*Econometrica Supplementary Material*

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

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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:

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

where $\widetilde{\text{Wage}}_{kt}$ is the demographically adjusted nominal wage series for prime-age men in year $t$ of state $k$, $\text{Wage}_{kt}^{g}$ 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 $\tau$. 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 $\text{Wage}_t$ 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.

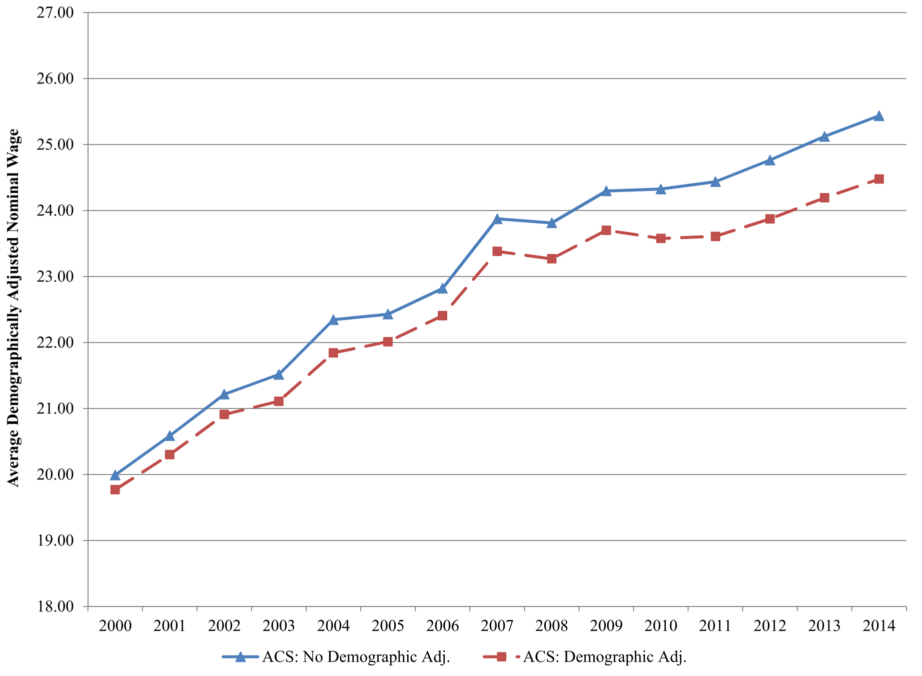



FIGURE A1.—Demographically adjusted versus demographically unadjusted nominal wages, ACS. Notes: Figure compares the demographically adjusted nominal wage series in the ACS used in the paper to the raw ACS nominal wage series. The $x$-axis refers to the survey year. The $y$-axis measures the average 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

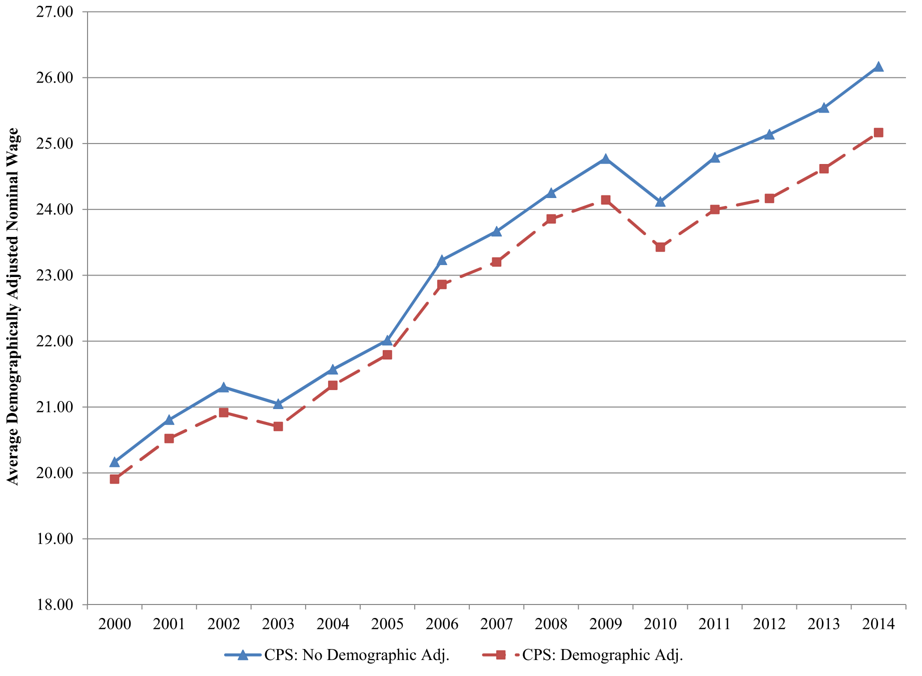



FIGURE A2.—Demographically adjusted versus demographically unadjusted nominal wages, CPS. Note: Figure compares the demographically adjusted nominal wage series in the CPS used in the paper to the raw CPS nominal wage series between 2000 and 2014. The $x$-axis refers to the survey year. The $y$-axis 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 $\text{Wage}_t$ 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:

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

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, $P^L_{j,k,t}$ 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 $P^L_{j,k,t}$. 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

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

[3]There 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

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

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.

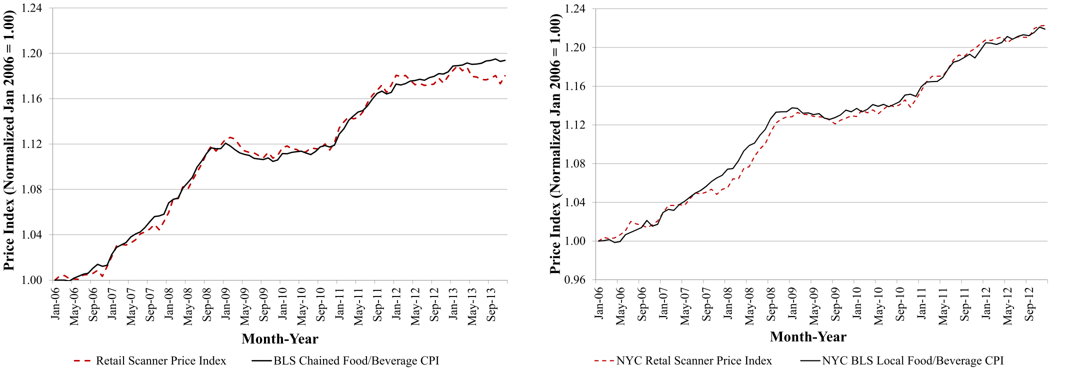
### A.4. *Benchmarking the Retail Scanner Price Index*

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

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

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

[6]There 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.

[7]For 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

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

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

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

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

where $P^{nr}_{t,k}$ is local prices in these sectors outside of the grocery/mass-merchandising sector and $\kappa_{nr}$ 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 ($P^r_{t,k}$) and prices in the other sectors ($P^{nr}_t$):

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

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

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

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, $\Delta \ln P^r_{t,k,k'}$. Formally,

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

If $\frac{\bar{\kappa}}{\kappa_r} > 1$, the local grocery/mass-merchandising sector will use a lower share of non-tradables in production than the composite local consumption good. In order to construct the scaling factor $\frac{\bar{\kappa}}{\kappa_r}$, it would be useful to have local indices for both grocery/mass-merchandising goods and for a composite local consumption good. While knowing the scaling factor is interesting in its own right, the results we present in our paper 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.

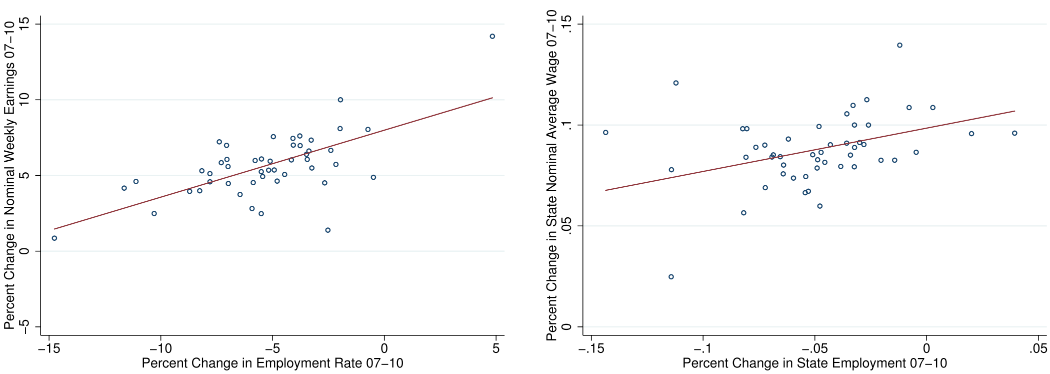
### A.6. *QEW and OES Wage Patterns*

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

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

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-




PANEL A: QEW DATA PANEL B: OES DATA

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).

[11]In 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 $\kappa_w$.

*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 $\kappa_w$ are nearly identical under these two robustness exercises to what we report in our base specification within the text. In particular, our estimates of $\kappa_w$ 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 $\kappa_w$ 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 $\vartheta$ 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:

$$\log \lambda_{kt}^{p} = \rho_p \log \lambda_{kt-1}^{p} + u_t^p + v_{kt}^p, \tag{A2}$$

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

2. Neutral technology shock:

$$z_t \equiv \Psi_t / \Psi_{t-1}, \tag{A4}$$

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

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

3. Tradable technology shock:

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

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

4. Retail technology shock:

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

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

5. Demand shock:

$$\log b_{kt} = \rho_b \log b_{kt-1} + u_t^b + v_{kt}^b, \tag{A11}$$

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

6. Marginal efficiency of investment shock:

$$\log\mu_{kt} = \rho_\mu \log\mu_{kt-1} + u_t^\mu + v_{kt}^\mu, \tag{A13}$$

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

7. Labor supply shock:

$$\log\varphi_{kt} = \rho_\varphi \log\varphi_{kt-1} + u_t^\varphi + v_{kt}^\varphi, \tag{A15}$$

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

8. Government spending shock:

$$\log\epsilon_{kt}^g = \rho_g \log\epsilon_{kt-1}^g + u_t^g + v_{kt}^g, \tag{A17}$$

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

9. Monetary policy shock:

$$\log\eta_t = \rho_\eta \log\eta_{t-1} + u_t^\eta, \tag{A19}$$

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

## B.2. *De-Trending*

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

- Stationary variables:

$$N_{kt}, \qquad N_{kt}^x, \qquad N_{kt}^y, \qquad u_{kt}, \qquad q_{kt}, \qquad R_t. \tag{A21}$$

- Scaled by technology:

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

- Scaled by price level:

$$\begin{aligned} &p_{kt}^x = \frac{P_t^x}{P_{kt}}, \qquad r_{kt}^K = \frac{R_{kt}^K}{P_{kt}}, \qquad mc_{kt} = \frac{\mathrm{MC}_{kt}}{P_{kt}}, \qquad \pi_{kt} = \frac{P_{kt}}{P_{kt-1}}, \\ &\tilde{p}_{kt} = \frac{\tilde{P}_{kt}}{P_{kt}}, \qquad \tilde{\Gamma}_{kt,t+s}^p = \Gamma_{kt,t+s}^p \frac{P_{kt}}{P_{kt+s}}. \end{aligned} \tag{A23}$$

- Scaled by technology and price level:

$$\tau_{kt} = \frac{T_{kt}}{\Psi_t P_{kt}}, \qquad D_{kt} = \frac{D_{kt}}{\Psi_t P_{kt}}, \qquad \lambda_{kt} = \Psi_t P_{kt} \Lambda_{kt},$$
$$\mathcal{B}_{kt} = \frac{B_{kt}}{\Psi_t P_{kt}}, \qquad w_{kt} = \frac{W_{kt}}{\Psi_t P_{kt}}, \qquad \pi^w_{kt} = \frac{W_{kt}}{W_{kt-1}}, \tag{A24}$$
$$\tilde{w}_{kt} = \frac{\tilde{W}_{kt}}{W_{kt}}, \qquad \tilde{\Gamma}^w_{kt,t+s} = \Gamma^w_{kt,t+s} \frac{P_{kt}\Psi_t}{P_{kt+s} A^y_{t+s}}.$$

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:

$$r^K_{kt} = a'(u_{kt}) = \zeta u^{\chi}_{kt}. \tag{A27}$$

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

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

- Investment:

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

- Wage setting:

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

- Wage law of motion:

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

- Wage inflation:

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

- Price setting:

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

- Price law of motion:

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

- Cost minimization:

$$\frac{k_{kt}(i)}{N^y_{kt}(i)} = \frac{\alpha_1}{1 - \alpha_1 - \alpha_2} \frac{w_{kt}}{r^K_{kt}}, \tag{A35}$$

$$\frac{k_{kt}(i)}{x_{kt}(i)} = \frac{\alpha_1}{\alpha_2} \frac{p^x_{kt}}{r^K_{kt}}. \tag{A36}$$

- Marginal cost:

$$mc_{kt} = \left( \frac{r^K_{kt}}{\alpha_1} \right)^{\alpha_1} \left( \frac{p^x_{kt}}{\alpha_2} \right)^{\alpha_2} \left( \frac{w_{kt}}{1 - \alpha_1 - \alpha_2} \right)^{1-\alpha_1-\alpha_2}. \tag{A37}$$

- Tradable production:

$$w_{kt} = (1 - \alpha_x) p^x_{kt} \big( a^x_{kt} \big)^{1-\alpha_x} \big( k^x_{kt} \big)^{\alpha_x} \big( N^x_{kt} \big)^{-\alpha_x}, \tag{A38}$$

$$R^K_{kt} = \alpha_x p^x_{kt} \big( a^x_{kt} \big)^{1-\alpha_x} \big( k^x_{kt} \big)^{\alpha_x - 1} \big( N^x_{kt} \big)^{1-\alpha_x}. \tag{A39}$$

- Effective capital:

$$k_{kt} = \frac{u_{kt} \bar{k}_{kt-1}}{z_t}. \tag{A40}$$

- Physical capital law of motion:

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

- Production function (ignoring price and wage dispersion):

$$y_{kt} = \big( k^y_{kt} \big)^{\alpha_1} x^{\alpha_2}_{kt} \big( N^y_{kt} \big)^{1-\alpha_1-\alpha_2} - F. \tag{A42}$$

- Taylor rule:

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

- Government spending:

$$g_{kt} = \left( 1 - \frac{1}{\epsilon^g_{kt}} \right) y_{kt}. \tag{A44}$$

- GDP identity:

$$gdp_t = c_t + i_t + g_t. \tag{A45}$$

- Goods market clearing:

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

- Labor market clearing:

$$N_{kt} = N^x_{kt} + N^y_{kt}. \tag{A47}$$

- Capital market clearing:

$$k_{kt} = k^x_{kt} + k^y_{kt}. \tag{A48}$$

- Tradable goods market clearing:

$$\sum_k x_{kt} = \sum_k \left(k^x_{kt}\right)^{\alpha_x} \left(a^x_{kt} N^x_{kt}\right)^{1-\alpha_x}. \tag{A49}$$

- Island resource constraint (balance of payments):

$$\mathcal{B}_{kt} - \frac{R_{t-1}}{\pi_{kt} z_t} \mathcal{B}_{kt-1} = p^x_{kt}\left[\left(k^x_{kt}\right)^{\alpha_x} \left(a^x_{kt} N^x_{kt}\right)^{1-\alpha_x} - x_{kt}\right] + \tau_{kt} + g_{kt}. \tag{A50}$$

- Budget constraint of federal government:

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

### B.4. *Log-Linearized Equilibrium Conditions*

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

- Marginal utility of consumption:

$$\hat{\lambda}_{kt} = \hat{b}_{kt} + \hat{\phi}_{kt} + \frac{h}{1-h}\hat{c}_{kt-1} - \frac{1}{1-h}\hat{c}_{kt}, \tag{A52}$$

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:

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

- Capital utilization:

$$\hat{r}^K_{kt} = \chi \hat{u}_{kt}. \tag{A54}$$

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

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

- Investment:

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

- New Keynesian Wage Phillips Curve (NKWPC):

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

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:

$$\hat{\pi}^w_{kt} = \hat{w}_{kt} + \hat{z}_t + \hat{\pi}_{kt} - \hat{w}_{kt-1}. \tag{A58}$$

- Price setting:

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

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

- Cost minimization:

$$\hat{k}^y_{kt} - \hat{N}^y_{kt} = \hat{w}_{kt} - \hat{r}^K_{kt}, \tag{A60}$$

$$\hat{k}^y_{kt} - \hat{x}_{kt} = \hat{p}^x_{kt} - \hat{r}^K_{kt}. \tag{A61}$$

- Marginal cost:

$$\widehat{mc}_{kt} = \alpha_1\hat{r}^K_{kt} + \alpha_2\hat{p}^x_{kt} + (1 - \alpha_1 - \alpha_2)\hat{w}_{kt}. \tag{A62}$$

- Tradable production:

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

$$\hat{r}^K_{kt} = \hat{p}^x_{kt} + (1-\alpha_x)a^x_{kt} + (1-\alpha_x)\left[\hat{n}^x_{kt} - \hat{k}^x_{kt}\right]. \tag{A64}$$

- Effective capital:

$$\hat{k}_{kt} = \hat{u}_{kt} + \hat{\bar{k}}_{kt-1} - \hat{z}_t. \tag{A65}$$

- Physical capital law of motion:

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

- Production function:

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

- Taylor rule:

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

- Government spending:

$$\hat{g}_{kt} = \hat{y}_{kt} + \frac{1-g}{g}\hat{\epsilon}^g_{kt}. \tag{A69}$$

- GDP identity:

$$\widehat{gdp}_t = \hat{y}_t - \frac{r^k k}{y}\hat{u}_t. \tag{A70}$$

- Goods market clearing:

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

- Labor market clearing:

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

- Capital market clearing:

$$\hat{k}_{kt} = \frac{k^x}{k}\hat{k}^x_{kt} + \frac{k^y}{k}\hat{k}^y_{kt}. \tag{A73}$$

- Tradable goods market clearing:

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

- Island resource constraint (balance of payments):

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

- Budget constraint of federal government:

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

- Price of tradables:

$$\hat{\pi}_t^x = \hat{\pi}_{kt} + \hat{p}_{kt}^x - \hat{p}_{kt-1}^x. \tag{A77}$$

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

$$\hat{k}_t^y - \hat{n}_t = \hat{w}_t - \hat{r}_t^K, \tag{A78}$$

$$\hat{w}_t = \hat{p}_t^x + \alpha_x\big[k_t^x - \hat{n}_t\big], \tag{A79}$$

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

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

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

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

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

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

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

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:

$$\tilde{w}_{kt} = a_{wb}\tilde{b}_{kt} + a_{ww}\tilde{w}_{kt-1} + a_{w\tilde{\mathcal{B}}}\tilde{\mathcal{B}}_{kt-1},$$

$$\tilde{n}_{kt} = a_{nb}\tilde{b}_{kt} + \frac{(1-\beta a_{\tilde{\mathcal{B}}\tilde{\mathcal{B}}})}{\frac{\beta p^x x}{\mathcal{B}}}\tilde{\mathcal{B}}_{kt-1},$$

$$\tilde{\mathcal{B}}_{kt} = -\frac{p^x x}{\mathcal{B}} a_{nb}\tilde{b}_{kt} + a_{\tilde{\mathcal{B}}\tilde{\mathcal{B}}}\tilde{\mathcal{B}}_{kt-1},$$

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

$$0 = \beta(a_{ww})^2 - (1+\beta+\kappa_w)a_{ww} + 1,$$

$$0 = (1-\beta a_{\tilde{\mathcal{B}}\tilde{\mathcal{B}}})(1-a_{\tilde{\mathcal{B}}\tilde{\mathcal{B}}}) - \frac{\beta p^x x}{\mathcal{B}}\phi_0,$$

$$a_{nb} = \frac{(1-\rho_b)}{(1-\rho_b) + \frac{1}{\beta} - a_{\tilde{\mathcal{B}}\tilde{\mathcal{B}}}},$$

$$a_{wb} = \frac{\kappa_w(1+\nu)}{1+\kappa_w - \beta(a_{ww}+\rho_b-1)}\frac{1+\kappa_w-\beta a_{ww}}{1+\kappa_w-\beta a_{ww}+\beta(1-a_{\tilde{\mathcal{B}}\tilde{\mathcal{B}}})}a_{nb},$$

$$a_{w\tilde{\mathcal{B}}} = \frac{\kappa_w(1+\nu)}{1-a_{\tilde{\mathcal{B}}\tilde{\mathcal{B}}}+\beta(1-a_{ww})+\kappa_w}\frac{(1-\beta a_{\tilde{\mathcal{B}}\tilde{\mathcal{B}}})}{\frac{\beta p^x x}{\mathcal{B}}}.$$

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

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

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

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

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

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

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

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

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

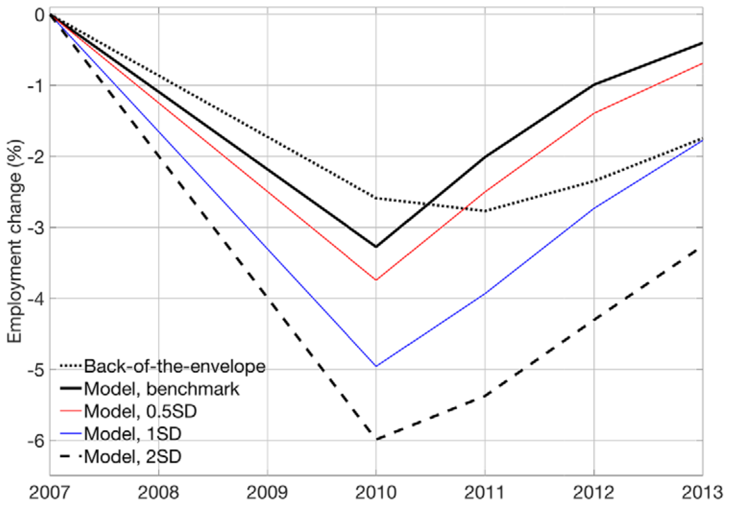



FIGURE A5.—Employment response to 2007–2010 household demand shocks.

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 $\vartheta$*

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

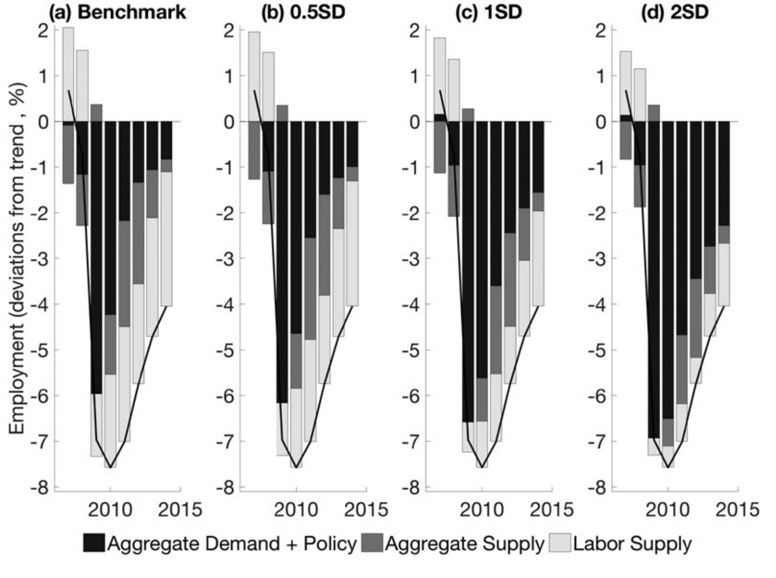



FIGURE A6.—Employment shock decomposition.

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