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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 U.S. states between local employment and wage growth during the Great Recession. This relationship is much weaker in U.S. 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 U.S. 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.

KEYWORDS: Regional, business cycles, wage stickiness, Great Recession, slow recovery, household demand, New Keynesian, Phillips curve, monetary union, Bayesian estimation.

1. INTRODUCTION

REGIONAL BUSINESS CYCLES during the Great Recession in the United States were strikingly different than their aggregate counterpart. This is the cornerstone observation on which this paper is built. Yet, the aggregate U.S. 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 important implications for our understanding of aggregate fluctuations.

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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 time series 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. While regional and aggregate reduced-form responses to shocks might differ, we show that key structural equations are common between the regional and aggregate economies under certain assumptions. Then, we show how exploiting regional variation can help researchers estimate common structural parameters that may be difficult to pin down using aggregate data alone. Finally, when it comes to understanding the Great Recession, we find that our methodology yields dramatically different results than if we either estimated our model solely with aggregate data or if we naively extrapolated from well-identified regional elasticities by performing back-of-the-envelope calculations.

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 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 0.5 percent decrease in nominal wages and a roughly 0.35 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 an aggregate component.

¹See, for example, Christiano, Eichenbaum, and Evans (2005), Smets and Wouters (2007), Justiniano, Primiceri, and Tambalotti (2010), Christiano, Motto, and Rostagno (2014), and Linde, Smets, and Wouters (2016).

²See, for example, Mian and Sufi (2011, 2014), Mian, Rao, and Sufi (2013), Charles, Hurst, and Notowidigdo (2016), Mehrotra and Sergeyev (2017), and Yagan (2017).

³For example, in her 2014 Jackson Hole Symposium, then-Chairwoman Janet 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.”

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”—that is, 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. 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 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 methodology is the fact that the Regional and Aggregate New Keynesian Wage Phillips Curves are identical under our model assumptions. Specifically, using regional data alone, in a first step we estimate via GMM the parameter governing wage stickiness in the New Keynesian Wage Phillips Curve by exploiting shocks to regional labor demand, given an initial guess for all other parameters. Using this point estimate and its standard error, we construct a prior over the degree of wage stickiness. We then estimate our aggregate model using aggregate time series data alone via full information Bayesian methods. This gives us a posterior distribution for the degree of wage stickiness and all remaining parameters in the model.⁴ Furthermore, by changing how tight the prior is around the point estimate coming from the first step, we can vary how much weight we put on the regional versus aggregate data in informing the degree of wage stickiness in the economy. For our main results, we consider two extreme cases: putting all the weight on the regional data or all the weight on aggregate data (as is standard in the literature). In the last step, we check whether our estimate of wage stickiness from the first step changes when we update the initial guess using the posterior from all other parameters. If it does, we repeat the full estimation algorithm.

We then show why using aggregate data alone could be problematic when trying to distinguish between economies with high versus low wage stickiness, as well as why using regional data may help. We begin by comparing how our estimates change when we put more or less weight on the regional data. Because we document that wages and employment were strongly positively correlated across regions but not in the aggregate during the

⁴In 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, Smets, and Wouters \(2016\)](#) for a recent survey of the use of full-information Bayesian methods for estimating DSGE models. See [Galí, Gertler, and López-Salido \(2005\)](#) for an example of using GMM techniques to estimate a “hybrid” New Keynesian Price Phillips Curve.

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 combining regional and aggregate data than when using aggregate data alone in estimation. In particular, we estimate that around three-quarters of wages adjust every year when putting most of the weight on the regional data, similar to micro estimates of annual wage adjustments using administrative data sources (e.g., Grigsby, Hurst, and Yildirmaz (2018)). Yet, when we estimate our model with only aggregate data, we find that only half of wages adjust every year, similar to estimates from Christiano, Motto, and Rostagno (2014) and Linde, Smets, and Wouters (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. Importantly, though, the fit to the aggregate data is very similar under both approaches, as measured by the log-marginal likelihood, which suggests that there is little information regarding the degree of wage stickiness in our relatively short aggregate time series sample. Then, through a series of thought experiments, we show that this could be the case because it is hard to distinguish between economies with high versus low wage stickiness whenever labor supply shocks are important relative to demand shocks and whenever the time series data sample is short. The regional data help in both dimensions. At least for the Great Recession, most of cross-region variation in economic conditions have been found to be driven by cross-region variation in demand shocks. Furthermore, we have significantly more observations in the regional panel data than we have in the aggregate time series data.

The last part of the paper uses our estimated model to explain: (i) why observed regional wage elasticities were higher than observed aggregate wage elasticities during the Great Recession, as well as (ii) what caused the decline in employment during the 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 (e.g., discount rate shocks) cannot explain why aggregate wages seemed much more sticky relative to their regional counterparts. Other demand shocks hitting the aggregate economy (e.g., investment efficiency shocks) cannot account for this fact either. Instead, we find that aggregate labor supply shocks explain why aggregate wages did not fall. 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 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 showed 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.

Last, we show how our conclusions differ from those of other leading approaches 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 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 U.S. 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, Rao, and Sufi \(2013\)](#), and [Jones, Midrigan, and Philippon \(2018\)](#) have exploited regional variation within the United States to explore the extent to which household leverage has contributed to the Great Recession. [Nakamura and Steinsson \(2014\)](#) and [Chodorow-Reich \(2018\)](#) used sub-national U.S. variation to inform the size of local government spending multipliers. [Autor, Dorn, and Hanson \(2013\)](#) and [Charles, Hurst, and Notowidigdo \(2016\)](#) documented 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, Fuster, Hurst, and Vavra \(2019\)](#) used regional variation to explore the time-varying aggregate effects of monetary policy, [Adao, Arkolakis, and Esposito \(2018\)](#) used a structural model to map well-identified estimates of the local employment effects to trade shocks to aggregate employment trends, [Acemoglu and Restrepo \(2017\)](#) used a combination of cross-region variation and a model of local economies that aggregate to explore the effects of automation on aggregate employment, as well as [Jones, Midrigan, and Philippon \(2018\)](#) who were one of the first to use regional data in an equilibrium dynamic macro model to study the Great Recession.

Third, our paper contributes to the recent literature trying to determine the drivers of the Great Recession and its aftermath. [Christiano, Eichenbaum, and Trabandt \(2015\)](#) estimated a medium-scale New Keynesian model using data from the recent recession. Although their model and identification are different from ours, they also concluded that other shocks beyond demand shocks are needed to explain the joint aggregate dynamics of prices and employment during the Great Recession. [Del Negro, Giannoni, and Schorfheide \(2015\)](#) estimated a medium-scale New Keynesian model with financial frictions and showed that it matches the joint patterns of declining output and low but positive inflation during the Great Recession. Likewise, [Gilchrist, Schoenle, Sim, and Zakrajšek \(2017\)](#) also used 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 focused on explaining the missing disinflation

during the Great Recession.⁵ 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, Kehoe, and Kydland (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) showed that trade links are key to understand the correlations of business cycles across countries, while others emphasized 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, Galí, and Gertler (2001), Galí and Monacelli (2008), and House, Proebsting, and Tesar (2017)) and studied regional stabilization in models of fiscal unions (e.g., Evers (2015), Farhi and Werning (2017), and Beraja (2018)). We borrow much of the modeling insights from these literatures. However, unlike them, we are not concerned with how shocks spill over and propagate across regions or the conduct of optimal monetary or fiscal policy within a monetary or fiscal 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.

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 U.S. population, while the 2001–2014 *ACS* 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, 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 months 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 1 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.⁶ 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

⁵Vavra (2014) and Berger and Vavra (2018) also documented that prices were very flexible during the Great Recession. They concluded that demand shocks alone cannot explain the aggregate employment dynamics given the missing aggregate disinflation.

⁶See, 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.

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 demographically adjusted nominal wage series is defined as follows:

$$\widetilde{\text{Wage}}_{kt} = \sum_{g=1}^{24} \text{Share}_{k\tau}^g \text{Wage}_{kt}^g, \quad (1)$$

where $\widetilde{\text{Wage}}_{kt}$ is the demographically 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 $\text{Share}_{k\tau}^g$ 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 demographically 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 $\tau = 2006$ 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 set 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 they are 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-run aggregate trends in both aggregate nominal and real wages. These longer-run trends are an input into estimation methodology discussed in subsequent sections. We compute the demographically adjusted nominal wage indices using the *CPS* data analogously to the way we computed the demographically adjusted nominal wage indices within the *Census/ACS* data.⁷ 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.

⁷A full discussion of our methodology to compute composition-adjusted wages in the *Census/ACS* and the *CPS* can be found in the Supplemental Material ([Beraja, Hurst, and Ospina \(2019\)](#)) 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 .

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 The Nielsen Company (US), LLC and made available at The University of Chicago Booth School of Business.⁸ The Retail Scanner data consist of weekly pricing, volume, and store environment information generated by point-of-sale systems for about 90 participating retail chains across all U.S. 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 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 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 2500 counties. The data come 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. The Supplemental Material shows summary statistics for the retail scanner data for years between 2006 and 2013 and for the sample as a whole.

In order to construct state-level price indices, we follow the BLS construction of the CPI as closely as possible. Specifically, our retail scanner price indices are built in two stages. In the first stage, we aggregate the prices of goods within roughly 1000 Nielsen defined narrow product categories (e.g., granulated sugar, brown sugar, powdered sugar). Each good is defined by its unique UPC. We next compute, for each good, the average price and total quantity sold in a given month and state. We then construct the quantity weighted average price for all goods in each detailed category in a given month and state. Finally, in the second stage, we aggregate the category-level price indices into an aggregate index for each state and month. A full discussion of our procedure can be found in the Supplemental Material.

In the Supplemental Material, we discuss further our Nielsen Retail Scanner Price Indices along three additional dimensions. First, we show that the aggregate version of our price index matches nearly identically the aggregate BLS's CPI for food and beverages, giving us confidence that our price index is broadly representative of aggregate food prices during the 2006–2013 period. Second, we show that our local-level price indices built from the Nielsen data match well BLS price indices for similar goods for larger MSAs where the BLS is able to produce reliable price indices. Again, this gives us confidence that our Nielsen price indices measure well food prices at the local level. Finally, we discuss under what conditions regional variation in food prices from our Nielsen price indices can be used to measure regional variation in the prices of a broader consumption basket. We

⁸The Nielsen data are made available through the Kilts Center for Marketing Data 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/>. The conclusions drawn from the Nielsen data are ours and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported in the paper.

show that under a relatively weak set of assumptions, the differential inflation rate across regions in a local composite consumption good is simply the differential inflation rate across regions in our Nielsen regional price indices scaled by the ratio of the non-tradable share of the composite good relative to the non-tradable share of the scanner grocery goods. Given the empirical work that follows in the rest of the paper, this scaling factor gets absorbed in the constant terms of our regressions.

3. COMPARING REGIONAL TO 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 1 shows the log-change in our demographically 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 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.⁹

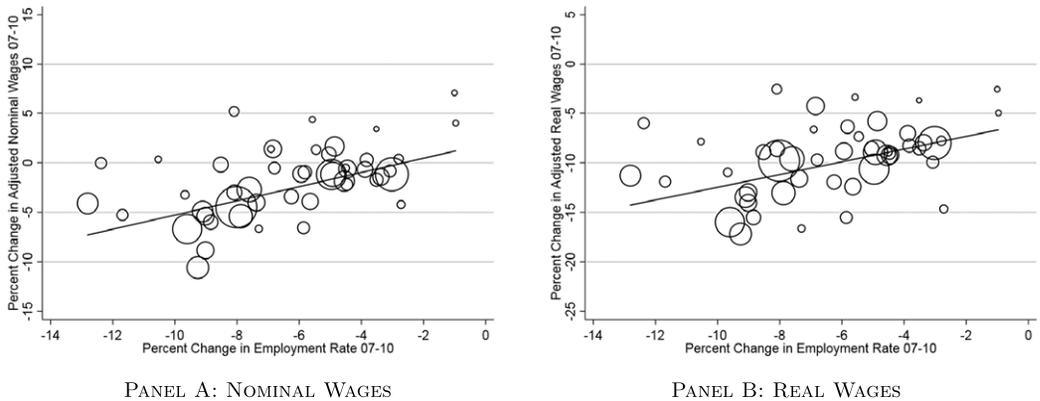


FIGURE 1.—State employment growth versus state wage growth. Note: Figure plots demographically adjusted wage growth for prime-age men during 2007–2010 versus growth in the employment rate during 2007–2010 for the cross-section of U.S. states. Nominal wages are measured using the ACS data set. Real wages 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 I.

⁹These 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

TABLE I
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 bivariate 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 parentheses.

The right panel of Figure 1 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). We summarize our estimated cross-state nominal and real wage elasticities in Table I. While adjusting for differences in local inflation 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.

3.2. Aggregate Patterns

Figure 2 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.¹⁰

A few things are of note from Figure 2. 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 data sets. 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 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.

run. For example, Blanchard and Katz (1992), Autor, Dorn, and Hanson (2013) and Charles, Hurst, and Notowidigdo (2018) all highlighted 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.

¹⁰In the Supplemental Material, 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 wage growth during the Great Recession.

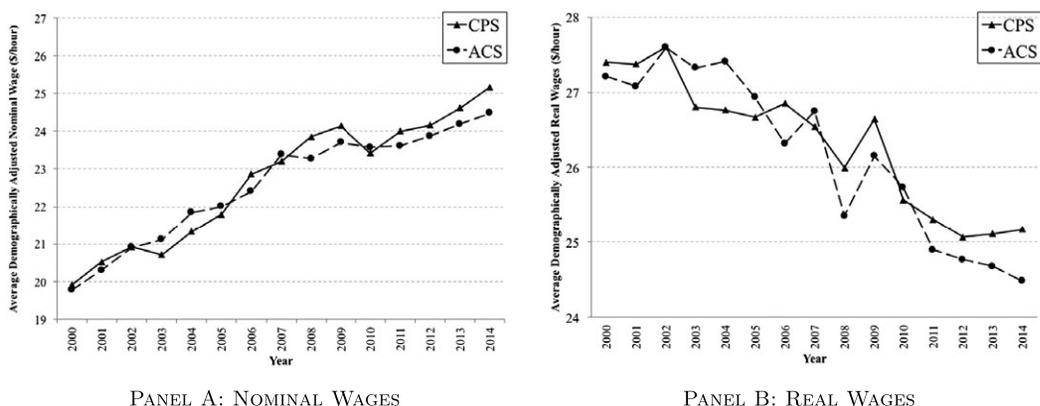


FIGURE 2.—Time series trends in aggregate wages (\$/hour), CPS and ACS. Note: Figure shows average demographically adjusted nominal wages (left panel) and real wages (right panel) for men aged 21–55 during the 2000–2014 period. Wages are reported as \$/hour. The solid line uses data from the CPS. The 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 II creates measures of aggregate time series wage elasticities that can be compared with the cross-region estimates in Table I. Given the time series trends in both real and nominal wages prior to the Great Recession as shown in Figure 2, we de-trend both series when examining patterns during the Great Recession.¹¹ For real wages, we compute the annual real wage growth in our demographically adjusted CPS data between the years of 1990 and 2007. According to the CPS data, real wages have been declining by 0.4 percent per year, on average, during the 1990 to 2007 period. When de-trending nominal wage growth, we assume an inflation rate of 2 percent per year. This implies that nominal wages would have grown by 1.6 percent per year during the 2007–2010 period absent the Great Recession (2 percent inflation plus –0.4 percent real wage growth).

TABLE II
TIME SERIES ESTIMATES OF WAGE ELASTICITIES DURING THE GREAT RECESSION

	CPS Data	ACS Data
Panel A: Nominal Wages		
De-Trended Nominal Wage Growth, 2007–2010	–3.9 percent	–4.1 percent
Nominal Wage Elasticity, 2007–2010	0.51	0.54
Panel B: Real Wages		
De-Trended Real Wage Growth, 2007–2010	–2.6 percent	–2.8 percent
Real Wage Elasticity, 2007–2010	0.34	0.37

Note: Table computes the aggregate wage elasticity to a 1 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. Panels A and B show de-trended nominal and real wage growth, respectively, during the 2007–2010 period.

¹¹We 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 had been steadily declining for many years prior to the start of the Great Recession.

The top panel displays the aggregate nominal wage elasticity. To obtain this, we take the de-trended demographically adjusted nominal wage growth using aggregate data from the CPS (column 1) and ACS (column 2) between 2007 and 2010 and divide it by the aggregate percentage change in the employment rate. According to BLS, the aggregate employment to population ratio in the United States fell by 7.7 percent between 2007 and 2010. In the aggregate time series data, the nominal wage elasticity during the Great Recession was between 0.51 and 0.54 depending on whether we use the CPS or ACS data. As a reminder, the corresponding wage elasticity from the cross-region estimates in Table I is 0.72. The bottom panel provides estimates of real wage elasticities over the same time period but at the aggregate level. Real wages fell between 2007 and 2010 by 2.6 percent in the CPS and 2.8 percent in the ACS relative to trend. Given that the aggregate employment to population rate fell by 7.7 percent, the aggregate elasticity of real wages with respect to employment changes was 0.34 in the CPS and 0.37 in the ACS. Note, these numbers are about half the magnitudes estimated from the cross-region estimates.

3.3. Robustness

As noted 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 is 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 time 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 this section is not altered by controlling for selection based on observables.

To further explore the extent to which selection based on unobservables is 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 are 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.¹²

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. 0.34). It is this difference in the relationship between wages and employment at the local level and at the aggregate level that 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 responded much less despite a sharp deterioration in aggregate employment conditions? 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, Primiceri, and Tambalotti (2010), Christiano, Motto, and Rostagno (2014), and Linde, Smets, and Wouters (2016) but extended to include multiple regions. We have two goals in mind: (i) to explain how and why aggregate and local wage and employment responses might differ following a given shock, and (ii) 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 responses 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 good and intermediates that go into its production. There are 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. 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. *Households and Wage Setting*

Each island is populated by a continuum of households indexed by $j \in [0, 1]$ who supply a differentiated labor service $N_{kt}(j)$ as in Erceg, Henderson, and Levin (2000). House-

¹²As a separate robustness exercise, we document that the cross-state relationship between employment changes and wage changes during the Great Recession was much stronger than the corresponding aggregate time series relationship using data from the BLS's *Quarterly Census of Employment and Wages* and the BLS's *Occupational Employment Survey*. The analog to Figure 1 using these alternate wage series is shown in the Supplemental Material.

holds maximize the utility function

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

where C_{kt} is consumption of a final good, b_{kt} is a stochastic process for the discount factor, and φ_{kt} is a stochastic process for leisure preference. Throughout, we will refer to shocks to φ_{kt} as “labor supply” shocks. We denote by h the parameter governing external habits in household consumption decisions, ν the inverse Frisch elasticity, and ϕ_{kt} the endogenous discount factor (which is treated as exogenous by households). As in [Schmitt-Grohé and Uribe \(2003\)](#), such addition to the model ensures the existence of a stationary distribution of bonds across islands.¹³ Also, consumption C_{kt} is not indexed by ‘ j ’ because, as in [Justiniano, Primiceri, and Tambalotti \(2010\)](#), we assume the existence of a full set of state-contingent securities that ensure that equilibrium consumption and asset holdings are the same for all households in an island.

Furthermore, we assume that households can save in a tradable one-period nominal bond B_{kt} (which pays the gross interest rate R_t that is common across islands) or in non-tradable physical capital \bar{K}_{kt} . The sequential budget constraint is then

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

where I_{kt} denotes investment in capital, u_{kt} is the utilization rate, $a(u_{kt})$ is a capital utilization cost, $S(\frac{I_{kt}}{I_{kt-1}})$ is a convex investment-adjustment cost, Π_{kt} are lump-sum transfers in the form of profit from local firms, T_{kt} are government transfers, $W_{kt}(j)N_{kt}(j)$ is labor income, $Q_{kt}(j)$ is the net cash flow from the portfolio of state-contingent securities, P_{kt} is the price of the final good, R_{kt}^K is the nominal capital rental rate, δ is the depreciation rate, and μ_{kt} is a stochastic process for the marginal efficiency of investment.

Also, as in [Erceg, Henderson, and Levin \(2000\)](#), we assume the existence of a large number of competitive labor agencies that buy all forms of differentiated labor services and transform them into homogeneous labor services, which they then sell for price W_{kt} . Their profit maximization problem is

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

The demand for differentiated labor is then

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

¹³See Supplemental Material Appendix B.5 for a formal description of the endogenous discount factor. In particular, we assume that it only depends on island-level bonds in log-deviations from the aggregate.

where $\lambda_w > 1$. The wage index is

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

Finally, we assume that only a fraction $1 - \xi_w$ of households can re-optimize their wages every period and the remaining wages adjust according to a backward-looking indexation rule. Re-optimizing households choose their wage $W_{kt}(j)$ to maximize

$$\begin{aligned} \max_{W_{kt}(j), \{N_{kt+s}(j)\}_{s=0}^{\infty}} \mathbb{E}_t \left\{ \sum_{s=0}^{\infty} (\beta \xi_w)^s \left[-b_{kt+s} \phi_{kt+s} \varphi_{kt+s} \frac{N_{kt+s}^{1+\nu}(j)}{1+\nu} + \Lambda_{kt+s} \Gamma_{kt,t+s}^w W_{kt}(j) N_{kt+s}(j) \right] \right\} \\ \text{s.t. } N_{kt+s}(j) = N_{kt+s} \left[\frac{W_{kt}(j) \Gamma_{kt,t+s}^w}{W_{kt+s}} \right]^{\frac{\lambda_w}{1-\lambda_w}} \quad \forall s, \end{aligned}$$

where Λ_{kt+s} is the Lagrange multiplier associated with the sequential budget constraint, $\Gamma_{kt,t+s}^w$ is the indexation term

$$\Gamma_{kt,t+s}^w \equiv \prod_{l=1}^s [\pi_{kt+l-1}^{\iota_w} \pi^{1-\iota_w} \gamma],$$

and π_{kt} is the inflation rate in island k at time t , π is the inflation target set by the monetary authority, γ is the long-run growth rate of productivity, and ι_w governs the degree of indexation. Note that, given our assumptions, all households that re-optimize will actually set the same wage.

4.2. Firms and Price Setting

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

$$\max_{\{Y_{kt}(i)\}_i} P_{kt} Y_{kt} - \int_0^1 P_{kt}(i) Y_{kt}(i) di \quad \text{s.t.} \quad Y_{kt} = \left[\int_0^1 Y_{kt}(i)^{\frac{1}{\lambda_{kt}^p}} di \right]^{\lambda_{kt}^p},$$

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 $\lambda_{kt}^p > 1$ 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

$$Y_{kt}(i) = Y_{kt} \left[\frac{P_{kt}(i)}{P_{kt}} \right]^{\frac{\lambda_{kt}^p}{1-\lambda_{kt}^p}}.$$

The zero profit condition implies that the price index satisfies

$$P_{kt} = \left[\int_0^1 P_{kt}(i)^{\frac{1}{1-\lambda_{kt}^p}} di \right]^{1-\lambda_{kt}^p}.$$

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_{kt}^x and capital K_{kt}^x and solves the profit-maximization problem

$$\max_{N_{kt}^x, K_{kt}^x} P_t^x A_{kt}^x (K_{kt}^x)^{\alpha_x} (N_{kt}^x)^{1-\alpha_x} - W_{kt} N_{kt}^x - R_{kt}^K K_{kt}^x,$$

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

$$\begin{aligned} W_{kt} &= (1 - \alpha_x) P_t^x A_{kt}^x (K_{kt}^x)^{\alpha_x} (N_{kt}^x)^{-\alpha_x}, \\ R_{kt}^K &= \alpha_x P_t^x A_{kt}^x (K_{kt}^x)^{\alpha_x-1} (N_{kt}^x)^{1-\alpha_x}. \end{aligned}$$

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

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

where F is the fixed cost of operating the technology that is common across islands, 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

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

Finally, we assume that retailers are also subject to a Calvo-style friction and can only change their prices infrequently. In each period, only a fraction $1 - \xi_p$ 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

$$\begin{aligned} \max_{P_{kt}(i), \{Y_{kt+s}(i)\}_{s=0}^{\infty}} \mathbb{E}_t \left\{ \sum_{s=0}^{\infty} (\beta \xi_p)^s M_{kt+s} Y_{kt+s}(i) [P_{kt}(i) \Gamma_{kt,t+s}^p - MC_{kt+s}] \right\} \\ \text{s.t. } Y_{kt+s}(i) = Y_{kt+s} \left[\frac{P_{kt}(i) \Gamma_{kt,t+s}^p}{P_{kt+s}} \right]^{\frac{\lambda_t^p}{1-\lambda_t^p}} \quad \forall s, \end{aligned}$$

where the pricing kernel coming from the households is

$$M_{kt+s} = b_{kt+s} \phi_{kt+s} \Lambda_{kt+s}$$

and the indexation term is defined as

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

where ι_p governs the indexation. Note that, given our assumptions, all retailers that re-optimize will actually set the same price.

4.3. Government Policy

Fiscal Policy

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

$$G_{kt} = \left(1 - \frac{1}{\epsilon_{kt}^g}\right) Y_{kt}.$$

The role of exogenous process ϵ_{kt}^g is to not only capture true government spending shocks but also to soak up variation in measured GDP due to changes in net exports when we fit our closed-economy aggregate model to the data. Also, federal transfers T_{kt} are identical across regions in each period.¹⁴

Monetary Policy

The nominal interest rate is common across all islands in the monetary union. It is set by a central authority according to a Taylor Rule

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

where GDP_t is aggregate GDP defined as

$$GDP_t = \sum_k [C_{kt} + I_{kt} + G_{kt}]$$

and η_t is an exogenous monetary policy stochastic process.

4.4. Shocks

The economy as a whole is perturbed by nine 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

¹⁴Alternatively, we could have made the transfers be island-dependent either by making them exogenously different or by following an endogenous transfer policy rule that depends on island-level variables as in Beraja (2018). This change would not have any effect on the aggregate log-linearized equilibrium, which is the focus of our quantitative exercises in Section 7. Nor would this change affect the estimation of our Regional New Keynesian Phillips Curve using cross-state variation. Thus, we abstract from island-specific transfers. Yet, as we discuss in Section 4.7 and as explored in Beraja (2018), the presence of regional transfer policy rules affects other aspects of the island-level log-linearized equilibrium.

considerations lead us to model Ψ_t as purely aggregate with innovations to its growth rate, and to center around it the island-specific transitory productivity shocks.¹⁵ 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 Supplemental Material Appendix B for a formal description of the exogenous processes.

4.5. Equilibrium

An equilibrium is prices $\{P_{kt}(i), P_{kt}^x, W_{kt}(j), R_{kt}^K, R_t\}$ and quantities $\{Y_{kt}, C_{kt}, I_{kt}, G_{kt}, \bar{K}_{kt}, K_{kt}^x, K_{kt}(i), u_{kt}, N_{kt}(j), N_{kt}^x, N_{kt}^y(i), X_{kt}, B_{kt}, D_{kt}\}$ such that, given the exogenous processes and government policies, all agents are optimizing and all markets clear. Formally, the final goods and labor markets clearing conditions and consolidated budget constraint in each island are

$$\begin{aligned} Y_{kt} &= C_{kt} + I_{kt} + G_{kt} + a(u_{kt})\bar{K}_{kt}, \\ N_{kt} &= N_{kt}^x + N_{kt}^y, \\ B_{kt} &= R_{t-1}B_{kt-1} + P_t^x(A_{kt}^x N_{kt}^x - X_{kt}) + T_{kt}. \end{aligned}$$

Letting D_t denote federal debt, the budget constraint of the federal government is

$$D_t = R_{t-1}D_{t-1} + \sum_k [P_{kt}G_{kt} + T_{kt}].$$

And, the tradable-good and bond markets clearing conditions in the aggregate are

$$\begin{aligned} \sum_k X_{kt} &= \sum_k A_{kt}^x N_{kt}^x, \\ \sum_k B_{kt} &= D_t. \end{aligned}$$

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

¹⁵Formally, the technology growth process is $z_t \equiv \Psi_t/\Psi_{t-1}$ with $\log z_t = (1 - \rho_z) \log \gamma + \rho_z \log z_{t-1} + u_t^z$ and u_t^z i.i.d. The tradable productivity process is $\log A_{kt}^x = (1 - \rho_x) \log \Psi_t + \rho_x \log A_{kt-1}^x + v_{kt}^x$ with v_{kt}^x i.i.d. The retail productivity process is analogous to the tradable productivity process.

and, instead, simply pose the existence of a representative aggregate economy that is driven by aggregate shocks alone.¹⁶

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 assumptions 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 both an exogenous 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 Supplemental Material Appendices B.5 and B.6.

Q.E.D.

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

$$\begin{aligned} \tilde{\pi}_{kt}^w &= \beta \mathbb{E}_t[\tilde{\pi}_{kt+1}^w] + \kappa_w \nu \tilde{n}_{kt} - \kappa_w \tilde{w}_{kt} + \iota_w (\tilde{\pi}_{kt-1} - \beta \tilde{\pi}_{kt}) \\ &+ \frac{\kappa_w}{1-h} (\tilde{c}_{kt} - h \tilde{c}_{kt-1}) + \tilde{\varphi}_{kt}, \end{aligned} \tag{2}$$

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 the Regional New Keynesian Wage Phillips curve is

$$\kappa_w \equiv \frac{(1 - \beta \xi_w)(1 - \xi_w)}{\xi_w} \frac{\lambda_w - 1}{\lambda_w(1 + \nu) - 1}, \tag{3}$$

¹⁶The 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 U.S. state, we believe this is not too egregious an assumption.

where $1 - \xi_w$ is the fraction of wages that reset 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

$$\hat{\pi}_t^w = \beta \mathbb{E}_t[\hat{\pi}_{t+1}^w] + \kappa_w \nu \hat{n}_t - \kappa_w \hat{w}_t + \iota_w (\hat{\pi}_{t-1} - \beta \hat{\pi}_t) + \frac{\kappa_w}{1-h} (\hat{c}_t - h \hat{c}_{t-1}) + \hat{\varphi}_t, \quad (4)$$

where lowercase variables with “^” 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 versus 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 7 presents quantitative results along these lines, in this section we provide a more qualitative analysis. We highlight three such channels in this paper: (i) monetary policy only affects aggregates in a monetary union, (ii) 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 (iii) 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. Beraja (2018) highlights yet another important difference: in a fiscal union like the United States, the federal tax-and-transfer system redistributes resources across regions in order to stabilize regional business cycles. This channel turns out to be quantitatively important, in particular during the Great Recession, but is entirely absent in the aggregate closed economy.

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 I and II.

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 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.

Supplemental Material Appendix B.7 derives the aggregate and regional employment responses and wage elasticities below:

$$\frac{d\hat{n}_0}{d\hat{b}_0} = \frac{1}{1-\alpha} \frac{1-\rho_b}{1-\rho_b+\phi_Y},$$

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

$$\frac{d\tilde{n}_{k0}}{d\tilde{b}_{k0}} = \frac{1 - \rho_b}{1 - \rho_b + \frac{1}{\beta} - a_{\tilde{b}\tilde{b}}},$$

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

where a_{ww} and $a_{\tilde{b}\tilde{b}}$ are the corresponding eigenvalues associated with the effects of past wages on current wages and past accumulated bonds on current bonds.¹⁷

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

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-form 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: differences in economic mechanisms at play can cause a wedge between regional and aggregate wage elasticities even if both regional and aggregate economies experience the same types of shocks.

¹⁷They are the solutions that are inside the unit circle to $0 = \beta(a_{ww})^2 - (1 + \beta + \kappa_w)a_{ww} + 1$ and $0 = (1 - \beta a_{\tilde{b}\tilde{b}})(1 - a_{\tilde{b}\tilde{b}}) - \frac{\beta p^* x}{\beta} \phi_0$.

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 to inform 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.

5.1. Methodology

The starting point of the methodology are the Regional and Aggregate New Keynesian Wage Phillips Curves, that is, equations (2) and (4). As we showed in Section 4.6, the first crucial implication of our modeling assumptions is that the parameters in both the Regional and Aggregate 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 remaining equations describing the aggregate log-linearized equilibrium, we can (compactly) write the system of such remaining equations as

$$A(\Theta, \Sigma)\mathbb{E}_t[X_{t+1}] + B(\Theta, \Sigma)X_t + C(\Theta, \Sigma)X_{t-1} = 0, \quad (5)$$

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 methodology in order to estimate the model combining a panel of regional data $\{\tilde{Y}_{kt}\}$ and time series aggregate data $\{\hat{Y}_t\}$. The algorithm below describes it:

Step 1: Fix Θ to an initial guess. Using only regional data $\{\tilde{Y}_{kt}\}$, estimate equation (2) via GMM. Obtain point estimate $\hat{\xi}_w$ and standard error $\hat{\sigma}_{\xi_w}$.

Step 2: Choose a constant $\vartheta \geq 0$ and a prior $p_\vartheta(\xi_w, \Theta, \Sigma)$ such that $\hat{\xi}_w$ and $\vartheta\hat{\sigma}_{\xi_w}$ are respectively the prior mean and standard deviation of ξ_w .

Step 3: Using only aggregate data $\{\hat{Y}_t\}$, estimate the aggregate model (equations (4) and (5)) via full-information Bayesian techniques with prior $p_\vartheta(\xi_w, \Theta, \Sigma)$. Obtain posterior $\hat{p}_\vartheta(\xi_w, \Theta, \Sigma|\{\hat{Y}_t\})$.

Step 4: Go back to step 1 and use the mean of Θ in posterior $\hat{p}_\vartheta(\xi_w, \Theta, \Sigma|\{\hat{Y}_t\})$ as the new initial guess. Iterate until convergence in $\hat{\xi}_w$.

A number of comments are in order. Regarding steps 2 and 3, we use full-information Bayesian estimation techniques in the tradition of Linde, Smets, and Wouters (2016), Christiano, Motto, and Rostagno (2014), and Justiniano, Primiceri, and Tambalotti (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 Supplemental Material Appendix B.8. However, we choose the prior mean and standard deviation of the degree of wage stickiness ξ_w based on our regional estimates. Crucially, by changing the constant ϑ , we can put more

or less weight on the regional versus aggregate data in informing this parameter. For example, when $\vartheta = 0$, we fix ξ_w to its point estimate $\hat{\xi}_w$ from our regional regression in step 1, thus putting all the weight on the regional data and none on the aggregate data. For our main results, we will consider $\vartheta = 0$ and $\vartheta = 2$. We pick $\vartheta = 2$ because this turns out to be equivalent to estimating the model with aggregate data alone and completely ignoring the regional evidence. It effectively imposes a flat prior over ξ_w . In Section 6, we discuss how the results change for intermediate values of ϑ as well as why $\vartheta = 0$ is our preferred benchmark.

Regarding step 1, beyond the Regional New Keynesian Wage Phillips Curve, our methodology does not use any other equations describing the regional equilibrium for estimation. Furthermore, it only uses the regional data to estimate ξ_w , given all other parameters. Section 5.3 describes this estimation step in detail. It is in the same spirit of the limited-information methods used in, for instance, Galí, Gertler, and López-Salido (2005) when estimating a “hybrid” New Keynesian Price Phillips Curve.¹⁸

5.1.1. *Why Use Only the Regional New Keynesian Wage Phillips Curve?*

One standard alternative to our methodology would have been to use all regional and aggregate equations describing the equilibrium and simply estimate all model parameters via full-information methods. Why do we present a methodology that only uses the Regional New Keynesian Phillips Curve and the aggregate equilibrium equations instead?

The first reason is data availability. There are no good available data for several variables at the state level in the United States that are needed for estimation (e.g., physical capital and current accounts). These variables do not show up in the Regional New Keynesian Wage Phillips Curve but do so in other structural equations describing the regional equilibrium.

The second reason is clarity. Our focus is on the implications of regional business cycles for wage stickiness and, as a result, on our understanding of the drivers of aggregate business cycles. As such, the regional evidence we presented in Section 3 is arguably informative about the degree of wage stickiness in the economy but less so about other parameters. Simultaneously estimating these parameters from regional data would make the aggregate implications of regional business cycles less transparent and the main results in the next sections less credible and harder to interpret.

The third reason is bridging the gap between those researchers estimating structural models and those estimating reduced-form responses to regional shocks. As the later literature does, our methodology also uses instruments at the regional level as a source of exogenous variation. Given that we are only using one equation from the regional block of our model, this arguably allows for more credible identification, a point we further explore in Section 6. However, we exploit such regional variation to estimate key structural parameters that, under certain assumptions, are common between regional and aggregate economies, as opposed to estimating reduced-form responses to shocks which, as we argued in Section 4.7, typically differ.

The last reason, and perhaps the most fundamental, is robustness to model misspecification. Suppose the researcher is unsure about other specific features of the economy that do not change the Regional and Aggregate New Keynesian Phillips Curves or the aggregation properties of the model in Lemma 1. Yet, assume that these other features matter for other regional equilibrium equations and thus change the regional responses to

¹⁸For a related methodology, see the sequential learning approach in Canova and Matthes (2018).

shocks.¹⁹ To make this discussion concrete, one such feature is the form of the endogenous discount factor ϕ_{kt} . Parameters governing it do not show up in any of the aggregate equations nor in the New Keynesian Wage Phillips Curves but matter greatly for the regional responses, as shown in our closed-form example in Section 4.7. If the estimated degree of wage stickiness is affected by using the Regional New Keynesian Phillips Curve in estimation jointly with misspecified regional equilibrium equations (e.g., a Euler equation with the “wrong” endogenous discount factor), then this would also affect the aggregate responses to shocks and result in drawing incorrect conclusions from our model. However, our methodology is robust to this type of misspecification precisely because it only uses the Regional New Keynesian Phillips Curve and no other regional equilibrium equations.

5.2. Benchmark Parameterization

There are five parameters embedded in Θ that show up in the estimation of (2) and (4): 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 (3), 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 externally calibrate β , ν , ι_w , and λ_w . We then use our algorithm 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 the combined extensive-margin and intensive-margin uncompensated labor supply elasticities in the range of 1 ($\nu = 1$).²⁰ Macro estimates identified off of business-cycle variation estimate uncompensated elasticities above 2 (ν below 0.5).²¹ 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, Smets, and Wouters \(2016\)](#) and set $\lambda_w = 1.2$. [Table III](#) 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.

¹⁹[Beraja \(2018\)](#) showed how thinking about misspecification in terms of equilibrium equations is also useful when considering whether counterfactuals with respect to policy rule changes are robust or not, as well as how to construct counterfactuals without having to fully specify a structural model when researchers are uncertain about features of the economy that may be difficult to distinguish in the data.

²⁰Prominent estimates of the intensive-margin Frisch include 0.71 from [Pistaferrri \(2003\)](#) and 0.54 from [Chetty, Guren, Manoli, and Weber \(2011\)](#). [Chetty et al. \(2011\)](#) also surveyed several quasi-experimental estimates of the extensive-margin Frisch and found 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 Río \(2015\)](#), 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, Motto, and Rostagno \(2014\)](#) who also exogenously set the Frisch to 1 when estimating their medium-scale DSGE model.

²¹See, for example, [King and Rebelo \(2000\)](#).

TABLE III
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 the two 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 (2), our cross-region estimate of ξ_w is determined, in part, by h . As it turns out, though, the cross-region estimate of ξ_w is not sensitive to changes in the initial guess for h around those in the literature (i.e., values between 0.3 and 0.6). We show this in Table VI. Hence, in practice, we only have to run the algorithm once whenever we set the initial guess for h to be anywhere in that range.

Table IV shows all estimated parameters. Our choices for the priors follow [Christiano, Motto, and Rostagno \(2014\)](#) as closely as possible, subject to the necessary frequency conversions from quarterly to annual data.²² The column “Posterior Benchmark” refers to our benchmark estimation results where we set $\vartheta = 0$, thus effectively fixing ξ_w to correspond to the point estimate from step 1 that only uses regional data. This means that, conditional on other parameters, we do not use any information on the aggregate data to discipline the degree of wage stickiness. Instead, the aggregate data inform the remaining parameters of the model, conditional on the ξ_w estimated from regional data. The column “Posterior Aggregate Data” corresponds to setting $\vartheta = 2$ in the estimation. The key difference between this case and our benchmark is that we now let the aggregate data inform the degree of wage stickiness. As it turns out, when $\vartheta = 2$, the prior standard deviation of ξ_w is so high that the estimated parameters are identical to those that would come from only using aggregate data in estimation. Thus, we refer to the case with $\vartheta = 2$ as the one that uses *aggregate data only* in estimation and the case with $\vartheta = 0$ as our benchmark procedure that *combines regional and aggregate data* in estimation. In robustness exercises, we will explore intermediate values of ϑ .

Our benchmark estimate of ξ_w using the regional data is 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 base wage adjustments using administrative data sources.²³ Had we estimated the model with aggregate data alone, we would have found that ξ_w equals

²²We use annualized data given that our demographically adjusted wage series from the CPS is only measured annually.

²³See, for example, [Grigsby, Hurst, and Yildirmaz \(2018\)](#).

TABLE IV
MODEL PRIORS AND POSTERIOR

		Posterior						
		Prior			Benchmark		Aggregate data	
		Dist	Mean	SD	Mean	SD	Mean	SD
<u>Wage Phillips Curve</u>								
ξ_w	Calvo wages	B	0.24	0.32	0.24	N/A	0.50	0.09
h	habit parameter	B	0.50	0.10	0.48	0.07	0.62	0.08
<u>Others</u>								
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	0.30	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	0.72
S''	capital adjust. cost	N	5.00	3.00	2.99	1.23	3.20	1.22
ϕ_π	reaction inflation	N	1.50	0.25	1.62	0.15	1.51	0.14
ϕ_Y	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	0.40	0.08
ρ_η	monetary policy	B	0.50	0.20	0.43	0.14	0.41	0.13
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	0.60	0.13
ρ_μ	investment	B	0.50	0.20	0.68	0.10	0.70	0.10
ρ_{λ_p}	price markup	B	0.50	0.20	0.67	0.12	0.56	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	0.71	0.08
$100\sigma_\eta$	monetary policy	IG	2.33	3.31	1.22	0.18	1.16	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	0.07
$100\sigma_\mu$	investment	IG	0.80	1.32	14.77	5.29	14.45	4.90
$100\sigma_{\lambda_p}$	price markup	IG	0.80	1.32	0.94	0.26	0.90	0.20
$100\sigma_\varphi$	labor supply	IG	0.80	1.32	1.95	0.31	1.15	0.29
$100\sigma_b$	discount factor	IG	0.80	1.32	0.67	0.14	0.52	0.12
Log-marginal likelihood					-592		-590	

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 with $\vartheta = 0$ which estimates ξ_w using only the regional data. “Aggregate data” corresponds to the estimation with $\vartheta = 2$ which effectively ignores regional data and is equivalent to estimating ξ_w solely from the aggregate data.

0.50. This is consistent with other recent estimates that use aggregate data alone to estimate their medium-scale New Keynesian models. See, for example, [Christiano, Motto, and Rostagno \(2014\)](#) and [Linde, Smets, and Wouters \(2016\)](#). Section 6 further comments on the differences between the two estimation strategies. The next subsection discusses in detail the step in the algorithm that uses regional data to estimate ξ_w given other parameters.

5.3. Estimating the Wage Phillips Curve Using Regional Data

In this subsection, we discuss how we estimate the degree of wage stickiness using cross-region variation during the Great Recession. This is step 1 in our fixed-point algorithm. In particular, we estimate equation (2) 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 rewrite equation (2) in levels as opposed to growth rates as

$$\tilde{W}_{kt} = \alpha_0 + \alpha_1 \tilde{W}_{kt+1} + \alpha_2 \text{MRS}_{kt} + \alpha_3 \tilde{W}_{kt-1} + \tilde{\varphi}_{kt} + \tilde{\varepsilon}_{kt+1}, \tag{6}$$

where $\tilde{\varepsilon}_{kt+1}$ is the expectational error of $E[\tilde{\pi}_{kt+1}^w] - \tilde{\pi}_{kt+1}^w$ and $\tilde{\varphi}_{kt}$ is the local-level labor supply shock, MRS_{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 (6), 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 MRS_{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 Supplemental Material that accompanies the paper. We estimate (6) using $t = 2007, 2008, 2009, 2010,$ and 2011 . We start in 2007 because our price data begin 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 (6). Our estimate of κ_w comes from taking the ratio of α_2 to α_3 .

There are a few challenges to estimating (6) 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.²⁴ 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 MRS_{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 (6) is that MRS_{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 that estimating (6) via OLS will bias our estimate of κ_w downward, which will bias our estimate of ξ_w upward, implying greater wage stickiness. Therefore, estimating (6) via OLS will give us a 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

²⁴As with all of our other state-level economic variables, we create a state-specific index for real log-per capita GDP with a value of 1 in 2005. All subsequent years are log-deviations from 2005.

is implied from aggregate data even in our OLS regression. However, to better identify κ_w , we instrument for the $\tilde{\text{MRS}}_{kt}$ 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 $\tilde{\text{MRS}}_{kt}$ that is related to changes in household demand.²⁵ In Section 6, we discuss in detail why using household demand shocks can help identify the degree of wage stickiness in a world where labor supply shocks are important.

Formally, 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. Furthermore, it is worth highlighting that our measure of the $\tilde{\text{MRS}}_{kt}$ includes local consumption. Thus, the identification assumption is not violated by changes in current or expected housing wealth that could shift labor supply through changes in consumption.

When we instrument for both \tilde{W}_{kt+1} and $\tilde{\text{MRS}}_{kt}$ 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 predicting $\tilde{\text{MRS}}_{kt}$ was 41.9. Table V shows our base specification estimates of (6) using cross-state variation. Column 1 shows our results when we instrument for only \tilde{W}_{kt+1} , while column 2 shows our results when we instrument for both \tilde{W}_{kt+1} and $\tilde{\text{MRS}}_{kt}$. 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 parentheses.

TABLE V
ESTIMATES OF κ_w FROM CROSS-STATE VARIATION 2007–2011, BASE SPECIFICATION

	(1)	(2)
$\hat{\alpha}_2$	0.08 (0.03)	0.15 (0.05)
$\hat{\alpha}_3$	0.46 (0.02)	0.43 (0.03)
$\hat{\kappa}_w$	0.18 (0.08)	0.35 (0.16)
$\hat{\xi}_w$	0.35	0.24
Instrument for \tilde{w}_{kt+1}	Yes	Yes
Instrument for $\tilde{\text{MRS}}_{kt}$	No	Yes
Year Fixed Effects	Yes	Yes
Sample Size	240	240

Note: Table shows the coefficients from estimating (6). 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 $\tilde{\text{MRS}}_{kt}$ using contemporaneous log-house prices as an additional instrument. All standard errors (in parentheses) 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 $\tilde{\text{MRS}}_{kt}$, we set $h = 0.48$ as determined by our fixed-point procedure.

²⁵Our housing data come from the Federal Housing Finance Authority (FHFA). The FHFA produces nominal state-level price indices for all states.

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 = 0.16). Our results in column 2 will be our benchmark estimate throughout the paper. Using equation (3), 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 (6), 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 V without imposing the constraints, $\alpha_1 = 0.65$ (standard error = 0.36), $\alpha_2 = 0.05$ (standard error 0.18), and $\alpha_3 = 0.31$ (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 V.

5.4. Robustness of Regional Estimates

Table VI 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 V. All other rows show estimates for alternative values of ν , h , and ι_w . For the

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

Note: Table shows the coefficients from estimating (6) 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 V. All standard errors (in parentheses) are bootstrapped to account for the two-stage procedure. Standard errors are also clustered at the state level. Row 1 redisplayes our estimates under our base parameterization shown in column 2 of Table V. 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 allow 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.

alternative estimates, we use the same specification as in column 2 of Table V. 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 has 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 is that ν also affects the mapping from κ_w to ξ_w . Across the various values of ν , our estimates of ξ_w only vary 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 (6) but still impose 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 Supplemental Material 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, 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 (6). 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 V.

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, e.g., [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.

6. THE VALUE OF COMBINING REGIONAL AND AGGREGATE DATA

In Section 4.7, we used a simplified version of our model to argue that using regional data alone to make inferences about the aggregate responses to shocks could be problematic—a point that we will come back to in Section 7 using our full model.

In this section, we instead ask: what is the “problem” with using aggregate data alone when trying to distinguish between models with high versus low wage stickiness? Why does combining regional and aggregate data help? We begin by comparing our estimation results under both approaches and then turn to these questions.

6.1. Comparing Estimation Results

In Table IV, we show the parameter estimates under both approaches. First, the degree of wage stickiness is much larger when estimating the model with aggregate data alone: the posterior mean of ξ_w increases from 0.24 to 0.50. This implies that, when using aggregate data alone, we estimate that 50 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) estimated a medium-scale DSGE model using only aggregate time series data over the 1985 to 2010 period and also found relatively large amounts of wage stickiness with their estimates of ξ_w equaling 0.43.²⁶ Second, the standard deviation of the labor supply shock σ_φ increases from 1.15 to 1.95 as the regional data are used and the persistence ρ_φ of the labor supply shock increases from 0.59 to 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.

Regarding the fit to the data, Table VII presents the fit of the aggregate model to the time series aggregate data and the fit of the regional New Keynesian Phillips Curve to the regional data. We do so for both approaches in Table IV. For the fit of aggregate model with respect to time series aggregate data, we see that the log-marginal likelihood is almost identical under both approaches (which just reproduces the last line of Table IV). This means that there is no discernible loss in model fit when effectively fixing ξ_w to the point estimate of 0.24 from regional data (i.e., the $\vartheta = 0$ case) or estimating it jointly with the rest of the parameters from aggregate data alone (i.e., the $\vartheta = 2$ case). The same is true for intermediate values of ϑ .²⁷ The fact that the log-marginal likelihood is relatively insensitive to alternate estimates of ξ_w suggests that this parameter is not well disciplined by the U.S. aggregate time series data. This is consistent with the fact that the model-implied estimates of wage stickiness using aggregate time series data vary substantively across papers within the literature.²⁸ Conversely, there is a substantial loss in the fit of the regional New Keynesian Wage Phillips Curve (equation (6)) when we set $\xi_w = 0.50$, that is, the estimated ξ_w resulting from the estimation using aggregate data alone. Specifically,

TABLE VII
FIT OF AGGREGATE MODEL AND REGIONAL NKWPC

	$\xi_w = 0.24 (\vartheta = 0)$	$\xi_w = 0.5 (\vartheta = 2)$
Aggregate model log-marginal likelihood	-592	-590
Mean squared error of regional NKWPC	0.0002	0.0146

Note: The first line is the aggregate model fit to the aggregate time series data, as measured by the log-marginal likelihood. The second line is the mean squared error of the regional NKWPC (equation (6)).

²⁶Because they used quarterly data, Christiano, Motto, and Rostagno (2014) reported quarterly estimates of ξ_w equal to 0.81. The implied annual ξ_w is $(0.81)^4 = 0.43$.

²⁷As explained by Jeffreys (1998), a difference in log-marginal likelihoods of 2 cannot be accepted as strong evidence in favor of one model over the other. Also, see Rabanal and Rubio-Ramírez (2005) for a use of log-marginal likelihoods to discriminate between New Keynesian DSGE models.

²⁸As noted above, Christiano, Motto, and Rostagno (2014) estimated an annual amount of wage stickiness of 43 percent. Alternatively, Christiano, Eichenbaum, and Evans (2005), Smets and Wouters (2007), and Linde, Smets, and Wouters (2016) provided annual estimates of ξ_w equal to 17 percent, 28 percent, and 39 percent, respectively.

the mean squared error of the regional regression increases from 0.0002 to 0.0146 when we set $\xi_w = 0.50$. Furthermore, the mean squared error increases sharply when going from $\vartheta = 0$ to more intermediate values of ϑ and their associated ξ_w estimates. For instance, for $\vartheta = 0.5$ and $\vartheta = 1$, the mean squared errors from the regional regression are 0.0013 and 0.0069, respectively.

The above discussion implies that, in our relatively short sample of 40 years of aggregate time series data, there seems to be little information regarding the degree of wage stickiness. For this reason, our preferred estimates are either the benchmark parameterization that only uses regional data in estimating ξ_w ($\vartheta = 0$) or the one associated with $\vartheta = 0.5$ because the mean squared error is still relatively small. Larger values of ϑ that put further weight on the aggregate data in estimating ξ_w bring essentially no gains in terms of fitting the aggregate time series but result in substantial losses in terms of fitting the regional patterns.

6.2. *Distinguishing Between High and Low Wage Stickiness Models: The Role of Demand and Labor Supply Shocks*

Through a series of thought experiments, this section explores why using aggregate data alone could be problematic when trying to distinguish models with high versus low wage stickiness, as well as why the regional data may help with identification. The bottom line of the analysis is that it becomes hard to distinguish across these models in aggregate data whenever labor supply shocks are important relative to demand shocks (e.g., discount rate shocks) and whenever the time series data have a relatively short sample.

Consider first a thought experiment along the following lines: assume that the data generating process is the “true” model of the economy in Section 4, parameterized with a low wage stickiness and a given relative volatility of discount rate shocks versus labor supply shocks. Specifically, for the thought experiment, assume the parameterization is exactly our benchmark specification from Table IV. Then, consider an “alternative” model that a researcher is estimating on a short sample of only 40 annual observations coming from the true data generating process. In this alternative model, the researcher only estimates the degree of wage stickiness (ξ_w) and the discount rate and labor supply shock volatilities (σ_b and σ_φ). All other parameters are known to be those from the true model and are thus not estimated. Importantly, suppose the researcher is rather dogmatic and believes with high confidence that there is a high degree of wage stickiness in the economy. Specifically, suppose the researcher imposes a tight prior around the mean of $\xi_w = 0.5$ when estimating the model, that is, the higher degree of wage stickiness we estimated from aggregate data alone in Table IV.

Panel (A) of Figure 3 shows the distribution of ξ_w posterior mode estimates that dogmatic researchers would obtain when estimating their alternative model from random short samples of 40 observations of data generated by the true model. Panel (A) of the figure also compares how the posterior mode distribution moves away from the dogmatic researcher’s prior when the true model has either higher or lower relative volatility of discount rate versus labor supply shocks than in our benchmark parameterization. Specifically, the distribution denoted by “Medium σ_b/σ_φ ” corresponds to the benchmark parameterization, the “High σ_b/σ_φ ” corresponds to increasing (decreasing) the true discount rate shock (labor supply shock) standard deviation by a factor of 2, and “Low σ_b/σ_φ ” to increasing (decreasing) the true labor supply shock (discount rate shock) standard deviation by a factor of 2.

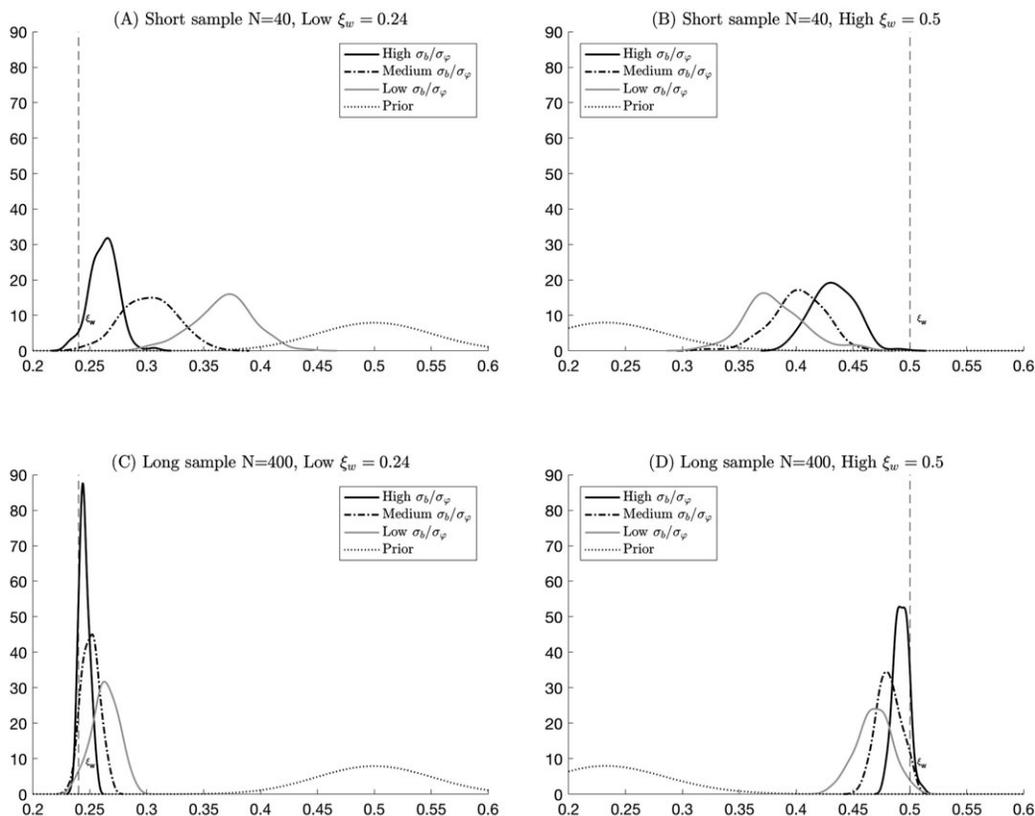


FIGURE 3.—Posterior mode distribution of ξ_w under different thought experiments. Note: Figure shows how the posterior mode distribution of ξ_w changes under different data generating processes, priors, and sample length. See text for details.

Panel (B) of Figure 3 considers the reverse thought experiment. The true model is one with high wage stickiness and a given relative volatility of discount rate versus labor supply shocks—the parameterization associated with the “aggregate data only” columns in Table IV. A dogmatic researcher in this economy is one who is then estimating the alternative model with a tight prior around the mean of $\xi_w = 0.24$, that is, the low posterior mean of wage stickiness estimated using only the regional data. In Panels (C) and (D), we repeat both experiments but instead estimate the wage stickiness parameter using longer random samples of 400 observations instead of 40 observations.

Both short sample experiments result in the same conclusions. Short samples from a true data generating process where demand shocks are more important than labor supply shocks command more information about the true degree of wage stickiness in the economy. To see this, consider how the relative importance of demand versus labor supply shocks influences how much the posterior moves away from the prior and towards the truth in Panel A. We see that when σ_b/σ_φ is low, so that demand shocks are small relative to labor supply shocks, the posterior only moves modestly closer to the truth. As σ_b/σ_φ increases, so that demand shocks become increasingly important relative to labor supply shocks, the posterior moves closer and closer to the truth. Thus, when demand shocks are small relative to labor supply shocks, a researcher with a high prior for wage stickiness would fail to recover the economy’s true low wage stickiness. But, when demand shocks

are relatively important, the estimated wage stickiness is close to the true low wage stickiness, even when starting with a high wage stickiness prior.

The results in Panels (A) and (B) stem from standard economic intuition. For simplicity, assume that prices are perfectly flexible and firms are on their labor demand schedule. Whenever demand shocks are the main drivers of economic fluctuations, observed movements in wages and employment are shifts in the labor demand schedule along the wage setting schedule. Thus, given a Frisch elasticity of around 1 ($\nu = 1$), the model will correctly infer the true degree of wages stickiness from such time series movements even when the underlying time series sample is short. However, if both demand and labor supply shocks are important, both the labor demand and wage setting schedules are shifting. Then, it becomes hard in a short sample to distinguish between, for example, a high degree of wage stickiness and offsetting labor demand and labor supply movements which move employment in the same direction but leave wages unchanged.

How do regional data help to overcome the problem of estimating the extent of wage stickiness when the aggregate time series data have a short sample? First, by exploiting cross-region panel data, sample sizes are larger. For example, in our analysis, we have roughly 250 state*time observations used in identifying the amount of wage stickiness. Second, and potentially more important, most of the cross-region variation in economic conditions during the Great Recession has been found to be driven by cross-region variation in demand shocks. As seen above, it is easier to identify the extent of wage stickiness in short panels when the underlying variation is being driven by demand shocks. Furthermore, as discussed above, we use an instrumental variable procedure to isolate only labor demand shocks when estimating the extent of wage stickiness from the regional data. It is worth stressing, however, that our cross-region estimation strategy relies on a few key strong assumptions. In particular, as noted above, our procedure relies on the assumption that the economy satisfies certain symmetry properties such that Lemmas 1 and 2 hold and the parameters in the Regional and Aggregate NKWPC coincide. This is because we cannot directly use the reduced-form regional wage elasticities as a target moment in estimating the aggregate model of the economy, since, as we have shown in Section 4.7, the regional and aggregate reduced-form responses to shocks typically differ.

7. 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 benchmark parameterization in Section 5—which follows from estimating the model with regional and aggregate data combined—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, which, as we have argued before, is equivalent to setting $\vartheta = 2$ in our methodology. 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, Rao, and Sufi (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.

7.1. *Why Do Aggregate Wages Look Stickier Than Regional Wages?*

As we discussed in 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.²⁹ 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 appeared 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, $\frac{d \log(w)}{d \log(n)}$, 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.³⁰ The question is then to decompose how much of the difference between aggregate and regional wage responses during the Great Recession was due to differing elasticities to the same shock versus differences between the shocks hitting the aggregate and regional economies.

7.1.1. *Different Aggregate and Regional Elasticities to Household Demand Shocks*

Similarly 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 $\frac{d \log(w^{\text{reg}})}{d \log(n^{\text{reg}})}$ to a regional household demand shock. This is the empirical analog to the theoretical regional wage elasticity $\frac{d \bar{w}}{d \bar{n}}$ we derived in Section 4.7. In particular, using the same state-level data underlying Table V, 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 latter

²⁹Many 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. See Mian and Sufi (2014) for an important contribution along these lines. Also, within our model, discount factor shocks can be interpreted as a proxy for such household demand shocks. See Werning (2015) for a formalization of this point.

³⁰See Nakamura and Steinsson (2017) for a related discussion on how both well-identified moments and portable statistics are helpful to discriminate across models.

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 I, 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 full model, we compute the aggregate wage elasticity $\frac{d\log(w^{\text{agg}})}{d\log(n^{\text{agg}})}$ to an aggregate discount factor shock. This is analogous to the theoretical aggregate wage elasticity $\frac{d\hat{w}}{d\hat{n}}$ in the simplified model from Section 4.7.³¹ Computing the impulse responses of real wages and employment over a 3-year horizon, we find an aggregate wage elasticity $\frac{d\log(w^{\text{agg}})}{d\log(n^{\text{agg}})}$ of 1.16 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 (1.16 versus 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.

7.1.2. Different Aggregate and Regional Shocks

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 its regional counterparts. However, this set of aggregate shocks gets 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 VIII 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 VIII shows that, when we feed the model with only the discount factor shock (b) realizations, the cumulative aggregate real wage elasticity between 2007 and 2010 is 0.97 under our benchmark parameterization. This is somewhat smaller than 1.16—that is, 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 0.37—that is, the aggregate elasticity we empirically estimated for the Great Recession shown in Table II. 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. However, when we

³¹Because we do not have plausibly exogenous time series variation in aggregate household demand during the Great Recession, we cannot estimate $\frac{d\log(w^{\text{agg}})}{d\log(n^{\text{agg}})}$ directly from the data as we did for the regional elasticity. Instead, we use our estimated model to compute the impulse responses to a discount factor shock. As we have mentioned, such discount factor shock is the closest theoretical analog to the changes in regional household demand we used to estimate $\frac{d\log(w^{\text{reg}})}{d\log(n^{\text{reg}})}$.

TABLE VIII
 PREDICTED $\frac{d\log(w^{agg})}{d\log(n^{agg})}$ DURING THE GREAT RECESSION IN RESPONSE TO VARIOUS SHOCKS

	Shocks		
	b	b and μ	$b, \mu, \text{ and } \varphi$
Benchmark	0.97	0.83	0.31
Aggregate data alone	0.39	0.40	0.25

Note: The 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.

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 is very close to the observed elasticity for the Great Recession (as shown in Table II).

Furthermore, Table VIII 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 appeared stickier relative to their regional 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.

7.2. 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 previous results showing that aggregate labor supply shocks can reconcile the differences between aggregate and regional wage elasticities, we perform a model-based shock decomposition to understand the extent to which these and other shocks were also important drivers of aggregate employment during the Great Recession and its aftermath.

7.2.1. The Contribution of Household Demand Shocks

Following our three alternative approaches, Figure 4 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. The solid and dashed lines show, respectively, the model-implied responses to discount factor shocks when using either our benchmark

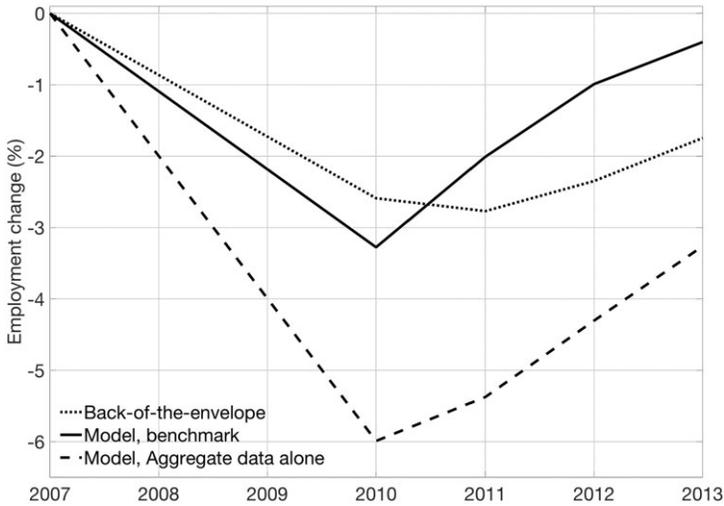


FIGURE 4.—Employment response to 2007–2010 household demand shocks. Note: “Model, benchmark” shows the employment response when feeding the model with the 2007–2010 discount factor shocks, under the benchmark parameterization that combines regional and aggregate data in estimation. “Model, aggregate 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 and 2010. Then, we multiply these elasticities with the aggregate house price changes between 2007 and 2010.

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 V, 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 2010.³² Then, in order to compute the aggregate employment response to household demand shocks, we simply multiply the reduced-form regional response by the aggregate decline in house prices between 2007 and 2010 of 30 percent.³³

³²House 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, Ludvigson, and Van Nieuwerburgh (2017)) or shifts in beliefs (Kaplan, Mitman, and Violante (2017)). As house prices change, they can generate both wealth effects and liquidity effects that can drive household demand (Berger, Guerrieri, Lorenzoni, and Vavra (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.

³³To 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>.

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).³⁴ 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 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.

7.2.2. Shock Decomposition

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 5 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). We refer to the combination of discount factor and investment efficiency shocks as “aggregate demand” shocks because they cause inflation and employment to move in the same direction. The dark gray bars are computed by feeding the model with the “aggregate supply” shocks (i.e., productivity and price markups). Finally, the light gray 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, em-

³⁴Mian and Sufi (2014) reported 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.

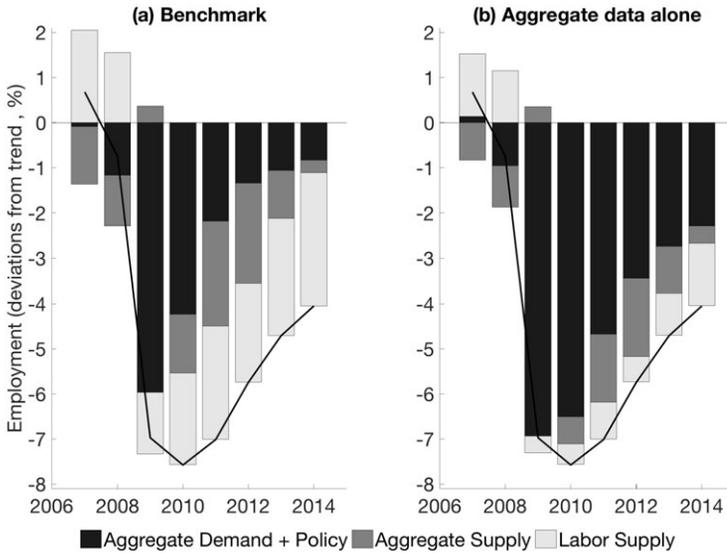


FIGURE 5.—Employment shock decomposition. Note: Bars are computed by feeding the model with groups of shocks, one at a time. Combined, they add up to the data (i.e., the solid line). “Aggregate Demand + Policy” feeds the discount factor, the investment efficiency, monetary policy, and government spending 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.

ployment would have recovered much faster in the aftermath of the Great Recession.³⁵ Instead, it is the combination of aggregate supply and labor supply shocks that account for the slow recovery. By 2012, it is primarily the labor supply shocks that are explaining the sluggish employment recovery in the United States 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. The reason for this is that the model estimated with only aggregate data finds a much higher level of wage stickiness. The differences between the two estimation procedures 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.

7.3. Robustness

We performed a number of robustness exercises to explore the sensitivity of our main quantitative results. First, we re-estimated our model using each alternative parameterization of habits h , Frisch elasticity ν , and indexation ι_w from Table VI. Also, we considered setting $\lambda_w = 1.5$, another common estimate in the literature. All of our main findings described in the previous sections remain essentially unchanged.

Additionally, in Supplemental Material Appendix B.9, we show how Figures 4 and 5 change when we re-estimate our model using intermediate values of ϑ in our methodol-

³⁵When we split the contribution further between demand and policy shocks, we find that policy shocks do not explain any of the decline in employment during the Great Recession and, if anything, employment would have recovered even more slowly without them.

ogy from Section 5. As a reminder, $\vartheta = 0$ corresponds to our benchmark estimates that only use regional data in estimating the degree of wage stickiness and $\vartheta = 2$ is equivalent to using aggregate data alone. We find that our results are essentially unchanged when we set $\vartheta = 0.5$ —which puts more weight in the aggregate data in disciplining the degree of wage stickiness by relaxing the prior standard deviation on ξ_w to be 0.5 standard errors of the regional estimates. For a larger $\vartheta = 1$, the results begin to change qualitatively and are somewhere in between the case with $\vartheta = 0$ and $\vartheta = 2$, assigning a larger role to demand shocks in explaining the sluggish employment recovery. Yet, as we discussed in Section 6, the cases of $\vartheta = 1$ and $\vartheta = 2$ entail a big loss in the fit of the regional New Keynesian Phillips Curve to our regional data without any significant gain in the fit of the aggregate model to the aggregate data. Hence, our preferred estimates are those associated with $\vartheta = 0$ or $\vartheta = 0.5$.

7.4. Discussion

To summarize, we find that aggregate demand 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 U.S. states. Relatedly, directly extrapolating from regional employment fluctuations to aggregate employment fluctuations in response to household demand shocks 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 a few 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 were 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 \(2017\)](#) showed 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.³⁶ 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, Hurst, and Notowidigdo \(2018\)](#) and [Charles, Hurst, and Schwartz \(2018\)](#) used reduced-form estimates to conclude that between 30 and 40 percent of the employment decline in the United States from prior to the Great Recession through 2014 can be attributed to secular declines in the manufacturing sector. [Şahin, Song, Topa, and Violante \(2014\)](#) developed a quantitative framework to assess the extent to which a mismatch in skills between job-seekers and firms that are hiring can lead to increasing unemployment. They also

³⁶See, for example, [Charles, Hurst, and Notowidigdo \(2016\)](#), and [Charles, Hurst, and Schwartz \(2018\)](#).

found that upwards of one-third of the increase in unemployment during the Great Recession can be attributed to such sectoral mismatch. Additionally, Charles, Hurst, and Notowidigdo (2016) used detailed household data to conclude that the housing boom masked some of the secular decline in the manufacturing sector during the early- to mid-2000s 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 explain why employment remained persistently low during the recovery.

Finally, the literature has also highlighted two other factors that could appear as labor supply shocks during the Great Recession. First, Aguiar, Bils, Charles, and Hurst (2018) showed how increased leisure technology shifted the labor supply curve for individuals during the 2000s. However, they estimated 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. Alternatively, both Mulligan (2012) and Hagedorn, Karahan, Manovskii, and Mitman (2016) discussed the importance of increased government transfers at the aggregate level in reducing labor supply. In particular, Hagedorn et al. (2016) suggested that the large aggregate extension of unemployment benefits during the Great Recession caused the aggregate unemployment rate within the United States to increase by roughly 2 percentage points. However, Chodorow-Reich, Coglianesi, and Karabarbounis (2018) used a different methodology and suggested that the effect of the large unemployment benefit extension only had a negligible effect on aggregate unemployment rates. To the extent that such aggregate policy changes did affect aggregate employment during the Great Recession, it would show up as a negative aggregate labor supply shock in our methodology.

8. CONCLUSION

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 shaping aggregate business cycles but which may be hard to pin down using aggregate data alone. In particular, we found 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 estimated using cross-region variation. Instead, we found that something akin to aggregate labor supply shocks—which are differenced out when exploiting cross-region variation—are needed to explain both 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 shocks in order to learn about the drivers of aggregate business cycles by performing back-of-the-envelope calculations. 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 credible identification, we have shown how combining regional and aggregate data can help discipline key structural parameters that, under certain assumptions, are common between regional and aggregate economies. As such, we hope this paper provides a bridge between researchers estimating structural models to perform quantitative exercises 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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SUPPLEMENT TO “THE AGGREGATE IMPLICATIONS OF REGIONAL
BUSINESS CYCLES”

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APPENDIX A: DATA AND EMPIRICS

IN THIS SECTION OF THE SUPPLEMENT, 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 our regional estimation as well as discussing some robustness exercises for our regional estimation.

A.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.¹ 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 12-month period by reported hours worked during that same time period. Hours worked are computed by multiplying weeks worked during the prior 12-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

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¹The 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.

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

$$\widetilde{\text{Wage}}_{kt} = \sum_{g=1}^{24} \text{Share}_{k\tau}^g \text{Wage}_{kt}^g, \quad (\text{A1})$$

where $\widetilde{\text{Wage}}_{kt}$ is the demographically 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 $\text{Share}_{k\tau}^g$ 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 demographically 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 (A1) 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.

Supplemental Appendix 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 set 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 they are 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.

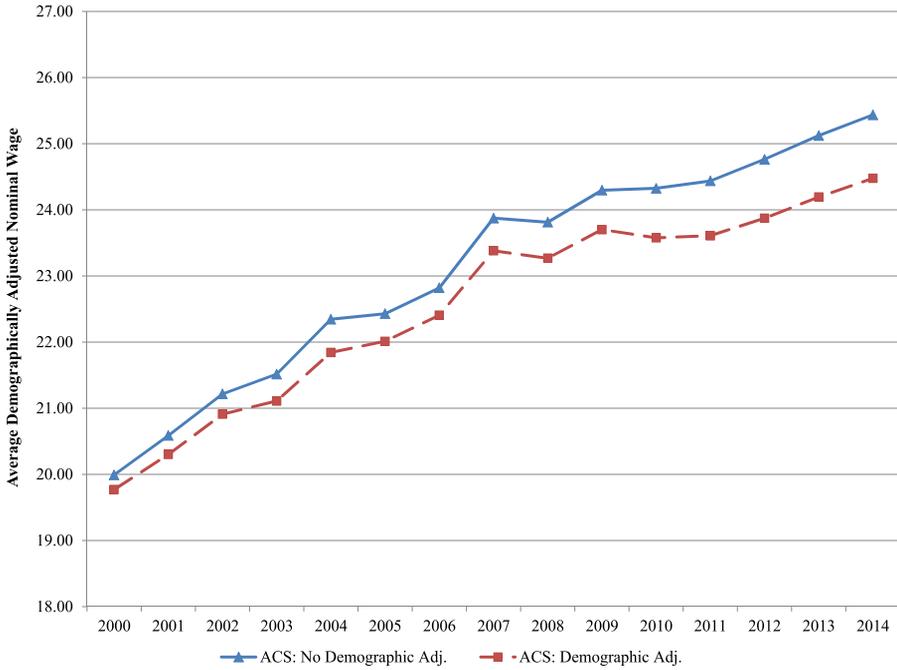


FIGURE A1.—Demographically adjusted versus demographically unadjusted nominal wages, ACS. Notes: Figure compares the demographically adjusted nominal wage series in the ACS used in the paper to the raw ACS nominal wage series. The x -axis refers to the survey year. The y -axis measures the average nominal wage (in wage per hour). The sample restrictions are identical between both series.

We compute the demographically adjusted nominal wage indices using the *CPS* data analogously to the way we computed the demographically 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 differs, 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 time 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 a 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 decomposition 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, we create a wage index between 1975 and 1991 and then a

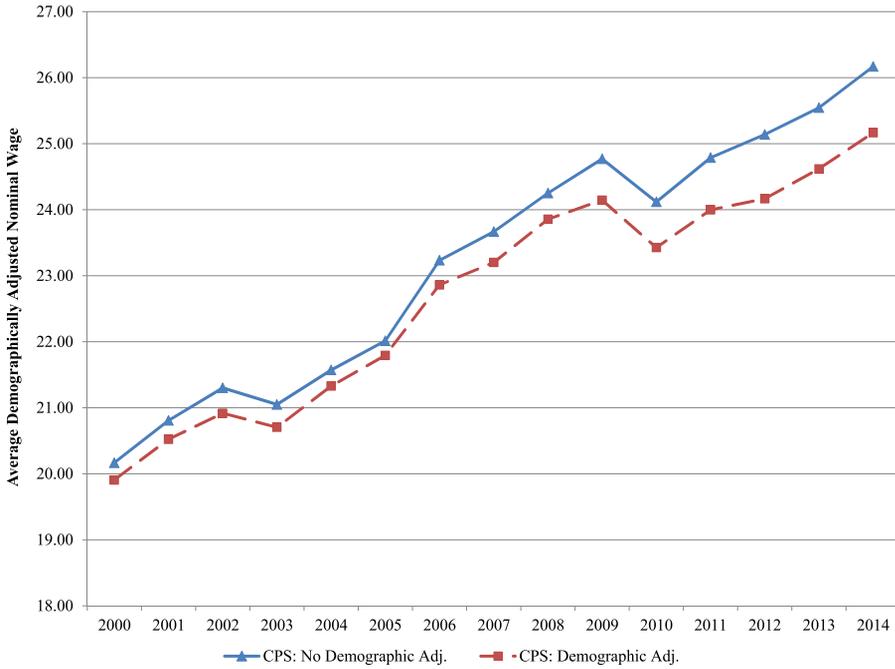


FIGURE A2.—Demographically adjusted versus demographically unadjusted nominal wages, CPS. Note: Figure compares the demographically adjusted nominal wage series in the CPS used in the paper to the raw CPS nominal wage series between 2000 and 2014. The x -axis refers to the survey year. The y -axis measures the average nominal wage (in wage per hour). The sample restrictions are identical between both series.

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.

Supplemental Appendix 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.

A.2. Descriptive Statistics for Retail Scanner Data

Supplemental Appendix Table A1 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—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 are about 1.5 million unique UPC codes

TABLE A1
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	1085	1086	1086	1083	1085	1081	1105	1113	1113	1091		
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	2385	2468	2500	2508	2519	2526	2547	2561	2593	2502		
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	1779.9	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 the underlying data that we used to create our Nielsen Scanner Price Index using the Nielsen Retail Scanner Database.

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 data set 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.²

A.3. Creating the Retail Scanner Price Index

In this subsection, we discuss our procedure for computing the Retail Scanner Price Index.³ Formally, the first step is to produce a category-level price index which can be expressed as follows:

$$P_{j,k,t}^L = P_{j,k,t-1}^L \times \frac{\sum_i p_{i,j,k,t} \bar{q}_{i,j,k,y-1}}{\sum_i p_{i,j,k,t-1} \bar{q}_{i,j,k,y-1}},$$

where $p_{i,j,k,t}$ is the price of good i , in category j , in state k , during month t , and $\bar{q}_{i,j,k,y-1}$ is the average monthly quantity sold of good i in category j during the prior year $y - 1$ in state k . Then, $P_{j,k,t}^L$ is the time-chained Laspeyres index for category j in state k at time t .

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 state, denoted by $P_{j,k,t}^L$. 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 are 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 (Ivancic, Diewert, and Fox (2011)). Notice that this procedure is very similar to the way the BLS builds category-level 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 t may not have a transacted price in month $t + 1$, 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

²To 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.

³There is a large literature discussing the construction of price indices. Melser (2011) and Ivancic, Diewert, and Fox (2011) discussed 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.

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 $\bar{q}_{i,j,k,2007} > 0$ and $q_{i,j,k,t} > 0$ for all $t \in 2008$.⁴ 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.⁵ The bottom row of Supplemental Appendix Table A1 includes the share of all expenditures (value weighted) that were included in our price index for a given year. In the last five 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

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

where $\bar{S}_{j,k,y}$ is the share of expenditure of category j in state k averaged over the year y . 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.

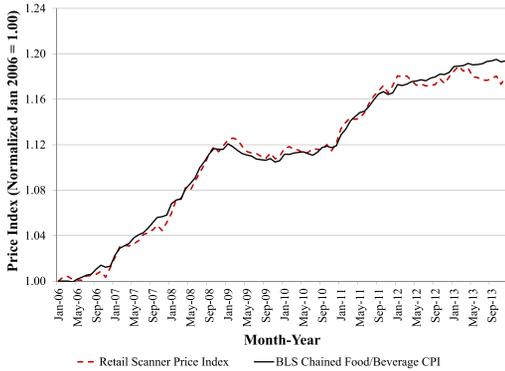
A.4. Benchmarking the Retail Scanner Price Index

As a consistency check, we compare our Retail Scanner Price Index for the aggregate United States 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 Supplemental Appendix Figure A3 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 2013.⁶ The BLS also puts out local price indices for 27 U.S. metro areas. These price indices

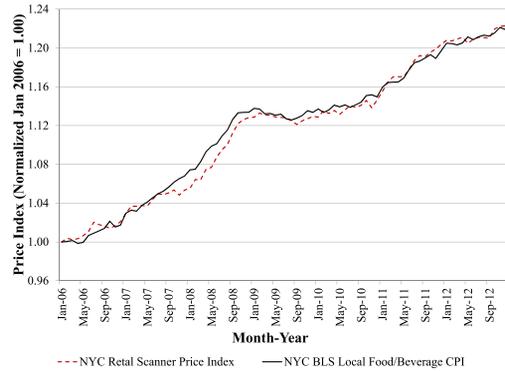
⁴The database starts in 2006. As a result, our baseline specification of the 2006 price indices only includes products that have positive sales in all months of 2006.

⁵This 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 the subsequent calendar year.

⁶There is a slight deviation of the two indices starting in 2013. This results from a seam when the Nielsen data were uploaded to the Kilts Center. When we estimate our cross-state regressions, we will exclude the 2013 data.



PANEL A: ALL U.S.



PANEL B: NYC

FIGURE A3.—Retail Scanner Price Index versus BLS Price Index. Note: In the left panel of this figure, we compare our monthly Retail Scanner Price Index for the United States 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.

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.⁷ 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 Retail Scanner Price Index matches well the BLS price indices for the larger MSAs. The right panel of Supplemental Appendix Figure A3 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 Retail Scanner Price Index at the local level matches well the BLS price indices for similar goods for the larger MSAs.

A.5. A State-Level Composite Price Index from the Retail Scanner Price Index

We use the state-level Retail Scanner 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 Retail Scanner 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.

⁷For example, the BLS noted 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>.

More substantively for us is whether the regional variation in the Retail Scanner 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.⁸ It is these cross-region differences in non-tradable prices that constitute cross-region differences in the evolution of regional prices indices.

In this section of the Supplemental Material, 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.

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

$$P_{t,k}^r = (P_t^T)^{1-\kappa_r} (P_{t,k}^{\text{NT}})^{\kappa_r},$$

where P_t^T is the tradable component of local retail scanner prices in period t (which does not vary across states) and $P_{t,k}^{\text{NT}}$ 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

$$P_{t,k}^{nr} = (P_t^T)^{1-\kappa_{nr}} (P_{t,k}^{\text{NT}})^{\kappa_{nr}},$$

where $P_{t,k}^{nr}$ 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.⁹

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 ($P_{t,k}^r$) and prices in the other sectors ($P_{t,k}^{nr}$):

$$P_{t,k} = (P_{t,k}^{nr})^{1-s} (P_{t,k}^r)^s \equiv (P_t^T)^{1-\bar{\kappa}} (P_{t,k}^{\text{NT}})^{\bar{\kappa}},$$

⁸Burstein, Neves, and Rebelo (2003) documented that such local costs represent more than 40 percent of retail prices in the United States.

⁹The 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 example, 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).

where s is expenditure share of grocery/mass-merchandising goods in an individual's consumption bundle and $\bar{\kappa} \equiv (1 - s)\kappa_{nr} + s\kappa_r$ is the non-tradable share in the aggregate consumption 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, $\Delta \ln P_{t,k,k'}^r$. Formally,

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

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 are invariant to the scaling factor as long as the scaling factor is constant across regions. Creating our 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 throughout the paper 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.¹⁰ 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.

A.6. QEW and OES Wage Patterns

As a separate robustness exercise, we explore the extent to which the patterns we document in Figure 1 of the main text also show up in other wage series. While there are no government data sets that produce broad-based composition-adjusted wage series at

¹⁰Some 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.

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 aggregate time series patterns, nominal weekly earnings in the *QEW* grew by 8.7 percent between 2007 and 2010. Similarly, average nominal hourly wages for the aggregate economy in the *OES* grew by 8.6 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.¹¹ 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*. Supplemental Appendix Figure A4 illustrates the cross-state relationship between nominal weekly earnings growth and employment growth be-

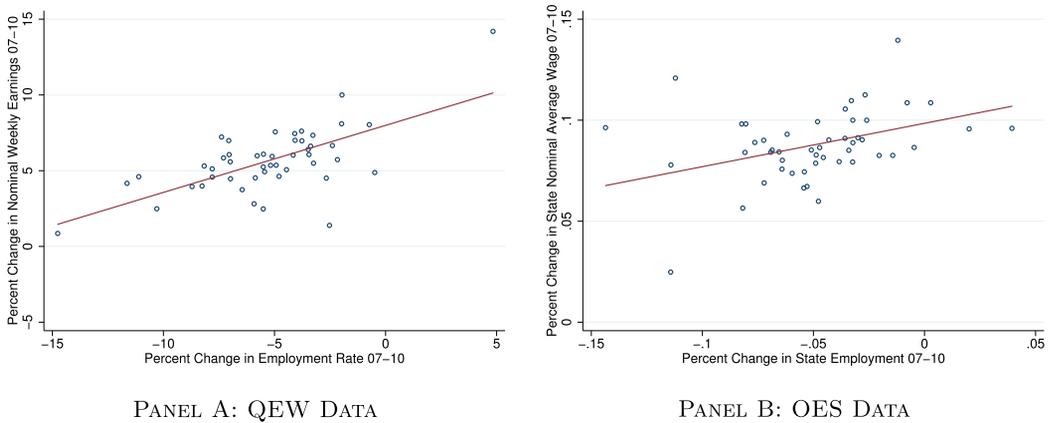


FIGURE A4.—Cross-region variation in nominal earnings/wages during the Great Recession, QEW and OES. Note: Left panel shows the relationship between state nominal weekly earnings growth between 2007 and 2010 and state employment growth between 2007 and 2010 using data from the QEW. The right panel shows 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 left and right panels, respectively, are 0.44 (s.e. = 0.07) and 0.18 (s.e. = 0.07).

¹¹In both the QEW and OES, total employment declined by about 6 percent.

tween 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 declines in nominal earnings or nominal wages as measured in other government data sources. While we are more confident about constructing 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 shows up in other data sources as well.

A.7. *Description of Data for Regional Analysis*

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

Nominal Wages: The measures 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. 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. We discussed the procedure in detail before.

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.

A.8. *Controlling for Industry Mix in Our Estimation of the Regional Wage Phillips Curve*

When estimating 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 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 were 0.38 when we include the state's 2006 manufacturing share as a control and 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.

APPENDIX B: MODEL AND ESTIMATION

We begin this section by stating all equations describing the nonlinear equilibrium in our economy. Then, we derive the log-linearized equations describing the log-linearized equilibrium. Next, we prove 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, and show how some of our main results change for intermediate values of ϑ that put more weight on the aggregate data when estimating the degree of wage stickiness than in our benchmark case.

B.1. Shocks

1. Retail markup shock:

$$\log \lambda_{kt}^p = \rho_p \log \lambda_{kt-1}^p + u_t^p + v_{kt}^p, \quad (\text{A2})$$

$$u_t^p \sim N(0, \sigma_p^2), \quad v_{kt}^p \sim N(0, \tilde{\sigma}_p^2). \quad (\text{A3})$$

2. Neutral technology shock:

$$z_t \equiv \Psi_t / \Psi_{t-1}, \quad (\text{A4})$$

$$\log z_t = (1 - \rho_z) \log \gamma + \rho_z \log z_{t-1} + u_t^z, \quad (\text{A5})$$

$$u_t^z \sim N(0, \sigma_z^2). \quad (\text{A6})$$

3. Tradable technology shock:

$$\log A_{kt}^x = (1 - \rho_x) \log \Psi_t + \rho_x \log A_{kt-1}^x + v_{kt}^x, \quad (\text{A7})$$

$$v_{kt}^x \sim N(0, \tilde{\sigma}_x^2). \quad (\text{A8})$$

4. Retail technology shock:

$$\log A_{kt}^y = (1 - \rho_y) \log \Psi_t + \rho_y \log A_{kt-1}^y + v_{kt}^y, \quad (\text{A9})$$

$$v_{kt}^y \sim N(0, \tilde{\sigma}_y^2). \quad (\text{A10})$$

5. Demand shock:

$$\log b_{kt} = \rho_b \log b_{kt-1} + u_t^b + v_{kt}^b, \quad (\text{A11})$$

$$u_t^b \sim N(0, \sigma_b^2), \quad v_{kt}^b \sim N(0, \tilde{\sigma}_b^2). \quad (\text{A12})$$

6. Marginal efficiency of investment shock:

$$\log \mu_{kt} = \rho_\mu \log \mu_{kt-1} + u_t^\mu + v_{kt}^\mu, \quad (\text{A13})$$

$$u_t^\mu \sim N(0, \sigma_\mu^2), \quad v_{kt}^\mu \sim N(0, \tilde{\sigma}_\mu^2). \quad (\text{A14})$$

7. Labor supply shock:

$$\log \varphi_{kt} = \rho_\varphi \log \varphi_{kt-1} + u_t^\varphi + v_{kt}^\varphi, \quad (\text{A15})$$

$$u_t^\varphi \sim N(0, \sigma_\varphi^2), \quad v_{kt}^\varphi \sim N(0, \tilde{\sigma}_\varphi^2). \quad (\text{A16})$$

8. Government spending shock:

$$\log \epsilon_{kt}^g = \rho_g \log \epsilon_{kt-1}^g + u_t^g + v_{kt}^g, \quad (\text{A17})$$

$$u_t^g \sim N(0, \sigma_g^2), \quad v_{kt}^g \sim N(0, \tilde{\sigma}_g^2). \quad (\text{A18})$$

9. Monetary policy shock:

$$\log \eta_t = \rho_\eta \log \eta_{t-1} + u_t^\eta, \quad (\text{A19})$$

$$u_t^\eta \sim N(0, \sigma_\eta^2). \quad (\text{A20})$$

B.2. De-Trending

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

- Stationary variables:

$$N_{kt}, \quad N_{kt}^x, \quad N_{kt}^y, \quad u_{kt}, \quad q_{kt}, \quad R_t. \quad (\text{A21})$$

- Scaled by technology:

$$\begin{aligned} y_{kt} &= \frac{Y_{kt}}{\Psi_t}, & c_{kt} &= \frac{C_{kt}}{\Psi_t}, & i_{kt} &= \frac{I_{kt}}{\Psi_t}, & k_{kt} &= \frac{K_{kt}}{\Psi_t}, \\ k_{kt}^x &= \frac{K_{kt}^x}{\Psi_t}, & k_{kt}^y &= \frac{K_{kt}^y}{\Psi_t}, & \bar{k}_{kt} &= \frac{\bar{K}_{kt}}{\Psi_t}, & & \\ x_{kt} &= \frac{X_{kt}}{\Psi_t}, & gdp_t &= \frac{GDP_t}{\Psi_t}, & g_{kt} &= \frac{G_{kt}}{\Psi_t}, & a_{kt}^x &= \frac{A_{kt}^x}{\Psi_t}. \end{aligned} \quad (\text{A22})$$

- Scaled by price level:

$$\begin{aligned} p_{kt}^x &= \frac{P_{kt}^x}{P_{kt}}, & r_{kt}^K &= \frac{R_{kt}^K}{P_{kt}}, & mc_{kt} &= \frac{MC_{kt}}{P_{kt}}, & \pi_{kt} &= \frac{P_{kt}}{P_{kt-1}}, \\ \tilde{p}_{kt} &= \frac{\tilde{P}_{kt}}{P_{kt}}, & \tilde{\Gamma}_{kt,t+s}^p &= \Gamma_{kt,t+s}^p \frac{P_{kt}}{P_{kt+s}}. \end{aligned} \quad (\text{A23})$$

- Scaled by technology and price level:

$$\begin{aligned}
 \tau_{kt} &= \frac{T_{kt}}{\Psi_t P_{kt}}, & D_{kt} &= \frac{D_{kt}}{\Psi_t P_{kt}}, & \lambda_{kt} &= \Psi_t P_{kt} \Lambda_{kt}, \\
 \mathcal{B}_{kt} &= \frac{B_{kt}}{\Psi_t P_{kt}}, & w_{kt} &= \frac{W_{kt}}{\Psi_t P_{kt}}, & \pi_{kt}^w &= \frac{W_{kt}}{W_{kt-1}}, \\
 \tilde{w}_{kt} &= \frac{\tilde{W}_{kt}}{W_{kt}}, & \tilde{\Gamma}_{kt,t+s}^w &= \Gamma_{kt,t+s}^w \frac{P_{kt} \Psi_t}{P_{kt+s} A_{t+s}^y}.
 \end{aligned} \tag{A24}$$

B.3. Nonlinear Equilibrium Conditions

- Marginal utility of consumption:

$$\lambda_{kt} = \frac{b_{kt} \phi_{kt}}{c_{kt} - hc_{kt-1}}. \tag{A25}$$

- Euler equation for bonds:

$$\lambda_{kt} = \beta \mathbb{E}_t \left[\frac{\lambda_{kt+1}}{z_{t+1}} \frac{R_t}{\pi_{kt+1}} \right]. \tag{A26}$$

- Capital utilization:

$$r_{kt}^K = a'(u_{kt}) = \zeta u_{kt}^x. \tag{A27}$$

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

$$\lambda_{kt} = \beta \mathbb{E}_t \left\{ \frac{\lambda_{kt+1}}{z_{t+1}} \frac{r_{kt+1}^K u_{kt+1} - a(u_{kt+1}) + (1 - \delta) q_{kt+1}}{q_{kt}} \right\}. \tag{A28}$$

- Investment:

$$\begin{aligned}
 \lambda_{kt} &= q_{kt} \lambda_{kt} \mu_{kt} \left[1 - S \left(\frac{i_{kt} z_t}{i_{t-1}} \right) - \frac{i_{kt} z_t}{i_{kt-1}} S' \left(\frac{i_{kt} z_t}{i_{t-1}} \right) \right] \\
 &+ \beta \mathbb{E}_t \left[\frac{\lambda_{kt+1}}{z_{t+1}} q_{kt+1} \mu_{kt+1} \left(\frac{i_{kt+1} z_{t+1}}{i_{kt}} \right)^2 S' \left(\frac{i_{kt+1} z_{t+1}}{i_{kt}} \right) \right].
 \end{aligned} \tag{A29}$$

- Wage setting:

$$\mathbb{E}_t \sum_{s=0}^{\infty} (\beta \xi_w)^s N_{kt+s}(j) [b_{kt+s} \phi_{kt+s} \varphi_{kt+s} N_{kt+s}(j)^\nu \lambda_w - \lambda_{kt+s} \tilde{\Gamma}_{kt,t+s}^w w_{kt} \tilde{w}_{kt}(j)] = 0. \tag{A30}$$

- Wage law of motion:

$$1 = (1 - \xi_w) \tilde{w}_{kt}^{\frac{1}{1-\lambda_w}} + \xi_w (\tilde{\Gamma}_{kt-1,t}^w)^{\frac{1}{1-\lambda_w}}. \tag{A31}$$

- Wage inflation:

$$\pi_{kt}^w = \frac{w_{kt} z_t \pi_{kt}}{w_{kt-1}}. \tag{A32}$$

- Price setting:

$$\mathbb{E}_t \sum_{s=0}^{\infty} (\beta \xi_p)^s \lambda_{kt+s} y_{kt+s}(i) [\tilde{p}_{kt}(i) - \lambda_{kt+s}^p mc_{kt+s}] = 0. \quad (\text{A33})$$

- Price law of motion:

$$1 = (1 - \xi_p) \tilde{p}_{kt}^{\frac{1}{1-\lambda^p}} + \xi_p (\tilde{\Gamma}_{t-1,t}^p)^{\frac{1}{1-\lambda^p}}. \quad (\text{A34})$$

- Cost minimization:

$$\frac{k_{kt}(i)}{N_{kt}^y(i)} = \frac{\alpha_1}{1 - \alpha_1 - \alpha_2} \frac{w_{kt}}{r_{kt}^K}, \quad (\text{A35})$$

$$\frac{k_{kt}(i)}{x_{kt}(i)} = \frac{\alpha_1}{\alpha_2} \frac{p_{kt}^x}{r_{kt}^K}. \quad (\text{A36})$$

- Marginal cost:

$$mc_{kt} = \left(\frac{r_{kt}^K}{\alpha_1} \right)^{\alpha_1} \left(\frac{p_{kt}^x}{\alpha_2} \right)^{\alpha_2} \left(\frac{w_{kt}}{1 - \alpha_1 - \alpha_2} \right)^{1 - \alpha_1 - \alpha_2}. \quad (\text{A37})$$

- Tradable production:

$$w_{kt} = (1 - \alpha_x) p_{kt}^x (a_{kt}^x)^{1 - \alpha_x} (k_{kt}^x)^{\alpha_x} (N_{kt}^x)^{-\alpha_x}, \quad (\text{A38})$$

$$R_{kt}^K = \alpha_x p_{kt}^x (a_{kt}^x)^{1 - \alpha_x} (k_{kt}^x)^{\alpha_x - 1} (N_{kt}^x)^{1 - \alpha_x}. \quad (\text{A39})$$

- Effective capital:

$$k_{kt} = \frac{u_{kt} \bar{k}_{kt-1}}{z_t}. \quad (\text{A40})$$

- Physical capital law of motion:

$$\bar{k}_{kt} = \frac{(1 - \delta) \bar{k}_{kt-1}}{z_t} + \mu_{kt} \left[1 - S \left(\frac{i_{kt} z_t}{i_{kt-1}} \right) \right] i_{kt}. \quad (\text{A41})$$

- Production function (ignoring price and wage dispersion):

$$y_{kt} = (k_{kt}^y)^{\alpha_1} x_{kt}^{\alpha_2} (N_{kt}^y)^{1 - \alpha_1 - \alpha_2} - F. \quad (\text{A42})$$

- Taylor rule:

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R} \right)^{\rho_R} \left[\left(\frac{\pi_t}{\pi} \right)^{\phi_\pi} \left(\frac{gdp_t / gdp_{t-1} z_t}{\gamma} \right)^{\phi_Y} \right]^{1 - \rho_R} \eta_t. \quad (\text{A43})$$

- Government spending:

$$g_{kt} = \left(1 - \frac{1}{\epsilon_{kt}^g} \right) y_{kt}. \quad (\text{A44})$$

- GDP identity:

$$gdp_t = c_t + i_t + g_t. \quad (\text{A45})$$

- Goods market clearing:

$$y_{kt} = c_{kt} + i_{kt} + g_{kt} + \frac{a(u_{kt})\bar{k}_{kt-1}}{z_t}. \quad (\text{A46})$$

- Labor market clearing:

$$N_{kt} = N_{kt}^x + N_{kt}^y. \quad (\text{A47})$$

- Capital market clearing:

$$k_{kt} = k_{kt}^x + k_{kt}^y. \quad (\text{A48})$$

- Tradable goods market clearing:

$$\sum_k x_{kt} = \sum_k (k_{kt}^x)^{\alpha_x} (a_{kt}^x N_{kt}^x)^{1-\alpha_x}. \quad (\text{A49})$$

- Island resource constraint (balance of payments):

$$\mathcal{B}_{kt} - \frac{R_{t-1}}{\pi_{kt} z_t} \mathcal{B}_{kt-1} = p_{kt}^x [(k_{kt}^x)^{\alpha_x} (a_{kt}^x N_{kt}^x)^{1-\alpha_x} - x_{kt}] + \tau_{kt} + g_{kt}. \quad (\text{A50})$$

- Budget constraint of federal government:

$$\mathcal{D}_{kt} - \frac{R_{t-1}}{\pi_{kt} z_t} \mathcal{D}_{t-1} = \sum_k [g_{kt} + \tau_{kt}]. \quad (\text{A51})$$

B.4. Log-Linearized Equilibrium Conditions

Lowercase variables with “ $\hat{\cdot}$ ” denote log-deviations from the balanced-growth path.

- Marginal utility of consumption:

$$\hat{\lambda}_{kt} = \hat{b}_{kt} + \hat{\phi}_{kt} + \frac{h}{1-h} \hat{c}_{kt-1} - \frac{1}{1-h} \hat{c}_{kt}, \quad (\text{A52})$$

where the endogenous component of the discount factor follows:

$$\hat{\phi}_{kt+1} = \hat{\phi}_{kt} + \phi_0 \left(\hat{\mathcal{B}}_{kt-1} - \sum_k \hat{\mathcal{B}}_{kt-1} \right).$$

- Euler equation for bonds:

$$\hat{\lambda}_{kt} = \hat{R}_t + \mathbb{E}_t [\hat{\lambda}_{kt+1} - \hat{z}_{t+1} - \hat{\pi}_{kt+1}]. \quad (\text{A53})$$

- Capital utilization:

$$\hat{r}_{kt}^K = \chi \hat{u}_{kt}. \quad (\text{A54})$$

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

$$\hat{q}_{kt} = \frac{\beta(1-\delta)}{\gamma} \mathbb{E}_t[\hat{q}_{kt+1}] + \left(1 - \frac{\beta(1-\delta)}{\gamma}\right) \mathbb{E}_t[\hat{r}_{kt+1}^k] - \mathbb{E}_t[\hat{R}_t - \hat{\pi}_{kt+1}]. \quad (\text{A55})$$

- Investment:

$$0 = \hat{q}_{kt} + \hat{\mu}_{kt} - \gamma^2 S''[\hat{i}_{kt} - \hat{i}_{kt-1} + \hat{z}_t] + \beta \gamma^2 S'' \mathbb{E}_t[\hat{i}_{kt+1} - \hat{i}_{kt} + \hat{z}_{t+1}]. \quad (\text{A56})$$

- New Keynesian Wage Phillips Curve (NKWPC):

$$\hat{w}_{kt} = \frac{\beta}{\kappa_w} \mathbb{E}_t[\hat{\pi}_{kt+1}^w - \iota_w \hat{\pi}_{kt}] - \frac{1}{\kappa_w} (\hat{\pi}_{kt}^w - \iota_w \hat{\pi}_{kt-1}) + \frac{1}{1-h} (\hat{c}_{kt} - h \hat{c}_{kt-1}) + \nu \hat{n}_{kt} + \hat{\varphi}_{kt}, \quad (\text{A57})$$

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:

$$\hat{\pi}_{kt}^w = \hat{w}_{kt} + \hat{z}_t + \hat{\pi}_{kt} - \hat{w}_{kt-1}. \quad (\text{A58})$$

- Price setting:

$$\hat{\pi}_{kt} - \iota_p \hat{\pi}_{kt-1} = \beta \mathbb{E}_t[\hat{\pi}_{kt+1} - \iota_p \hat{\pi}_{kt}] + \kappa_p (\widehat{mc}_{kt} + \hat{\lambda}_{kt}^p), \quad (\text{A59})$$

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

- Cost minimization:

$$\hat{k}_{kt}^y - \hat{N}_{kt}^y = \hat{w}_{kt} - \hat{r}_{kt}^K, \quad (\text{A60})$$

$$\hat{k}_{kt}^y - \hat{x}_{kt} = \hat{p}_{kt}^x - \hat{r}_{kt}^K. \quad (\text{A61})$$

- Marginal cost:

$$\widehat{mc}_{kt} = \alpha_1 \hat{r}_{kt}^K + \alpha_2 \hat{p}_{kt}^x + (1 - \alpha_1 - \alpha_2) \hat{w}_{kt}. \quad (\text{A62})$$

- Tradable production:

$$\hat{w}_{kt} = \hat{p}_{kt}^x + (1 - \alpha_x) \hat{a}_{kt}^x + \alpha_x [\hat{k}_{kt}^x - \hat{n}_{kt}^x], \quad (\text{A63})$$

$$\hat{r}_{kt}^K = \hat{p}_{kt}^x + (1 - \alpha_x) \hat{a}_{kt}^x + (1 - \alpha_x) [\hat{n}_{kt}^x - \hat{k}_{kt}^x]. \quad (\text{A64})$$

- Effective capital:

$$\hat{k}_{kt} = \hat{u}_{kt} + \hat{k}_{kt-1} - \hat{z}_t. \quad (\text{A65})$$

- Physical capital law of motion:

$$\hat{k}_{kt} = \frac{1-\delta}{\gamma} [\hat{k}_{kt-1} - \hat{z}_t] + \left(1 - \frac{1-\delta}{\gamma}\right) [\hat{\mu}_{kt} + \hat{i}_{kt}]. \quad (\text{A66})$$

- Production function:

$$\hat{y}_{kt} = \frac{y+F}{y} [\alpha_1 \hat{k}_{kt}^y + \alpha_2 \hat{x}_{kt} + (1 - \alpha_1 - \alpha_2) \hat{n}_{kt}^y]. \quad (\text{A67})$$

- Taylor rule:

$$\hat{R}_t = \rho_R \hat{R}_{t-1} + (1 - \rho_R) [\phi_\pi \hat{\pi}_t + \phi_Y (\widehat{gdp}_t - \widehat{gdp}_{t-1} + \hat{z}_t)] + \hat{\eta}_t. \quad (\text{A68})$$

- Government spending:

$$\hat{g}_{kt} = \hat{y}_{kt} + \frac{1-g}{g} \hat{\epsilon}_{kt}^g. \quad (\text{A69})$$

- GDP identity:

$$\widehat{gdp}_t = \hat{y}_t - \frac{r^k k}{y} \hat{u}_t. \quad (\text{A70})$$

- Goods market clearing:

$$\hat{y}_{kt} = \frac{c}{y} \hat{c}_{kt} + \frac{i}{y} \hat{i}_{kt} + \frac{g}{y} \hat{g}_{kt} + \frac{r^k k}{y} \hat{u}_{kt}. \quad (\text{A71})$$

- Labor market clearing:

$$\hat{N}_{kt} = \frac{N^x}{L} \hat{N}_{kt}^x + \frac{N^y}{L} \hat{N}_{kt}^y. \quad (\text{A72})$$

- Capital market clearing:

$$\hat{k}_{kt} = \frac{k^x}{k} \hat{k}_{kt}^x + \frac{k^y}{k} \hat{k}_{kt}^y. \quad (\text{A73})$$

- Tradable goods market clearing:

$$\sum_k \hat{x}_{kt} = \sum_k \alpha_x \hat{k}_{kt}^x + (1 - \alpha_x) [\hat{a}_{kt}^x + \hat{n}_{kt}^x]. \quad (\text{A74})$$

- Island resource constraint (balance of payments):

$$\begin{aligned} & \hat{B}_{kt} - \beta^{-1} [\hat{B}_{kt-1} + \hat{R}_{t-1} - \hat{\pi}_{kt} - \hat{z}_t] \\ &= \frac{p^x (k^x)^{\alpha_x} (N^x)^{1-\alpha_x}}{\mathcal{B}} \{ \alpha_x \hat{k}_{kt}^x + (1 - \alpha_x) [\hat{a}_{kt}^x + \hat{n}_{kt}^x] - \hat{x}_{kt} \} \\ &+ \frac{g}{\mathcal{B}} \hat{g}_{kt} + \frac{\tau}{\mathcal{B}} \hat{\tau}_{kt}. \end{aligned} \quad (\text{A75})$$

- Budget constraint of federal government:

$$\hat{\mathcal{D}}_t - \beta^{-1}[\hat{\mathcal{D}}_{t-1} + \hat{R}_{t-1} - \hat{\pi}_t - \hat{z}_t] = \sum_k \left[\frac{g}{\mathcal{D}} \hat{g}_{kt} + \frac{\tau}{\mathcal{D}} \hat{\tau}_{kt} \right]. \quad (\text{A76})$$

- Price of tradables:

$$\hat{\pi}_t^x = \hat{\pi}_{kt}^x + \hat{p}_{kt}^x - \hat{p}_{kt-1}^x. \quad (\text{A77})$$

B.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 equations characterizing aggregate variables while achieving stationarity 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 (A74) becomes $\hat{x}_t = \alpha_x \hat{k}_t^x + (1 - \alpha_x) \hat{n}_t^x$, and (A63) becomes $\hat{w}_t - \hat{p}_t^x = \alpha_x (\hat{k}_t^x - \hat{N}_t^x)$. Next, subtract (A61) from (A60) 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, (A72) implies that they equal \hat{n}_t .

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

Claim 1 implies that (A60), (A63), (A64) become

$$\hat{k}_t^y - \hat{n}_t = \hat{w}_t - \hat{r}_t^K, \quad (\text{A78})$$

$$\hat{w}_t = \hat{p}_t^x + \alpha_x [k_t^x - \hat{n}_t], \quad (\text{A79})$$

$$\hat{r}_t^K = \hat{p}_t^x + (1 - \alpha_x) [\hat{n}_t - \hat{k}_t^x]. \quad (\text{A80})$$

Subtracting (A80) from (A79) implies that $\hat{w}_t - \hat{r}_t^K = \hat{k}_t^x - \hat{n}_t$. Combine this with (A78) to get $\hat{k}_t^y = \hat{k}_t^x$. The capital market clearing condition (A73) 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 (A79) 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 (A62) proves the claim.

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

Plug the previous results into the production function (A67).

• Claim 5: Assuming that $\phi_{kt+1} = \phi_{kt} e^{\phi_0 \frac{\mathcal{B}_{kt}-1-\mathcal{B}_{t-1}}{\mathcal{B}_{t-1}}}$, the endogenous discount factor cancels from (A52).

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

Combine the island resource constraint (A75) with tradable market clearing (A74), then compare to federal budget constraint (A76).

B.6. Proof of Lemma 2

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

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

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.

B.7. Derivation of Aggregate versus Regional Shock Responses

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

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

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

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

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

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

and regional policy functions:

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

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

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

The expressions for the employment responses and wage response on impact to a discount factor shock follow directly from the policy functions evaluated at $t = 0$ and setting $\hat{w}_{t-1} = \tilde{w}_{t-1} = \tilde{B}_{kt-1} = 0$. The expressions for the wage elasticities follow from dividing the employment and wage responses on impact.

B.8. Bayesian Estimation and Aggregate Data

The model is estimated via full-information Bayesian techniques in the tradition of Linde, Smets, and Wouters (2016), Christiano, Motto, and Rostagno (2014), and Justiniano, Primiceri, and Tambalotti (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 two chains with 120,000 draws, discarding 24,000 of them.

The likelihood is based on seven U.S. 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 are 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

TABLE A2
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	

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.

Supplemental Appendix Table A2 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 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

$$x_{\text{obs}} = 100 \cdot \Delta \log \left(\frac{Y_t}{\text{Pop}_t \cdot P_t} \right) = \hat{x}_t - \hat{x}_{t-1} + \hat{z}_t + 100 \log \gamma, \quad (\text{A81})$$

$$c_{\text{obs}} = 100 \cdot \Delta \log \left(\frac{C_{nd,t} + C_{se,t}}{\text{Pop}_t \cdot P_t} \right) = \hat{c}_t - \hat{c}_{t-1} + \hat{z}_t + 100 \log \gamma, \quad (\text{A82})$$

$$i_{\text{obs}} = 100 \cdot \Delta \log \left(\frac{I_t + C_{du,t}}{\text{Pop}_t \cdot P_t} \right) = \hat{i}_t - \hat{i}_{t-1} + \hat{z}_t + 100 \log \gamma, \quad (\text{A83})$$

$$w_{\text{obs}} = 100 \cdot \Delta \log \left(\frac{W_t}{P_t} \right) = \hat{w}_t - \hat{w}_{t-1} + \hat{z}_t + 100 \log \gamma, \quad (\text{A84})$$

$$N_{\text{obs}} = 100 \cdot \log \left(\frac{H_t}{\text{Pop}_t} \right) = \hat{N}_t + \log N, \quad (\text{A85})$$

$$\pi_{\text{obs}} = 100 \cdot \Delta \log P_t = \hat{\pi}_t + 100 \log \pi, \quad (\text{A86})$$

$$R_{\text{obs}} = R_t = \hat{R}_t + 100 \log R. \quad (\text{A87})$$

Finally, and following [Christiano, Motto, and Rostagno \(2014\)](#), we take the sample mean out of $\{x_{\text{obs}}, c_{\text{obs}}, i_{\text{obs}}, w_{\text{obs}}\}$ to minimize the problem of violating balanced growth at low frequencies. This would be particularly problematic given our goal of interpreting wage

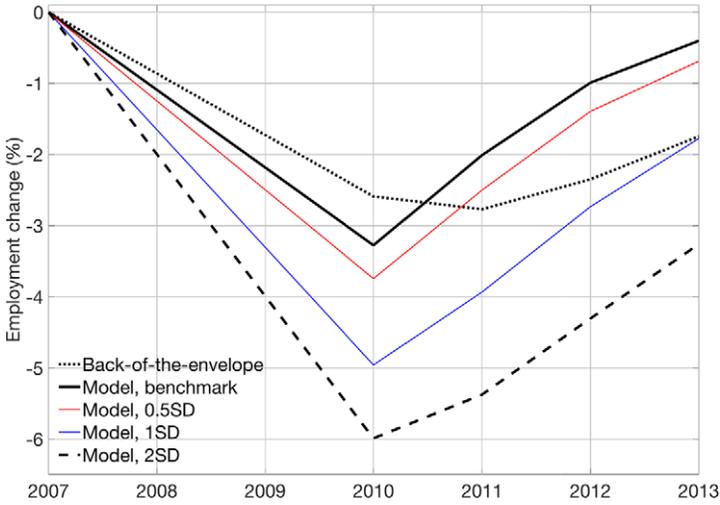


FIGURE A5.—Employment response to 2007–2010 household demand shocks.

and employment movements in the Great Recession, because real wages have been growing much less than consumption, investment, or GDP since the 1990s.

B.9. Sensitivity to Varying ϑ

We re-estimate our model using intermediate values for ϑ in our methodology of Section 5. Then, we reproduce our main results for the Great Recession in Supplemental Appendix Figures A5 and A6.

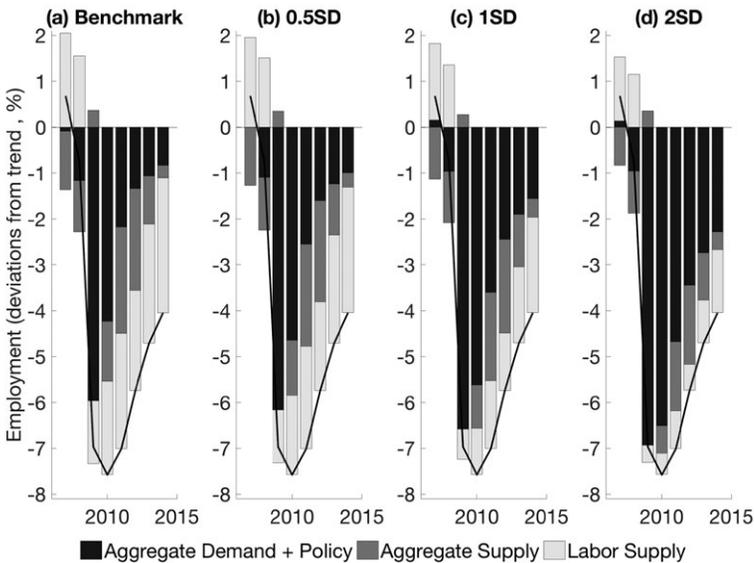


FIGURE A6.—Employment shock decomposition.

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