The Aggregate Implications of Regional Business Cycles*

Martin Beraja  Erik Hurst  Juan Ospina
University of Chicago
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Abstract

We argue that it is difficult to make inferences about the drivers of aggregate business cycles using regional variation alone because (i) the local and aggregate elasticities to the same type of shock are quantitatively different and (ii) purely aggregate shocks are differenced out when using cross-region variation. We highlight the importance of these issues in a monetary union model, and by contrasting the behavior of US aggregate time-series and cross-state patterns during the Great Recession. In particular, using household and retail scanner data for the US, we document a strong relationship across states between local employment growth and local nominal and real wage growth. These relationships are much weaker in US aggregates. In order to identify the shocks driving aggregate (and regional) business cycles we develop a methodology that combines regional and aggregate data. The methodology uses theoretical restrictions implied by a wage setting equation that holds in many monetary union models with nominal wage stickiness. We show how to estimate this equation using cross-state variation—thus linking particular regional patterns to particular aggregate shock decompositions. Applying the methodology to the US, we find that a combination of both "demand" and "supply" shocks are necessary to account for the joint dynamics of aggregate prices, wages and employment during the 2007-2012 period while only "demand" shocks are necessary to explain most of the observed cross-state variation. We conclude that the wage stickiness necessary for demand shocks to be the primary cause of aggregate employment decline during the Great Recession is inconsistent with the flexibility of wages estimated from cross-state variation.

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1 Introduction

A large and growing literature is exploiting regional variation to learn about the determinants of aggregate economic variables. However, we argue that making inferences about the aggregate economy using only regional variation is complicated by two issues. First, we show that, in a monetary union model, local and aggregate elasticities to the same type of shock are quantitatively different both because of factor mobility and general equilibrium forces. This discrepancy makes it problematic to use local shock elasticities estimated from regional data to ascertain the importance of a given aggregate shock. Second, purely aggregate shocks get differenced out when using cross-region variation. As a result, it is not possible to learn anything about these aggregate shocks by exploiting variation across regions. Furthermore, we provide evidence of both these issues by contrasting the behavior of US aggregate time-series and cross-state patterns during the Great Recession. We document a strong relationship across states between local employment growth, and local nominal and real wage growth. These relationships are much weaker in US aggregates. In summary, we cannot expect to understand the joint evolution of aggregate variables by using cross-regional variation alone.

Therefore, we present a methodology that uses regional data along with aggregate data in order to identify aggregate shocks driving business cycles. The methodology exploits theoretical restrictions implied by a wage setting equation that hold in many monetary union models with wage stickiness. In turn, the extent to which aggregate wages are sticky is a key restriction in identifying the type of shocks driving aggregate fluctuations (e.g., "demand" vis a vis "supply" shocks). Under certain conditions, we show how to use cross-region variation in wages, prices, and employment to estimate this wage setting equation—thus parameterizing the theoretical restrictions and linking regional business cycles to shock decompositions of aggregate business cycles.

Using household and retail scanner data for the US, we construct state-level wage and price indices as well as a measure of employment. Given the strong comovement of wages and employment across states, our estimates of the wage setting equation suggest that wages are relatively flexible—thus limiting the contribution of "demand" shocks to aggregate employment decline during the Great Recession. Instead, we find that a combination of "demand" and other shocks are necessary to account for the joint dynamics of aggregate prices, wages and employment during the 2007–2012 period. In particular, the relative stability of aggregate wages in the time-series compared to state-level wages is not caused by wage stickiness, but because different aggregate shocks have relatively offsetting effects on aggregate wages. We conclude that the wage stickiness necessary for demand shocks to be the primary cause of aggregate employment decline during the Great Recession is inconsistent with the flexibility of wages estimated from cross-state variation.

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2 We refer to a "demand" shock as a shock that moves employment and real wages in opposite directions and moves employment and prices in the same direction. In the model of the monetary union we develop below, these shocks can be formalized as shocks to the household’s discount rate or as shocks to the aggregate nominal interest rate rule. Our model also allows for a productivity/markup shock and a shock to household preference for leisure.
The paper is organized as follows. In Sections 2 and 3, we begin by documenting a series of new facts about the variation in nominal and real wages across US states during the Great Recession. Using data from the 2000 US Census and the 2000 - 2012 American Community Surveys (ACS), we construct state-level nominal wage indices during the 2000 to 2012 period. We restrict our sample to full time workers with a strong attachment to the labor force. We adjust our wage measures to cleanse them from observable changes in labor force composition over the business cycle. In order to construct a measure of real wages we deflate our nominal wage indices with state-level price indices created using data from Nielsen’s Retail Scanner Database. The Retail Scanner Database includes weekly prices and quantities for given UPC codes at over 40,000 stores from 2006 through 2012. While the price indices we create from this data are based mostly on consumer packaged goods, we show how under certain assumptions the indices can be scaled to be representative of a composite local consumption good. Furthermore, we show that an aggregate price index created with the retail scanner data matches the BLS’s Food CPI nearly identically.

Using our indices, we show that states that experienced larger employment declines between 2007 and 2010 had significantly lower nominal and real wage growth during the same time period. These cross-state patterns stand in sharp contrast with the well documented aggregate time-series trends for prices and wages during the same time period. As both aggregate output and employment contracted sharply in the US during the 2007-2012 period, aggregate nominal wage growth remained robust and real wage growth did not break trend. In sum, while aggregate wages appear to be sticky during the Great Recession, state-level wages do not.

In Section 4, we present a monetary union model that we use for two purposes. First, a calibrated version of the model allows us to sign the elasticities to a given shock and quantify the differences between aggregate and local elasticities. Second, the model makes explicit assumptions that are sufficient to estimate the parameters in an aggregate wage setting equation using cross-state variation in employment, wages and prices. As we highlight below, these parameters help us identify the underlying aggregate drivers of the joint dynamics of employment, wages and prices.

The model has many islands linked by trade in intermediate goods which are used in the production of a non-tradable final consumption good. The only asset is the economy is a one-period, non-state contingent nominal bond. The nominal interest rate on this asset follows a rule that endogenously responds to aggregate variables and is set at the union level. Labor is the only other input in production, which is not mobile across islands. We assume that nominal wages are only partially flexible. This is the only nominal rigidity in the model. Finally, the model includes multiple shocks: a shock to the household’s discount rate, shocks to non-tradable and tradable productivity markup, a shock to the household’s preference for leisure, and a monetary policy shock. Aside from the monetary policy shock, all shocks have both local and aggregate components. By definition the weighted average of the local shocks sum to zero. We show that, under relatively few assumptions, the log-linearized economy aggregates. This allows us to study the aggregate and log-

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3The robust growth in nominal wages during the recession is viewed as a puzzle for those that believe that the lack of aggregate demand was the primary cause of the Great Recession. For example, this point was made by Krugman in a recent New York Times article ("Wages, Yellen and Intellectual Honesty", NYTimes 8/25/14).
cal behavior separately, a property that we will exploit when estimating the aggregate and regional shocks through our methodology.

Using a calibrated version of the model, we show that local employment elasticities to a local discount rate shock are two to three times larger than the aggregate employment elasticity to a similarly sized aggregate discount rate shock. This implies that elasticities often estimated for "demand" shocks (i.e., our discount rate shock) using cross-region variation are likely to dramatically overstate the elasticities of aggregate variables to "demand" shocks in the aggregate. The key general equilibrium forces in the model that may dampen aggregate elasticities are the endogenous response of nominal interest rates to aggregate variables and trade in the intermediate input. We show that local and aggregate elasticities get much closer together when the interest rate does not endogenously respond to changes in aggregate prices or employment (as when the economy is close to the zero lower bound).4

In Section 5 we turn to estimation of aggregate shocks. We present a procedure that allow us estimate the shocks in a larger class of monetary union models than the benchmark model outlined above, thus imposing less a-priori structure and making the analysis more persuasive. In particular, we consider models where the aggregate and local equilibria can be represented as a structural vector autoregression (SVAR) in price inflation, nominal wage inflation, and employment with three shocks. We refer to the three shocks as the discount rate shock (which is a combination of the discount rate and monetary policy shock), the productivity/markup shock (which is a combination of the productivity/markup shocks in the tradable and non tradable sectors) and the leisure shock (which is the shock to leisure preference). In order to identify the aggregate shocks, we estimate a SVAR and impose certain properties of our benchmark monetary union model. Our results will be consistent with monetary union models that satisfy all of these. First, we use the aggregate wage setting equation to derive a series of linear restrictions linking the reduced form errors to the underlying structural shocks. Second, we use the sign of the joint-response of employment, wages and prices (on impact) to a discount rate and a productivity/markup shock.5 These two, together with the usual shock-orthogonality conditions, are sufficient to identify the structural shocks.

The methodology requires parameterizing the structural wage setting equation. We use state-level data on prices, wages and employment during the 2006-2012 period to estimate the two parameters in our base specification, i.e., the Frisch elasticity of labor supply and the degree of wage stickiness. Across a variety of specifications and identification procedures, including instrumenting for local labor demand shocks, we estimate only a modest degree of wage stickiness. These estimates are much smaller than estimates of wage stickiness obtained using only aggregate time-series data.

4A similar point is made in Nakamura and Steinsson(2014) with respect to local estimates of fiscal multipliers.

5We view this methodology as an additional contribution of our paper. Beraja (2015) presents an extension of this scheme to a more general class of models. These are part of a growing literature developing “hybrid” methods that, for instance, constructs optimal combinations of econometric and theoretical models (Carriero and Giacomini (2011), Del Negro and Schorfheide (2004)) or uses the theoretical model to inform the econometric model’s parameter (An and Schorfheide (2007), Schorfheide(2000)). Our procedure is closest in spirit to the procedure recently developed in Baumeister and Hamilton (2015).
With the parameterized aggregate wage setting equation, we use the SVAR identification procedure described above to estimate the shocks driving aggregate employment, prices, and wages during the Great Recession. Our results suggest that during the early part of the recession (2008-2009) roughly 30 percent of the aggregate employment decline can be attributed to the discount rate shock (i.e., the "demand" shock). The leisure shock explains roughly 30 percent of the decline in aggregate employment while the productivity/markup shock explains the remaining 40 percent. Over a longer period (2008-2012), however, the discount rate shock cannot explain any of the persistence in employment decline. Instead, it is the productivity/markup and labor supply shocks that explain why employment remained low from 2010-2012. In sum, while "demand" shocks may have been important in the early part of the recession, they cannot explain the persistently low levels of employment in the US after 2009. Furthermore, we find that the aggregate leisure shock - not sticky wages - explains why aggregate wages did not fall during the Great Recession.

Our paper contributes to many 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 and 2014), Mian, Rao, and Sufi (2013) and Midrigan and Philippon (2011) have exploited regional variation within the US to explore the extent to which household leverage has contributed to the Great Recession. Nakamura and Steinsson (2014) use sub-national US variation to inform the size of local government spending multipliers. Blanchard and Katz (1991), Autor et al. (2013), and Charles et al. (2015) use regional variation to measure the responsiveness of labor markets to labor demand shocks. Our work contributes to this literature on two fronts. First, we show that local wages also respond to local changes in economic conditions at business cycle frequencies. Second, we provide a procedure where local variation can be combined with aggregate data to learn about the nature and importance of certain mechanisms for aggregate fluctuations. With respect to the latter innovation, our paper is similar in spirit to Nakamura and Steinsson (2014).

Second, our paper contributes to the recent literature trying to determine the causes of the Great Recession. In many respects, our model is more stylized than others in this literature in that we include a broad set of shocks without trying to uncover the underlying micro-foundations for these shocks. However, the shocks we chose to focus on were designed to proxy for many of the popular theories about the drivers of the Great Recession. For example, our discount rate shock can be thought of as reduced form representation of tightening of household borrowing limits. For example, such shocks have been proposed by Eggertsson and Krugman (2012), Guerrieri and Lorenzoni (2011) and Mian and Sufi (2014) as an explanation of the 2008 recession. Likewise, our

discussion and identification are different from ours, they also conclude that something akin to a supply shock is needed to explain the joint aggregate dynamics of prices and employment during the Great Recession. Likewise, Vavra (2014) and Berger and Vavra (2015) document that prices were very flexible during the Great Recession. They also conclude that something more than a demand shock is needed to explain aggregate employment dynamics given the missing aggregate disinflation.

There has been an explosion of papers using regional data to better understand aggregate dynamics during the Great Recession. Some recent papers include: Giroud and Mueller (2015), Hagedorn et al. (2015), Mehrotra and Sergeyev (2015), and Mondragon (2015).
productivity/markup shock can be interpreted as anything that changes firms’ demand for labor.
In a reduced form sense, credit supply shocks to firms, such as those proposed by Gilchrist et al (2014), would be similar to our productivity/markup shock. Finally, our leisure shock can be seen as a proxy for increased distortions in the labor market due to changes in government policy (e.g., Mulligan (2012) or as a reduced form representation of a skill mismatch story within the labor market (e.g., Charles et al. (2013, 2015)).

2 Creating State-Level Price And Wage Indices

2.1 State-Level Wage Index

To construct nominal wage indices at the state level, we use data from the 2000 Census and the 2001-2012 American Community Surveys (ACS). The 2000 Census includes 5 percent of the US population while the 2001-2012 ACS’s includes around 600,000 respondents per year between 2001 and 2004 and around 2 million respondents per year between 2005 and 2012. 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 with a strong attachment to the labor force. In particular, we restrict our sample to only males between the ages of 21 and 55, who were employed at the time of the Census, who reported usually working at least 30 hours per week, and who worked at least 48 weeks during the prior 12 months. 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 prior 12 months.

Despite our restriction to prime-age males with a strong attachment to the labor force, the composition of workers on other dimensions may still differ across states and within a state over time. The changing composition of workers could be explaining some of the variation in nominal wages across states over time. To cleanse our wage indices from these compositional issues, we create a composition adjusted wage measure (at least based on observables) by running the following regression on the ACS data:

\[ \ln(w_{ikt}) = \gamma_t + \Gamma_t X_{it} + \eta_{itk} \]

where \( \ln(w_{ikt}) \) is log nominal wages for household \( i \) in period \( t \) residing in state \( k \) and \( X_{it} \) is a vector of household specific controls. The vector of controls include a series of dummy variables for usual hours worked (with "40-49 hours per week" being the omitted group), a series of five year age dummies (with "40-44" being the omitted group), four educational attainment dummies (with "some college" being the omitted group), three citizenship dummies (with "native born" being the omitted group), and a series of race dummies (with "white" being the omitted group). We run these regressions separately for each year so that both the constant, \( \gamma_t \), and the vector of coefficients on

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Total labor income during the prior 12 months is the sum of both wage and salary earnings and business earnings. Total hours worked during the previous 12 month is the product of total weeks worked during the prior 12 months and the respondents report of their usual hours worked per week.
the controls, $\Gamma_t$, can differ for each year. Then, we take the residuals from these regressions, $\eta_{itk}$, and add back the constant, $\gamma_t$. Adding back the constant from the regression preserves differences over time in average log-wages. To compute average wages in a state holding composition fixed, we average $e^{\eta_{itk} + \gamma_t}$ across all individuals in state $k$. We refer to this measure as the "adjusted nominal wage index" in time $t$ in state $k$. This is the series we use to exploit cross-state variation in wages during the Great Recession.

The benefit of the Census/ACS data is that it is large enough to compute detailed labor market statistics at state levels. However, one drawback of the Census/ACS data is that it is not available at an annual frequency prior to 2000. To complement our analysis, we use data from the March Supplement of the Current Population Survey (CPS) to examine longer run aggregate trends in both nominal and real wages. These longer run trends are an input into our aggregate shock decomposition procedure discussed below. We compute the wage indices using the CPS data analogously to the way we computed the wage indices within the Census/ACS data. 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 2000-2012 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 series have a correlation of 0.99 during this time period.

2.2 State-Level Price Index

2.2.1 Price Data

State-level price indices are necessary to measure state-level real wages. In order to construct state-level price indices we use the Retail Scanner Database collected by AC Nielsen and made available at The University of Chicago Booth School of Business. The Retail Scanner data consists of weekly pricing, volume, and store environment information generated by point-of-sale systems for about 90 participating retail chains across all US markets between January 2006 and December 2012. 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

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9In particular, we compute hourly wages for men 21-55 with a strong attachment to the labor force (those currently working at least 30 hours a week and those who worked at least 48 weeks during the prior year). Again, like for the ACS data, we adjust the wages to account for a changing vector of observables over time. A full discussion of our methodology to compute composition adjusted wages in the CPS can be found in the Online Appendix that accompanies the paper.

10The data is made available through the Marketing Data Center at the University of Chicago Booth School of Business. Information on availability and access to the data can be found at http://research.chicagobooth.edu/nielsen/. Contemporaneously, Coibion et al. (2015), Kaplan and Menzio (2015) and Stroebel and Vavra (2014) also use local scanner data/household price data to estimate that local prices vary with local economic conditions at business cycle frequencies. Our paper complements this literature by actually making price indices using the Nielsen scanner data for each state at the monthly frequency and using those price indices to estimate structural parameters of the local wage setting equation.
transactions, at a given store during a given week. The database only includes items with strictly positive sales in a store-week and excludes certain products such as random-weight meat, fruits, and vegetables since they do not have a UPC assigned. Nielsen sorts the different UPCs into over one thousand narrowly defined "categories". For example, sugar can be of 5 categories: sugar granulated, sugar powdered, sugar remaining, sugar brown, and sugar substitutes. We use these categories when defining our price indices.

Finally, the geographic coverage of the database is outstanding and is one of its most attractive features. It includes stores from all states except for Alaska and Hawaii. Likewise, it covers stores from 361 Metropolitan Statistical Areas (MSA) and 2,500 counties. The data comes with both zip code and FIPS codes for the store’s county, MSA, and state. Over the seven year period, the data set includes total sales across all retail establishments worth over $1.5 trillion. In this paper, we aggregate data to the level of US states and compute state-level retail scanner data price indices. Online Appendix Table R1 shows summary statistics for the retail scanner data for each year between 2006 and 2012 and for the sample as a whole.11

2.2.2 A Retail Scanner Data Price Index

In order to construct state-level price indices we follow the BLS construction of the CPI as closely as possible.12 While we briefly outline the price index construction in this sub-section, the full details of the procedure are discussed in the Online Appendix that accompanies our paper. Our retail scanner price indices are built in two stages. In the first stage, we aggregate the prices of goods within the roughly 1,000 categories described above. For our base indices, a good is a given store-UPC pair such that a UPC in store A is treated as a different good than the same UPC sold in store B. This allows for the possibility that prices may change as households substitute from a high cost store (that provides a different shopping experience) to a low cost store when local economic conditions deteriorate. Then, we compute, for each good, the average price and total quantity sold in a given month and state. Next, we construct the quantity weighted average price for all goods in each detailed category in a given month and state. We aggregate our index to the monthly level to reduce the number of missing values.13

Specifically, for each category, we compute:

\[^{11}\text{The Online Appendix is available at http://faculty.chicagobooth.edu/erik.hurst/research/regional_online_appendix.pdf}\]
\[^{12}\text{There is a large literature discussing the construction of price indices. See, for example, Diewert (1976). Cage et al (2003) discuss the reasons behind the introduction of the BLS’s Chained Consumer Price Index. Melser (2011) discuss problems that arise with the construction of price indices with scanner data. In particular, if the quantity weights are updated too frequently the price index will exhibit ‘chain drift’. This concern motivated us to follow the BLS procedure and keep the quantity weights fixed for a year when computing the first stage of our indices rather than updating the quantities every month. Such problems are further discussed in Dielwert et al. (2011).}\]
\[^{13}\text{One issue discussed in greater depth in the Online Appendix is how we deal with missing data when computing the price indices. Monthly prices may be missing, for instance, in the case of seasonal goods, the introduction of new goods, and the phasing out of existing goods. When computing our price indices, we restrict our sample to only include (1) goods that had positive sales in the prior year and (2) goods that had positive sales in every month of the current year. Online Appendix Table R1 shows the share of sales included in the price index for each sample year.}\]
\[ P_{j,t,y,k} = P_{j,t-1,y,k} \times \frac{\sum_{i \in j} p_{i,t,k} \bar{q}_{i,t-1,k}}{\sum_{i \in j} p_{i,t-1,k} \bar{q}_{i,t-1,k}} \] (1)

where \( P_{j,t,y,k} \) is category level price index for category \( j \), in period \( t \), with a base year \( y \), in state \( k \). \( p_{i,t,k} \) is the price at time \( t \) of the specific good \( i \) (from category \( j \)) in state \( k \) and \( \bar{q}_{i,t-1,k} \) is the average monthly quantity sold of good \( i \) in the prior year in state \( k \). By fixing quantities at their prior year’s level, we are holding fixed household’s consumption patterns as prices change. We update the basket of goods each year and produce the chained index for each category in each state.

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

\[ \frac{P_{t,k}}{P_{t-1,k}} = \prod_{j=1}^{N} \left( \frac{P_{j,t,y,k}}{P_{j,t-1,y,k}} \right)^{S_{t_j,k}^{t-1} / S_{t_j,k}^{t}} \] (2)

where \( S_{t_j,k} \) is the share of expenditure of category \( j \) in month \( t \) in state \( k \) averaged over the year.

Finally, as a consistency check, we compare our retail scanner price index for the aggregate US to the BLS’s CPI for food. We choose the BLS Food CPI as a benchmark given that approximately 60 percent of the goods in our database can be classified as food. Figure 1 shows that our retail scanner aggregate price index matches nearly exactly the BLS’s Food CPI at the monthly level between 2006 and 2012.

### 2.2.3 A State-Level Price Index from the Retail Scanner Price Index

The previous subsection described the construction of a state-level price index for goods sold in retail grocery and mass merchandising stores. However, our goal is to construct state-level price indices that are representative of the composite basket of consumer goods and services. In this subsection, we describe conditions under which our retail scanner price index and a composite local price index differ only by a scaling factor. We then propose to estimate this scaling factor using available data from the BLS. Nonetheless, as we highlight throughout, using this scaling factor (as opposed to using our retail scanner price indices directly) has little effect on the quantitative results of the paper.

Most goods in our sample are produced outside a local market and are simultaneously sold to many local markets. These intermediate production costs represent the traded portion of local retail prices. If there were no additional local distribution and/or trade costs, one would expect little variation in retail prices across states; the law of one price would hold. However, these "non-tradable" costs do exist, including the wages of workers in the retail establishments, the rent of the

\footnote{The non-food goods in our sample include health and beauty products (13 percent), alcoholic beverages (6 percent), and paper products and household cleaning supplies (13 percent). The remaining items includes batteries, cutlery, pots and pans, candles, cameras, small consumer electronics, office supplies, and small household appliances.}
retail facility, and expenses associated with local warehousing and transportation.\textsuperscript{15} Assuming that the shares of these non-tradable costs are constant across states and identical for all firms in the retail industries, we can express local retail scanner prices, $P^r$, in region $k$ during period $t$ as:

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

where $P^T_t$ is the tradable component of local retail scanner prices in period $t$ (which does not vary across states) and $P^{NT}_{t,k}$ is the non-tradable component of local retail prices in period $t$ (which potentially does vary across states). $\kappa_r$ 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:

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

where $P^{nr}_{t,k}$ is local prices in these sectors outside of the grocery/mass-merchandising sector and $\kappa_{nr}$ is the share of non-tradable costs in the total price for these other sectors.\textsuperscript{16}

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 ($P^{nr}_{t,k}$):

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

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

\textsuperscript{15} Burstein et al (2003) document that distribution costs represent more than 40 percent of retail prices in the US.

\textsuperscript{16} 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 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).
a composite local consumption good. While we do not have such indices for every US state, we can compare the relationship between local food inflation and local total inflation using BLS metro area price indices. These indices are only available for 27 MSAs at varying degrees of frequency (monthly, bi-monthly, semi-annually).\footnote{In the online appendix that accompanies this paper, we discuss the BLS local price indices in greater depth.} As a result, they are not overly useful in measuring prices for a broad set of local areas. However, for the MSAs covered, the BLS creates both a local food price index and a price index for the total local consumption basket. One approach to estimate $\kappa$, therefore, would be to estimate a regression of local food inflation on local total inflation using data for these 27 MSAs. However, the BLS cautions against such a regression because they report that the local price indices contain a substantial amount of measurement error.\footnote{See, for example, http://www.bls.gov/opub/btn/volume-1/pdf/consumer-price-index-data-quality-how-accurate-is-the-us-cpi.pdf} Such measurement error will bias our estimate of $\kappa$ towards zero.

To get around the measurement error problem, we follow the lead of Fitzgerald and Nicolini (2014) and regress food (total) inflation on some measure of local economic activity that is measured with relatively more precision. Taking a ratio of the coefficients from these two separate regressions can yield an estimate of $\kappa$. Specifically, we regress the 3-year inflation rate (either for food or total CPI) at the MSA level on the 3 year change in the unemployment rate during the 2007-2010 period. Within the BLS data, we find that a 1 percentage point increase in the local unemployment rate is associated with a 0.34 percentage point decline in the local food inflation rate (standard error = 0.22) and 0.47 percentage point decline the local composite inflation rate (standard error = 0.15). These estimates are very similar to those reported by Fitzgerald and Nicolini (2014) who use data over a longer time period. The fact that the coefficient on the change in unemployment rate is smaller in the food inflation regression than the total inflation regression is consistent with our belief that the tradable share of food is higher than the tradable share of the local composite consumption good. Given these coefficients, the BLS data suggests a measure of $\kappa$ of 1.4 (-0.47/-0.34). We will use this as our base adjustment factor throughout the paper. However, our main decompositions later in the paper are robust to any scaling factor between 1.0 and 2.0.

### 3 Comparing Cross-State Patterns to Aggregate Time-series 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.

The left hand panel of Figure 3 shows the log-change in our demographic adjusted nominal wage indices between 2007 and 2010 across states against the log-change in the employment rate. As seen from the figure, nominal growth was strongly, positively correlated with employment growth in the 2007-2010 period. A simple linear regression through the data (weighted by the state’s 2006 labor force) suggests that a 1 percent change in a state’s employment rate is associated with a 0.62 percent change in nominal wages (standard error = 0.10). These findings are consistent with the extensive literature in labor economics and public finance showing that local labor demand shocks cause both
employment and wages to vary together in the short to medium run. For example, Blanchard and Katz (1991), Autor, Dorn and Hanson (2013) and Charles, Hurst and Notowidigdo (2013) all find that negative local labor demand shocks cause substantial declines in local wages over the three to five year horizon. Our results further suggest that wages are fairly flexible in response to labor demand shocks at the local level. However, we illustrate the patterns at business cycle frequencies.

The right hand panel of Figure 3 shows similar patterns for real wage variation. We compute local real wages by deflating local nominal wage growth with the growth in the prices of a composite local consumption good \( (P_{t,k})^{20} \). A simple linear regression through the data (weighted by the state’s 2006 labor force) suggests that a 1 percent change in a state’s employment rate is associated with a 0.52 percent change in real wages (standard error = 0.15). Growth in local nominal and real wages were highly correlated with changes in many other measures of state economic activity during the 2007-2010 period as well. Although not shown, lower GDP growth, lower unemployment growth, lower hours growth and lower house price growth were all strongly correlated with lower nominal and real wage growth during the recent recession.

Figure 2 shows our composition adjusted aggregate wage indices for the 2000 to 2012 period calculated using CPS data. To construct aggregate composition adjusted real wages, we deflate the aggregate nominal adjusted wages from the CPS by the aggregate June CPI-U with 2000 as the base year. Between 2007 and 2010, average composition adjusted nominal wages in the US increased by roughly 4 percent despite aggregate employment falling substantively. The patterns in our data replicate the aggregate nominal wage growth patterns documented by many others in the literature. Given that consumer prices increased by 5 percent during the same period, aggregate real wages in the US fell by roughly 1 percent between 2007 and 2010. This was similar to the trend in real wages prior to the start of the recent recession. As seen from Figure 2, nominal wages increased slightly and real wage growth did not seem to break trend during the Great Recession. The "puzzle" is why aggregate wages did not decline relative to trend despite the very weak aggregate labor market. Wage stickiness is one potential explanation. However, as seen from Figure 3, local nominal and real wages moved quite a bit with changes in local employment during the same time period.

Table 1 compares these cross-state elasticities with the corresponding aggregate time-series elasticities during the Great Recession. The top panel displays the local wage elasticities from the simple scatter plots shown in Figure 3. The bottom panel provides an estimate of similar elasticities.

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19 The patterns we document in Figure 3 also show up in other wage series. While there are no government data sets that produce broad based composition adjusted wage series at the local level, the Bureau of Labor Statistics’s Quarterly Census of Employment and Wages (QEW) collects firm level data on employment counts and total payroll at local levels. In Online Appendix Figures R1 and R2 we present results using local wage indices constructed from the QEW data instead. In these data, a one percent increase in a state’s employment growth between 2007 and 2010 was associated with a roughly 0.5 increase in the state’s nominal per capita earnings growth during the same time period.

20 As discussed in the previous section, we scale the growth in the retail scanner price index by a factor of 1.4 to account for the fact that grocery/mass merchandising goods have a higher tradable share than the composite local consumption good.

21 See, for example, Daly and Hobijn (2015).

22 We thank Bob Hall for giving us the idea for this table. We base it on the analysis he did as part of his discussion of our paper at the 2015 NBER summer EFG program meeting.
over the same time period at the aggregate level. In particular, the last row shows the aggregate nominal (and real) wage elasticity with respect to changes in employment between 2007 and 2010. To construct these elasticities we use our adjusted nominal wage measure from the CPS (in the case of real wages, we deflate them with June CPI-U) and the aggregate employment-to-population ratio from the BLS. We de-trend all variables by estimating a linear trend between 2000 and 2007. The de-trended employment decline between 2007 and 2010 was 6.8 percent whereas the de-trended nominal wage decline was 1.7 percent. De-trended real wages actually increased by 1.2 percent during the 2007-2010 time period. Therefore, the implied aggregate wage elasticities with respect to employment during the Great Recession are 0.25 for nominal wages (-1.7/-6.8) and -0.17 for real wages (1.2/-6.8).

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 nominal wage elasticity with respect to employment changes was over twice as big as the aggregate elasticity (0.62 vs. 0.25). It is these differences in the relationships 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 hardly responded at all despite a sharp deterioration in aggregate employment conditions? Can aggregate wages be sticky when local wages adjust so much? We turn to answering these questions next.

4 A Monetary Union Model

In this section we present a monetary union model with several goals in mind. First, the model allows us to discuss the patterns we documented in the previous section in a formal environment where local economies aggregate. Second, the model makes explicit our assumptions on how wages are set. The nominal wage stickiness we specify will be essential to our identification strategy in later parts of the paper. Third, a calibrated version of the model allows us to quantify differences in aggregate vis a vis local elasticities to a variety of different shocks. While the theoretical possibility of these differences are known, much less is known about the their magnitudes. The calibration exercise provides guidance to researchers who want to take an estimated local elasticity to a given shock and apply it to the aggregate economy. Fourth, the model provides an example of an economy that is encompassed by our SVAR procedure in Section 5 of the paper. The SVAR approach will allow us to estimate shocks for a larger set of models than the one we write down in this section. Finally, the model provides us with theoretical co-movements between variables that help us identify the shocks in the SVAR as well as give them an economic interpretation.

Formally, our model economy is composed of many islands inhabited by infinitely lived households and firms in two distinct sectors that produce a final consumption good and intermediates that go into its production. The only asset in the economy is a one-period nominal bond in zero
net supply where the nominal interest rate is set by a monetary authority. We assume intermediate goods can be traded across islands but the consumption good is non-tradable. 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 Firms and Households

Producers of tradable intermediate goods $x$ in island $k$ use local labor $N^x_k$ and face nominal wages $W_k$ (equalized across sectors) and prices $Q$ (equalized across islands $k$). The time subscripts are omitted for clarity. Their profits are

$$\max_{N^x_k} Qe^{z^x_k}(N^x_k)^\theta - W_kN^x_k$$

where $z^x_k$ is a tradable productivity shock in island $k$ and $\theta < 1$ is the labor share in the production of tradables. Final (retail) goods $y$ producers face prices $P_k$ and obtain profits

$$\max_{N^y_k,X_k} P_xx^{y_k}(N^y_k)\alpha(X_k)^\beta - W_kN^y_k - QX_k$$

where $z^y_k$ is a final good (retail) productivity shock and $(\alpha, \beta) : \alpha + \beta < 1$ are the labor and intermediates shares. Unlike the tradable goods prices, final good prices ($P_k$) vary across islands.

Households preferences are given by

$$E_0 \left[ \sum_{t=0}^{\infty} e^{-\rho t - \delta t} \left( C_{kt} - e^{\epsilon_{kt}} \frac{\phi N^1_{kt}}{1+\phi} \right)^{1-\sigma} \right]$$

where $C_{kt}$ is consumption of the final good, $N_{kt}$ is labor, and $\delta_{kt}$ and $\epsilon_{kt}$ are exogenous processes driving the household’s discount factor and the disutility of labor, respectively. Our base preferences abstract from income effects on labor supply. However, we show in section 7.4 that relaxing this assumption does not quantitatively change the conclusions of the paper.

Households are able to spend their labor income $W_{kt}N_{kt}$, profits accruing from firms $\Pi_{kt}$, financial income $B_{kt}$, and transfers from the government $T_t$, where $B_{kt}$ are nominal bond holdings at the beginning of the period and $i_t$ is the nominal interest (equalized across islands given our assumption of a monetary union where the bonds are freely traded). Thus, they face the period-by-period

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23The final good can be thought of as being retail goods and services purchased in places such as: restaurants, barbershops and stores; and the intermediate sector providing physical goods such as: food ingredients, scissors and cellphones.

24We explore the issue of labor mobility during the Great Recession when we take the model to the data.

25It is worth noting that all model shocks will generate endogenous variation in markups given our assumption of decreasing returns to scale. Additionally, what we call a “productivity shock” is isomorphic to any shifter of unit labor costs and, hence, labor demand schedules. Later we will refer to it as the productivity/markup shock. We do not attempt to distinguish between the different interpretations of this shock in this paper.
budget constraint

\[ P_{kt}C_{kt} + B_{kt+1} \leq B_{kt}(1 + i_t) + W_{kt}N_{kt} + \Pi_{kt} + T_{kt} \]

A well known issue in the international macroeconomics literature is that under market incompleteness of the type we just described there is no stationary distribution for bond holdings across islands in the log-linearized economy; and all other island variables in the model have unit roots. We follow Schmitt-Grohe and Uribe (2003) and let \( \rho_{kt} \) be the endogenous component of the discount factor that satisfies \( \rho_{kt+1} = \rho_{kt} + \Phi(.) \) for some function \( \Phi(.) \) of the average per capita variables in an island. As such, agents do not internalize this dependence when making their choices. This modification induces stationarity for an appropriately chosen function \( \Phi(.) \). Schmitt-Grohe and Uribe (2003) show that alternative stationary inducing modifications (a specification with internalization, a debt-elastic interest rate or convex portfolio adjustment costs) all deliver similar quantitative results in the context of a small open economy real business cycle model.

4.2 Sticky Wages

We allow for the possibility that nominal wages are sticky and use a partial-adjustment model where a fraction \( \lambda \) of the gap between the actual and frictionless wage is closed every period. Formally:

\[ W_{kt} = (P_{kt}e^{\epsilon_{kt}}(N_{kt})^{1/\delta})^{\lambda}(W_{kt-1})^{1-\lambda} \]

Given our assumption on household preferences, \( P_{kt}e^{\epsilon_{kt}}(N_{kt})^{1/\delta} \) corresponds to the marginal rate of substitution between labor and consumption and the parameter \( \lambda \) measures the degree of nominal wage stickiness. In particular, when \( \lambda = 1 \) wages are fully flexible and when \( \lambda = 0 \) they are fixed. This implies that workers will be off their labor supply curves whenever \( \lambda < 1 \). A similar specification has been used by Shimer (2010) and, more recently, by Midrigan and Philippon (2011). Shimer (2010) argues that in labor market search models there is typically an interval of wages that both the workers are willing to accept and firms willing to pay. To resolve this wage indeterminacy he considers a wage setting rule that is a weighted average of a target wage and the past wage. The target wage in our case is the value of the marginal rate of substitution.

Popular alternatives in the literature include the wage bargaining model in the spirit of Hall and Milgrom (2008) as in Christiano, Eichenbaum and Trabandt (2015b); and the monopsonistic competition model where unions representing workers set wages period by period as in Gali (2009). The key difference with the partial adjustment model is that both alternatives result in a forward looking component in the wage setting rule that is absent in our specification. In fact, this wage setting rule can be derived from the monopsonistic competition setup in the case where agents are myopic about the future; or from the labor market search setup in the special case where firms make take-it-or-leave-it offers and the probability of being employed in the future is independent of the current employment status.²⁶

²⁶While there is no forward looking component in the reset wage in our base specification, we consider the implications of including forward looking behavior in Section 7.4.
4.3 Equilibrium

An equilibrium is a collection of prices \( \{P_{kt}, W_{kt}, Q_t\} \) and quantities \( \{C_{kt}, N_{kt}, B_{kt}, N^c_{kt}, N^\gamma_{kt}, X_{kt}\} \) for each island \( k \) and time \( t \) such that, for an interest rate rule \( i_t = i(\cdot)e^{\mu t} \) and given exogenous processes \( \{z^y_{kt}, z^x_{kt}, \epsilon_{kt}, \delta_{kt}, \mu_t\} \), they are consistent with household utility maximization and firm profit maximization and such that the following market clearing conditions hold:

\[
\begin{align*}
C_{kt} &= e^{z^y_{kt}} (N^y_{kt})^\alpha X^\beta_{kt} \\
N_{kt} &= N^y_{kt} + N^\gamma_{kt} \\
\sum_k X_{kt} &= \sum_k e^{z^\gamma_{kt}} (N^\gamma_{kt})^\theta
\end{align*}
\]

4.4 Shocks

We assume exogenous processes are AR(1) processes, with an identical autoregressive coefficient across islands (and sectors in the case of productivity), and that the innovations (i.e., shocks) to these processes are iid, mean zero, random variables with an aggregate and island specific component. Let \( \gamma_{kt} \equiv \delta_{kt} - \delta_{kt-1} - \mu_t \) be a combination of the discount rate exogenous growth and the monetary policy exogenous process that shows up as a wedge in the Euler equation. Then, we write the exogenous processes as:

\[
\begin{align*}
z^y_{kt} &= \rho_z z^y_{kt-1} + \sigma_z u^y_t + \bar{\sigma}_y v^y_{kt} \\
z^x_{kt} &= \rho_z z^x_{kt-1} + \sigma_z u^x_t + \bar{\sigma}_x v^x_{kt} \\
\gamma_{kt} &= \rho_\gamma \gamma_{kt-1} + \sigma_\gamma u^\gamma_t + \bar{\sigma}_\gamma v^\gamma_{kt} \\
\epsilon_{kt} &= \rho_\epsilon \epsilon_{kt-1} + \sigma_\epsilon u^\epsilon_t + \bar{\epsilon}_\epsilon v^\epsilon_{kt}
\end{align*}
\]

with \( \sum_k v^y_{kt} = \sum_k v^x_{kt} = \sum_k v^\gamma_{kt} = \sum_k v^\epsilon_{kt} = 0 \). By assumption, we assume the weighted average of the island specific shocks sums to zero in all periods.

Let \( u^\gamma_t \equiv u^y_t + \beta u^x_t \) be a combination of productivity shocks in both sectors. We will call \( u^\gamma_t \), \( u^y_t \) and \( u^x_t \) the aggregate Productivity/Markup, Discount rate and Leisure shocks respectively. These are the shocks that the econometric procedure aims to identify. Analogously, \( v^y_{kt}, v^x_{kt}, v^\gamma_{kt}, v^\epsilon_{kt} \) are the Regional shocks. The interpretation of the Leisure and Productivity/Markup shocks is relatively straightforward given our model environment. They are shifters of households and firms’ labor supply (wage setting) and labor demand schedules, respectively. On the other hand, what we identify as a “discount rate shock” \( (\gamma_{kt}) \) is the combination of two more fundamental shocks. First, a shock to the marginal rate of substitution between consumption in consecutive periods. Second, a shock to the nominal interest rate rule set by the monetary authority. Our procedure is unable to distinguish between the two given that they both show up in the household’s Euler equation, thus we treat them as a single shock.
4.5 Aggregation

Our first key assumption for aggregation is that all islands are identical with respect to their underlying production parameters ($\alpha$, $\beta$, and $\theta$), their underlying utility parameters ($\sigma$ and $\phi$) and the degree of wage stickiness ($\lambda$). Our second assumption is that islands are identical in the steady state and that price and wage inflation are zero. The last assumption is that the joint distribution of island-specific shocks is such that its cross-sectional sum is zero. If $K$, the number of islands, is large this holds in the limit because of the law of large numbers. We log-linearize the model around this steady state and show that it aggregates up to a representative economy where all aggregate variables are independent of any cross-sectional considerations to a first order approximation.

We denote with lowercase letters a variable’s log-deviation from its steady state. Variables without a $k$ subscript represent aggregates. For example, $n_{kt} = \log \left( \frac{N_{kt}}{N_t} \right)$ and $n_t = \sum_k \frac{1}{K} n_{kt}$. We assume that the monetary authority announces a nominal interest rate rule which is a function of aggregate variables. In log-linearized form, the rule is: $i_{t+1} = \varphi_\pi \pi^E_t \left[ \pi_t + 1 \right] + \varphi_y (y_t - y^*_t) + \mu_{t+1}$ where $\pi_t$ is the aggregate inflation rate and $y_t - y^*_t$ is the output gap, defined as the difference between actual output and the flexible wage equilibrium output for the same realization of shocks. Finally, we assume that the endogenous component of the discount factor is $\Phi(.) = \Phi_0 (c_{kt} - c_t)$. The following lemmas present a useful aggregation result and show that we can write the island-level equilibrium in log-deviation from the aggregate union equilibrium. Let $w^r_t$ be real wage growth and $\pi^w_t$ be nominal wage growth. Formally, $w^r_t = \log \left( \frac{W_t / P_t}{W_t / P_t} \right)$ and $\pi^w_t = w^r_t - w^r_{t-1} + \pi_t$.

**Lemma 1** The behavior of $\pi^w_t$, $w^r_t$, $n_t$ in the log-linearized economy is identical to that of a representative economy with only a final goods sector with labor share in production $\alpha + \theta \beta$, no endogenous discount factor, and only 3 exogenous processes $\{z_t, \epsilon_t, \gamma_t\}$.

Denote any variable $\hat{x}_t \equiv x_{kt} - x_t$ as corresponding to island’s $k$ log-deviation from aggregates at time $t$, where the subscript $k$ is dropped for notational simplicity.

---

27 When implementing our procedure using data on US states, we discuss the plausibility of this assumption. Given that the broad industrial composition at the state level does not differ much across states, the assumption that productivity parameters and wage stickiness are roughly similar across states is not dramatically at odds with the data. As a robustness exercise, we estimate our key equations with industry fixed effects and show that our key cross section estimates are unchanged.

28 The model we presented has many islands subject to idiosyncratic shocks that cannot be fully hedged because asset markets are incomplete. By log-linearizing the equilibrium, we gain in tractability but ignore these considerations and the aggregate consequences of heterogeneity. The approximation will be good as long as the underlying volatility of the idiosyncratic shocks is not too large. If our unit of study was an individual, as for example in the precautionary savings literature with incomplete markets, the use of linear approximations would likely not be appropriate. However, since our unit of study is an island the size of a small country or a state, we believe this is not too egregious of an assumption. The volatilities of key economic variables of interest at the state or country level are orders of magnitude smaller than the corresponding variables at the individual level.

29 $\Phi_0 > 0$ is enough to induce stationary of island-level variables in log-deviations from the aggregate. Furthermore, since $\Phi(.)$ depends only on these deviations, the aggregate equilibrium will feature a constant endogenous discount factor $\rho$. 

16
Lemma 2. For given \( \tilde{z}_t, \tilde{y}_t, \tilde{\gamma}_t, \tilde{\epsilon}_t \), the behavior of \( \{ \tilde{p}_t, \tilde{\omega}_t, \tilde{n}_t, \tilde{n}_t^\nu \} \) in the log-linearized economy for each island in deviations from aggregates is identical to that of a small open economy where the price of intermediates and the nominal interest rate are at their steady state levels, i.e. \( q_t = i_t = 0 \ \forall t \).

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

4.6 Aggregate vs. Local Shock Elasticities

Having described the model, we now explore the extent to which aggregate employment, price and wage elasticities to a given shock differ from local employment, price and wage elasticities to the same shock. Many researchers use clever identification strategies exploiting regional variation to estimate local elasticities to a given shock. For example, Mian and Sufi (2014) uses variation in debt across US metropolitan areas to isolate the extent to which a local "demand" shock (i.e., our discount rate shock) affects local employment. We show in this sub-section that the local employment (price, wage) elasticity to a given discount rate shock (productivity shock, leisure shock) is different, in general, from the aggregate elasticity to the same shock. Moreover, we calibrate the model in order to quantify the difference.

To gain some intuition as to the difference between local and aggregate elasticities in our model, we first consider the special case where there is an endowment of the tradable good and no labor is used in its production, i.e. \( \theta = 0 \). Focusing on a discount rate shock in this special case makes the comparison very transparent. We let \( \xi_{agg0} \equiv \frac{dn_0}{d\gamma_0} \) and \( \xi_{reg0} \equiv \frac{\tilde{dn}_0}{\tilde{d}\gamma_0} \) be the employment elasticities to the discount rate shock on impact. By solving for the recursive laws of motion in equilibrium we obtain,

\[
\begin{align*}
\xi_{agg0} & = \frac{(1 - \lambda)}{(1 - \alpha + \frac{\lambda}{\phi})(\varphi_p - 1) + (\varphi_y\alpha - (\varphi_p - 1)(1 - \alpha)) \frac{1 - \lambda}{\rho_y}}\
\xi_{reg0} & = \frac{dn_0}{d\gamma_0} = \left(1 - \alpha + \frac{\lambda}{\phi} + \left(\frac{\varphi(1 - \lambda(\alpha - \frac{1}{\phi}))(1 + \frac{\lambda}{\phi})}{1 - \frac{\varphi}{\rho_y}} - (1 + \frac{\lambda}{\phi})\right) \frac{1 + \frac{\tau}{\rho_y} - 1}{1 - \lambda + \lambda \beta}\right)
\end{align*}
\]

These expressions help understand the general equilibrium forces that make local and aggregate elasticities different. From the perspective of the closed economy, the endogenous response of the nominal interest rate rule \( \{ \varphi_p \text{ and } \varphi_y \} \) reduces the aggregate employment impact elasticity to an unanticipated discount rate shock. A negative discount rate shock puts downward pressure on employment and prices. The monetary authority can lower interest rates to offset such a shock. The parameters of the interest rate rule are entirely absent in the expression for the regional elasticity. Therefore, the aggregate employment elasticity to a discount rate shock is typically smaller than the local employment elasticity to a local discount rate shock.

From the local perspective, since island level economies in deviations from the aggregate are small open economies, there are two 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 ($\beta > 0$) decreases the regional employment elasticity to the shock (as long as the term \( \left( \frac{\sigma(1-\lambda(a-\frac{1}{2}))}{1-\frac{\phi_1}{\phi_{1/\alpha}}\phi_1 - \phi_{1/\alpha}} - 1 \right) \) is positive). Second, the possibility to transfer resources intertemporally through saving/borrowing at the interest rate \( r \), as seen in the term \( \left( \frac{1 + r}{\phi_{1/\alpha}} - 1 \right) \), decreases the regional employment elasticity. Theoretically, therefore, the aggregate employment elasticity to an aggregate discount rate shock can be either greater or smaller than the local employment elasticity to a local discount rate shock.

It is also interesting to compare how these discount rate elasticities change with the degree of nominal wage stickiness. Our identification procedure allows us to do this exercise when we estimate the impulse response to a discount rate shock. When \( \phi_p > 1 \), both elasticities are decreasing in \( \lambda \). In particular, employment does not respond to discount rate shocks at all in the limit when wages are perfectly flexible \( (\lambda \rightarrow 1) \).

While it is generally understood that local and aggregate elasticities can differ, there has been little quantitative work assessing the potential size of these differences. A parameterized version of our model allows us to directly compute the local and aggregate employment elasticities to different types of shocks. To this end, Table 3 quantifies the employment impact elasticities to each of the shocks in the full model. Table 2 presents and explains the parameterization of our model. Most of the parameters are standard from the literature or are chosen to match the labor share in the tradable and non-tradable sectors. The Online Appendix has an extended discussion of our baseline parameter choice. For our base specification, we use estimates of \( \lambda \) and \( \phi \) of 2 and 0.7, respectively. These are the parameters that show up in the aggregate and local wage setting equations. The value of these parameters are the ones that we estimate using local variation in Section 6.

Column 1 of Table 3 shows our base estimates of the local and aggregate employment elasticities. In columns 2 - 8 of Table 3, we show how the elasticities change across alternate parameterization. Specifically, in column 2, we re-compute the elasticities reducing the Frisch elasticity of labor supply \( (\phi) \) from 2 to 1. In column 3, we make wages more sticky by reducing \( \lambda \) from 0.7 to 0.5 (returning the Frisch elasticity to our base parameterization). In column 4, we set \( \beta = 0 \), thus shutting down the possibility to substitute labor for intermediate goods in the production of final goods. In the next two columns, we shut down the endogenous feedback in the nominal interest rate to changes in the employment gap such that \( \phi_y \) is set to zero. In the first of those two columns, we leave the response of the nominal interest rate to the inflation target \( (\phi_p) \) at its base parameterization. In the second of those two columns, we lower \( \phi_p \) such that the local and aggregate responses to a discount rate shock are the same on impact. Finally, in the last two columns, we explore how the elasticities change as the persistence of the demand shock changes.

In our base specification, we find that the regional employment elasticity to a discount rate shock is 2.3 times larger than the aggregate employment elasticity to a discount rate shock. This implies that using cross-region variation to estimate local employment elasticities to demand shocks dramatically overstates employment responses when those local elasticities are applied to the aggregate. The conclusion remains unchanged across the different parameterizations of the wage setting rule, as shown in columns 2 and 3. Local employment elasticities to discount rate shocks are always
two to three times larger than the aggregate employment elasticities. In columns 4 to 6, we see the importance of general equilibrium forces. As we shut down the ability to substitute labor for intermediate goods ($\beta = 0$), the gap between the regional and aggregate elasticities gets larger. The ability to trade intermediates across regions dampens the local employment elasticity to discount rate (demand) shocks. In columns 5 and 6, we see that the endogenous monetary policy response also dramatically dampens the aggregate response to a discount rate shock. This suggests that in periods where the economy is at the zero lower bound, aggregate and local employment elasticities to a demand shock are more similar, a point also made in Nakamura and Steinsson (2014). The last column explores the sensitivity to changes in the persistence of the discount rate shock. The less persistent is the local discount rate shock, the smaller the local employment elasticity because the regions can borrow from and lend to each other. Table 3 also shows the local and aggregate employment response to local and aggregate productivity/markup and leisure shocks. For these two shocks, the local employment elasticities are usually smaller than their aggregate counterparts. For the most part, this results from the particular specification of the nominal interest rate rule. To summarize, the quantitative difference between aggregate and local employment elasticities depends on the type underlying shock and can be quite large.

Tables 4 and 5 summarize the aggregate and regional impulse responses, respectively, for all variables and shocks in our benchmark calibration. We show results upon impact (the "short-run" elasticities) and after 5 years (the "long-run" elasticities). These tables allow us to assess the model’s predictions. We use the same parameterization as in Table 2. The short run responses in Columns 1 of Table 4 and Table 5 just restate the employment elasticities in column 1 of Table 3. The remainder of the tables show the estimates for the price, nominal wage and real wage elasticities to all the underlying shocks in the model upon impact. As seen from Table 4, an aggregate negative discount rate shock (households become less patient) lowers aggregate employment, lowers aggregate prices, and lowers (slightly) aggregate real wages. Conversely, an aggregate negative productivity shock lowers aggregate employment, raises aggregate prices, and raises aggregate real wages. We will use the sign of these impact elasticities to help identify the shocks in the SVAR in Section 5.

5 A Procedure for Identifying Aggregate Shocks

In this section, we develop a procedure that allow us estimate the shocks in a larger class of monetary union models than the benchmark model outlined above, thus imposing less a-priori structure and making the analysis more persuasive. Specifically, we consider models where aggregate equi-
libria can be represented as a structural vector autoregression (SVAR) in price inflation, nominal wage inflation, and employment with three shocks. In order to identify the shocks, we use three properties of our benchmark monetary union model: the wage setting equation, the sign of the impact elasticities to a discount rate and productivity/markup shocks, and the orthogonality of shocks. Our results will be consistent with monetary union models that satisfy all of these. Beraja (2015) discusses this identification procedure in detail, as well as its application to more general SVARs and theoretical models than the ones in this paper.

We begin by noting that the recursive solution to the equilibrium system of equations in Lemma 1 can be written as a SVAR(∞) in \( \{ \pi_t, \pi^w_t, n_t \} \):

\[
(I - \rho(L)) \begin{bmatrix}
\pi_t \\
\pi^w_t \\
n_t
\end{bmatrix} = \Lambda \begin{bmatrix}
u^e_t \\
u^z_t \\
u^\gamma_t
\end{bmatrix}
\]

Knowledge of \( \rho(L) \) and an invertible matrix \( \Lambda \) together with aggregate data on prices, nominal wages and employment allow recovering the structural shocks.

The first step in our procedure consists of estimating the reduced form VAR to obtain the autoregressive matrix \( \rho(L) \) and the reduced form errors covariance matrix \( V \). In practice we will truncate \( \rho(L) \) to be of finite order as it is typically done in the literature. The second step involves deriving a set of theoretical restrictions to identify the structural shocks from the reduced form errors.

As a reminder, the wage setting equation in log-linearized form is:

\[
\pi^w_t = \lambda (\pi_t + \epsilon_t - \epsilon_{t-1} + \frac{1}{\phi} (n_t - n_{t-1})) + (1 - \lambda) \pi^w_{t-1}
\]

Applying the conditional expectation operator \( E_{t-1}(\cdot) \) on both sides and constructing expectational errors, we obtain:

\[
\begin{bmatrix}
\lambda & -1 & \frac{1}{\phi}
\end{bmatrix} \Lambda \begin{bmatrix}
u^e_t \\
u^z_t \\
u^\gamma_t
\end{bmatrix} + \lambda \sigma_e u^e_t = 0
\]

Similarly, constructing \( E_{t-1}(\cdot) - E_{t-2}(\cdot) \), we obtain:

\[
\left( \begin{bmatrix}
\lambda & -1 & \frac{1}{\phi}
\end{bmatrix} \rho_1 + \begin{bmatrix}
0 & 1 - \lambda & 0
\end{bmatrix} \right) \Lambda \begin{bmatrix}
u^e_{t-1} \\
u^z_{t-1} \\
u^\gamma_{t-1}
\end{bmatrix} + \lambda (\rho_\epsilon - 1) \sigma_e u^e_{t-1} = 0
\]

where \( \rho_1 \) is the matrix collecting the first order autoregressive coefficients in the reduced form VAR.

The above equations (3) and (4) have to hold for all realizations of the shocks. In particular, equation (3) gives us two linear restrictions in the elements of \( \Lambda \) for given parameters in the wage

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31 The exogenous processes are AR(1) and the system of equations characterizing the equilibrium is of first order. When written in matrix form it is easy to show that there is a representation as a SVAR(∞).

32 At the end of Section 7, we show the sensitivity of our estimation procedure to alternative wage setting equations.
setting equation when there are either contemporaneous discount rate or productivity/markup shocks. These two restrictions, together with the six restrictions coming from the orthogonalization of the shocks, are sufficient to identify the column in the impulse response matrix \( \Lambda \) corresponding to the leisure shock \((u_{\epsilon}^t)\). In order to identify the discount rate and productivity/markup shocks \((u_{\gamma}^t, u_{z}^t)\) we proceed as follows. From equation (4), we obtain two extra linear restrictions that hold when there is a lagged discount rate shock or a lagged productivity/markup shock. However, these restrictions alone cannot "separate" the discount rate from the productivity/markup shocks because they are identical for both. Therefore, we use the sign of the impact elasticities from our model to a discount rate and productivity/markup shock \((u_{\gamma}^t \text{ and } u_{z}^t)\), respectively. Specifically, we search over all linear combinations \( \psi \in [0, 1] \) of the independent restrictions coming from equation (4) such that a discount rate (productivity shock/markup) shock: (i) moves prices and employment in the same (opposite) direction on impact, and (ii) moves real wages and employment in opposite (same) direction on impact. If more than one linear combination of the restrictions satisfy these, we pick the one that is closer to giving equal weighting to both restrictions.

For completeness, the matrix \( \Lambda \) solves the system:

\[
\begin{bmatrix}
\lambda & -1 & \frac{1}{\phi} \\
0 & 0 & 1 \\
0 & 1 & 0
\end{bmatrix}
\begin{bmatrix}
0 \\
1 \\
0
\end{bmatrix}
= \begin{bmatrix}
0 \\
0
\end{bmatrix}
\]

\[
\begin{bmatrix}
\lambda & -1 & \frac{1}{\phi} \\
0 & 0 & 1 - \lambda \\
0 & 1 - \frac{1}{\phi}
\end{bmatrix}
\begin{bmatrix}
0 \\
\psi \\
0
\end{bmatrix}
= 0
\]

\[
\Lambda \Lambda' = V
\]

It is worth noting that, when \( \lambda = 1 \), this procedure cannot identify all columns in the impulse response matrix \( \Lambda \) because the system above is underdetermined (i.e., equation (4) implies linear restrictions that are merely linear combinations of the restrictions implied by equation (3)). Therefore, some degree of wage stickiness is key for identification of the shocks through this procedure. The next section shows how to estimate \( \lambda \) using regional data—thus linking particular regional patterns to particular aggregate shock decompositions when combined with the procedure in this section.

### 6 Estimating the Wage Setting Equation Using Regional Data

In this section, we discuss how we estimate \( \lambda \) and \( \phi \) which are necessary inputs in our shock identification procedure. Given the above assumptions, the aggregate and local wage setting equations can be expressed as:

\[
\pi_{w}^{ag} = \lambda(\pi_t + \frac{1}{\phi}(n_t - n_{t-1}) + (1 - \lambda)\pi_{w}^{ag-1} + \lambda(u_t^\gamma - (1 - \rho_e)\epsilon_{t-1})
\]

21
\[ \pi_{kt}^w = \lambda (\pi_{kt} + \frac{1}{\phi} (n_{kt} - n_{kt-1})) + (1 - \lambda) \pi_{kt-1}^w + \lambda (u_t^\phi - (1 - \rho_e) \epsilon_{t-1}) + \lambda v_{kt}^\phi \]

The aggregate and local wage setting curves are functions of the Frisch elasticity of labor supply \((\phi)\) and the wage stickiness parameter \((\lambda)\). There is a literature on estimating micro and macro labor supply elasticities. However, it is hard to estimate the degree of wage stickiness using aggregate data given the small degrees of freedom inherent to aggregate data and given that at the aggregate level it is hard to isolate movements in employment growth and price growth that are arguably uncorrelated with the aggregate leisure shock \((u_t^\phi)\). In some instances, regional data can be used to estimate these parameters.

In order for regional data to be used to estimate \(\lambda\) and \(\phi\), one of the following must hold: either (1) the leisure shock has no regional component \((v_{kt}^\phi = 0)\) or (2) the regional component of the leisure shock must be uncorrelated with changes in local economic activity (i.e., \(\text{cov}(v_{kt}^\phi, (n_{kt} - n_{kt-1})) = 0\) and \(\text{cov}(v_{kt}^\phi, \pi_{kt}) = 0\)). The latter condition holds if a valid instrument can be found that isolates movement in \(n_{kt} - n_{kt-1}\) and \(\pi_{kt}\) that is orthogonal to \(v_{kt}^\phi\). In this section, we estimate \(\lambda\) and \(\phi\) using regional data on prices, wages and employment growth during the Great Recession. We argue that state-level leisure shocks were small during the Great Recession, thus allowing us to estimate \(\lambda\) and \(\phi\) by OLS. Additionally, we use state-level house price variation during the early part of the Great Recession as an instrument to isolate movements in \(n_{kt} - n_{kt-1}\) and \(\pi_{kt}\) that are orthogonal to local leisure shocks. Both procedures yield estimates of \(\lambda\) and \(\phi\) that are fairly similar.

### 6.1 Estimating Equation and Identification Assumptions

Formally, we estimate the following specification using our state-level data:

\[ \pi_{kt}^w = b_0 + b_1 \pi_{kt} + b_2 (n_{kt} - n_{kt-1}) + b_3 \pi_{kt-1}^w + \Psi D_t + \Gamma X_k + e_{kt} \]

where \(b_1 = \lambda\), \(b_2 = \lambda / \phi\), \(b_3 = (1 - \lambda)\), and \(b_0 = \lambda (u_t^\phi - (1 - \rho_e) \epsilon_{t-1})\). Any aggregate leisure shocks are embedded in the constant term. The local error term includes \(\lambda v_{kt}^\phi\) as well as measurement error for the local economic variables. We estimate this equation pooling together all annual employment, price and wage data for years between 2007 and 2011. When estimating the above regression, we include year fixed effects \((D_t)\). This ensures that we are only using the cross-state variation to estimate the parameters. We estimate this equation annually because we only have annual measures of wages at the state level. Our annual nominal wage measures at the state level are the composition adjusted nominal log wages computed from the American Community Survey discussed above. \(\pi_{kt}^w\), therefore, is the log-growth rate in adjusted nominal wages in the state between year \(t\) and \(t - 1\). Our measure of employment growth at the state level is calculated using data from the US Bureau of Labor Statistics. The BLS reports annual employment counts and population numbers for each state in each year. We divide employment counts by population to make an annual employment rate measure for each state. \(n_{kt} - n_{kt-1}\) is the log-change in the employment rate between year \(t\) and \(t - 1\). \(\pi_{kt}\) is log-change in the average price index in each state \(i\) in year \(t\). In our base specification, we use
the retail scanner data local inflation rate scaled to account for the difference between the local non-tradable share in the retail sector and the composite consumption good. In alternative specifications, we use the raw inflation rate from the retail scanner data as our measure of local inflation. Finally, in some specifications, we include controls for the state’s industry mix in 2007. This allows for the possibility that local leisure shocks, to the extent that they exist, may be correlated with the state’s industry structure. Given that we have observations on 48 states for 4 years of growth rate data, our estimating equation includes 192 observations in our base specification. We also show results restricting our data to the period from 2007 to 2009, before the large changes in unemployment benefits extension starting in 2010.

Two additional comments are needed about our estimating equation. First, the theory developed above implies that \( b_1 + b_3 = 1 \). We impose this condition when estimating the cross-state regression. Second, we believe our local wage and price indices are measured with error. The measurement error, if classical, will attenuate our estimates of \( b_1 \) and \( b_3 \). Additionally, because we are regressing wage growth on lagged wage growth, any classical measurement error in wages in year \( t \) will cause a negative relationship between wage growth today and lagged wage growth. We proceed as follows to deal with this issue. Given the large sample sizes on which our wage indices (price indices) are based, we split the sample in each year and compute two measures of wage indices (price indices) for each state in each year. For example, if we have 1 million observations in the 2007 American Community Survey, we split the sample into two distinct samples with 500,000 observations each. Within each sub-sample, we compute a wage measure for each state. Both these wage measures are measured with error. Then, we use the growth rates in wages in one sub-sample as an instrument for growth rate in wages in the other sub-sample. We discuss these procedure in detail in the Online Appendix that accompanies the paper. As we show in that appendix, the procedure corrects the attenuation bias from measurement error in our estimates.\(^{33}\)

In order to recover unbiased estimates of \( \lambda \) and \( \phi \) via OLS, we must assume \( \epsilon_{kt} = 0 \). The assumption that there are no local leisure shocks cannot generically be true. However, in the Online Appendix, we provide some evidence suggesting that this assumption may be roughly valid during the 2007-2011 period. We show that many potential leisure shocks highlighted in the literature to explain the Great Recession had large aggregate components but varied little in across US states. For example, the decline in routine jobs (Jaimovich and Siu (2014), Charles et al (2013, 2015)) was dramatic at the aggregate level during the 2007-2011 period, but occurred in all US states with roughly equal propensity. We show these results in Online Appendix Figure R7. Likewise, some have argued that the expansion of government policies acted like a leisure shock that discouraged work (Mulligan (2012)). We show that many of these government policies—such as the expansion of the Supplemental Nutrition Assistance Program (SNAP) —was large at the aggregate level but had little cross state variation. In Online Appendix Figure R4, we show that SNAP benefits per recipient increased by roughly 30 percent between 2007 and 2011. Because the increase in per recipient benefit occurred at the federal level, there was statutorily no variation in per recipient benefits across US states.

\(^{33}\)This procedure is similar to the split sample instrumental variable estimation in Angrist and Krueger (1995).
states during this time period.\textsuperscript{34}

One policy that has received considerable attention in its potential to act as a labor supply shock is the differential extension of the duration of unemployment benefits across states during the Great Recession. By law in 2010, weeks of unemployment benefits were tied to the state’s unemployment rate. However, as of 2010, most US states met triggers that resulted in the duration of unemployment benefits being close to the maximum of 99 weeks. These states comprised the bulk of the US population. However, some smaller states, mostly in the Plains region of the US, had smaller employment declines and, as a result, had a smaller extension of unemployment benefits.\textsuperscript{35} Despite the fact that there was little population-weighted variation across states in unemployment benefit extensions during the Great Recession, we still perform two additional robustness exercises to account for the fact that the small policy differences across states that did occur may have discouraged labor supply. First, when using our full time period, we exclude any state that had less than 85 weeks of unemployment benefit extensions leaving us with a sample of states that had essentially no remaining variation in unemployment benefit extensions. Given that the exclude states were small in population terms, such exclusion had essentially no effect on our estimates. Additionally, we re-estimate our key parameters using only data prior to 2010. Prior to 2010, the duration of extended unemployment benefits were the same across all states. We discuss these results below.

While we defend that OLS estimation of the above equation yields unbiased estimates of $\lambda$ and $\phi$ using cross state variation during the Great Recession, it is impossible to completely rule out that leisure shocks are causing some of the variation in state business cycles during this period. To further explore the robustness of our results, we also estimate IV specifications of the above equation. Following the work of many recent papers, including Mian and Sufi (2014), we use contemporaneous and lagged variation in local house prices as our instruments for local employment and price growth. The argument is that local house price variation during the 2007-2011 period (in our base specification) or during the 2007-2009 period (in our restricted specification) is orthogonal to movements in local leisure shocks. This seems like a plausible assumption for the 2007-2009 period as state policy changes did not occur prior to 2009. In the Online Appendix, we discuss the IV procedure in detail. We also show that contemporaneous housing price growth strongly predicts contemporaneous employment growth and lagged measures of housing growth predicts price growth. We find that IV and OLS estimates are very similar.

Before turning to the estimation, it is also worth discussing the no cross-state migration assumption that we have imposed throughout. If individuals were more likely to migrate out of poor performing states and into better performing states, our estimated labor supply elasticities from the state regression may be larger than the aggregate labor supply elasticity. While theoretically

\textsuperscript{34}In the Online Appendix, we also show that there was no systematic variation in state labor income tax rates during the 2007-2010 period. Additionally, we show that there was little state variation in Federal programs to help underwater homeowners (like HAMP) that occurred during the 2007-2010 period. The reason is that take up rates of the program during this time period were very low (with take up rates being essentially zero prior to 2010).

\textsuperscript{35}States also had some discretion as to whether they opted into the program. This explains why some states did not have the maximum weeks of unemployment benefits even when their unemployment rate was higher. We discuss these policies and how they varied across states in detail in the Online Appendix.
interstate migration could be problematic for our results, empirically it is not the case. 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 (Yagan 2014). This can be seen from Appendix Figure A1. Both the low level of inter-state migration and the fact that it is uncorrelated with employment growth during this period makes us confident that our estimated parameters of our local wage setting curve can be applied to the aggregate.

6.2 Estimates of $\lambda$ and $\phi$

Column 1 of Table 6 shows the estimates of our base OLS specification where we use all data from 2007-2011 and do not include any additional controls. Our base estimates are $b_1 = 0.69$ (standard error = 0.13) and $b_2 = 0.31$ (standard error = 0.08). As noted above, $b_1$ is $\lambda$ and $b_2$ is $\lambda/\phi$. Given our base estimates, the cross sectional variation in prices and wages implies a labor supply elasticity of 2.2. Standard macro models imply a labor supply elasticity of 2 to 4 based on time-series variation. The estimates from the cross-section of states are in-line with these macro time-series estimates. Our base estimate of $\lambda = 0.69$ suggests only a modest amount of wage stickiness. Perfectly flexible wages imply $\lambda = 1$ while perfectly sticky wages imply $\lambda = 0$. In other words, lagged wage growth predicts current wage growth conditional on current employment and price growth, but the effect is much less than one for one (as would be implied by perfectly sticky wages). Below, we show that similar regressions run on aggregate date yield much smaller estimates of $\lambda$ implying a greater amount of wage stickiness.

Columns 2 and 3 of Table 6 show a variety of robustness checks for our base estimates. In column 2 we include industry controls. Specifically, we include the share of workers in 2007 working in manufacturing occupations or in routine occupations. This allows us to proxy for different degrees of wage stickiness or different potential leisure shocks that are correlated with industrial mix. In column 3, we use the actual retail scanner data price index as opposed to the scaled price index representative of the composite local consumption good. Neither the inclusion of controls for local industry mix nor changing the scaling on local retail price variation affect our estimates of $\lambda$ and $\phi$ in any meaningful way. In columns 4 and 5, we re-estimate our base specification with and without industry controls using only data from 2007-2009 prior to the changes in national policy extending unemployment benefit duration. Again, our estimates $\lambda$ and $\phi$ remain 0.73 and 1.9, respectively. Finally, in columns 6 and 7, we show our IV estimates for the 2007-2011 period and the 2007-2009 period where we instrument local employment growth and local price growth with contemporaneous and one lag of local house price growth. Our estimates of $\lambda$ and $\lambda/\phi$ are 0.77 (standard error = 0.13) and 0.76 (standard error = 0.17) implying an estimated Frisch elasticity of 1.0.

Regardless of our specification we estimate labor supply elasticities of between roughly 1.0 and

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36 Additionally, we estimated our base specification excluding CA, NV, AZ, and FL. In both cases, our estimates were nearly identical to our base specification in column 1 of Table 3.
2.0. More importantly, all of our estimates imply a fair degree of wage flexibility with our estimates of $\lambda$ ranging from about 0.7 to 0.8. These results are consistent with the patterns shown in Figure 3 where local wages co-moved strongly with local employment during the Great Recession. The estimation that wages are fairly flexible is a key insight that is important for our main results in the next section and has broader implications for the literature. In the context of the methodology we presented in the previous section as well as our monetary union model, it is hard to get aggregate "demand" shocks to be the primary shock driving economic conditions during the Great Recession if wages are fairly flexible. In other words, if wages were sticky enough in the aggregate to have "demand" shocks be the primary driver of aggregate employment decline during the recent recession, we would not have observed wages moving as much as they did in the cross-section of states during the same time period.

To show the stark difference between local and aggregate estimates of wage stickiness, we use aggregate data on prices, nominal wages, and employment between 1976 and 2012. This is the same data that we will use in our SVAR estimation in the next section. Given the short time-series sample, power is an issue. However, across all specifications we explored, estimates of $\lambda$ using aggregate data ranged from about 0.4 to 0.6. These estimates are below the estimates of 0.7 to 0.8 using local variation. If aggregate leisure shocks occur along with shocks that shift labor demand, wages will appear sticky in the aggregate time-series. The assumption of no aggregate leisure shocks is a common one when estimating wage stickiness using aggregate data (see, for example, Christiano et al. (2015b)).

7 The US Great Recession: From Regional to Aggregate

The cross-regional facts presented above represent a puzzle. Aggregate nominal wages did not fall much (relative to trend) during the Great Recession. However, local nominal wages and employment were significantly, negatively correlated. Why did aggregate wages respond so little during the Great Recession while there was a strong relationship across states?

One potential explanation is that a series of shocks made aggregate employment fall. Some of these shocks put downward pressure on wages while others put upward pressure, thus making wages seem unresponsive. However, if the shocks putting upward pressure on wages were purely aggregate, they would be differentiated when considering variation across states—thus resulting in the observed negative correlation between employment and wages across states. Our methodology allows us to quantify the relative magnitudes of these shocks and to assess their contributions to the behavior of prices, wages and employment.

7.1 Findings in the Aggregate

We follow the procedure described in Section 5. We first estimate the VAR with two lags in aggregate employment growth, price growth and nominal wage growth via OLS equation by equation using annual data from 1976 to 2012. We obtain sample estimators of the covariance matrix
\[ \hat{V} = \frac{UU'}{\text{Years} \times \#\text{Variables} \times \#\text{Lags}} \] from reduced form errors \( U \).

We construct aggregate variables that are comparable to our regional measures. Given that our cross-sectional equations are estimated using annual data, we analogously define our aggregate data at annual frequencies. We use data from the CPI-U to create our measure of aggregate prices. Specifically, we take log-change in the CPI's between the second quarter of year \( t \) and \( t - 1 \) for our measure of \( p_t \). For \( n \), we use BLS data on the aggregate employment to population rate of all males 25-54. We choose this age range so as to abstract from the downward trend in employment rates due to the aging of the population over the last 30 years. Finally, we use data from the Current Population Survey (CPS), discussed above, to construct our aggregate composition adjusted wage measure. As with the CPI, we take the log-change in this wage measure between \( t \) and \( t - 1 \) for our measure of \( w_t \). For all data, we use years between 1976 and 2012.

Figures 4, 5, and 6 report the impulse response of aggregate employment, nominal wages and price growth to each of the shocks using our benchmark estimates for \( \lambda \) and \( \phi \) reported in column 1 of Table 6 (\( \lambda = 0.69 \) and \( \phi = 2.2 \)). Figure 4 shows their behavior after a one-standard deviation discount rate (\( \gamma \)). Qualitatively, after a discount rate shock both prices and employment increase sharply relative to trend while real wages decline slightly relative to trend. These results are identical to the theoretical predictions shown in Table 4. Figure 5 shows the impulse responses to a one-standard deviation productivity/markup (\( z \)) shock. Prices decrease on impact while employment increases sharply. Nominal wages, however, only decline slightly. Again, these predictions match the predictions of our simple theoretical model shown in Table 4. While both \( \gamma \) and \( z \) shocks increase employment, the \( \gamma \) shock puts upward pressure on prices while the \( z \) shock puts downward pressure on prices. Figure 6 shows the impulse response of employment, prices, and nominal wages to the leisure shock. Upon impact, the leisure shock reduces employment and prices while it increases wages. Again, these predictions match the predictions from the benchmark monetary union model.

We now turn to quantifying the contribution of each shock to explaining the behavior of the aggregate US economy during the Great Recession. To do so, we present the counterfactual cumulative response of each individual variable when we feed the VAR with the sequence of shock realizations between 2008 and 2012, one at a time. Our analysis suggests that "demand" shocks cannot be solely responsible for the employment decline during the Great Recession. If "demand" shocks (i.e., discount rate shocks) were solely responsible, price and wage inflation would have been lower. Instead a combination of "supply" shocks (i.e., productivity/markup and leisure shocks) explain the "missing price and wage deflation".

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37 We detrend all data when estimating the VAR. Specifically, we allow for a linear trend in the employment to population ratio between 1978 and 2007. For the price inflation rate and the nominal wage inflation rate, we use an HP filter (with a smoothing parameter of 100). Given that we detrend the data, our results are essentially unchanged when we use the employment to population ratio for all individuals as opposed to using it just for prime age males.

38 For the interested reader, the actual realizations of the shocks we estimate can be seen in Figure 7.

39 The robust growth in consumer prices during the recession is also viewed as a puzzle for those that believe that the lack of aggregate demand was the primary cause of the Great Recession. For discussions of the "missing deflation", see Hall (2011), Ball and Mazumder (2011), Stock and Watson (2012), and Del Negro et al. (2015).
Figure 8 presents the counterfactual employment response. Employment fell by more than 4 percent between 2008-2009 (relative to trend) and remained at this low level thereafter. The counterfactual exercise shows that the productivity/markup, discount rate, and leisure shocks contributed about the same amount to the initial decline during the 2008-2009 period (each explaining roughly one-third of the aggregate employment decline). However, the discount rate and leisure shocks do not explain any of the persistence in the employment decline post 2009. Instead, it is the productivity/markup shock that explains most of the sluggish response of employment post 2009.

Figures 9 and 10 help understand the "missing price and wage deflation puzzle". Figure 9 shows the counterfactual price response to each of the shocks. Aggregate prices fell relative to trend between 2008 and 2009 and quickly stabilized thereafter despite the weak employment situation post-2009. This is the sense in which there was "missing price deflation". Both the discount rate and the leisure shock put downward pressure on aggregate prices. However, the productivity/markup shock put upward pressure on aggregate prices. The counterfactual analysis shows that if the economy had only been hit by the productivity/markup shock, prices would have risen (by upwards of 1 percent) relative to trend during the Great Recession. Instead, we find that it is this countervailing productivity/markup shock that arises as the explanation for the missing deflation puzzle—particularly post 2009. This finding is consistent with the results of Christiano et al. (2015a).

Figure 10 shows the cumulative nominal wage response to each of the shocks. Again, the figure shows the "missing wage deflation puzzle" during the Great Recession. Throughout the recession, nominal wage growth was close to zero (relative to trend). However, if the economy had only experienced the discount rate shock, nominal wages would have fallen by roughly 1.5 percent relative to trend by 2009 and would have remained below trend in 2011. It is the leisure and productivity/markup shocks that explain why nominal wages did not fall during the Great Recession.

7.2 Sensitivity to Alternative Parameters $\lambda$ and $\phi$

How do our estimated parameters affect our employment, price and wage counterfactuals? In Table 7, we report the contribution of each shock to aggregate employment declines implied by different combinations of $\{\phi, \lambda\}$. We do this for both the initial years of the recession (2008 to 2009) and over the longer period encompassing the recovery (2008 to 2012). Each cell in Table 7 shows how much of the employment change during the time period can be attributed to the discount rate shock ($\gamma$) and how much can be explained by the productivity/markup shock ($z$). The sum of all three shocks sums to 100 percent. So, the difference between the sum of the $\gamma$ and $z$ contributions and 100 percent is attributed to the leisure shock ($\epsilon$). The qualitative conclusions of the previous section still hold for the range of $\{\phi, \lambda\}$ estimates in Table 6. These go from roughly 0.7 to 0.8 for $\lambda$ and from roughly 1.0 to 2.5 for $\phi$.

Table 7 offers several further results worth discussing. First, we observe that the relative importance of the leisure shock vis-a-vis the discount rate and productivity/markup shocks combined is governed by the Frisch labor supply elasticity ($\phi$). We estimate a relatively large elasticity, in the
range of that used to calibrate standard macro models. However, suppose we used a much lower elasticity instead, e.g., $\phi = 0.5$, which is in line with some microeconomic estimates in the literature. In this case, the leisure shock would account for a much larger fraction of the employment decline in the Great Recession. In other words, if labor supply is fairly elastic, large movements in employment are consistent with relatively small movements in real wages (as we observe in US data), without the need of large leisure shocks. While this sensitivity analysis results from re-estimating the shocks under different parameterizations for $\phi$ using our procedure, the intuition is in line with the benchmark monetary union model from Section 4.

The intuition for the decomposition between discount rate and productivity/markup shocks is more subtle but also in line with the our benchmark monetary union model. We find that the degree of wage flexibility ($\lambda$) affects their relative contribution to the remaining, unexplained part by the leisure shock alone. For example, if we increased the degree of wage flexibility, the productivity/markup shock would account for a much larger fraction of the employment decline in the Great Recession. Theoretically, it is clear that when $\lambda$ is large, the discount rate shock should not matter much for the determination of employment. To see this, consider the extreme case where wages are perfectly flexible and the discount rate shock is only composed of the monetary shock. Then the equilibrium in the simple theoretical model satisfies monetary neutrality. We formalized this point in Section 4.6 when we derived the model’s implied elasticity of aggregate employment to a discount rate shock. Conversely, when wages are very rigid ($\lambda = 0.1$), our procedure suggest that discount rate shocks explain essentially all of the decline in the early part of the recession and much of the persistence in employment decline during the 2008-2012 period.

### 7.3 Sensitivity to Alternative Identifying Assumptions

The above results are based on the particular functional form of our wage setting equation:

$$W_{kt} = (P_{kt}e^{\epsilon_{kt}} (N_{kt})^{\frac{\phi}{2}} \lambda (W_{kt-1})^{1-\lambda})$$

This wage setting equation reflects our assumption of GHH preferences as well as no forward looking behavior when wages are reset. Both of these assumptions were made for tractability. In this sub-section, we explore the sensitivity of our results to relaxing both of these assumptions.

In Appendix B1, we derive the aggregate and local wage setting equations under a broad set of utility functions where consumption and leisure are non-separable. This class of utility functions

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40 This result may be of independent interest to the reader familiar with the macro v. micro labor supply elasticities (see Chetty, Guren, Manoli, and Weber (2011)). Using cross-sectional data (same as in most of the micro labor-supply elasticity literature) we arrive at an estimate similar to the macro elasticity (estimated from aggregate time-series data). We believe this is because the regional variation in employment rates that we use to estimate this elasticity only incorporates the extensive margin adjustment in the labor supply, which is the same margin that is most important in accounting for aggregate fluctuations in total hours over the business cycle.

41 It is worth mentioning that for large values of $\lambda$ and small values of $\phi$, the results in Table 2 become rather sensitive to small variations in parameters. This is because our shock identification procedure needs a certain degree of wage stickiness, as explained in the Section 5. For example, for values of $\lambda$ around 0.95 it is not possible to identify the productivity/markup and discount rate shocks.
allows for arbitrarily large income and substitution effects. As we show in the appendix, the use of local consumption data allows us to estimate the extent of wage stickiness as well as to estimate the parameters that encompass both the income and substitution effects on labor supply. In particular, we can estimate the following equation using local data:

\[ \pi_{kt} = \tilde{b}_t + \tilde{b}_1 \pi_{kt} + \tilde{b}_2 (n_{kt} - n_{kt-1} + \tilde{b}_3 \pi_{kt-1} + \tilde{b}_4 (c_{kt} - c_{kt-1}) + \Psi D_t + \Gamma X_k + e_{kt}. \]

This equation is identical to our estimating equation above aside from the addition of local consumption growth (i.e., \( c_{kt} - c_{kt-1} \)). As outlined in Appendix B1, the coefficients \( \tilde{b}_1 \) and \( \tilde{b}_3 \) sum to 1 even under the broader preference specification. We impose this restriction when estimating the modified equation. We measure local real consumption growth using the log-change in real retail expenditures at the state level computed within the Nielsen sample. We obtain real expenditures by deflating nominal expenditures with our local price indices. For our base specification, our estimates of \( \tilde{b}_1, \tilde{b}_2, \) and \( \tilde{b}_4 \) are 0.72 (standard error = 0.12), 0.25 (standard error = 0.08), and 0.16 (standard error = 0.06), respectively. A positive and significant coefficient on real consumption growth (\( \tilde{b}_4 \)) reflects the presence of income effects on labor supply. Controlling for this income effect, our estimate of wage flexibility (\( \tilde{b}_1 \)) is slightly higher than our base specification where income effects are not allowed.

In the aggregate wage setting equation, we can substitute out consumption growth using the model definition (\( c_t = w_t + n_t - p_t \)). Appendix B1 shows that the aggregate wage setting equation still takes the following form:

\[ \pi_{it} = \lambda \pi_t + \frac{\lambda}{\phi} (n_t - n_{t-1}) + (1 - \lambda) \pi_{it-1} + \frac{\lambda}{1 - \omega} e_t \]

where \( \omega \) is a parameter that represents the strength of the income effect on labor supply (and maps directly to \( \tilde{b}_4 \) from the above local labor supply regression, see equation (5) in Appendix B1). Aside from the coefficient scaling the aggregate leisure shock, this equation is identical to the identification restriction we imposed when estimating the aggregate SVAR. The only difference is that there is no longer a direct mapping between \( \lambda \) and \( \lambda/\phi \)—in the above aggregate wage setting equation that we impose to identify the SVAR—and the reduced-form parameters \( \tilde{b}_1 \) and \( \tilde{b}_2 \)—in the local wage setting equation. However, as shown in Appendix B1, there is still a one-to-one mapping between the parameters we estimate from the local regression (\( \tilde{b}_1, \tilde{b}_2, \) and \( \tilde{b}_4 \)) and the aggregate parameters we need to identify the SVAR (\( \lambda \) and \( \phi \)). With the correctly specified \( \lambda \) and \( \phi \), we can just use the matrix in Table 7 to read off the decomposition of shocks during the Great Recession. While \( \lambda \) and \( \phi \) are no longer structural parameters (instead being combinations of structural parameters), knowing them still helps identifying the aggregate SVAR. Using our estimates of \( \tilde{b}_1, \tilde{b}_2, \) and \( \tilde{b}_4 \) and the procedure developed in Appendix B1, we estimate \( \lambda \) and \( \phi \) (allowing for income effects on labor

---

42 This measure of real expenditures is (1) highly correlated with measures of local employment and (2) highly correlated with the BEA’s recent state level personal expenditures measure. Our results are similar if we use the BEA’s local consumption measure. However, we prefer our measure given that much of the BEA’s local consumption measure is imputed (where the imputation uses local employment measures).
supply) to be 0.68 and 2.0, respectively. These parameters are nearly identical to our base specification without income effects. The take-away from this sensitivity exercise is that abstracting from income effects on labor supply is not biasing our decomposition of the shocks driving aggregate employment declines during the Great Recession in any meaningful way.

In Appendix B2, we specify an alternative wage setting equation allowing for forward looking behavior when wages are reset. We show that ignoring forward looking wage setting behavior biases up our estimates of wage flexibility. That is, the amount of wage flexibility that we estimate using cross-state variation is too large relative to the true amount of wage flexibility in the aggregate. We show that the bias depends on two parameters: (1) the extent to which firms put weight on forward looking behavior when setting wages (which we call $\kappa$) and (2) the underlying persistence process of local wages (which we call $\bar{\rho}_w$). Assuming that at the aggregate level the monetary authority wants to stabilize expected nominal wage growth, we quantify the extent to which our estimates of $\lambda$ from the local regressions are biased upwards as a function of these two parameters. Under a range of plausible parameter estimates for $\kappa$ and $\bar{\rho}_w$, we show that the bias is quite small. For our baseline parameter estimates, we show that $\kappa(1 - \bar{\rho}_w)$ must exceed 2.5 for the true $\lambda$ to be lower than 0.4. This is an order of magnitude larger than any plausible parametrization for either $\kappa$ or $\bar{\rho}_w$. Moreover, as seen in Table 7, our estimates of the role of demand shocks in explaining employment decline during the Great Recession are broadly similar for values of $\lambda$ between 0.4 and 0.69. These results suggest that our abstraction from including expectations in our wage setting equation is not quantitatively altering the paper’s conclusions.

7.4 Discussion: Aggregate v. Regional Shock Decomposition

The above results suggest that aggregate wages appeared sticky during the Great Recession because a combination of aggregate shocks resulted in relatively offsetting effects on aggregate wages. By extending our procedure to allow for the estimation of regional shocks in a regional SVAR, we find that that the discount rate shock explains roughly 80 percent of the change in non-tradable employment between 2007 and 2010 across states. This is consistent with results found in Mian and Sufi (2014) suggesting that housing price declines explained much of the cross-state variation in non-tradable employment. We conclude that even though discount rate shocks only explained a portion of aggregate employment decline early in the Great Recession and very little of its persistence, the discount rate shock was primarily responsible for much of the cross-state variation during this time period.

We relegate the discussion of the estimation procedure and identification assumptions to the Online Appendix—given that the estimation of regional shocks is not central to the paper. However, this exercise allow us to highlight the difficulty in extrapolating findings from cross-region variation to interpret aggregate time-series patterns. The fact that local discount rate shocks explain much of the cross-state variation in employment during the Great Recession does not imply that an aggregate discount rate shock explains much of the aggregate time-series variation in employment during the Great Recession. If the discount rate shock would have been the main driver of aggregate em-
ployment decline during the Great Recession then aggregate wages would have behaved similarly to state-level wages.

8 Conclusion

Regional business cycles during the Great Recession in the US were strikingly different than their aggregate counterpart. This is the cornerstone observation on which we built this paper. Yet, the aggregate US economy is just a collection of these regions connected by trade of goods and assets. We argued that their aggregation cannot be arbitrary and that regional business cycle patterns have interesting implications for aggregate business cycles.

Our paper offers four takeaways. The first is that the relationship between wages and employment in the aggregate time-series during the 2006-2011 period is very different than the cross-state relationship between these variables during the same time period. For example, while aggregate wages appeared to be sticky despite aggregate employment falling sharply, both local nominal and real wages co-varied strongly with local employment growth in the cross-section of US states. Both documenting the regional facts and the creation of the underlying local price and wage indices are the first innovations of the paper.

The second take-away is that wages seem to be modestly sticky when using cross-state variation to estimate our wage setting equation. The amount of wage stickiness is often a key parameter in many macro models. Despite its importance, there are not many estimates of the frequency with which wages adjust (particularly relative to estimates of price adjustments). We develop a procedure to estimate the amount of wage stickiness using cross-region variation. The wage stickiness parameter is key to our empirical methodology to estimate the underlying shocks and elasticities. The fact that we estimate that wages are only modestly sticky limits the importance of "demand" shocks at the aggregate level in explaining the Great Recession. If wages are only modestly sticky, aggregate demand shocks should have resulted in falling aggregate wages—which was not observed in the aggregate time-series. Regardless of the use of this parameter in our empirical work, our estimate of wage stickiness could be of independent interest to researchers.

The third take-away from this paper is developing a methodology that allows us to estimate aggregate shocks by combining aggregate and regional data. This methodology is a hybrid method that merges restrictions imposed by a theoretical model with aggregate and cross-sectional data when estimating a SVAR and identifying the corresponding shocks. We view this as a contribution to the growing literature that uses model-based structure to estimate SVARs.

Finally, the fourth take-away is perhaps the most important for the goals of the paper. We show that a combination of both "demand" and "supply" shocks are necessary to account for the joint dynamics of aggregate prices, wages and employment during the 2007-2012 period in the US. In contrast with the aggregate results, we find that discount rate shocks explain most of the observed employment, price and wage dynamics across states. These results suggest that solely using cross-region variation to explain aggregate fluctuations is insufficient when some shocks do not have a
substantive regional component. The fact that aggregate wages did not fall cannot be explained by large degrees of wages stickiness. The reason aggregate wages did not fall is that the series of shocks experienced by the aggregate economy were such that some shocks put downward pressure on prices and wages (discount rate shocks) while other shocks put upward pressure on prices and wages (productivity/markup and leisure shocks). In the cross-section, however, the discount rate shocks caused prices, wages and employment to move in the same direction. Lastly, in our calibrated monetary union model, we show that the local employment elasticity to a local discount rate shock is substantially larger than the aggregate employment elasticity to an identically-sized aggregate discount rate shock. These results suggest that even when the aggregate and regional shocks are the same, it is hard to draw inferences about the aggregate economy using regional variation. Collectively, our results suggest that researchers should be cautious when extrapolating cross-sectional variation to make statements about aggregate business cycles.
References


Appendix A  Proof of Lemma 1 and 2

The following equations characterize the log-linearized equilibrium

\[
\begin{align*}
\kappa_{kt} &= \lambda (\epsilon_{kt} + \frac{1}{\phi} n_{kt}) + (1 - \lambda) (\kappa_{kt-1} - \pi_{kt}) \\
\kappa_{kt}^r &= -(1 - (\alpha + \theta \beta)) n_{kt}^r - \beta (1 - \theta) (n_{kt}^x - n_{kt}^y) + z_{kt}^r + \beta z_{kt}^x \\
0 &= E_t \left[ \mu_{kt+1} - \mu_{kt} - \pi_{kt+1} - \gamma_{kt+1} - \Phi_0 (c_{kt} - c_t) + \varphi_p \pi_t + \varphi_y (c_t - c_t^y) \right] \\
\mu_{kt+1} &= -\frac{\sigma}{C - \frac{\phi}{1 + \phi} N^x \frac{1}{\phi}} \left( C (\kappa_{kt+1} + n_{kt+1}) - N^y \frac{1}{\phi} (1 + \phi) \kappa_{kt+1} + n_{kt+1} \right) \\
N n_{kt} &= N^x n_{kt}^x + N^y n_{kt}^y \\
c_{kt} &= \kappa_{kt}^r + n_{kt}^y \\
b_{kt} &= (1 + r) (b_{kt-1} + i_t) + \frac{X}{B} (z_{kt}^x + \theta n_{kt}^x - x_{kt}) - r \tau_t \\
0 &= z_{kt}^x - (\kappa_{kt}^r - q_t) - (1 - \theta) n_{kt}^x \\
x_{kt} &= n_{kt}^y + (w_{kt} - q_t) \\
\sum_k x_{kt} &= \sum_k (z_{kt}^x + \theta n_{kt}^x)
\end{align*}
\]

From the last 3 equations, after adding up, it holds that \(n_t^x = n_t^y\). Then the aggregate log-linearized equilibrium evolution of \(\{\pi^w_t, \kappa^r_t, n_t\}\) is characterized by

\[
\begin{align*}
0 &= E_t (\mu_{t+1} - \mu_t - \pi_{t+1} - \gamma_{t+1}) + \varphi_p E_t [\pi_{t+1}] + \varphi_y (\kappa^r_t + n_t) \\
\pi^w_t &= \frac{\lambda}{1 - \lambda} (\epsilon_t + \frac{1}{\phi} n_t - \kappa^r_t) \\
\kappa^r_t &= -(1 - (\alpha + \theta \beta)) n_t + z_t \\
\mu_{t+1} &= -\frac{\sigma}{C - \frac{\phi}{1 + \phi} N^x \frac{1}{\phi}} \left( C (\kappa^r_{t+1} + n_{t+1}) - N^y \frac{1}{\phi} (1 + \phi) \kappa^r_{t+1} + n_{t+1} \right) \\
\pi_{t+1} &= \pi^w_{t+1} - (\kappa^r_{t+1} - \kappa^r_t)
\end{align*}
\]

which is equivalent to the system of equations characterizing the log-linearized equilibrium in a representative agent economy with a production technology that utilizes labor alone with an elasticity of \(\alpha + \theta \beta\), no endogenous discounting and only 3 exogenous processes \(\{z_t, \epsilon_t, \gamma_t\}\). The top equation is the aggregate Euler equation. The second equation is the aggregate wage setting equation. The third equation is effectively the aggregate labor demand curve.

To prove Lemma 2, just take log-deviations from the aggregate in the original system. This
results in the system characterizing the evolution of \( \{ \bar{p}_t, \bar{w}_t, \bar{n}_t^x, \bar{n}_t^y \} \) for given \( \{ \bar{z}_t^x, \bar{z}_t^y, \bar{\gamma}_t, \bar{\epsilon}_t \} \),

\[
\bar{w}_t = \lambda \left( \bar{p}_t + \bar{\epsilon}_t + \frac{1}{\phi} \left( \frac{N^x}{N} \bar{n}_t^x + \frac{N^y}{N} \bar{n}_t^y \right) \right) + (1 - \lambda) \bar{w}_{t-1}
\]

\[
\bar{w}_t = \bar{p}_t - (1 - (\alpha + \theta \beta)) \bar{n}_t^y - \beta (1 - \theta) (\bar{n}_t^x - \bar{n}_t^y) + \bar{z}_t^y + \beta \bar{z}_t^x
\]

\[
\bar{w}_t = \bar{z}_t^x - (1 - \theta) \bar{n}_t^x
\]

\[
0 = \mathbb{E}_t \left( \bar{m}_{u_{t+1}} - \bar{m}_{u_t} - (\bar{p}_{t+1} - \bar{p}_t) \right) - \Phi_0 (\bar{w}_t - \bar{p}_t + \bar{n}_t^y) - \bar{\gamma}_t + 1
\]

\[
\bar{m}_{u_{t+1}} = -\frac{\sigma}{C - \frac{\phi}{1 + \phi} N^{1+\phi}} \left( C (\bar{w}_{t+1} - \bar{p}_{t+1} + \bar{n}_{t+1}^y) - N^{1+\phi} \left( \frac{1 + \phi}{\phi} \bar{\epsilon}_{t+1} + \left( \frac{N^x}{N} \bar{n}_{t+1}^x + \frac{N^y}{N} \bar{n}_{t+1}^y \right) \right) \right)
\]

\[
\bar{b}_t = (1 + r) \bar{b}_{t-1} + \frac{X}{B} (\bar{n}_t^x - \bar{n}_t^y)
\]

This system is identical to the original where we have set \( i_t = q_t = 0 \) and dropped the market clearing condition in the intermediate goods market.

### Appendix B Alternative wage setting specifications

#### Appendix B.1 Preferences with wealth effects in labor supply

In our benchmark specification for the wage setting equation we assumed that the marginal rate of substitution between consumption and hours worked is independent of consumption (as is the case with GHH preferences). In this section we explore the consequences of moving away from this assumption for our econometric procedure in Section 5. For a general set of preferences represented by \( u(c, n) \), we can write the marginal rate of substitution in log-deviations from steady state as,

\[
mrs_{kt} = \left( \frac{u_{ct}}{u_n} - \frac{u_{cc}}{u_c} \right) c_{kt} + \left( \frac{u_{nt}}{u_n} - \frac{u_{nc}}{u_n} \right) n_{kt}
\]

\[
\equiv \omega c_{kt} + \left( \omega + \frac{1}{\phi} \right) n_{kt}
\]

which nest the special case with no wealth effects (\( \omega = 0 \)) and so we obtain the marginal rate of substitution from our benchmark specification. The aggregate and state level wage setting equations become,

\[
\pi_t^w = \lambda (\pi_t + \epsilon_t - \pi_{t-1}) + \left( \frac{1}{\phi} + \omega \right) (n_t - n_{t-1}) + \omega (c_t - c_{t-1}) + (1 - \lambda) \pi_{t-1}^w
\]

\[
\bar{w}_{kt} = \lambda (\bar{p}_{kt} + \epsilon_{kt} + \left( \frac{1}{\phi} + \omega \right) \bar{n}_{kt} + \omega \bar{c}_{kt}) + (1 - \lambda) \bar{w}_{kt-1}
\]

Replacing aggregate consumption with the model implied \( \bar{w}_t + n_t - p_t \) we obtain

\[
\pi_t^w = \lambda \pi_t + \frac{\lambda}{\phi} (n_t - n_{t-1}) + (1 - \lambda) \pi_{t-1}^w + \frac{\lambda}{1 - \omega} (\epsilon_t - \epsilon_{t-1})
\]

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where \( \lambda \equiv \frac{\lambda(1-\omega)}{1-\lambda\omega} \) and \( \frac{1}{\phi} \equiv \frac{1}{\lambda + 2\omega} \). Also, we can re-write the state level equation as

\[
\tilde{w}_{kt} = \lambda \tilde{p}_{kt} + \frac{\lambda}{\phi} \tilde{n}_{kt} + (1 - \lambda)\tilde{w}_{kt-1} + \frac{\lambda \omega}{1 - \omega} (\tilde{p}_{kt} + \tilde{c}_{kt} - (\tilde{w}_{kt} + \tilde{n}_{kt})) + \frac{\lambda}{1 - \omega} \tilde{\epsilon}_{kt}
\] (5)

Since state level economies are open economies, in general, the term \( \tilde{p}_{kt} + \tilde{c}_{kt} - (\tilde{w}_{kt} + \tilde{n}_{kt}) \) will be different from zero. By omitting it in our cross-sectional regressions we could be obtaining biased estimates of \( \lambda, \phi \).

### Appendix B.2 Forward looking wages

In our benchmark specification for the wage setting equation we assumed that there was no forward looking term in the target wage. In this section we explore the consequences of having a forward looking component in the wage setting equation for our econometric procedure in Section 5. In particular, consider the aggregate and state level wage setting equations

\[
\pi^w_t = \lambda (\pi_t + \epsilon_t - \epsilon_{t-1} + \frac{1}{\phi} (n_t - n_{t-1})) + \lambda \kappa \mathbb{E}_t[\pi^w_{t+1}] + (1 - \lambda) \pi^w_{t-1}
\]

\[
\tilde{w}_{kt} = \lambda (\tilde{p}_{kt} + \tilde{c}_{kt} + \frac{1}{\phi} \tilde{n}_{kt}) + \lambda \kappa \mathbb{E}_t[\tilde{w}_{kt+1} - \tilde{w}_{kt}] + (1 - \lambda) \tilde{w}_{kt-1}
\]

where \( \kappa \) parameterizes the importance of the forward looking term. Also, let’s consider the case where local wages follow an AR(1) process in equilibrium with coefficient \( \tilde{\rho}_w \) and aggregate expected wage inflation is zero. Our model from Section 4, would imply this, for instance, when \( \theta \to 1 \) so that \( \tilde{w}_{kt} = \tilde{x}_{kt}^w \) in equilibrium and \( \tilde{\rho}_w = \rho_x \); and the monetary authority fully stabilizes expected aggregate nominal wage growth. We obtain,

\[
\pi^w_t = \lambda (\pi_t + \epsilon_t - \epsilon_{t-1} + \frac{1}{\phi} (n_t - n_{t-1})) + (1 - \lambda) \pi^w_{t-1}
\]

\[
\tilde{w}_{kt} = \frac{\lambda}{1 + \lambda \kappa (1 - \tilde{\rho}_w)} (\tilde{p}_{kt} + \tilde{c}_{kt} + \frac{1}{\phi} \tilde{n}_{kt}) + \frac{1 - \lambda}{1 + \lambda \kappa (1 - \tilde{\rho}_w)} \tilde{w}_{kt-1}
\]

Then, we can write,

\[
\lambda = \frac{1 - \beta_w}{1 + \beta_w \kappa (1 - \tilde{\rho}_w)}
\]

where \( \beta_w \equiv \frac{1 - \lambda}{1 + \lambda \kappa (1 - \tilde{\rho}_w)} \). From this expression we see that our estimates for \( \lambda \) using cross-state variation are upward biased. However, we can get a notion on the magnitude of the bias by asking what would \( \kappa (1 - \tilde{\rho}_w) \) have to be in order for \( \lambda \) to be less than some \( \lambda_0 \). We obtain,

\[
\kappa (1 - \tilde{\rho}_w) > \frac{1 - \beta_w - \lambda_0}{\beta_w \lambda_0}
\]

For example, given our lower estimate for \( \beta_w = 0.5 \), in order for \( \lambda \) to be below 0.1 we would need a \( \kappa (1 - \tilde{\rho}_w) \) larger than 8.
Figure 1: Nielsen Retail Price Index vs. CPI Food Price Index

Note: In this figure, we compare our monthly retail scanner price index for the U.S. as a whole (dashed line) to the CPI’s aggregate monthly food price index (solid line). We normalize both indices to 1 in January of 2006.

Figure 2: The Evolution of Aggregate Real and Nominal Composition Adjusted Wages

Note: Figure shows the evolution of aggregate real and nominal log wages within the U.S. between 2000 and 2012 using data from the Current Population Survey. The sample is restricted to only males between the ages of 21 and 55, who are currently employed, who report usually working 30 hours per week, and who worked at least 48 weeks during the prior 12 months. As discussed in the text, we adjust wages for the changing labor market condition over time by controlling for age, race, education, and usual hours worked. We compute real wages by deflating our nominal wage index by the CPI-U of the corresponding year.
Figure 3: State Employment Growth vs. State Nominal and Real Wage Growth, 2007-2010

Note: Figure shows a simple scatter plot of the percent growth in the state employment rate between 2007 and 2010 against nominal wage growth (left panel) and real wage growth (right panel) during the same period. The state employment rate comes dividing state employment from the BLS by total state population from the BLS. Nominal wages are computed from the ACS and are adjusted for the changing labor market composition of workers within each state over time. We restrict wage measures to a sample of men between the ages of 21 and 55 with a strong attachment to the labor market. Our composition adjustment controls for age, education, race, nativity and usual hours worked. See text for details. To compute real wages, we adjust our nominal wage measures by our local price indices created using the retail scanner data. The size of the underlying state is represented by the size of the circle in the figure. The line represents a weighted regression line from the bi-variate regression.
Figure 4: Impulse Response to a Discount rate Shock

Note: Figure shows the impulse response to a one standard deviation discount rate shock. The horizontal axis are years after the shock.

Figure 5: Impulse Response to a Productivity / Markup Shock

Note: Figure shows the impulse response to a one standard deviation productivity/markup shock. The horizontal axis are years after the shock.
Figure 6: Impulse Response: Leisure Shock

Note: Figure shows the impulse response to a one standard deviation leisure shock. The horizontal axis are years after the shock.

Figure 7: Shock time-series

Note: Figure shows the estimated aggregate shock realizations from 1980 to 2012.
Figure 8: Counterfactual Employment Response

Note: Figure shows the cumulative response of employment when we feed the VAR with the sequence of shocks between 2008 and 2012; one at a time.

Figure 9: Counterfactual Price Response

Note: Figure shows the cumulative response of Prices when we feed the VAR with the sequence of shocks between 2008 and 2012; one at a time.
Figure 10: Counterfactual Wage Response

Note: Figure shows the cumulative response of Wages when we feed the VAR with the sequence of shocks between 2008 and 2012; one at a time.

Figure A1: State Net Migration Rate 2009-2010 vs. State Employment Growth 2007-2010

Note: Figure shows state net migration rate between 2009 and 2010 against employment growth in the state during 2007-2010. Employment growth comes from the BLS and is defined in the text. State net migration rates come from American Community Survey.
Table 1: Comparison of Cross-State and Time-Series Estimates of Wage Elasticities During the Great Recession

<table>
<thead>
<tr>
<th></th>
<th>Employment Rate</th>
<th>Nominal Wage</th>
<th>Real Wage</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Cross-State</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cross-State Wage Elasticity With Respect to Employment, 2007-2010</td>
<td>0.62 (0.10)</td>
<td>0.52 (0.15)</td>
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</tr>
<tr>
<td><strong>Aggregate</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Actual Aggregate Growth, 2007-2010</td>
<td>-7.7 percent</td>
<td>3.8 percent</td>
<td>-0.9 percent</td>
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<tr>
<td>Expected Aggregate Growth, 2007-2010 (Based on 2000-2007 Trend)</td>
<td>-0.9 percent</td>
<td>5.5 percent</td>
<td>-2.1 percent</td>
</tr>
<tr>
<td>Aggregate Deviation from Expected Growth, 2007-2010</td>
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<td>-1.7 percent</td>
<td>1.2 percent</td>
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<tr>
<td>Aggregate Wage Elasticity With Respect to Employment, 2007-2010</td>
<td>0.25</td>
<td>-0.17</td>
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</table>

Note: Table compares the wage elasticity to a one percent change in the employment rate estimated off of cross-state data (top panel) to a similarly defined wage elasticity estimated off of aggregate time-series data during the 2007 to 2010 period (bottom panel). The cross-state elasticities come from the simple scatter plots shown in Figure 3. Standard errors from the regression line in the scatter plots are shown in parentheses. The aggregate time-series elasticity is computed using aggregate data. For the aggregate nominal wage data, we use the adjusted wage series we created using data from the CPS. See text for details. For aggregate real wages, we adjust the nominal wage data by the June CPI-U. To get predicted nominal and real wage growth between 2007 and 2010, we take a simple linear prediction of the corresponding nominal and real growth between the 2000 and 2007 period. Once we get the deviation between actual wage growth and predicted wage growth between 2007 and 2010, we divide that difference by -6.8 percent. -6.8 percent is the decline in the aggregate employment rate between 2007 and 2010 above and beyond what would have been predicted from changes in the employment rate between 2000 and 2007. We use aggregate data from the BLS to compute the employment rate in 2000, 2007 and 2010.
Table 2: Calibration

<table>
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<th>Value</th>
<th>Target</th>
<th>Target</th>
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<tr>
<td>$\alpha$</td>
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<td>Aggregate labor share in the non-tradable sector in 2006</td>
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<tr>
<td>$\theta$</td>
<td>0.55</td>
<td>Aggregate labor share in the tradable sector in 2006</td>
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<td>$\beta$</td>
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<td>Aggregate labor share in 2006 (0.61). See on-line appendix</td>
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<td>$\sigma$</td>
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<td>Intertemporal elasticity of substitution</td>
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<td>$\phi$</td>
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<td>Frisch elasticity. See Section 6.2 for estimation</td>
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<td>$\lambda$</td>
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<td>Wage stickiness. See Section 6.2 for estimation</td>
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<td>Taylor Rule from Galí (2011)</td>
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<tr>
<td>$\varphi_y$</td>
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<td>Taylor Rule from Galí (2011)</td>
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<tr>
<td>$\rho_y$</td>
<td>0.9</td>
<td>Persistence of discount rate shock</td>
</tr>
<tr>
<td>$\rho_z$</td>
<td>0.76</td>
<td>Persistence of productivity shock from the model. See on-line appendix</td>
</tr>
<tr>
<td>$\rho_\epsilon$</td>
<td>0.66</td>
<td>Persistence of leisure shock from the model. See on-line appendix</td>
</tr>
</tbody>
</table>

Table 3: Aggregate v. Regional Employment Impact Elasticities

<table>
<thead>
<tr>
<th>$\rho_y$</th>
<th>0.9</th>
<th>0.9</th>
<th>0.9</th>
<th>0.6</th>
<th>0.1</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta$</td>
<td>0.16</td>
<td>0</td>
<td>0.16</td>
<td>0.16</td>
<td></td>
</tr>
<tr>
<td>$\varphi_p$</td>
<td>1.5</td>
<td>1.5</td>
<td>1.5</td>
<td>1.31</td>
<td>1.5</td>
</tr>
<tr>
<td>$\varphi_y$</td>
<td>0.5</td>
<td>0.5</td>
<td>0</td>
<td>0.5</td>
<td></td>
</tr>
<tr>
<td>$(\lambda, \phi)$</td>
<td>(0.7,2)</td>
<td>(0.7,1)</td>
<td>(0.5,2)</td>
<td>(0.7,2)</td>
<td>(0.7,2)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Aggregate</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma$</td>
<td>0.77</td>
<td>0.53</td>
<td>1.29</td>
<td>0.74</td>
<td>1.11</td>
</tr>
<tr>
<td>$z$</td>
<td>0.29</td>
<td>0.20</td>
<td>-0.35</td>
<td>0.28</td>
<td>-0.24</td>
</tr>
<tr>
<td>$\epsilon$</td>
<td>-0.65</td>
<td>-0.51</td>
<td>-0.28</td>
<td>-0.69</td>
<td>-0.26</td>
</tr>
<tr>
<td>Regional</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\gamma$</td>
<td>1.76</td>
<td>1.26</td>
<td>2.95</td>
<td>2.85</td>
<td>1.76</td>
</tr>
<tr>
<td>$z^y$</td>
<td>0.44</td>
<td>0.38</td>
<td>-0.18</td>
<td>0.10</td>
<td>0.44</td>
</tr>
<tr>
<td>$z^x$</td>
<td>0.08</td>
<td>-0.06</td>
<td>0.23</td>
<td>0.05</td>
<td>0.08</td>
</tr>
<tr>
<td>$\epsilon$</td>
<td>-0.64</td>
<td>-0.52</td>
<td>-0.16</td>
<td>-0.43</td>
<td>-0.64</td>
</tr>
</tbody>
</table>

Note: The table summarizes the response of employment on impact to each of the model shocks under our base calibration (column 1) and alternate calibrations (columns 2-8). The rows represent the employment response to different aggregate shocks (top three rows) and different local shocks (bottom three rows). Columns 2 and 3, explore the elasticities under different calibrations of wage stickiness and the Frisch elasticity of labor supply. Column 4 examines the robustness to changes in the tradable share of the intermediate good. Columns 5 and 6 examine the results under alternate Taylor Rule parameters. The final two columns change the persistence of the demand shock. The units are percentage deviations from the steady state, in the case of aggregate employment, and percentage deviations from the aggregate in the case of regional employment.
## Table 4: Aggregate Elasticities ($\lambda=0.7$, $\phi=2$)

<table>
<thead>
<tr>
<th></th>
<th>$\gamma$</th>
<th>$\pi$</th>
<th>$\pi^w$</th>
<th>$w^r$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short run</td>
<td>0.77</td>
<td>1.64</td>
<td>1.42</td>
<td>-0.22</td>
</tr>
<tr>
<td></td>
<td>0.29</td>
<td>-2.73</td>
<td>-1.81</td>
<td>0.92</td>
</tr>
<tr>
<td></td>
<td>-0.65</td>
<td>0.94</td>
<td>1.13</td>
<td>0.19</td>
</tr>
<tr>
<td>Long run</td>
<td>0.56</td>
<td>1.01</td>
<td>1.03</td>
<td>-0.16</td>
</tr>
<tr>
<td></td>
<td>0.12</td>
<td>-0.66</td>
<td>-0.79</td>
<td>0.40</td>
</tr>
<tr>
<td></td>
<td>-0.18</td>
<td>0.35</td>
<td>0.32</td>
<td>0.05</td>
</tr>
</tbody>
</table>

Note: The table summarizes the response of each aggregate variable to the shocks in percentage deviations from the steady state. The "short" elasticity is the response at date $t = 0$. The "long" elasticity is the response after 5 years.

## Table 5: Regional Elasticities ($\lambda=0.7$, $\phi=2$)

<table>
<thead>
<tr>
<th></th>
<th>$\gamma$</th>
<th>$\pi$</th>
<th>$\pi^w$</th>
<th>$w^r$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short run</td>
<td>1.76</td>
<td>2.54</td>
<td>2.40</td>
<td>-0.14</td>
</tr>
<tr>
<td></td>
<td>0.44</td>
<td>-2.00</td>
<td>-1.25</td>
<td>0.75</td>
</tr>
<tr>
<td></td>
<td>0.08</td>
<td>0.29</td>
<td>0.31</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>-0.64</td>
<td>0.71</td>
<td>0.97</td>
<td>0.26</td>
</tr>
<tr>
<td>Long run</td>
<td>0.12</td>
<td>-0.28</td>
<td>-0.30</td>
<td>0.19</td>
</tr>
<tr>
<td></td>
<td>0.63</td>
<td>0.31</td>
<td>0.23</td>
<td>0.21</td>
</tr>
<tr>
<td></td>
<td>-0.06</td>
<td>-0.03</td>
<td>-0.04</td>
<td>0.04</td>
</tr>
<tr>
<td></td>
<td>-0.44</td>
<td>-0.12</td>
<td>-0.20</td>
<td>0.14</td>
</tr>
</tbody>
</table>

Note: The table summarizes the response of each island level variable to the shocks in percentage deviations from the steady state. The "short" elasticity is the response at date $t = 0$. The "long" elasticity is the response after 5 years.
Table 6: Estimates of $\lambda$ and $\frac{\lambda}{\phi}$ using Cross-Region Data

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(5)</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>0.69</td>
<td>0.69</td>
<td>0.75</td>
<td>0.73</td>
</tr>
<tr>
<td></td>
<td>(0.13)</td>
<td>(0.13)</td>
<td>(0.13)</td>
<td>(0.17)</td>
</tr>
<tr>
<td>$\frac{\lambda}{\phi}$</td>
<td>0.31</td>
<td>0.32</td>
<td>0.31</td>
<td>0.39</td>
</tr>
<tr>
<td></td>
<td>(0.08)</td>
<td>(0.08)</td>
<td>(0.07)</td>
<td>(0.09)</td>
</tr>
<tr>
<td>Implied $\phi$</td>
<td>2.2</td>
<td>2.2</td>
<td>2.4</td>
<td>1.9</td>
</tr>
<tr>
<td>Year Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Industry Controls</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Scaling Factor of Prices</td>
<td>1.4</td>
<td>1.4</td>
<td>1.0</td>
<td>1.4</td>
</tr>
</tbody>
</table>

Note: Table shows the estimates of $\lambda$ and $\frac{\lambda}{\phi}$ from our base wage setting specification using the regional data. Each observation in the regression is state-year pair. Each column shows the results from different regressions. The regressions differ in the years covered and additional control variables added. The first three columns show the OLS results using all local data between 2007 and 2011. Columns 4 and 5 show OLS results using only data from 2007 through 2009. The final two columns show IV results for the different time periods. In the IV specifications, we instrument contemporaneous employment and price growth with contemporaneous and lagged house price growth. We adjust for measurement error in wage growth, lagged wage growth, and price growth using the split sample methodology discussed in the Online Data Appendix. All regressions included year fixed effects. All standard errors are clustered at the state level.

Table 7: Discount/Interest rate ($\gamma$) and Productivity/Markup ($z$) shocks’ contribution to aggregate employment change

<table>
<thead>
<tr>
<th>$\lambda$</th>
<th>0.5</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\phi$</td>
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<tr>
<td>0.1</td>
<td>103</td>
<td>83</td>
<td>108</td>
<td>107</td>
<td>108</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>-3</td>
<td>22</td>
<td>-3</td>
<td>-1</td>
<td>-2</td>
</tr>
<tr>
<td>$z$</td>
<td>2</td>
<td>16</td>
<td>45</td>
<td>71</td>
<td>1</td>
</tr>
<tr>
<td>0.3</td>
<td>47</td>
<td>66</td>
<td>51</td>
<td>29</td>
<td>101</td>
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<tr>
<td>$\gamma$</td>
<td>2</td>
<td>16</td>
<td>45</td>
<td>71</td>
<td>1</td>
</tr>
<tr>
<td>$z$</td>
<td>2</td>
<td>16</td>
<td>45</td>
<td>71</td>
<td>1</td>
</tr>
<tr>
<td>0.5</td>
<td>8</td>
<td>36</td>
<td>31</td>
<td>13</td>
<td>92</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>6</td>
<td>16</td>
<td>48</td>
<td>74</td>
<td>0</td>
</tr>
<tr>
<td>$z$</td>
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<td>48</td>
<td>74</td>
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<td>21</td>
<td>11</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>3</td>
<td>33</td>
<td>33</td>
<td>53</td>
<td>69</td>
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<tr>
<td>$z$</td>
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<td>33</td>
<td>33</td>
<td>53</td>
<td>69</td>
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<tr>
<td>0.9</td>
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<td>0</td>
<td>0</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>$\gamma$</td>
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<td>54</td>
<td>64</td>
<td>69</td>
</tr>
<tr>
<td>$z$</td>
<td>-1</td>
<td>24</td>
<td>54</td>
<td>64</td>
<td>69</td>
</tr>
</tbody>
</table>

Note: Table shows the percent contribution of the demand and supply shocks to the aggregate employment change implied by our procedure for different combinations of the parameters. For a given pair $\{\phi, \lambda\}$, the ‘$\gamma$’ entry corresponds to the demand shock. The ‘$z$’ entry to the supply shock. The percent contribution of the leisure shock can be calculated by subtracting the sum of both entries from 100. Entries with * are such that no decomposition of the shocks satisfy the identification restrictions for those parameter values.