k}_t^x = \hat{k}_t$

  Claim 1 implies that (A59), (A62), (A63) become

$$\hat{k}_t^y - \hat{n}_t = \hat{w}_t - \hat{r}_t^K, \tag{A77}$$

$$\hat{w}_t = \hat{p}_t^x + \alpha_x \left[k_t^x - \hat{n}_t\right], \tag{A78}$$

$$\hat{r}_t^K = \hat{p}_t^x + (1-\alpha_x)\left[\hat{n}_t - \hat{k}_t^x\right]. \tag{A79}$$

  Subtracting (A79) from (A78) implies that $\hat{w}_t - \hat{r}_t^K = \hat{k}_t^x - \hat{n}_t$. Combine this with (A77) to get $\hat{k}_t^y = \hat{k}_t^x$. The capital market clearing condition (A72) implies that they equal $\hat{k}_t$.

- Claim 3: $\widehat{mc}_t = (\alpha_1 + \alpha_2\alpha_x)\hat{r}_t^K + (1-\alpha_1-\alpha_2\alpha_x)\hat{w}_t$

  The previous claims imply that the aggregate cost minimization equation is

$$\hat{k}_t - \hat{n}_t = \hat{w}_t - \hat{r}_t^K$$

  Combine this with (A78) to get

$$\hat{p}_t^x = (1-\alpha_x)\hat{w}_t + \alpha_x \hat{r}_t^K.$$

Substituting for $\hat{p}_t^x$ in the marginal cost equation (A61) proves the claim.

- Claim 4: $\hat{y}_t = \frac{y+F}{y}\left[(\alpha_1 + \alpha_2\alpha_x)\hat{k}_t + (1-\alpha_1-\alpha_2\alpha_x)\hat{n}_t\right]$

  Plug in the previous results into the production function (A66).

- Claim 5: the endogenous discount factor cancels from (A51).

- Claim 6: $\hat{\mathcal{B}}_t = \hat{\mathcal{D}}_t$.

  Combine the island resource constraint (A74) with tradable market clearing (A73), then compare to federal budget constraint (A75).

Appendix A.6 Proof of Lemma 2

Let tilde refer to log-deviations from aggregates. Since we assume that islands are identical in the balanced-growth path, the following holds for any variable

$$\begin{aligned}
\tilde{x}_{kt} &= \log(x_{kt}) - \log(x_t) \\
&= \log(x_{kt}) - \log(x) - \left[\log(x_t) - \log(x)\right] \\
&= \hat{x}_{kt} - \hat{x}_t
\end{aligned}$$

The proof consists of rewriting equations and verifying that aggregate variables cancel. The resulting system of equations is identical to the original one where we have set $\hat{R}_t = \hat{P}_t^x = 0$ and dropped the market clearing condition in the intermediate goods market.

Appendix A.7 Derivation of Aggregate v. Regional Shock responses

In the simplified model, the system of equations characterizing the aggregate equilibrium behavior of $\hat{n}_t, \hat{w}_t$ is:

$$\begin{aligned}
0 &= \beta\mathbb{E}_t\left[\hat{w}_{t+1} - \hat{w}_t\right] - (\hat{w}_t - \hat{w}_{t-1}) + \kappa_w((1-\alpha+\nu)\hat{n}_t - \hat{w}_t) \\
0 &= -\mathbb{E}_t\left[(1-\alpha)\hat{n}_{t+1}\right] + \varphi_y(1-\alpha)\hat{n}_t - (1-\rho_b)\tilde{b}_t + (1-\alpha)\hat{n}_t
\end{aligned}$$

Assuming the endogenous discount factor follows $\tilde{\phi}_{kt+1} = \tilde{\phi}_{kt} + \phi_0\tilde{\mathcal{B}}_{kt-1}$, the system characterizing the regional equilibrium behavior of $\tilde{n}_{kt}, \tilde{w}_{kt}, \tilde{\mathcal{B}}_{kt}$ is:

$$
\begin{aligned}
0 &= \beta E_t\left[\tilde{w}_{kt+1} - \tilde{w}_{kt}\right] - (\tilde{w}_{kt} - \tilde{w}_{kt-1}) + \kappa_w((1+\nu)\tilde{n}_{kt} - \tilde{w}_{kt}) \\
0 &= -E_t\left[\tilde{n}_{kt+1}\right] - (1-\rho_b)\tilde{b}_{kt} + \tilde{n}_{kt} - \phi_0 \tilde{\mathcal{B}}_{kt-1} \\
0 &= \tilde{\mathcal{B}}_{kt-1} - \beta\tilde{\mathcal{B}}_{kt} - \frac{\beta p^x x}{\mathcal{B}}\tilde{n}_{kt}
\end{aligned}
$$

Using the method of undetermined coefficients, we find the aggregate policy functions:

$$
\begin{aligned}
\hat{w}_t &= \frac{\kappa_w(1-\alpha+\nu)}{1+\kappa_w - \beta(1-\rho_b - a_{ww})}\hat{b}_t + a_{ww}\hat{w}_{t-1} \\
\hat{n}_t &= \frac{1}{(1-\alpha)}\frac{1-\rho_b}{(1-\rho_b)+\varphi_y}\hat{b}_t
\end{aligned}
$$

and regional policy functions:

$$
\begin{aligned}
\tilde{w}_{kt} &= a_{wb}\tilde{b}_{kt} + a_{ww}\tilde{w}_{kt-1} + a_{w\tilde{\mathcal{B}}}\tilde{\mathcal{B}}_{kt-1} \\
\tilde{n}_{kt} &= \frac{(1-\rho_b)}{\frac{1}{\beta}(1-\beta a_{\tilde{\mathcal{B}}\tilde{\mathcal{B}}}) + (1-\rho_b)}\tilde{b}_{kt} + \frac{(1-\beta a_{\tilde{\mathcal{B}}\tilde{\mathcal{B}}})}{\frac{\beta p^x x}{\mathcal{B}}}\tilde{\mathcal{B}}_{kt-1} \\
\tilde{\mathcal{B}}_{kt} &= -\frac{p^x x}{\mathcal{B}}a_{nb}\tilde{b}_{kt} + a_{\tilde{\mathcal{B}}\tilde{\mathcal{B}}}\tilde{\mathcal{B}}_{kt-1}
\end{aligned}
$$

where $\{a_{wb}, a_{ww}, a_{w\tilde{\mathcal{B}}}, a_{\tilde{\mathcal{B}}\tilde{\mathcal{B}}}\}$ solve:

$$
\begin{aligned}
0 &= \beta(a_{ww})^2 - (1+\beta+\kappa_w)a_{ww} + 1 \\
0 &= (1-\beta a_{\tilde{\mathcal{B}}\tilde{\mathcal{B}}})(1-a_{\tilde{\mathcal{B}}\tilde{\mathcal{B}}}) - \frac{\beta p^x x}{\mathcal{B}}\phi_0 \\
a_{wb} &= \frac{\kappa_w(1+\nu)}{1+\kappa_w+\beta(1-\rho_b-a_{ww})}\left(1 - \frac{\frac{1}{\beta}(1-\beta a_{\tilde{\mathcal{B}}\tilde{\mathcal{B}}})}{1-a_{\tilde{\mathcal{B}}\tilde{\mathcal{B}}}+\beta(1-a_{ww})+\kappa_w}\right)a_{nb} \\
a_{w\tilde{\mathcal{B}}} &= \frac{\kappa_w(1+\nu)}{1-a_{\tilde{\mathcal{B}}\tilde{\mathcal{B}}}+\beta(1-a_{ww})+\kappa_w}a_{n\tilde{\mathcal{B}}}
\end{aligned}
$$

The expressions for the employment responses and wage elasticities on impact to a discount factor shock follow directly from the policy functions evaluated at $t = 0$.

Appendix A.8 Bayesian Estimation and Aggregate Data

The model is estimated via full-information Bayesian techniques in the tradition of Linde et al. (2016), Christiano et al. (2014) and Justiniano et al. (2010). We follow their choices as closely as possible while ensuring consistency with our state-level data and regressions.

All estimations were done with Dynare. We use the Metropolis-Hastings algorithm, using 2 chains with 120,000 draws, discarding 24,000 of them.

The likelihood is based on seven US time series: the annual growth rate of real GDP, of real consumption, of real investment, and of the real wage, then log employment, inflation, and the federal funds rate. There are a few differences in the data compared to the aforementioned literature estimating medium scale New Keynesian models. First, our frequency is annual because our state-level data is not available on a quarterly basis. Higher frequency variables are annualized by taking the mean of all observations within a calendar year. This time aggregation is always done for levels, not the growth rates. Second, for wages and employment, we use the aggregated versions of our state-level measures. That is, the composition-adjusted male wages and male employment rate from Section 3. Third, we use the CPI instead of the GDP deflator to deflate nominal variables as well as to define inflation. This is because, as we show in Section 2, the CPI is consistent with the Nielsen scanner data.

Table A1 below clarifies what each of the underlying aggregate time series are. The time span is 1975–2015, again dictated by the availability of state-level data. The observable

Table A1: Raw data downloaded from FRED

name	notation	units	seasonally adj.
Nominal GDP (GDP)	Y	billions of \$, annual	✓
Nondurable consumption (PCND)	C_{nd}	billions of \$, annual	✓
Services consumption (PCESV)	C_{se}	billions of \$, annual	✓
Durable consumption (PCDG)	C_{du}	billions of \$, annual	✓
Private investment (GPDI)	I	billions of \$, annual	✓
CPI (CPIAUCSL)	P	index 2009 = 100	✓
Population (CNP16OV)	Pop	thousands of persons	
Federal funds rate (FF)	R	percent, annualized	

series is constructed as follows. First, we aggregate to an annual frequency by taking the mean of the monthly/quarterly observations. Second, Pop is HP-filtered with $\lambda = 10,000$ to get rid of spurious hikes in its growth rate due to revisions after national censuses.

Then, the observation equations are defined as

$$x_{obs} = 100 \cdot \Delta \log \left(\frac{Y_t}{Pop_t \cdot P_t} \right) \qquad = \hat{x}_t - \hat{x}_{t-1} + \hat{z}_t + 100 \log \gamma \tag{A80}$$

$$c_{obs} = 100 \cdot \Delta \log \left(\frac{C_{nd,t} + C_{se,t}}{Pop_t \cdot P_t} \right) \qquad = \hat{c}_t - \hat{c}_{t-1} + \hat{z}_t + 100 \log \gamma \tag{A81}$$

$$i_{obs} = 100 \cdot \Delta \log \left(\frac{I_t + C_{du,t}}{Pop_t \cdot P_t} \right) \qquad = \hat{i}_t - \hat{i}_{t-1} + \hat{z}_t + 100 \log \gamma \tag{A82}$$

$$w_{obs} = 100 \cdot \Delta \log \left(\frac{W_t}{P_t} \right) \qquad = \hat{w}_t - \hat{w}_{t-1} + \hat{z}_t + 100 \log \gamma \tag{A83}$$

$$N_{obs} = 100 \cdot \log \left(\frac{H_t}{Pop_t} \right) \qquad = \hat{N}_t + \log N \tag{A84}$$

$$\pi_{obs} = 100 \cdot \Delta \log P_t \qquad = \hat{\pi}_t + 100 \log \pi \tag{A85}$$

$$R_{obs} = R_t \qquad = \hat{R}_t + 100 \log R. \tag{A86}$$

Finally, and following Christiano et al. (2014), we take the sample mean out of $\{x_{obs}, c_{obs}, i_{obs}, w_{obs}\}$ to minimize the problem of violating balanced-growth at low frequencies. This would be particularly problematic given our goal of interpreting wage and employment movements in the Great Recession, because real wages have been growing much less than consumption, investment, or GDP since the 90's.

Appendix B Data and Empirics

In this section of the Appendix, we describe the data used in our paper as well as discuss a variety of empirical robustness specifications. We begin with a discussion of the ACS and CPS data used to make our demographically adjusted wage indices. Next, we show descriptive statistics for the data underlying our Retail Scanner Price Index. We then discuss issues with making our Retail Scanner Price Index including discussing how we deal with missing data. This appendix also discusses how we can use cross-region variation in Retail Price Index to learn about cross-region variation in a broader price index for a composite consumption good. We end with a description of the data used in both our regional estimation as well as discussing some robustness exercises for our regional estimation.

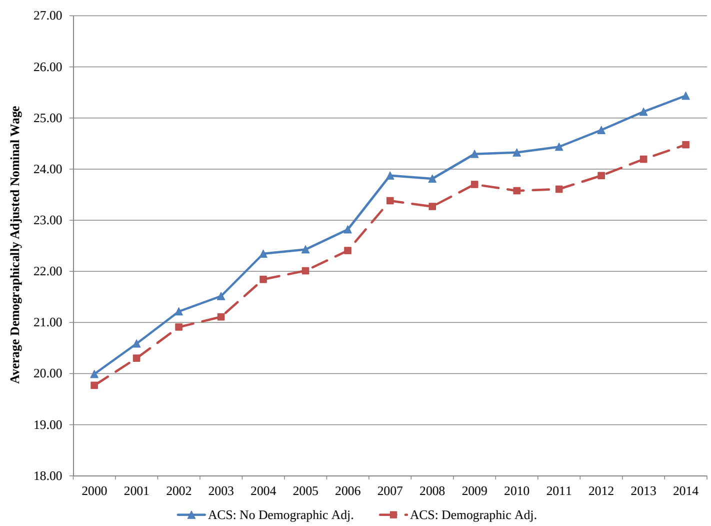
Appendix B.1 Creating Composition Adjusted Wage Measures in the ACS and CPS

To make the composition adjusted wage measures in the 2000 U.S. Census and the 2001-2012 American Community Survey (ACS), we start with the raw annual data files that we downloaded directly from the IPUMS website.[44] For each year, we restrict our sample to only males between the ages of 25 and 54, who live outside of group-quarters, are not in the military, and who have no self-employment income. For each individual, we create a measure of hourly wages. We do this by dividing annual labor income earned during the prior twelve month period by reported hours worked during that same time period. Hours worked are computed by multiplying weeks worked during the prior twelve month period by usual weekly hours worked. With the data, we compute wage measures for each year between 2000 and 2014. We wish to stress that within the ACS, the prior year refers to the prior 12 months before the survey takes place (not the prior calendar year). Individuals interviewed in January of year t report earnings and weeks worked between January and December of year $t-1$. Individuals in June of year t report earnings between June of year $t-1$ and May of year t. Given that the ACS samples individuals in every month, the wage measures we create for year t can be thought of as representing average wages between the middle of year $t-1$ through middle of year t. This differs slightly from the timing in the Current Population Survey (CPS) which we discuss below. In the ACS, weeks worked last year are only consistently measured in intervals. We take the mid-point of the range as weeks worked during the prior year. Finally, we trim the top and bottom 1 percent of wages within each year to minimize the effects of extreme measurement error in the creation of our demographically adjusted wage indices.

Despite our restriction to prime-age males, the composition of workers on other dimensions may still differ across states and within a state over time. As a result, the changing composition of workers could be explaining some of the variation in nominal wages across states over time. For example, if lower wage workers are more likely to exit employment during recessions, time series patterns in nominal wages will appear artificially more rigid than they actually are. To partially clean our wage indices from these compositional issues, we follow a procedure similar to Katz and Murphy (1992) by creating a composition adjusted wage measure for each U.S. state and for the aggregate economy (at least based on observables). Specifically, within each state-year pair, we segment our sample into six age bins (25-29, 30-34, etc.) and four education groupings (completed years of schooling < 12, $=$

[44] The ACS is just the annual survey which replaces the Census long form in off Census years. The national representative survey started in 2001. As a result, the Census and ACS questions are identical.

Figure A1: Demographically Adjusted vs. Demographically Unadjusted Nominal Wages, ACS



Note: Figure compares the demographically adjusted nominal wage series in the ACS used in the paper to the raw ACS nominal wage series. The x-axis refers to the survey year. The y-axis measures the average nominal wage (in wage per hour). The sample restrictions are identical between both series.

12, between 13 and 15, and 16+). Our demographic adjusted nominal wage series is defined as follows:

$$\widetilde{Wage_{kt}} = \sum_{g=1}^{24} Share_{k\tau}^{g} \, Wage_{kt}^{g} \tag{A87}$$

where $\widetilde{Wage_{kt}}$ is the demographic adjusted nominal wage series for prime age men in year t of state k, $Wage_{kt}^{g}$ is the average nominal wage for each of our 24 demographic groups g in year t of state k and $Share_{k\tau}^{g}$ is the share of each demographic group g in state k during some fixed pre-period τ. By holding the demographic shares fixed over time, all of the wage movements in our demographic adjusted nominal wage series result from changes in nominal wages within each group and not because of a compositional shift across groups. When making our *aggregate* composition adjusted nominal wage series, we follow a similar procedure as (A87) but omit the k's. For the *Census/ACS* data, we set $\tau = 2005$ when examining cross-state patterns during the Great Recession and set $\tau = 2000$ when examining time series patterns of aggregate wages during the 2000s.

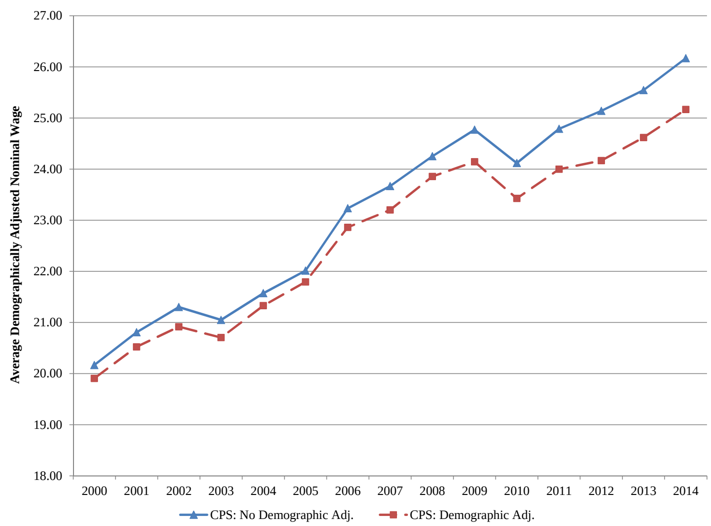
Figure A1 compares the demographically adjusted nominal wage series in the ACS for years 2000-2014 with the raw nominal wage series (with no demographics adjustments). For the raw wage series, we use the exact same sample, but just measure $Wage_t$ as the average wage for those individuals with positive wages in year t. As seen from the figure, the two wage series diverge over time in a way consistent with lower wage demographic groups leaving the sample over time. The demographically adjusted wage series shows a less steep wage increase during the 2000s.

To examine longer aggregate trends in composition adjusted wages, we use data from the March Current Population Survey. We download the data directly from the IPUMS website. As with the ACS data, we restrict the sample to men between the ages of 25 and 54 who do not live in group quarters. We also exclude individuals in the military, those with non-zero business or farm income, and those with non-positive survey weights. The benefit of the *Census/ACS* data is that it is large enough to compute detailed labor market statistics at state levels. However, one drawback of the *Census/ACS* data is that it not available at an annual frequency prior to 2000. These longer run trends are an input into our aggregate shock decomposition procedure discussed in subsequent sections.

We compute the demographic adjusted nominal wage indices using the *CPS* data analogously to the way we computed the demographic adjusted nominal wage indices within the *Census/ACS* data.. Before proceeding, we wish to highlight one difference between the measurement of wages between the two surveys. Within the *March CPS*, respondents are asked to report their earnings over the prior calendar year as opposed to over the prior 12 months. Given this, March CPS respondents in year t report their earnings from year $t-1$. Given this, we refer to wages in year t within the CPS as being the responses provided by survey respondents in year $t+1$. This implies that the timing of the CPS wage data and the ACS wage data differ, on average, by about 6 months.

We compute demographically adjusted wages in the CPS analogously to our methodology in the ACS. When comparing aggregate time series trends in demographically adjusted wages between both the ACS and CPS during the 2000s, we set $\tau = 2000$. When computing aggregate time series trends in demographically adjusted nominal wages for our aggregate shock decomposition, we set $\tau = 1975$. The demographic adjustments for our long timer series results in the CPS necessitate one further adjustment. The education variables changed in the CPS in 1992. Despite an attempt to harmonize the education variable by the CPS, there is still slight seam in the data that causes a discrete downward decline in our demographically adjusted nominal wage series between 1991 and 1992 that is not present in the raw data. When using the long time series data from the CPS in our shock composition analysis, we simply smooth out this seam in the data by assuming there was no growth in our demographically adjusted nominal wage measure between 1991 and 1992. Specifically,

Figure A2: Demographically Adjusted vs. Demographically Unadjusted Nominal Wages, CPS



Note: Figure compares the demographically adjusted nominal wage series in the ACPS CS used in the paper to the raw CPS nominal wage series between 2000 and 2014. The x-axis refers to the survey year. The y-axis measures the average nominal wage (in wage per hour). The sample restrictions are identical between both series.

we create a wage index between 1975 and 1991 and then a separate wage index between 1992 and 2016. We then anchor the 1992 value of the second index at the 1991 value of the first index. This preserves the relative growth rates of nominal wages in all other years. None of the results in the paper are altered by this adjustment.

Figure A2 compares the demographically adjusted nominal wage series in the CPS for years 2000-2014 with the raw nominal wage series (with no demographics adjustments). For the raw wage series, we use the exact same sample, but just measure $Wage_t$ as the average wage for those individuals with positive wages in year t. As seen from the figure, the two wage series diverge over time in a way consistent with lower wage demographic groups leaving the sample over time. The demographically adjusted wage series shows a less steep wage increase during the 2000s. The divergence between the two series in the CPS is nearly identical to the divergence found in the ACS data.

Appendix B.2 Descriptive Statistics For Retail Scanner Data

Online Appendix Table A2 shows descriptive statistics for the Nielsen Retail Scanner Database for each year between 2006 and 2013. A few things are of particular note. The sample sizes

Table A2: **Descriptive Data for the Nielsen Scanner Price Data, By Individual Year**

	Individual Years								Combined	
	2006	2007	2008	2009	2010	2011	2012	2013	Total	Average
Number of Obs. (million)	12,013.1	12,812.2	13,037.5	12,968.3	13,153.4	13,646.7	13,618.8	13,801.3	105,051.0	13,131.4
Number of UPCs	725,224	762,469	759,989	753,984	739,768	742,074	753,318	769,136	1,487,003	750,745
Number of Categories	1,085	1,086	1,086	1,083	1,085	1,081	1,105	1,113	1,113	1,091
Number of Chains	86	85	87	86	86	86	82	79	88	85
Number of Stores	32,642	33,745	34,830	35,343	35,807	35,645	36,059	36,316	40,350	35,048
Number of Zip Codes	10,869	11,123	11,357	11,476	11,589	11,639	11,626	11,553	11,797	11,404
Number of Counties	2,385	2,468	2,500	2,508	2,519	2,526	2,547	2,561	2,593	2,502
Number of MSAs	361	361	361	361	361	361	361	361	361	361
Number of States	49	49	49	49	49	49	49	49	49	49
Transaction Value (US billion)	187.9	207.8	219.6	223.7	227.6	235.2	239.5	238.7	1,779.9	222.5
Pct. Value used in Price Index	54.3%	50.0%	66.4%	66.0%	68.3%	68.0%	67.7%	67.2%	63.9%	63.5%

Note: Table shows descriptive statistics for underlying data that we used to create our Nielsen Scanner Price Index using the Nielsen Retail Scanner Database.

- in terms of stores covered - increased from 32,642 stores (in 2006) to 36,316 stores (in 2013). Second, notice that the number of observations (store*week*UPC code) is massive. The database includes over *105 billion* unique observations. Third, during the entire sample, there is about 1.5 million unique UPC codes within the database. On average, each year contains roughly 750,000 UPC codes. Fourth, the geographic coverage of the database is substantial in that it includes stores for about 80 percent of all counties within the United States. Moreover, the number of geographical units (zip codes) is very similar from year to year highlighting that the geographical coverage is consistent through time. Finally, the dataset includes between \$188 billion and \$240 billion of transactions (sales) within each year. For the time periods we study, this represents roughly 30 percent of total U.S. expenditures on food and beverages (purchased for off-premise consumption) and roughly 2 percent of total household consumption.[45]

Appendix B.3 Creating the Scanner Data Price Index

In this sub-section, we discuss our procedure for computing the Retail Scanner Price Indices. Formally, the first step is to produce a category-level price index which can be expressed as follows:

$$P_{j,t}^{L,k} = P_{j,t-1}^{L,k} \times \frac{\sum_{i \in (j,k)} p_{i,t} \bar{q_{i,y}}}{\sum_{i \in (j,k)} p_{i,t-1} \bar{q_{i,y}}}$$

[45]To make these calculations, we compare the total transaction value in the scanner data to BEA reports of total spending on food and beverages (purchased for off-premise consumption) and total household consumption.

with $\{t, t-1\} \in y+1$ for all months except when $t = January$ and $t \in y+1$, $t-1 \in y$ when $t = January$, where $P_{j,t}^{L,k}$ is the time t chained Laspeyres-type index for category j in geography/region k, $p_{i,t}$ is the price at time t of good i (in category j and geography/region k), $\bar{q_{i,y}}$ is the average monthly quantity sold of good i in state k in the prior (base) year y. For our analysis, geographies will either be U.S. states or the country as a whole. By fixing quantities at their prior year's level, we are holding fixed household's consumption patterns as prices change. We update the basket of goods each year, and chain the resulting indices to produce one chained index for each category in each geography, denoted by $P_{j,t}^{L,k}$. In this way, the index for months in 2007 uses the quantity weights defined using 2006 quantities and the index for months in 2008 uses the quantity weights defined using 2007 quantities. This implies that the price changes we document below with changing local economic conditions is not the result of changing household consumption patterns. Fixing the basket also minimizes the well documented chain drift problems of using scanner data to compute price indices (Dielwert et al. (2011)). Notice, this procedure is very similar to the way the BLS builds category-level first stage for their price indices.

When computing our monthly price indices, one issue we confront is how to deal with missing values from period to period. For example, a product that shows up in month m may not have a transacted price in month $m+1$ making it impossible to compute the price change for that good between the two months. Missing values may be due to new products entering the market, old products withdrawing from the market, and seasonality in sales. Our results in the paper are robust to the various ways we dealt with missing values but clearly the price indices will generally differ depending on how one treats such data points. Although we could have used some ad hoc imputation methods like interpolation between observed prices or keeping a price fixed until a new observation appears, we chose to follow a more conservative approach. Looking at the above equation, we see that we can handle the missing values without imputation by restricting the goods that enter the basket to those that have positive sales over at least one month in the previous year and over the 12 months of the current year. This is what we do when creating our indices. For example, when computing the category prices in 2008 we use the reference basket for 2007. In doing so, we only take the goods that have $\bar{q_{i \in k, 2007}} > 0$ and $q_{i \in k,t} > 0$ for all $t \in 2008$.[46] This ensures that for a given product in the price index during year t, we will have a weight for this product based on $t-1$ data and we will have a non-missing transaction price in all months in which the price index is computed during that year.[47] The bottom row of Appendix Table A2

[46]The database starts in 2006. As a result, our baseline specification of the 2006 price indices only includes products that have positive sales in all months of 2006.

[47]This procedure implies that we will miss products that are introduced within a given year. These products, however, will be incorporated in next year's basket as long as they have continuous sales during

includes the share of all expenditures (value weighted) that were included in our price index for a given year. In the five later years of the sample, our price index includes roughly two-thirds of all prices (value weighted).

The second stage of our price indices also follows the BLS procedure in that we aggregate the category-level price indices into an aggregate index for each location k. The inputs are the category-level prices and the total expenditures of each category. Specifically, for each state we compute:

$$\frac{P_t^k}{P_{t-1}^k} = \prod_{j=1}^{N} \left(\frac{P_{j,t}^{L,k}}{P_{j,t-1}^{L,k}} \right)^{\frac{\bar{S}_{j,k}^t + \bar{S}_{j,k}^{t-1}}{2}}$$

where $\bar{S}_{j,k}^t$ is the share of expenditure of category j in month t in location k averaged over the year. We calculate the shares using total expenditure on all goods in each category, even though for the category-level indices some goods were not included due to missing data. For the purposes of this paper, we make our baseline specification one that fixes the weights of each category for a year in the same fashion as we did for the category-level indices. However, as a robustness specification, we allowed the weights in the second step to be updated monthly. The results using the two methods were nearly identical.

Appendix B.4 A State Level Composite Price Index from the Retail Scanner Index

The previous section described the construction of a state-level price index for goods sold in retail grocery and mass merchandising stores. However, our goal is to construct state-level price indices that are representative of the composite basket of consumer goods and services. When converting nominal variables to real variables at the aggregate level, we deflate by the June aggregate CPI-U for all items. During the 2000s, the aggregate CPI-U for food is positively correlated – but not perfectly correlated – with the aggregate CPI-U for all items.

In this section of the Data Appendix, we describe conditions under which our local Retail Scanner Price Index and a composite local price index differ only by a scaling factor. Under certain conditions, this procedure holds despite the fact that the aggregate CPI for all goods and the aggregate CPI for food are not perfectly correlated during the 2000s.

Most goods in our sample are produced outside a local market and are simultaneously sold to many local markets. These intermediate production costs represent the traded portion of local retail prices. If there were no additional local distribution and/or trade costs, one

the subsequent calendar year.

would expect little variation in retail prices across states; the law of one price would hold. This would be true for local variation in any tradable price index regardless of whether those tradable price indices tracked each other at aggregate levels. However, "non-tradable" costs do exist for the tradable goods in our sample, including the wages of workers in the retail establishments, the rent of the retail facility, and expenses associated with local warehousing and transportation.[48] It is these cross-region differences in non-tradable prices that constitute cross-region differences in the evolution of regional prices indices.

Assuming that the shares of these non-tradable costs are constant across states and identical for all firms in the retail industries, we can express local retail scanner prices, P^r, in region k during period t as:

$$P^r_{t,k} = (P^T_t)^{1-\kappa_r}(P^{NT}_{t,k})^{\kappa_r}$$

where P^T_t is the tradable component of local retail scanner prices in period t (which does not vary across states) and $P^{NT}_{t,k}$ is the non-tradable component of local retail prices in period t (which potentially does vary across states). κ_r represents the share of non-tradable costs in the total price for the retail scanner goods in our sample.

Analogously, we can express local prices in other sectors for which we do not have data as:

$$P^{nr}_{t,k} = (P^T_t)^{1-\kappa_{nr}}(P^{NT}_{t,k})^{\kappa_{nr}}$$

where $P^{nr}_{t,k}$ is local prices in these sectors outside of the grocery/mass-merchandising sector and κ_{nr} is the share of non-tradable costs in the total price for these other sectors.[49]

Next, assume that the price of household's composite basket of goods and services in a state can be expressed as a composite of the prices in the retail scanner sectors ($P^r_{t,k}$) and prices in the other sectors (P^{nr}_t):

$$P_{t,k} = (P^{nr}_t)^{1-s}(P^r_{t,k})^s \equiv (P^T_t)^{1-\bar{\kappa}}(P^{NT}_{t,k})^{\bar{\kappa}}$$

where s is expenditure share of grocery/mass-merchandising goods in an individuals consumption bundle and $\bar{\kappa} \equiv (1-s)\kappa_{nr} + s\kappa_r$ is the non-tradable share in the aggregate con-

[48]Burstein et al (2003) document that distribution costs represent more than 40 percent of retail prices in the US.

[49]The grocery/mass-merchandising sector is only one sector within a household's local consumption bundle. For example, there are other sectors where the non-tradable share may differ from those in our retail-scanner data. For exmaple, many local services primarily use local labor and local land in their production (e.g., dry-cleaners, hair salons, schools, and restaurants). Conversely, in other retail sectors, the traded component of costs could be large relative to the local factors used to sell the good (e.g., auto dealerships).

sumption good, constant across all states.

Given these assumptions, we can transform the variation in retail scanner prices across states into variation in the broader consumption basket across states. Taking logs of the above equations and differencing across states we get that the variation in log-prices of the composite good between two states k and k', $\Delta \ln P_{t,k,k'}$, is proportional to the variation in log-retail scanner prices across those same states, $\Delta \ln P^{r}_{t,k,k'}$. Formally,

$$\Delta \ln P_{t,k,k'} = \left(\frac{\bar{\kappa}}{\kappa_r}\right) \Delta \ln P^{r}_{t,k,k'}$$

If $\frac{\bar{\kappa}}{\kappa_r} > 1$, the local grocery/mass-merchandising sector will use a lower share of non-tradables in production than the composite local consumption good. In order to construct the scaling factor $\frac{\bar{\kappa}}{\kappa_r}$, it would be useful to have local indices for both grocery/mass-merchandising goods and for a composite local consumption good. While knowing the scaling factor is interesting in its own right, the results we present in our paper our invariant to the scaling factor as long as the scaling factor is constant across regions. Creating our Nielsen Retail Scanner Price Index with a base year of 2006, all subsequent years of the price index will differ by only the scaling factor $\frac{\bar{\kappa}}{\kappa_r}$. Given our assumptions that this is constant across states and that we take logs when making our real wage measures, this term will become embedded in the constant of our cross state regressions. The scaling factor, therefore, will not have any effect on the elasticities we estimate in the paper. Furthermore, when estimating our structural Wage Phillips Curve equations using state level data, we can even allow for the scaling factor to vary over time. Any time variation in the scaling factor will be embedded in the regression time dummies.

Again, the maintained assumption is that the scaling factor is common across states. We have no reason to believe that the scaling factor varies spatially. Remember, the scaling factor is the non-tradable share of the regional composite consumption good relative to the non-tradable share of the grocery/mass-merchandising sector.[50] For example, if a region has a large housing boom, this will increase both non-tradable costs in the grocery industry and non-tradable costs in the local composite consumption bundle. We cannot think of a reason why the ratio of the non-tradable share in groceries to the non-tradable share in a composite consumption good will evolve differentially across space in response to sector shocks that move housing prices.

[50] Some people who have read our paper have thought that the necessary assumption is that the food share relative to the non-tradable share has to be constant across regions. This is NOT the case. What is important is the non-tradable portion of the grocery sector relative to the non-tradable share of the composite local consumption bundle is constant across space. If non-tradable costs are rising (due to rising land prices or rising local wages), this will increase both non-tradable costs in the grocery sector and non-tradable costs in a broader local composite consumption good.

Appendix B.5 Description of Data for Regional Analysis

Here we review the data we use in for our regional estimates of κ_w.

Nominal Wages: The measure of nominal wages in our main estimating equation (W_{kt-1}, W_{kt}, and W_{kt+1}) are our demographically adjusted nominal wages measures calculated from the ACS. We discuss the procedure for calculating these wages above. To make the state level measures, we average the demographically adjusted nominal wages calculated using the underlying micro data over all individuals in a given state k in a given year t. We use the underlying ACS survey weights when making this measure.

Employment Rate: To make state level employment rates, we use data from the U.S. Bureau of Labor Statistics (BLS). We download directly from the BLS website state level measures of total employment by year and state level total population by year. We compute state level employment rates by dividing state measure employment by state level population for each year.

Prices: Our measure of state level prices is the state level measures of prices made using the Nielsen Retail Scanner Database. We discuss the creation of these price indices above.

Consumption: For state level consumption, we download measures of state level personal consumption expenditures (PCE) directly from the U.S. Bureau of Economic Analysis (BEA) website.

Real Per Capita GDP: Our measure of per-capita GDP also comes directly from the U.S. Bureau of Economic Analysis. We download the data directly from the BEA website.

House Price Data: Our measure of state level house price indices comes from the Federal Housing Finance Agency (FHFA). For the data, we use the FHFA's state level house price indices based on all housing transactions. We download the data directly from FHFA website.

Appendix B.6 Controlling for Industry Mix in Our Estimation of the Regional Wage Phillips Curve

When estimating of our Wage Phillips Curve using regional data we assume that all states have the same parameters. One concern with our estimation, therefore, is that states could potentially differ in their underlying wage setting parameters. This could be the case if the parameters differ by industry and industrial mix differs by state. For example, unions are more prevalent in the manufacturing sector and manufacturing employment is very spatially concentrated.

To explore the robustness of our results to the possibility that different regions have different exposures to aggregate shocks because of different industry composition, we perform two additional exercises. First, we include the state's 2006 manufacturing share as an additional regressor in our estimation of the Wage Phillips Curve using regional data. Second, we omit any state with with a 2006 manufacturing share greater than 15 percent and then re-estimate our Wage Phillips curve only using data from the remaining states. The 13 states that had a 2016 manufacturing share greater than 15 percent were: Alabama, Arkansas, Indiana, Iowa, Kansas, Kentucky, Michigan, Mississippi, North Carolina, Ohio, South Carolina, Tennessee, and Wisconsin.

Our IV estimates of κ_w are nearly identical under these two robustness exercises to what we report in our base specification within the text. In particular, our estimates of κ_w was 0.38 when we include the state's 2006 manufacturing share as a control and was 0.42 when the high manufacturing states were excluded completely from the regression. The fact that the estimate of κ_w is similar when the manufacturing states were excluded suggests that if the underlying parameters of the Wage Phillips Curve differ across states with differing industrial mixes, the parameters are not differing by much.