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# BUSINESS CYCLES AND HEALTHCARE EMPLOYMENT

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**ABSTRACT**

Is healthcare employment recession proof? We examine the hypothesis that healthcare employment is stable across the business cycle. We explicitly distinguish between negative aggregate demand and supply shocks in studying how healthcare employment responds to recessions, and show that this response depends largely on the type of the exogenous shock triggering the recession. We find that healthcare employment responds procyclically to demand-induced recessions; and the reduction is driven by layoffs and discharges rather than voluntary quits. In evaluating additional mechanisms, we find evidence of a reduction in real personal healthcare expenditures resulting from an adverse demand shock. By contrast, we find that healthcare employment is fairly stable and even responds countercyclically to supply-induced recessions, suggesting compositional changes such as downskilling particularly in nursing sectors. Our findings establish that employment responses during economic downturns are heterogeneous across healthcare sub-sectors. More generally, by isolating the impact of the structural demand shock from supply shock on healthcare employment, we provide new empirical evidence that healthcare employment is not recession proof.

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# I. Introduction

The simple scatter plots of unemployment rate and healthcare employment over the period 1990-2021 in the U.S. in Figure 1 show null or small positive co-movements. Does this indicate that healthcare employment remains stable during recessions? Does the healthcare sector enjoy insulation from the factors that cause other sectors to experience expansions and contractions? These questions are important, yet untapped in the literature. Although the business cycle literature confirms that employment across industries in general exhibit procyclical behavior during economic downturns, there is limited evidence on how employment in the healthcare industry react to economic downturns.[1] Understanding how the healthcare industry responds to macroeconomic conditions is important because staffing arrangements can affect the quality and cost of care (Cohen and Spector, 1996; Needleman et al., 2006, 2011; Lin, 2014), an issue that was explicitly magnified during the COVID-19 health crisis.

In this paper, we study the impact of recessions on healthcare employment caused by two fundamental sources of business cycle fluctuations: aggregate demand shocks and aggregate supply shocks.[2] We explicitly distinguish between a negative aggregate demand shock and a negative aggregate supply shock in studying how healthcare employment responds to recessions, and show that this response is heterogeneous across sub-sectors depending on the type of the exogenous shock hitting the economy. Specifically, we find evidence that healthcare employment is *not* recession proof during economic downturns caused by a negative aggregate demand shock.

Since the seminal work by Ruhm (2000) an extensive literature has studied the re-

[1] The amplitude and duration of the labor market response during business cycles varies across industries, demographic sub-groups, and geographies due to different degrees of labor market frictions and adjustment (Clark and Summers, 1980; Greenwald and Stiglitz, 1993; Kose, 2002; Wall and Zoega, 2003; Hoynes, Miller, and Schaller, 2012; Boz, Durdu, and Li, 2015; Bredemeier and Winkler, 2017; Bredemeier, Juessen, and Winkler, 2020; De et al., 2021).

[2] To make these shocks clear, examples of "aggregate demand shocks" include unexpected changes in income, consumer or producer sentiment/expectations or credit standards, while "aggregate supply shocks" can include things such as extreme weather shocks, war, labor strikes, productivity shocks, oil shocks, or any shock that affects the economy's contemporaneous ability to produce goods and services. According to a report released by St. Louis Fed, the COVID-19 pandemic features elements of both supply and demand shocks (Smith, 2020).

lationship between macroeconomic conditions and different health outcomes as well as health behavior (Ruhm, 2005, 2015; Tekin, McClellan, and Minyard, 2018; Peng, Chen, and Guo, 2022; Hollingsworth, Ruhm, and Simon, 2017; Currie, Duque, and Garfinkel, 2015; Carpenter, McClellan, and Rees, 2017; Charles and DeCicca, 2008; Lindo, 2015). However, a very small number of studies have explored the relationship between macroeconomic conditions and healthcare employment, in particular, the impact of recessions on healthcare employment (see, e.g., Dillender et al., 2021). This could be owing to the inherent complexities of the healthcare sector that can generate mixed responses during recessions. On the one hand, economic downturns and job losses as well as falling financial resources is expected to reduce the demand for healthcare (just like any other normal good) and lead to decrease in healthcare employment. This is in conformity with a procyclical response of employment in the healthcare sector (similar to other sectors of the economy) to business cycles. On the other hand, there are several features typical to the healthcare sector alone, which holds the ability to insulate the sector from business cycle fluctuations.

First, the healthcare labor market overall features extensive licensing that makes substitution of healthcare workers in response to cost pressures more difficult (Garber and Skinner, 2008). Second, in certain sectors like nursing, prior studies have shown evidence of labor substitution towards less skilled forms of labor or "downskilling" (Konetzka et al., 2018; Alameddine et al., 2012; Zabalegui and Cabrera, 2010; Heitlinger, 2003). Third, prior studies also document evidence that economic downturns can have negative effects on health outcomes such as mental health for certain sub-groups of the population (Charles and DeCicca, 2008; Tefft, 2011; Bradford and Lastrapes, 2014), which might also increase the demand for healthcare workers during recessions, especially in psychiatric or substance abuse treatment hospitals. Moreover, health insurance paying for a large fraction of the patients' out-of-pocket healthcare cost (a feature again typical of the healthcare industry) also makes their healthcare demand less price sensitive, though it might vary largely across different income groups (Manning et al., 1987). Even if individuals lose private insurance coverage during economic downturns, they can be eligible for public health insurance. These features can possibly explain why healthcare sector might react differently during recessions compared to other sectors. Ex ante, it is not clear whether or not employment in the healthcare sector should exhibit procyclical, countercyclical or acyclical response to business cycle fluctuations.

We are aware of only four studies in the literature that study the impact of business cycles on healthcare employment (Dillender et al., 2021; Konetzka et al., 2018; Chen, Sasso, and Richards, 2018; Stevens et al., 2015). These studies focus either on certain sub-sectors of the healthcare industry or a specific group of healthcare workers such as physicians. Further, all these studies do so using linear or multivariate regression models with variation in unemployment rate as their primary measure of recession.[3] Specifically, these models regress the share of employment in the healthcare sector on the local unemployment rate, after controlling for unit (often state or county) and year fixed effects, and find no effect (and in some cases positive effect) of recession on healthcare employment. This approach of identifying recessions and studying its impact on healthcare employment (or any sector of the economy) has its limitations for several reasons.

First, the existing approach relies on the assumption that variation in unemployment rate is an exogenous predictor of healthcare employment.[4] This assumption might be restrictive in the context of business cycles, since the time path of unemployment rate is affected by current and past realizations of itself as well as other macroeconomic indicators and vice-versa, i.e., there are contemporaneous feedback effects between macroeconomic indicators (Enders, 2008). Even if existing studies only establish association but not causality, it is still not clear what drives the underlying correlation and how to formally interpret it. Additionally, prior studies do not identify the types of exogenous structural shocks causing the economic downturn, and consequently the propagation mechanism of these shocks on the healthcare employment. For instance, economic downturns caused by demand side disturbances can have significantly different impact on healthcare em-

[3]This is also a conventional method in the papers that use health and health behaviors as a dependent variable.

[4]Note that there could be regional or other unit-level time-varying shocks that simultaneously affect healthcare employment and the unemployment rate. Including unit and time fixed effects alone is not typically sufficient to account for such shocks.

ployment from those caused by supply side disturbances or even credit shocks.

Business cycles have pervasive effects throughout the economy including output, employment, prices and other macroeconomic variables in response to different types of aggregate macroeconomic disturbances: demand shocks, supply shocks, monetary policy shocks, credit shocks, etc. We therefore rely on the conventional and popularly known class of time series models called vector autoregression models (VAR models) to study the impact of business cycles on healthcare employment, where the structure of the system can accommodate many macroeconomic indicators simultaneously and incorporate feedback between them, along with some theoretical assumptions to identify types of exogenous shocks hitting the economy and the use of monetary and/or fiscal policies to smooth or moderate the business cycle.

This study makes a number of important and novel contributions to the literature on recessions and U.S. healthcare employment. A novel contribution of our paper is the use of a structural factor-augmented vector autoregression (FAVAR) model to conduct this study, which is a more rigorous econometric framework than the standard VAR approach and allows for accurately capturing the propagation mechanism of structural shocks. The relatively small scale of the VAR models poses a question of whether or not all relevant information about the economy has been included in the analysis. It is well known that informationally deficient VARs can lead to bias in the transmission of shocks. FAVAR models allow for the study of economic concepts such as "economic activity", "price level" or "monetary conditions" that are imperfectly observable and may not be captured by single variables that are used in traditional VARs (Bernanke, Boivin, and Eliasz, 2005; Stock and Watson, 2016; Forni and Gambetti, 2014). Many alternative measures of these concepts are informative and the FAVAR framework provides an integrated approach for combining multiple data series through factor analysis. Bernanke, Boivin, and Eliasz (2005) further explain that combining multiple data series through factor analysis provides superior estimates of economic concepts as opposed to using single reported data series for each concept. While prior literature on recessions and U.S. healthcare employment has employed simple linear or multivariate regression models assuming exogeneity in unemployment variation, our data-rich structural FAVAR approach allows us to jointly model the interaction between the healthcare employment and U.S. macroeconomic conditions (from over a 100 variables reflecting economic activity, prices, and monetary policy) in studying the impact of recessions on healthcare employment.[5]

As discussed above, a key step in investigating the impact of recessions on healthcare employment lies in identifying structural macroeconomic shocks plausibly. We identify two fundamental sources of business cycle fluctuations: a negative aggregate demand shock and a negative aggregate supply shock using the pure sign restrictions approach standard in time series literature. We find that the response of employment in healthcare industry overall, as well as the different sectors and sub-sectors of healthcare industry to recession is significantly different (both qualitatively and quantitatively) from those found in the few previous studies, and depends largely on the type of the shock hitting the economy. This reinforces the importance of first identifying the type of macroeconomic shock correctly, and second conditioning the analysis on the true information set, thereby accounting for the full interaction between the healthcare employment and U.S. macroeconomic conditions when studying the transmission of macroeconomic shocks and impact of recessions on healthcare employment.

To the best of our understanding, our paper is the first in the literature to study the impact of recessions on healthcare employment using a macro-econometric structural FAVAR framework. By conditioning our analysis on the broad information set in one large dynamic common factor model and using the robust sign restrictions identification strategy, our study is able to accurately track the dynamic effects of a negative aggregate demand and supply shock separately on healthcare employment. Further, through variance decomposition, we are also able to assess the quantitative importance of demand

[5]We also conduct the robustness of our findings using a simple structural sign-identified VAR model for a system of variables including standard measurements of economic activity (national unemployment rate), price level (consumer price index), interest rate (federal funds rate), money supply (M2 money supply), and healthcare employment. Overall, qualitatively our robustness results support our main findings. However, quantitatively, the magnitude and persistence of the responses we find differ between the estimated FAVAR and VAR model. These differences therefore reinforce the importance of conditioning this sort of analysis on a broader/true information set and accounting for the full interaction between the U.S. macroeconomy, monetary policy, and healthcare employment when studying the transmission of structural shocks on healthcare employment. To conserve space, the robustness results are available upon request.

and supply shocks in driving labor market dynamics in U.S. healthcare industry.

Previewing our results, we find that a negative aggregate demand and supply shock have significantly different effects on healthcare employment, which again reinforces the need to distinguish between the type of shock causing the economic downturn. We find that overall employment in healthcare industry decline significantly in response to recessions caused by adverse demand side disturbances. Our results are in striking contrast to earlier studies, which find healthcare employment to remain stable during recessions. Additionally, we find strong heterogeneity in employment responses across different healthcare sub-industries (ambulatory healthcare services, hospitals, and nursing and residential care facilities as well as sub-sectors of those industries) in terms of the magnitude, direction, as well as the persistence of the impact. In particular, general medical and surgical hospitals experience the largest decline in employment, followed by other residential care facilities, as well as physicians' offices. We also explore the mechanisms behind our findings. We find that a negative aggregate demand shock slows down the economy causing recessions, and lessens the overall demand for healthcare services, thus leading to a decline in healthcare employment. The drop in healthcare employment, following an adverse demand shock is coming from an increase in "layoffs and discharges" and not voluntary labor market "quits". Our study documents robust evidence in favor of a labor demand channel of shock transmission on the healthcare sector during recessions caused by a negative aggregate demand shock. Further, our variance decomposition results suggest that demand shocks explain up to 11-12% of the movement in the U.S. healthcare employment at all horizons, and up to 14-15% of the variation in hospital employment and 19% of the variation in office of physicians over a 5-year horizon. The forecast error variance decomposition results suggest that demand shocks explain a non-trivial fraction of the variation in healthcare employment, indicating that these shocks are important drivers of healthcare employment and cannot be ignored.

Next, we discuss our findings for healthcare employment during economic downturns caused by a negative aggregate supply shock. We find that employment in healthcare industry behaves very differently during recessions caused by unexpected adverse supply side disturbances compared to those caused by unexpected adverse demand side disturbances. Interestingly, employment in the healthcare sector remains fairly stable (and even increases) during economic downturns caused by adverse supply side disturbances. This is primarily driven by a surge in employment in nursing care facilities during such times.[6] On the one hand, negative aggregate supply shocks (i.e., supply constraints and bottlenecks, as well as global supply chain disruptions) can prompt a shortage of medical supplies and operational failures, thereby setting off diminishing marginal productivity of labor and an increase in the likelihood of burnouts and voluntary quits among healthcare staff, especially among registered nurses who spend disproportionately more time with patients (Butler et al., 2018). On the other hand, previous studies show that economic downturns are associated with increased supply of nurses in the labor market matched by a corresponding increase in their employment (Stevens et al., 2015).[7] However, this can potentially change the composition of the nursing workforce if the new entrants comprise less skilled nurses and the employers are willing to offset budgetary pressures caused by wage hikes (due to the supply shock) by hiring them. Konetzka et al. (2018) provide evidence of downskilling in nursing homes that substitute away from registered nurses (RNs) to licensed practical nurses (LPNs). Our study also finds evidence of increased staffing hours for less expensive nursing aides and reduced staffing hours for more expensive RNs during COVID-19 period, again providing evidence of downskilling during recessions caused by supply shocks. Since voluntary quits among high skilled nurses are likely to be more prevalent during supply side disturbances due to potential burnouts, the increased hiring of less skilled workers and hence an increase in total healthcare employment can be a natural response to these type of shocks.

Specifically, we do find that the healthcare sector enjoys some insulation from supply-induced recessions. Our results for a stable and countercyclical response of healthcare employment during recessions in this scenario complement prior studies. Finally, our

[6]Note that nursing care facilities in general respond countercyclically to both demand and supply induced recessions, however the responses are much stronger during economic downturns caused by supply shocks.

[7]The increase in the supply of nurses can be explained by increased layoffs in non-nursing jobs and the added worker effect (Stephens, 2002). Put differently, more females enter the labor force to take nursing jobs when their partners lose jobs during economic downturns.

forecast error variance decomposition results suggest that supply shocks also explain a considerable fraction of variation in the healthcare employment (though less than demand shocks), indicating that these shocks are important drivers of healthcare employment as well.

Our prior view on why previous studies in the literature find healthcare employment to be stable and recession-proof is owing to the limitation of not being able to disentangle the effects of demand-induced recessions from supply-induced recessions on healthcare employment. Due to this limitation, previous studies find a null (or maybe positive) overall effect of recessions (generated from both demand and supply side disturbances together) on healthcare employment, thereby concluding that healthcare employment is recession proof. However, our findings suggest that this does not seem to be the case. Instead, the impact of recession on healthcare employment and the consequent mechanisms at play, both depend largely on the type of the exogenous shock triggering the recession. Our study documents that while healthcare employment overall responds procyclically to demand-induced recessions, it is fairly stable and even responds countercyclically to supply induced recessions. Our study is the first in the literature to show that healthcare employment in general is *not* recession proof. This is the most significant contribution of our study, and a novel finding in the literature of business cycles and healthcare employment.

The rest of the paper is organized as follows. Section II describes the data used in the main analysis. In Section III, we present the FAVAR model and discuss our model specification, identification, and estimation. We discuss our main results and investigate mechanisms in greater detail in Section IV. We offer concluding thoughts in Section V.

## II. Data

Our dataset consists of monthly time series data for 131 macroeconomic variables from 1990:01 to 2021:07. Out of the 131 variables, 118 are macroeconomic indicators for the U.S. economy that assist in identifying the structural macroeconomic shocks, and

13 are labor market indicators for the U.S. healthcare industry that are our primary variables of interest.[8] For the 118 U.S. macroeconomic indicators, we rely on St. Louis Federal Reserve Economics Data (FRED) and Institute for Supply Management (ISM). The variables are similar to those used in Bernanke, Boivin, and Eliasz (2005) as well as Stock and Watson (2016). We seasonally adjust all data prior to use and transform the variables to first differences of the logarithm in order to induce stationarity (except for those reported in percent which we use directly) and standardize them.[9] Next, we describe the labor market indicators for the U.S. healthcare industry below.

**Healthcare employment** The data on healthcare employment come from the Current Employment Statistics (CES) program, which is a monthly survey conducted by the U.S. Bureau of Labor Statistics. We obtain the seasonally adjusted number of employees in healthcare services per thousands of individuals at a monthly frequency. In our analysis, we take the natural log of this measure. We further disaggregate healthcare employment into sub-industry sectors using the North American Industry Classification System (NAICS) codes.[10] The first set of sub-industries we use in our empirical framework include ambulatory health care services (NAICS 621), hospitals (NAICS 622), and nursing and residential care facilities (NAICS 623). While previous studies stratify health services into a few sub-sectors within the healthcare industry (see, e.g., Dillender et al., 2021), our empirical design has the advantage of including all the major sub-sectors for which data are available. More granular and comprehensive information about the healthcare industry allows us to formally explore heterogeneity across sub-sectors, as well as within broad industry categories such as ambulatory health care services, hospitals, and nursing and residential care facilities. Specifically,

[8] We select the sample period based on the availability of all 131 time series indicators, though note this does provide an extensive sample of 367 months of data (30 years of data).

[9] We follow Bernanke, Boivin, and Eliasz (2005) for choice of series and their transformations. The macroeconomic indicators, their transformation codes, as well as the matrix of factor loading is reported in Appendix Tables A1-A4.

[10] Another alternative outcome variable can be the unemployment rate from the Current Population Survey (CPS). However, we intentionally do not use the unemployment data from the CPS. The main reason is the break in series with the switch from the Standard Industrial Classification (SIC)- to NAICS-based classification of industries in 2000. While the CES program have revised their data backwards over time to create comparable series, the CPS do not provide comparable unemployment data by industry.

we focus on the sub-sectors of the healthcare industry displayed in Table 1. We plot the annualized growth rate of employment in all the healthcare sectors, as well as the major sub-sectors over our sample period of 367 months or 30 years (1990:01-2021:07) in Figure 2. Note that most sectors and sub-sectors of healthcare industry experienced a decline in employment during the COVID-19 period followed by a subsequent spike.

**Layoffs and quits** To assess the mechanisms behind potential labor turnover during recessions, we draw data on layoffs and discharges as well as quits from the Job Openings and Labor Turnover Survey (JOLTS). Specifically, we use these separation indicators to explore whether changes in employment due to macroeconomic shocks are driven by the labor demand or the labor supply channel. A caveat of the data is the inaccessibility of historical monthly data. As of this writing, the monthly data are available from 2000 to 2021. Moreover, we cannot disaggregate the series for layoffs and quits beyond the healthcare and social assistance sector, which is part of the super-sector of health and education. Employment in the healthcare sector, however, accounts for about 80 percent of total employment in the healthcare and social assistance sector.

**Personal consumption expenditures** We use (real) personal consumption expenditures by major type of product to test *a priori* hypothesis that economic downturns reduce demand for healthcare due to reductions in personal income. Specifically, we use personal health expenditures to proxy for healthcare demand. We obtain the seasonally adjusted series from the Bureau of Economics Analysis at a monthly frequency for the sample period 1990-2021.

**Payroll-based staffing** To observe how staffing levels change in nursing homes during COVID-19, we use facility-level data from the Centers for Medicare & Medicaid Services' (CMS) Payroll-Based Journal (PBJ) from 2017 to 2021Q2. It is critical to emphasize that long-term care facilities are required by the Affordable Care Act to submit auditable data on resident census as well as staffing. Using data on daily resident census and the payroll-based number of hours, we calculate staffing hours per resident day by each staff category (e.g., registered nurses, nursing aides, etc.). We also aggregate this measure across facilities and over weeks to obtain weekly national estimates of staffing levels. These data provide staffing levels with higher accuracy and has been used in Nursing Home Compare and the Five-Star Quality Rating System since 2018 (Geng, Stevenson, and Grabowski, 2019). Following the health-labor literature, we measure staffing levels as nursing hours per resident day (see, e.g., Konetzka et al., 2018 and Geng, Stevenson, and Grabowski, 2019).

# III. Empirical Framework

## III.A. The FAVAR Model

The purpose of our study is to investigate the impact of a negative aggregate demand and supply shock on employment in healthcare industry as well as sub-sectors of healthcare industry. To achieve our objective, we make use of a structural factor-augmented vector autoregression model (Bernanke, Boivin, and Eliasz, 2005; Stock and Watson, 2016). Our primary motivation in using a factor-augmented vector autoregression (FAVAR) model is its multiple distinct advantages over traditional low-dimensional VARs. The relatively small scale of traditional VAR models poses a question of whether or not all relevant information about the economy has been included in measuring business cycles. For example, "economic activity", "price level", "interest rate and monetary conditions" are not perfectly observable and likewise cannot be captured by a single reported data series (as in traditional VARs). Many alternative measures of these concepts may be informative and the FAVAR framework provides one integrated approach for combining multiple data series through factor analysis. The richer information set in the FAVAR model provides superior estimates of economic concepts over using any single reported data series, more closely reflects the true information set used by policymakers, and assists in more accurate measurement and transmission of structural macroeconomic shocks (Bernanke, Boivin, and Eliasz, 2005; Forni and Gambetti, 2014; Bahadir and Lastrapes, 2015). We therefore use the FAVAR framework, allowing us to condition our investigation of macroeconomic shocks on healthcare employment using a richer information set without giving up the statistical merits of traditional VARs. Our model is detailed below.

Let $X_t$ be a $n$-dimensional vector stochastic process for a set of "informational" U.S. macroeconomic variables, and $F_t$ be a $q$-dimensional vector of common latent factors. $\Lambda$ is a $n \times q$ matrix of "factor loadings". The informational variables are primarily used to extract the common latent factors. Given a time series realization of $X_t$ and the observable subset of $Z_t$, we estimate the following FAVAR model of Bernanke, Boivin, and Eliasz (2005); Stock and Watson (2016) in Equations (1) and (2):

$$X_t = \Lambda F_t + \upsilon_{xt} \tag{1}$$

$$\begin{bmatrix} Y_t \end{bmatrix} = \begin{bmatrix} F_t \\ Z_t \end{bmatrix} = B(L) \begin{bmatrix} F_{t-1} \\ Z_{t-1} \end{bmatrix} + \epsilon_t, \tag{2}$$

where $Y_t$ follows the following linear dynamic process

$$Y_t = B_1 Y_{t-1} + ....B_p Y_{t-p} + \epsilon_t, \tag{3}$$

where $Y_t$ is a $m \times 1$ vector of data at date $t = 1, ..., T$, $B_i$ are coefficient matrices of size $m \times m$ and $\epsilon_t$ is the one-step ahead prediction error with variance-covariance matrix $\Sigma$. The system in Eq. (3) is the reduced form, obtained from a dynamic structural model. We are not interested in the reduced form shocks, but rather identifying how the variables in $Y_t$ respond to aggregate structural shocks. The structural counterpart to Eq. (3) in moving average form is given by:

$$Y_t = (I - B_y L)^{-1} D_y u_t \tag{4}$$

$$Y_t = (D_0 + D_1 L + D_2 L^2 + .....) u_t \tag{5}$$

where $u_t$ is a vector of aggregate structural shocks, $E\left(u_t u_t^{\prime}\right)$ is normalized to be the identity matrix. The mapping from the reduced form to the structural form imposes restrictions on the covariance structure:

$$\Sigma = E\left(\epsilon_t \epsilon_t^{'}\right) = D_y E\left(u_t u_t^{'}\right) D_y^{'} = D_y D_y^{'} \tag{6}$$

Once we identify the $m \times m$ matrix $D_y$ from this mapping, we obtain the dynamic multipliers of interest from Eq. (3) using (4) and (5).[11] We provide details on our model specification (factors and observables entering $Y_t$) and identification in sub-section III.B. In particular, we utilize the sign restrictions approach of Peersman (2005) and Farrant and Peersman (2006) to identify the structural macroeconomic demand and supply shock.

## III.B. Model Specification, Identification, and Estimation

We use the two-step principal component estimation approach in which we estimate the factors using principal component analysis prior to estimating the FAVAR model (Bernanke, Boivin, and Eliasz, 2005; Stock and Watson, 2016; De and Sun, 2019; De et al., 2021).

### 1. Model Specification

The first step is to extract the common latent factors $F_t$. The observable set $X_t$ in Eq. (1) consists of monthly time series of 118 macroeconomic indicators for the U.S. economy over the sample period 1990-2021.[12] We partition $X_t$ into four subsets of broad economic concepts required to identify macroeconomic shocks, $X_{st}, s \in (1, 4)$: economic activity, price level, interest rate, monetary aggregate; and extract a static factor $\hat{F_{st}}$ from each of the four subsets. For each subset $s$, that is, we estimate $\hat{F_{st}}$ as the first principal component of $X_{st}$: $\hat{F_{st}} = \left(\frac{1}{n}\right) \hat{\Lambda}' X_{st}$, where $\hat{\Lambda}$ contains the eigenvectors of $X_{st}$, normalized so that $\left(\frac{1}{n}\right) \Lambda' \Lambda = I$. The "U.S. economic activity factor" is loaded with 74 indicators broadly reflecting the U.S. macroeconomic environment- industrial production, employ-

[11]Note that we need not fully identify $D_y$ because we are solely interested in two types of structural macroeconomic disturbances impacting the economy: a negative aggregate demand shock and a negative aggregate supply shock. We therefore need to impose identifying restrictions only to columns of matrix $D_y$ that correspond to the two structural shocks above.

[12]The rest of the variables reflecting healthcare employment enter our baseline model directly as observables.

ment, income, labor earnings, capacity utilization, consumption, business and residential investment, ISM manufacturing, consumer sentiment, housing sales, and trade indicators in the U.S. The "U.S. price factor" is loaded with 28 different consumer and producer prices as well as import and export prices, stock prices and oil prices for the U.S. The "U.S. interest rate factor" is loaded with 9 treasury interest rates of different maturities as well as the bank prime loan rate, and mortgage rates for the U.S. The "U.S. money supply factor" is loaded with 6 measures of US monetary aggregates. Thus, $\left[\hat{F_{1t}}, \hat{F_{2t}}, \hat{F_{3t}}, \hat{F_{4t}}\right]$ are the estimated common latent factors that serve as a proxy respectively for economic activity, price level, interest rate, and money supply in the U.S. These factors comprise the macroeconomic sub-system $F_t$ in Eq. (2), and assist in identification of the structural macroeconomic shocks.[13] The observable subset $Z_t$ in Eq. (2) includes the employment in the healthcare industry, the variable of primary interest to us.

The FAVAR $[Y_t]$ given by Eq. (2) now reduces to a standard VAR augmented with the latent factors from the first step, and the observable employment in healthcare industry. In the second step, we proceed to identifying structural shocks within this framework using sign restrictions, and estimating the model. We also estimate FAVAR models separately for the different healthcare sub-industries, such that the the observable subset $Z_t$ in Eq. (2) includes healthcare employment of the different sub-industries.[14]

## 2. Identification: Demand and Supply Shock

We use the sign restriction strategy of Peersman (2005) to identify the structural macroeconomic demand and supply shock in our work. The primary advantage of using sign restriction is that shocks are identified not based on zero restrictions on the contemporaneous matrix, but rather the direction of their impact on the variables in the system (which makes it less restrictive than Cholesky decomposition or long-run identification

[13] A detailed description of the entire dataset that has been used to construct the respective factors, and the matrix of factor loading is reported in Appendix Tables A1-A4.

[14] We estimate 13 different model specifications for the whole healthcare industry and various sub-industries. These sub-industries include ambulatory health care services, hospitals, and nursing and residential care facilities, as well as the sub-sectors of these industries explained in Table 1. Each FAVAR model includes economic activity, price level, interest rate, and money supply in the the macro sub-system $F_t$; and employment in the specific healthcare sub-industry in $Z_t$.

restrictions); see, for example, Arias, Caldara, and Rubio-Ramirez (2019); Mumtaz, Pinter, and Theodoridis (2018); Abdallah and Lastrapes (2013); Rubio-Ramirez, Waggoner, and Zha (2010); Scholl and Uhlig (2008); Dedola and Neri (2007); Farrant and Peersman (2006).[15] Further, the sign restrictions identification strategy eliminates any kind of puzzling responses, which are often regarded as failures in identification; see, for example, Christiano, Eichenbaum, and Evans (1999) and Uhlig (2005). Table 2 summarizes the sign restrictions used to identify the structural shocks in our model. These widely accepted restrictions are based on standard IS-LM and AD-AS models. After a negative aggregate demand shock, the response of economic activity and price is not positive, and there is not an immediate increase in the interest rate. Following a negative aggregate supply shock, economic activity does not increase and prices do not fall over a selected horizon.[16] It is important to note here that no restrictions are imposed on employment in the healthcare industry; we are agnostic about the variables under investigation.[17]

## 3. Estimation

We fit the FAVAR model (with four factors and one observable) in Equations (2)-(3) with 7 lags in first differences of the logarithm of the variables except those reported in percentages, which we use directly (interest rate).[18] We also add a constant and a time

[15] Mumtaz, Pinter, and Theodoridis (2018) find that structural vector autoregression (SVAR) with sign restrictions deliver the best performance producing impulse responses that match those from the dynamic stochastic general equilibrium (DSGE) model. In contrast, the recursive SVAR is sensitive to ordering and measurement error and can produce estimates that are very misleading.

[16] Farrant and Peersman (2006) argue that a restriction on interest rate to identify supply shock is not necessary. There is no strong rationale for monetary policy tightening in response to a negative supply shock. To the extent that an adverse supply shock is both recessionary and inflationary at the same time, it would not be obvious that the appropriate monetary policy response on balance would be to raise the interest rate. So we stay agnostic about the interest rate response to a negative supply shock, and leave it unrestricted.

[17] Even though the sign-restriction approach has many advantages over alternative just identifying schemes, it does not completely lack for criticism. Fry and Pagan (2011) and Baumeister and Hamilton (2020) argue that there is a multiple models problem with the use of sign restrictions identification strategy, and recommend the use of additional identifying restrictions such as quantitative information about the magnitude of the impulse responses to reduce the set of models. As a robustness check, we therefore additionally use penalty function approach (similar to that in Uhlig (2005)) to narrow down the set of admissible models to a singleton. We find a sharpening of our results using penalty function approach (compared to pure sign restrictions approach) due to additionally desirable properties imposed on the restricted impulse responses. Note that our baseline model uses the standard pure sign restrictions approach, which is sufficient for our purpose to identify and disentangle the structural demand and supply shock.

[18] We follow Bernanke, Boivin, and Eliasz (2005) for choice of series and their transformations.

trend to Eq. (3). To identify the structural shocks, we impose the sign restrictions on $k$ = 2 months (including the initial impact period of the shock). We use Bayesian methods (with standard Jefferey's prior) to estimate the posterior densities of the parameters, conditional on observing the sample data, for the baseline model and alternatives to check for robustness of different model specification.[19] Following the sign restrictions literature, we report the median along with the 16% and 84% quantiles for the sample of impulse responses. To quantify the relative importance of the structural shocks, we also report the forecast error variance decomposition.

# IV. Empirical Results

## IV.A. Effects of Negative Aggregate Demand Shock on the U.S. Healthcare Employment

We first consider the effects of a negative aggregate demand shock on U.S. healthcare employment. The impulse responses of the macroeconomic sub-system and the employment in the healthcare industry to a one standard deviation negative aggregate demand shock are reported in Figure 3. In response to a one standard deviation negative aggregate demand shock, economic activity declines by 0.60% on impact, and by 1% over a two month horizon before slowly increasing, and reaching its long-run normal level at the end of fifteen months. Prices fall by 1.20% over a ten month horizon, and continue to remain permanently low at 1%. The adverse demand shock prompts an expansionary monetary policy in the form of lower interest rates and higher money supply. Note that following an adverse demand shock, economic activity, prices, and interest rates fall, lending justification to our identification scheme discussed in Table 2, and suggesting reliability in the result for healthcare employment. The main focus of our paper is the response of healthcare employment to this adverse demand shock. We find and document that a one standard deviation negative aggregate demand shock in U.S. economy triggers a negative

[19]For complete details of the algorithm refer to Rubio-Ramirez, Waggoner, and Zha (2010). To check for robustness, we estimate our model with 13 lags and $k$=3,6 respectively. Our results are robust to changes in lag length.

and significant decline in healthcare employment by 0.25% over a 0-2 month horizon, and by 0.10% in the long run (though the response turns insignificant after ten months).

The ability to distinguish a negative aggregate demand shock from supply shock provides a deeper understanding as to why healthcare employment is not recession proof. This is where we ask whether the reduction in healthcare employment is a labor supply or a labor demand response and what economic behavior influences this response. The gist of the mechanism we explore provide evidence of reduction in healthcare demand which in turn increases discharges and layoffs in the healthcare industry. We will return to our discussion of these mechanisms in Section IV.D.

We now turn to the employment responses in different healthcare sub-industries to the negative demand shock (Figure 4). These sub-industries include ambulatory health care services, hospitals, and nursing and residential care facilities, as well as the sub-sectors of these industries explained in Table 1. Overall employment in all three sub-industries: ambulatory healthcare services, hospitals, nursing and residential care facilities respond negatively to the adverse demand shock in short run, however there is substantial heterogeneity in the employment responses across the different sub-sectors of these healthcare industries. An interesting observation is that not all sub-sectors respond negatively to the adverse demand shock. While most sub-sectors of these three healthcare industries witness a drop in employment in the short run, some also witness an increase in employment. Specifically, in our quest for identifying heterogeneous effects across sub-sectors, a striking pattern emerges in sectors that predominantly hire nurses such as home healthcare services and nursing and residential care facilities. We show later that these nursing sectors also exhibit similar responses to an adverse supply shock, particularly during the COVID-19 period. As will be seen later, we carefully examine why employment responses are different in these nursing sectors, but before doing so we provide an overview of our benchmark findings.

**Ambulatory Healthcare Services** Employment in ambulatory healthcare services go down by 0.40% over a two month horizon before slowly recovering and reaching its long-run normal levels at the end of 25 months, however the results turn insignificant post 10 months. In particular, employment in office of physicians decline significantly and permanently by 0.35%. Even within ambulatory healthcare services not all sub-sectors respond negatively to the adverse demand shock. While most sub-sectors of ambulatory healthcare services experience a drop in employment in the short run, home health care services experience an increase in employment following the negative demand shock; this is significant and permanent.

**Hospitals** Hospitals within the healthcare industry experience the largest decline in employment following the adverse demand shock. Employment declines significantly and permanently by 0.75% in overall hospital sub-industry, as well as general medical and surgical hospitals. Strikingly, and in contrast to general medical and surgical hospitals, psychiatric and substance abuse hospitals experience an increase in employment following the adverse demand shock, however the response is largely insignificant. This is consistent with the literature showing that mental health and addiction problems as well as drug-related emergency room visits and deaths increase during economic downturns (Carpenter, McClellan, and Rees, 2017; Hollingsworth, Ruhm, and Simon, 2017; Tefft, 2011; Bradford and Lastrapes, 2014). Therefore, psychiatric and substance abuse hospitals are special cases where we do not observe a decrease in the demand for healthcare services when economic conditions worsen. Note that this finding holds regardless of the type of the shock (as we also show later in case of a supply shock).

**Nursing and Residential Care Facilities** Employment in nursing and residential care facilities overall decline on impact, however recover quickly, and start rising post 25 months. While the initial decline in employment in nursing and residential care facilities is driven by declining employment in other residential care facilities, the subsequent rise in employment in this sector is driven largely by hiring in the nursing care facilities. Nursing care facilities interestingly respond countercyclically to recessions caused by an adverse demand shock, recording a 0.40% rise in employment in the long run.This response in nursing and residential care facilities is not unique to an adverse demand shock. We show later that a similar and stronger response also emerges in the case of an adverse supply shock.

Taken together, our findings show that first, overall employment in healthcare industry decline in the short run during recessions caused by a negative aggregate demand shock. Second, there is strong heterogeneity in the employment responses faced by different healthcare sub-industries (ambulatory healthcare services, hospitals, and nursing and residential care facilities as well as sub-sectors of those industries) in terms of the magnitude, direction, as well as the persistence of the impact. In particular, general medical and surgical hospitals experience by far the largest decline in employment and the decline is significant and fairly permanent, followed by the decline in other residential care facilities, as well as physicians' offices. In contrast, home healthcare services, psychiatric and substance abuse hospitals, and nursing care facilities respond countercyclically to recessions caused by the adverse demand shock.

## IV.B. Effects of Negative Aggregate Supply Shock on the U.S. Healthcare Employment

Next, we analyze how the U.S. healthcare employment responds to a negative aggregate supply shock. The impulse responses of the macroeconomic sub-system and the employment in the healthcare industry to a one standard deviation negative supply shock are reported in Figure 5. In response to a one standard deviation adverse supply shock, economic activity declines by 0.35% on impact, and by 0.60% in the long run. Prices increase significantly, reaching a peak impact of 1% over a five month horizon, and 0.70% permanently. Note that the response of economic activity and prices to the negative aggregate supply shock is consistent with standard macroeconomic theory and the sign restrictions identification strategy employed in this paper (see Table 2), suggesting that the supply shock has been correctly identified.

While a negative aggregate supply shock is associated with high interest rate environment, the decline in economic activity could also prompt expansionary monetary policy in the form of lower interest rates. Therefore, due to these opposing channels while overall we do not see much effects on interest rate, we do find evidence of an increase in money supply and expansionary monetary policy (in the medium to long run) to stabilize some of the recessionary effects of the adverse supply shock. Perhaps more importantly, we do not find evidence that the Federal Reserve tightens monetary policy in response to an unexpected supply disruption, thus subsequently amplifying recessions. Finally, our primary interest is employment response in the healthcare industry to the adverse supply shock. We find that in response to a one standard deviation negative aggregate supply shock, employment in the healthcare industry increased by 0.17% over a five month horizon, and by 0.07% in the long run, albeit these results are largely insignificant throughout.

We next examine the employment responses in different healthcare sub-industries to the negative supply shock (Figure 6). We find evidence that employment in all three sub-industries: ambulatory healthcare services, hospitals, nursing and residential care facilities respond positively to the adverse supply shock; however while the results for ambulatory healthcare services and hospitals are insignificant, those for nursing and residential care facilities are significant. Similar to our previous findings, we observe strong heterogeneity in the employment responses faced by different sub-sectors of these healthcare sub-industries. In our analysis, we find that most sub-sectors of the healthcare sub-industries (ambulatory healthcare services, hospitals, nursing and residential care facilities) experience an initial spike in employment followed by a subsequent smoothing during economic downturns caused by supply side disturbances. We explain more below.

**Ambulatory Healthcare Services** In response to the adverse supply shock, employment in ambulatory healthcare services go by 0.15% over a five month horizon, before slowly coming back to its long-run normal levels over a 25 month horizon, however the response is insignificant throughout. We find evidence of an initial jump in employment following the adverse supply shock in all sub-sectors of ambulatory healthcare services. However, home healthcare services need a particular mention as this sector witnesses a significant and permanent increase in employment, driving much of the increase in employment in overall ambulatory healthcare services.

**Hospitals** In response to the negative aggregate supply shock, employment in hospital sub-industry goes up 0.30% over a five month horizon, before slowly coming back to its long-run normal levels at the end of 50 months, however again the response is insignificant throughout. Both surgical and medical hospitals, as well as psychiatric and substance abuse hospitals experience an increase in employment, even though insignificant.

**Nursing and Residential Care Facilities** The estimated effects suggest a strong, significant, and permanent increase in employment among nursing and residential care facilities in response to the negative supply shock. Employment in nursing care facilities increase by 0.60% in the long run, driving much of the increase in employment in overall nursing and residential care facilities. In contrast to nursing care facilities, employment in other residential care facilities fall by 0.10% in the long run, however the results are insignificant.

Overall, these results suggest that employment in healthcare industry behaves differently in recessions caused by unexpected supply side disturbances compared to those caused by unexpected demand side disturbances. Specifically, we find that the healthcare sector enjoys some insulation from an aggregate supply shock that cause economic downturns. Employment in overall healthcare industry and most sub-industries of ambulatory healthcare services, hospitals, nursing and residential care facilities respond positively to the adverse supply shock in the immediate short run. In particular, home healthcare services and nursing care facilities experience a significant and permanent increase in employment as a result of the adverse supply shock, driving much of the increase in overall healthcare employment. We discuss some of the potential explanations behind this behavior later.

Taken as a whole, our findings highlight that employment in the healthcare sector remain fairly stable (and even increase) during economic downturns caused by supply side disturbances, which remain in striking contrast to those found for demand side disturbances, excluding the nursing sector and psychiatric and substance abuse hospitals.

## IV.C. Comparison: Pre- and Post-COVID-19 Period

In the previous section, we find that while economic downturns caused by unexpected demand side disturbances lead to a decline in overall healthcare employment, those caused by unexpected supply side disturbances lead to an increase in overall healthcare employment. An important question confronting our findings is whether or not these results are driven by post-COVID-19 data. To answer this, we test the robustness of our findings by conducting our study using pre-COVID-19 (1990-2019) data, i.e., by cutting off our sample period in 2019. The full set of IRF's is reported in Appendix Figures A1-A4.

Previewing our results, we find that over the pre-COVID-19 period overall employment in the healthcare sector declines in the short run in response to a negative aggregate demand shock as well. This finding is consistent with our benchmark analysis. What is interesting however is that, we do not find any evidence of a (strong) persistent positive overall employment response to supply side disturbances before COVID-19 (except home healthcare and nursing care facilities), suggesting that the nature of the shock causing the recession may necessitate a specific employment response. We next compare the employment responses across sub-industries of the healthcare sector using data over the full sample period (1990-2021) vs. pre-COVID-19 period (1990-2019).

Figure 7 compares the impulse responses from FAVAR model over the full sample period (1990-2021) vs. pre-COVID-19 period (1990-2019) to a one standard deviation negative aggregate demand shock. Note that over the pre-COVID-19 period, employment in the healthcare sector, as well as two of the prominent industries in the healthcare sector (ambulatory healthcare services and hospitals) respond strongly negatively to the adverse demand shock in short run; these negative responses are much stronger than those found for the full sample period. In particular, we find that employment goes down in the healthcare sector by 1.50%, and in the hospital industry by 2.25% permanently in response to the negative demand shock.

We ask whether countercyclicality of the nursing sector and psychiatric and substance abuse hospitals is also prevalent in data prior to COVID-19. The answer is affirmative. Similar to results found for the full sample period, home healthcare services, psychiatric and substance abuse hospitals, and nursing care facilities also experience an increase in employment over the pre-COVID-19 period, following the adverse demand shock. This robustness check concludes that while overall healthcare sector and sub-sectors respond procyclically to demand induced recessions; home healthcare, psychiatric and substance abuse hospitals, and nursing care facilitates respond countercyclically to demand induced recessions over both sample periods in the medium to long run.

Figure 8 compares the impulse responses from FAVAR model over the full sample period (1990-2021) vs. pre-COVID-19 period (1990-2019) to a one standard deviation negative aggregate supply shock. In response to an adverse supply shock, we find considerable heterogeneity in the responses of healthcare employment over the two sample periods (full sample period vs. pre-COVID-19 period). While employment in healthcare industry when estimated over the full sample period increases permanently, that over the pre-COVID-19 period follows a boom-bust cycle in response to the adverse supply shock.

We find further evidence that within the healthcare sector, ambulatory healthcare services and hospitals show significant heterogeneity in their employment response to the adverse supply shock. Specifically, we find that when estimated over the full sample period these sectors (and their respective sub-sectors) experience an initial spike in employment and subsequent smoothing, however when we cut off the time period at 2019, they witness overall a decline in employment. This indicates that the nature of the COVID-19 shock could have generated the initial strong spike in employment in ambulatory healthcare services and hospitals, when estimated over the full sample period. That is, the initial increase in employment could have been a response to the staffing crisis during early months of the pandemic. As hospitals and ambulatory care centers (e.g., urgent care clinics, medical offices and clinics, etc.) surged capacity, patient-to-staff ratios spiked, creating the need to hire more healthcare workers. In fact, as hospitals started bidding for nursing staff, there has been a huge shift from permanent nursing positions to travel nursing positions, soaring hospital labor cost expenses per discharge (American Hospital Association, 2021).[20] An interesting question is how do healthcare facilities cope with budgetary pressures stemming from high labor costs? A potential answer turns out to be compositional changes, especially in nursing sectors that do *not* necessarily require high skilled nurses on a mass level. This is an interesting avenue of study, and hence, we revisit it in Section IV.D.

Consistent with the dynamics above and similar to those found for the negative aggregate demand shock, home healthcare services and nursing care facilities experience an increase in employment in response to the negative aggregate supply shock as well over both sample periods, however the increase is more prominent when estimated over the full sample period. In sum, employment in healthcare industry to adverse supply shock seems to be more "recession proof" when estimated over the full sample period (which covers the COVID-19 period) as opposed to the pre-COVID-19 period.

An important discovery from this section is that by using our sign-identified structural FAVAR approach, we find employment in healthcare industries and most sub-industries to respond procyclically to both the negative aggregate demand and supply shock when estimated over the pre-COVID-19 period (1990-2019), even though there are heterogeneity in terms of magnitude of response. The exceptions that stand out are home healthcare services (under ambulatory healthcare services) and nursing care facilities (under nursing and residential care facilities) which respond countercyclically to both the adverse demand and supply shock. For the pre-COVID-19 period (1990-2019), we conclude that while healthcare employment overall and in most of the broad sectors and sub-sectors goes down, that in home healthcare services and nursing care facilities goes up significantly and permanently during economic downturns. In contrast, Dillender et al. (2021) using multivariate regression models and data from 2005-2017 conclude that healthcare

[20] We provide a snapshot of the data on nursing salaries. According to the 2022 data from ZipRecruiter, rural hospitals pay on average about $1,200 per week for permanent nursing jobs. However, travel nursing assignments can pay up to $10,000 per week. This is based on the travel nursing job listings on Vivian in 2022, a major healthcare hiring platform. The travel nurse job listings can be accessed from the following link: https://www.vivian.com/nursing-jobs/.

employment overall remains stable and may even increase during economic downturns. Our prior view for the strikingly different results between our study and Dillender et al. (2021) is that in the latter study the response of overall healthcare employment might just be netting out the procyclical and countercyclical responses of the different healthcare sub-industries and perhaps even capturing the largely dominant countercyclical response of home healthcare services and nursing care facilities, thus showing a stable and countercyclical response *on average* of healthcare employment during economic downturns.

## IV.D. Establishing Mechanisms

An important yet unanswered question so far is whether these underlying labor market responses in the healthcare industry to adverse macroeconomic shocks are being driven by labor demand or labor supply dynamics. As a first step in identifying mechanisms, we re-run the FAVAR model with job separation indicators, and investigate their responses to an adverse demand and supply shock. Specifically, we use "layoffs and discharges" as an indicator of labor demand and "quits" as an indicator of labor supply. This analysis also sheds light on how long term responses in employment and economic activity may be shaped by the type of separations from jobs, since layoffs are likely to result in unemployment whereas quits may involve individuals flowing to a new job (Elsby, Hobijn, and Sahin, 2010). For example, in nursing sectors, voluntary quits may imply transitions from permanent nursing jobs to travel nursing jobs, particularly during COVID-19.

As a second step, we investigate *a priori* hypothesis in the health economics literature that the reductions in the demand for healthcare during economic downturns could be limited (Dillender et al., 2021). The main reasoning is that although individuals may lose access to private insurance coverage during recessions, public health insurance (e.g., Medicaid or Medicare) or other alternative forms of insurance coverage such as subsidized health insurance may weaken the linkages between personal financial constraints and the demand for healthcare. On the one hand, the strand of literature analyzing healthcare utilization during economic downturns is relatively underdeveloped and the findings are largely mixed (McInerney and Mellor, 2012; Peng, Chen, and

Guo, 2022). On the other hand, there is a vast literature exploring the relationship between business cycles and health outcomes. In fact, a large number of studies report a procyclical pattern in health and health behaviors, particularly mortality (Ruhm, 2000; Stevens et al., 2015), drinking (Ruhm and Black, 2002; Ruhm, 2005; Cotti, Dunn, and Tefft, 2015), and other health-compromising behaviors (Ásgeirsdóttir et al., 2016), which in turn can yield procyclical patterns in healthcare utilization.[21] Taking these into account, we find it natural to investigate how real personal consumption expenditures (PCE) for health responds during economic downturns. If individuals increase demand for healthcare during economic downturns, there could be countercyclical response (or an increase) of real health expenditures. We explain below in detail that we do not find supporting evidence for this hypothesis, rather we find reductions in healthcare expenditures resulting from an adverse demand shock, which serves as a mechanism through which overall healthcare employment declines.

**Demand Shock** Figure 9 presents the impulse responses of healthcare employment as well as "layoffs and discharges" and "quits" to a one standard deviation negative aggregate demand shock. Note that in the healthcare industry while layoffs and discharges are increasing in response to the adverse demand shock, voluntary quits are going down. We find that during demand driven economic downturns, employment in healthcare industry goes down primarily due to an increase in layoffs and discharges and not due to voluntary labor market quits. This suggests that the procyclical response of healthcare employment to the demand shock is likely driven by the labor demand channel.

We further ask whether changes in healthcare utilization prompt employers to reduce their demand for healthcare workers. To investigate this mechanism, in another exercise we proxy real personal healthcare expenditures for the demand for healthcare and re-run the FAVAR model. Consistent with our previous findings, healthcare expenditures drop significantly in response to the adverse demand shock, a proxy showing a drop in overall

[21] The literature shows that these findings can be sensitive to the level of geographic aggregation, and socioeconomic and demographic characteristics of the sub-population, and further that the procyclical response of mortality become smaller and statistically insignificant over time (Charles and DeCicca, 2008; Lindo, 2015; Tekin, McClellan, and Minyard, 2018; Ruhm, 2015).

healthcare demand which ultimately contributes to the decline in healthcare employment (see Figure 10). One can be tempted to claim that the reductions in demand for formal healthcare would be limited during economic downturns (maybe because of access to public health insurance). That claim would be premature mainly because it does not take into consideration the potential substitution of informal care for formal care during such times (which can play a significant role in reducing demand for formal healthcare). Our mechanism complement the findings in the literature that economic downturns are associated with increases in the availability of informal care and declines in revenues in the healthcare sector (Costa-Font, Karlsson, and Øien, 2016; Konetzka et al., 2018). Moreover, aside from its implications on demand for care, Aslim (2022) shows that access to public health insurance also reduces full-time employment, particularly among females through income effect.

Taken together, we find robust evidence in favor of a labor demand channel of macroeconomic shock transmission as an explanation for the drop in employment in the healthcare industry during economic downturns caused by a negative aggregate demand shock. The adverse demand shock slows down the economy (causing recessions), reduces personal healthcare expenditures, and lessens the overall labor demand in the healthcare industry leading to a drop in the employment.

**Supply Shock** Figure 11 presents the impulse responses of healthcare employment as well as "layoffs and discharges" and "quits" to a one standard deviation negative aggregate supply shock. Taking into account the COVID-19 period, economic downturns caused by supply side disturbances yield very different employment responses and mechanisms. Our key finding is that overall healthcare employment goes up in the short run. Different from the demand shock, there is a decrease in layoffs and discharges in the short run, while quits in healthcare jobs go up in the medium to long run. While the pandemic disrupted the healthcare sector in many ways, how staffing arrangements in the healthcare workforce affected job outcomes has received less attention and remains an important focus of our study. First, given extensive licensing in healthcare tasks and absent staffing legislation, there was a substantial increase in patient-to-nurse staffing ratios during COVID-19, which increased the number of nurses experiencing high burnout and the likelihood of job dissatisfaction and the intent to leave job within a year (Lasater et al., 2021). Additionally, these studies highlight that the healthcare staff in these practices often experienced operational failures and interruptions due to supply constraints and bottlenecks during COVID-19, which could set off diminishing marginal productivity and also ultimately contribute to increase in likelihood of burnouts and voluntary quits among healthcare staff. Our findings about the labor supply channel measured by quits in the aftermath of the adverse supply shock are largely consistent with this literature.

**Nursing Sectors** A unique finding of our study and worth investigating is that employment in nursing care facilities (a sub-sector of nursing and residential care facilities) or other nursing sectors such as home healthcare services experience an increase in employment following economic downturns caused by both the negative aggregate demand and supply shock. This is robust to changes in sample period (i.e., pre-COVID-19 and full sample period) although the results are more persistent and significant for the supply shock and for the full sample period (including the COVID-19 period). We therefore focus on the full sample period to investigate the reasons behind the countercyclical response of nursing care facilities to the adverse supply shock. We use a novel payroll-based data on nurse staffing hours to explore the dynamics in long-term care facilities such as nursing homes.

Figure 12 plots staffing hours per resident day for registered nurses and nursing aides. We find an inverted U-shaped pattern in staffing hours for registered nurses during the COVID-19 period suggestive of the evidence of an increase in staffing hours of registered nurses during initial months of the pandemic, followed by a subsequent sharp decline in staffing hours.[22] Relying on standard New-Keynesian literature that features rigidity

[22]Our findings are not likely to be explained by an increase in the number of residents. Even if there is an increase in the denominator of RN staffing hours per resident day, the increase in nurse aide staffing hours per resident day imply that the increase in the numerator (total nurse aide staffing hours) more than offsets the increase in the denominator, i.e., number of residents. Therefore, this is suggestive of a

of labor contracts (existing worker hours and wages) (Gertler, Sala, and Trigari, 2008; Del Negro and Schorfheide, 2008), the previous observation is consistent with our findings from the structural FAVAR model of an increase in employment or hiring in nursing sector. We observe a spike in healthcare employment in response to the negative supply shock in Figure 6, as well as an increase in voluntary quits in the medium term in Figure 11. These findings are quite informative. However, we are also curious about the dynamics behind the persistent increase in employment in nursing sectors in our impulse response functions (such as that of nursing homes or home healthcare services). We ask whether there are any compositional changes such as downskilling that could be contributing to this observed increase. As discussed earlier, healthcare facilities experience an increase in labor costs due to registered nurses taking on more expensive travel nurse assignments, creating budgetary pressures. This may prompt certain healthcare facilities, particularly nursing homes or rural health clinics, to substitute away from high skilled nurses towards low skilled nurses (such as nursing aides). Since the staffing positions for nursing aides do not require any postsecondary education or formal training, labor supply of nursing aides may in fact increase due to the added worker effect.[23] Our findings are consistent with these dynamics. We find a striking pattern in nurse aide staffing hours during COVID-19. There is about a 63 percent increase in nurse aide staffing hours by the first week of 2021 relative to the pre-COVID period. Jointly, together with a decline in registered nurse staffing hours, these findings lend validity to compositional changes in nursing homes in the form of downskilling, discussed earlier.

## IV.E. How Important are Demand and Supply Shocks in Explaining Healthcare Employment?

In this section we consider the extent to which macroeconomic shocks can account for labor market dynamics in the U.S. healthcare industry. That is, whereas the previous section focuses on characterizing whether macroeconomic shocks affect the employment

potential compositional change.

[23] That is, nursing aide positions may be a feasible avenue for women entering into the labor force due to their partners losing jobs during economic downturns.

in the healthcare industry and sub-industries, we now turn to the question of assessing the quantitative importance of this relationship. Variance decomposition report what fraction of the movement in the variables can be accounted for by the structural shocks. If a shock explains a large fraction of the variation in a reported variable, then the shock is an important driver of movements in the variable. This measure provides one metric of the extent to which demand and supply shocks are quantitatively important in driving labor market dynamics in the healthcare industry. Table 3 reports the variance decomposition results for employment in the healthcare industry and sub-industries to the structural demand and supply shock. We first discuss the variance decomposition results for demand shocks followed by supply shocks.

Demand shocks explain up to 11-12% of the movement in the U.S. healthcare employment at all horizons, and up to 14-15% of the variation in hospital employment and up to 19% of the variation in office of physicians over a 5-year horizon. Further, we note that demand shocks account for 12-15% of the variation in employment in ambulatory healthcare, office of dentists, office of other health practitioners, office of physicians, and outpatient care centers at all horizons, suggesting that these shocks play a non-trivial role in accounting for cyclical labor market dynamics in the healthcare industry. The forecast error variance decomposition suggests that the contribution of demand shocks to fluctuations in healthcare employment is of a similar order of magnitude as the contribution of these shocks to other macroeconomic factors like economic activity and inflation, indicating that these shocks are important and should be taken into account by policy-makers.[24]

Supply shocks explain up to 7-10% of the movement in overall U.S. healthcare employment at all horizons. Additionally, supply shocks account for up to 11% of the movement in employment in the following healthcare sectors: office of physicians, outpatient care centers, and nursing and residential care facilitates over a 1-2 year horizon. Similarly, our variance decomposition results suggest that supply shocks explain a considerable fraction of variation in the healthcare employment, indicating that these shocks are important

[24]To save space, the full set of variance decomposition results (i.e., for economic activity, price, money supply, and interest rate) are not reported here, but can be made available upon request.

drivers of healthcare employment and cannot be ignored.

# V. Conclusion

In this paper, we attempt to answer an important yet untapped question in the literature of business cycles and healthcare employment: how do recessions affect U.S. healthcare employment? We study the impact of recessions on U.S. healthcare employment caused by two fundamental sources of business cycle fluctuations: an aggregate demand shock and an aggregate supply shock. We utilize a factor augmented vector autoregression framework with 131 macroeconomic variables from 1990:01 to 2021:07, and sign restrictions to conduct our study.[25] Our methodological framework allows us to explicitly distinguish the effects of a negative aggregate demand shock from a negative aggregate supply shock, when examining the impact of recession on healthcare employment.

We find that employment in healthcare industry declines significantly in response to recessions caused by demand side disturbances, which is in striking contrast to earlier studies that find healthcare employment to remain stable during recessions. Additionally, we find strong heterogeneity in employment responses across different healthcare subindustries. In particular, general medical and surgical hospitals experience the largest decline in employment, followed by other residential care facilities, as well as physicians' offices. Further, we note that demand shocks account for a significant fraction of the variation in healthcare employment, suggestive of the evidence that these shocks are important drivers of healthcare employment.

Next, we find that a negative supply shock have significantly different effects on healthcare employment compared to a negative demand shock, which further reinforces the need to distinguish between the types of shock causing the economic downturn. We find that employment in the healthcare sector remains fairly stable (and even increases) during economic downturns caused by supply side disturbances. In particular, nursing care facilities experience a significant and permanent increase in employment as a result of an adverse supply shock. Specifically, we do find that the healthcare sector enjoys some

[25] We identify negative innovations to aggregate demand and aggregate supply using sign restrictions.

insulation from supply-induced recessions, which is consistent with prior studies. Similar to demand shocks, supply shocks also explain a considerable fraction of the movements in healthcare employment, indicating that these shocks are important drivers of healthcare employment as well (though less than demand shocks).

Finally, we note that two subsectors of healthcare sub-industries in particular stand out: home healthcare services and nursing care facilities. These two sub-sectors experience increase in employment following both an adverse demand and supply shock. To carefully examine these dynamics, we use payroll-based nurse staffing data. Two major observations are noticeable. First, we observe an inverted U-shaped response of registered nurse hours per resident day, indicative of an initial increase in staffing levels and subsequent voluntary quits due to potentially high burnouts and job dissatisfaction during COVID-19. Second, we observe an increase in less expensive nursing aide staffing hours jointly with a decrease in registered nurses' staffing hours, thus lending justification to compositional change and downskilling in these sectors.

From a more general perspective, the impact of recessions on healthcare employment and the consequent mechanisms at play, both depend largely on the type of the shock causing the recession. The novelty of our paper is that we are able to disentangle the effects of demand-induced recessions from supply-induced recessions on healthcare employment. Our study is the first in the literature to show that healthcare employment responds procyclically to demand-induced recessions, but is fairly stable and even responds countercyclically to supply induced recessions. We provide new robust evidence that U.S. healthcare employment in general is *not* recession proof. This is a novel finding in the literature of business cycles and healthcare employment, and comprise the most significant contribution of our study.

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## Table 1. Selected Sub-Sectors of Healthcare Services

| Healthcare Services | | |
|---|---|---|
| Ambulatory Health Care Services | Hospitals | Nursing and Residential Care Facilities |
| Offices of physicians (NAICS 6211) | General medical and surgical hospitals (NAICS 6221) | Nursing care facilities (NAICS 6231) |
| Offices of dentists (NAICS 6212) | Psychiatric and substance abuse hospitals (NAICS 6222) | Other residential care facilities (NAICS 6239) |
| Outpatient care centers (NAICS 6214) | | |
| Home health care services (NAICS 6216) | | |
| Other ambulatory health care services (NAICS 6219) | | |

*Notes:* The sub-sectors that do not have available monthly data from 1990 to 2021 are excluded from the analysis. These sub-sectors are as follows: offices of other health practitioners (NAICS 6213), specialty hospitals, except psychiatric and substance abuse (NAICS 6223), residential mental retardation, mental health and substance abuse facilities (NAICS 6232), and community care facilities for the elderly (NAICS 6233).

## Table 2. Sign Restrictions

| Structural Shocks | Economic Activity (factor) | Price Level (factor) | Interest Rate (factor) | Money supply (factor) | Employment Healthcare (observable) |
|---|---|---|---|---|---|
| Negative Aggregate Demand Shock | $\leq 0$ | $\leq 0$ | $\leq 0$ | ? | ? |
| Negative Aggregate Supply Shock | $\leq 0$ | $\geq 0$ | ? | ? | ? |

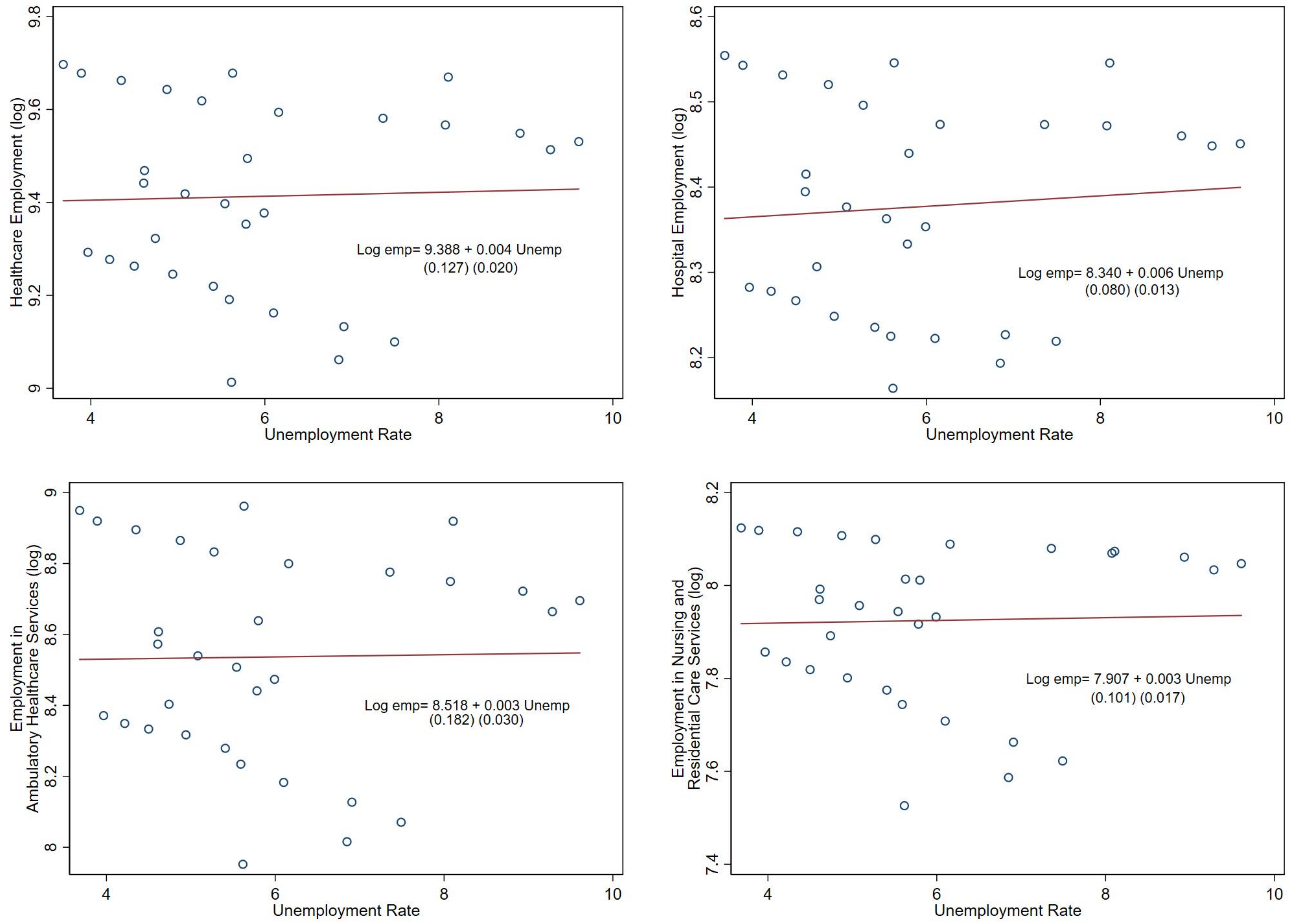
*Notes:* This table summarizes the sign restrictions used to identify the structural macroeconomic demand and supply shock. The time period over which we impose sign restrictions to identify the structural shocks is $k = 2$ months, including the impact period of the shock. Note that no restrictions are imposed on employment in the healthcare industry; here we are agnostic about the variables under investigation.

## Table 3. K-step ahead forecast error variance that can be explained by the structural shocks (in %)

| | Demand Shock | | | Supply Shock | | |
|---|---|---|---|---|---|---|
| Factors/Observables | 1-year | 2-year | 5 year | 1-year | 2-year | 5 year |
| Healthcare | 11.92 | 12.12 | 12.54 | 9.80 | 8.73 | 7.30 |
| Ambulatory Health Care | 14.19 | 14.27 | 14.40 | 9.26 | 7.02 | 4.43 |
| Home Health Care | 5.76 | 6.46 | 8.86 | 6.49 | 5.73 | 4.84 |
| Offices of Dentists | 13.08 | 12.57 | 11.91 | 8.54 | 7.00 | 4.83 |
| Offices of Other Health Practitioners | 13.01 | 13.34 | 13.95 | 7.64 | 5.61 | 3.83 |
| Offices of Physicians | 14.45 | 16.06 | 19.12 | 10.37 | 8.82 | 7.20 |
| Outpatient Care Centers | 14.06 | 13.53 | 14.06 | 10.38 | 6.86 | 4.05 |
| Hospitals | 8.45 | 12.64 | 14.39 | 9.26 | 8.07 | 7.24 |
| General Medical and Surgical Hospitals | 7.71 | 12.71 | 14.46 | 7.73 | 6.41 | 5.40 |
| Psychiatric and Substance Abuse Hospitals | 3.84 | 5.28 | 5.70 | 3.46 | 3.52 | 3.29 |
| Nursing and Residential Care Facilities | 6.21 | 6.69 | 7.22 | 9.40 | 10.57 | 10.89 |
| Nursing Care Facilities | 4.29 | 4.75 | 6.23 | 6.12 | 6.40 | 6.24 |
| Other Residential Care Facilities | 7.14 | 10.09 | 12.05 | 4.30 | 5.05 | 5.17 |

*Notes:* The numbers show the median estimates of the k-step ahead forecast error variance decomposition of the observables/factors explained by the two structural shocks from our model using sign restrictions.

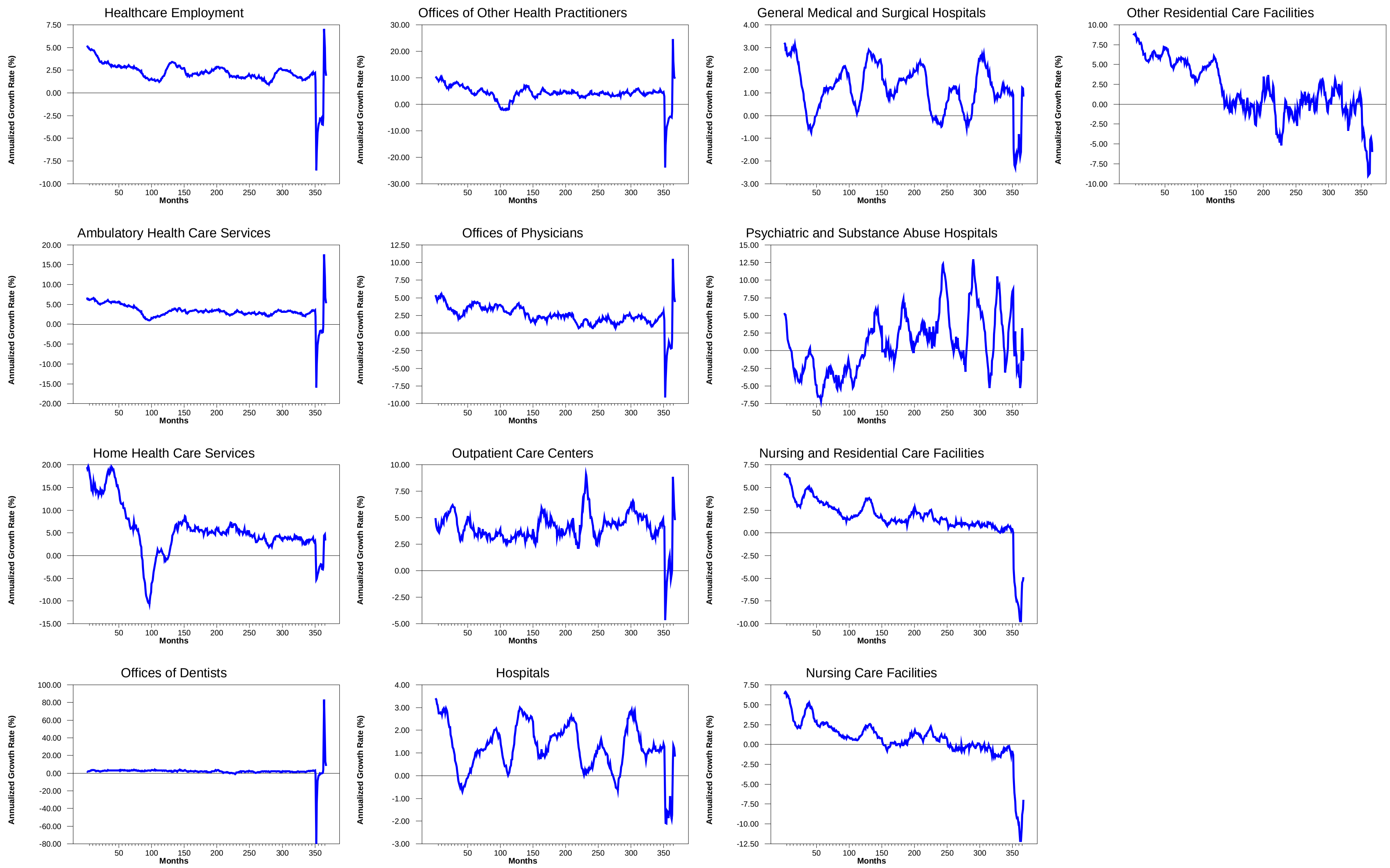
**Figure 1. The Relationship Between the Unemployment Rate and Employment in Healthcare Sectors, 1990-2021**




*Notes*: This figure presents the relationship between the unemployment rate and the log of employment in selected healthcare sectors. Circles represent the mean unemployment rate and employment in healthcare sectors from 1990-2021 in the U.S. The red lines are linearly fitted lines. Robust standard errors are in parentheses.

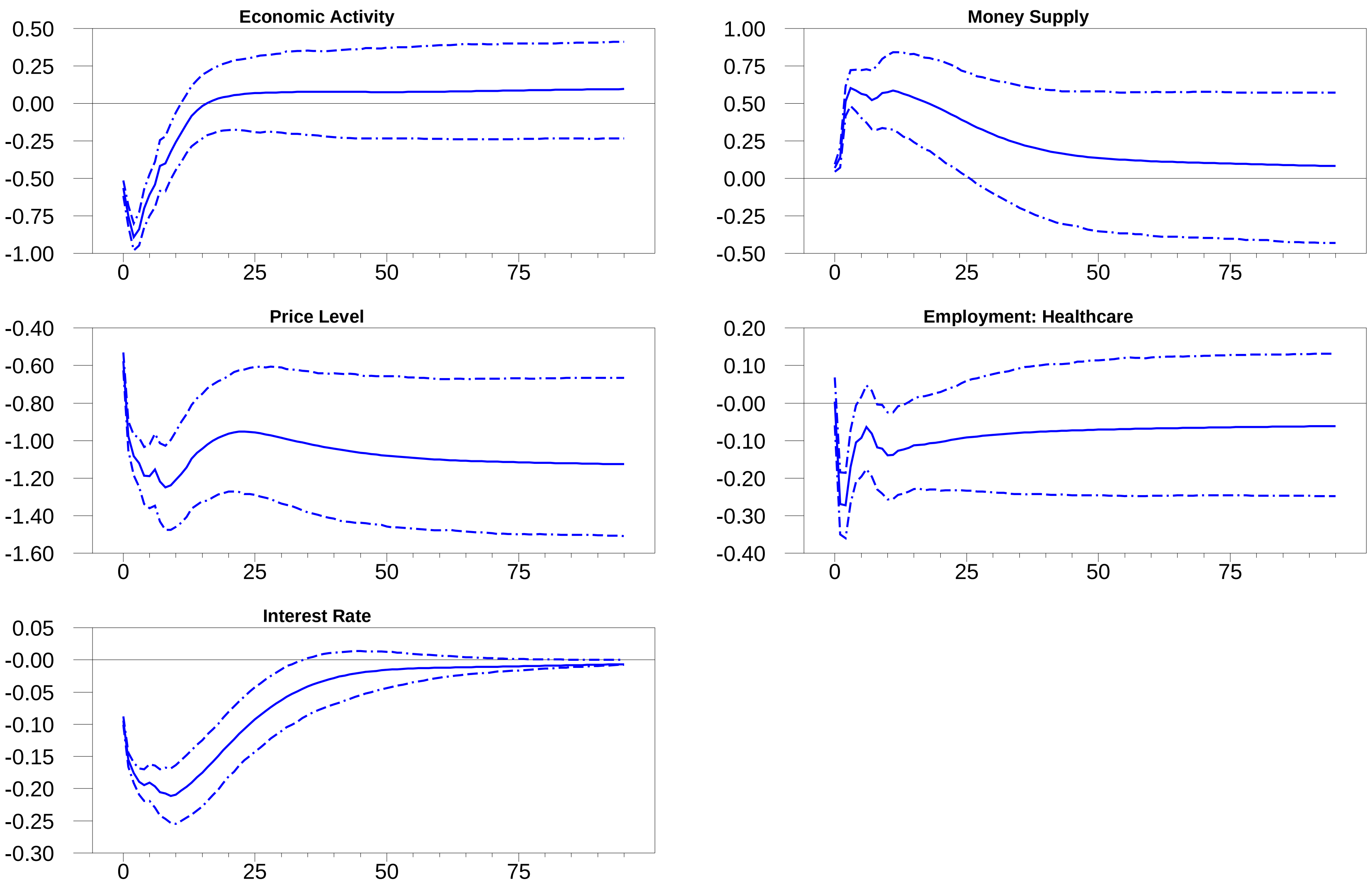
*Data Sources*: Current Employment Statistics from the U.S. Bureau of Labor Statistics and Federal Reserve Economic Database (FRED) of the St. Louis Fed.

**Figure 2. Annualized Growth Rate of Employment in the US Healthcare Industry, 1990-2021**



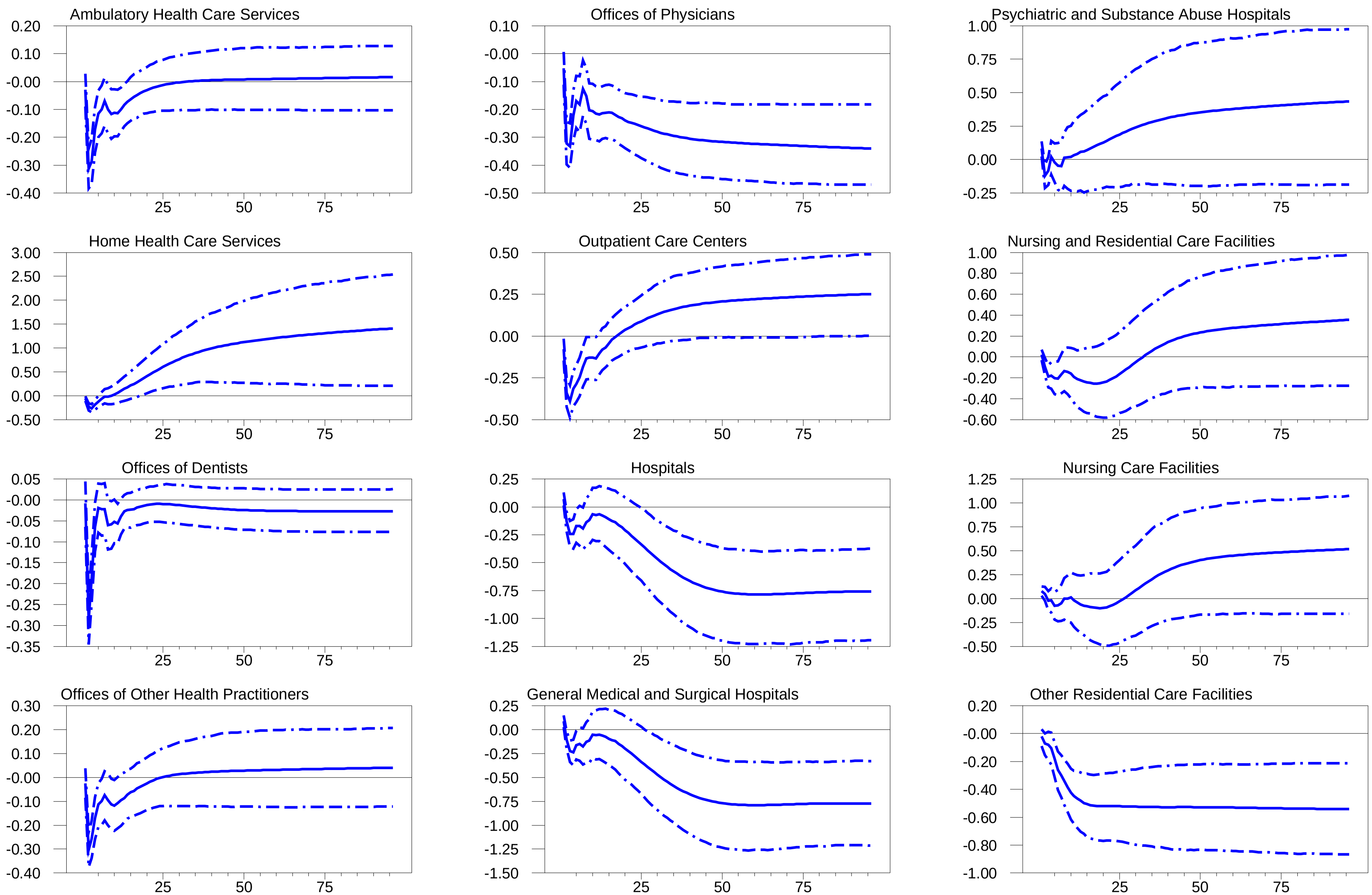

*Notes*: This figure presents the annualized growth rate of employment in U.S. healthcare sector over our sample period, 1990-2021.

## Figure 3. IRFs of Health Care Employment to Negative Demand Shock



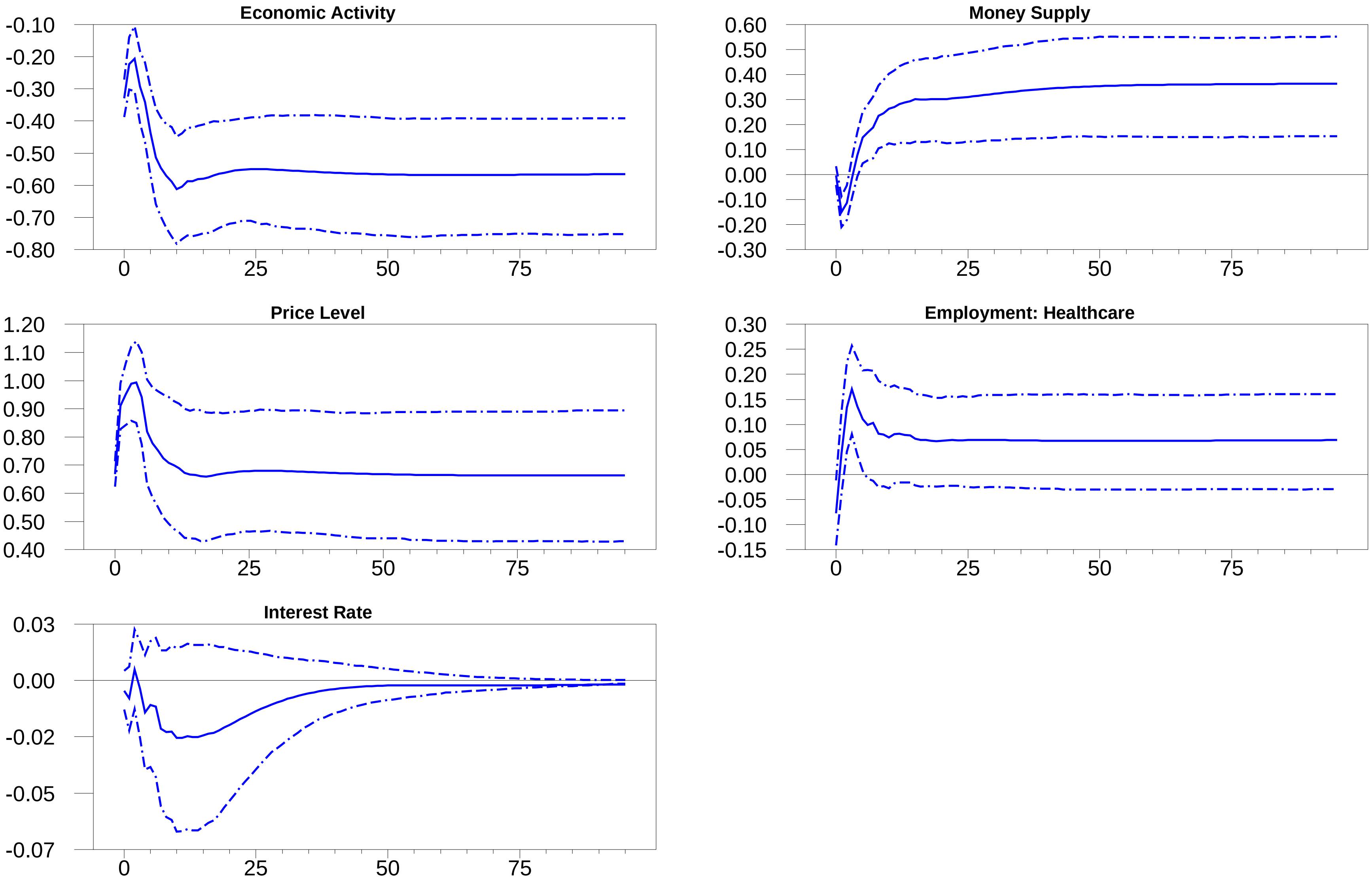

*Notes*: This figure presents the accumulated impulse responses of the variables/factors to a one standard deviation negative aggregate demand shock using sign restrictions. The sample period is 1990-2021. The three lines are 16% quantile, the median and the 16% quantile of the posterior distribution. The vertical axis reports quantitative magnitude of the response (in %), while the horizontal scale reports months.

## Figure 4. Differential Response of Employment in Healthcare Industry to Negative Demand Shock



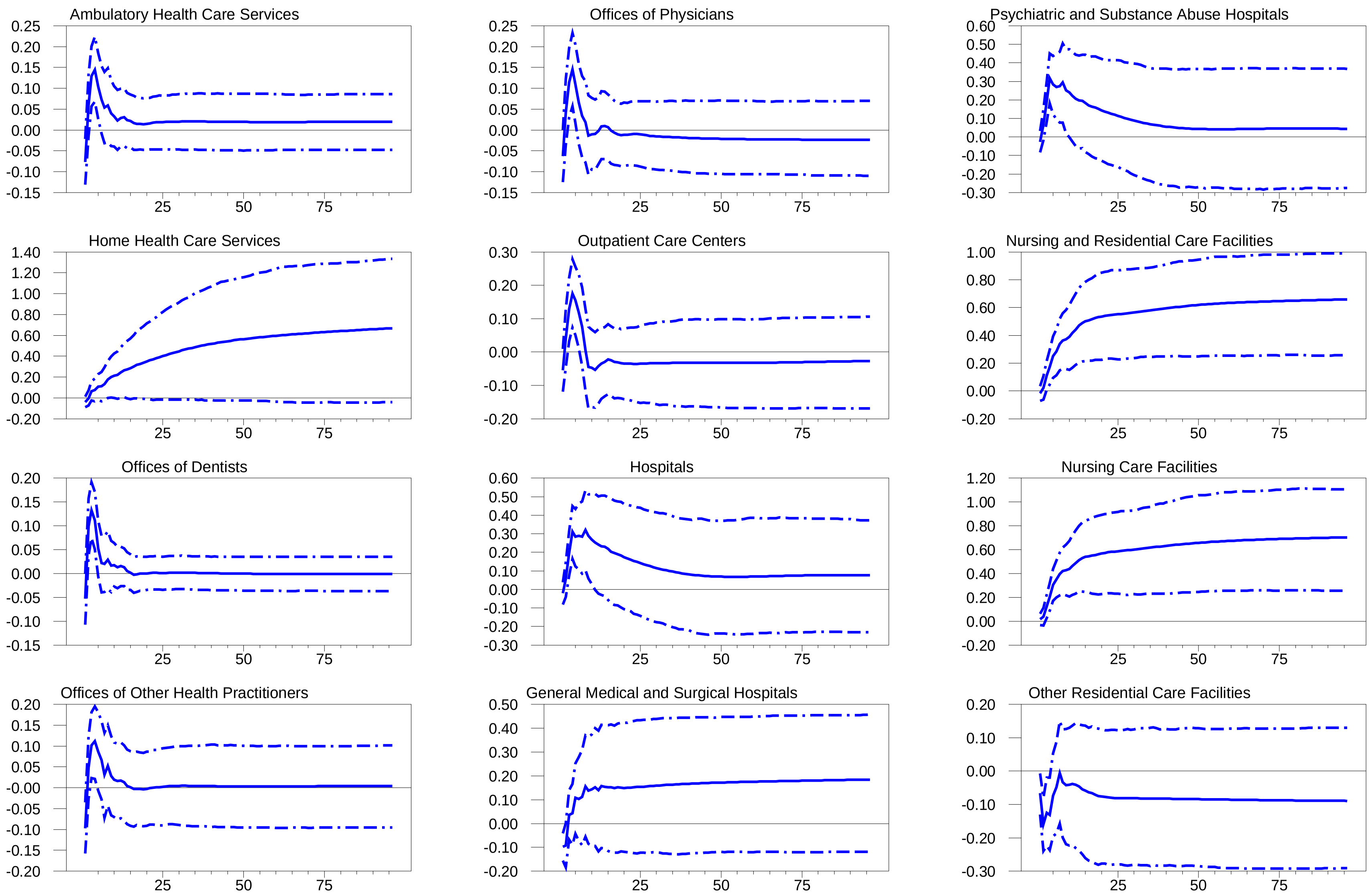

*Notes*: This figure presents the accumulated impulse responses of employment in the different healthcare sectors to a one standard deviation negative aggregate demand shock using sign restrictions. The sample period is 1990-2021. The three lines are 16% quantile, the median and the 16% quantile of the posterior distribution. The vertical axis reports quantitative magnitude of the response (in %), while the horizontal scale reports months.

**Figure 5. IRFs of Health Care Employment to Negative Supply Shock**



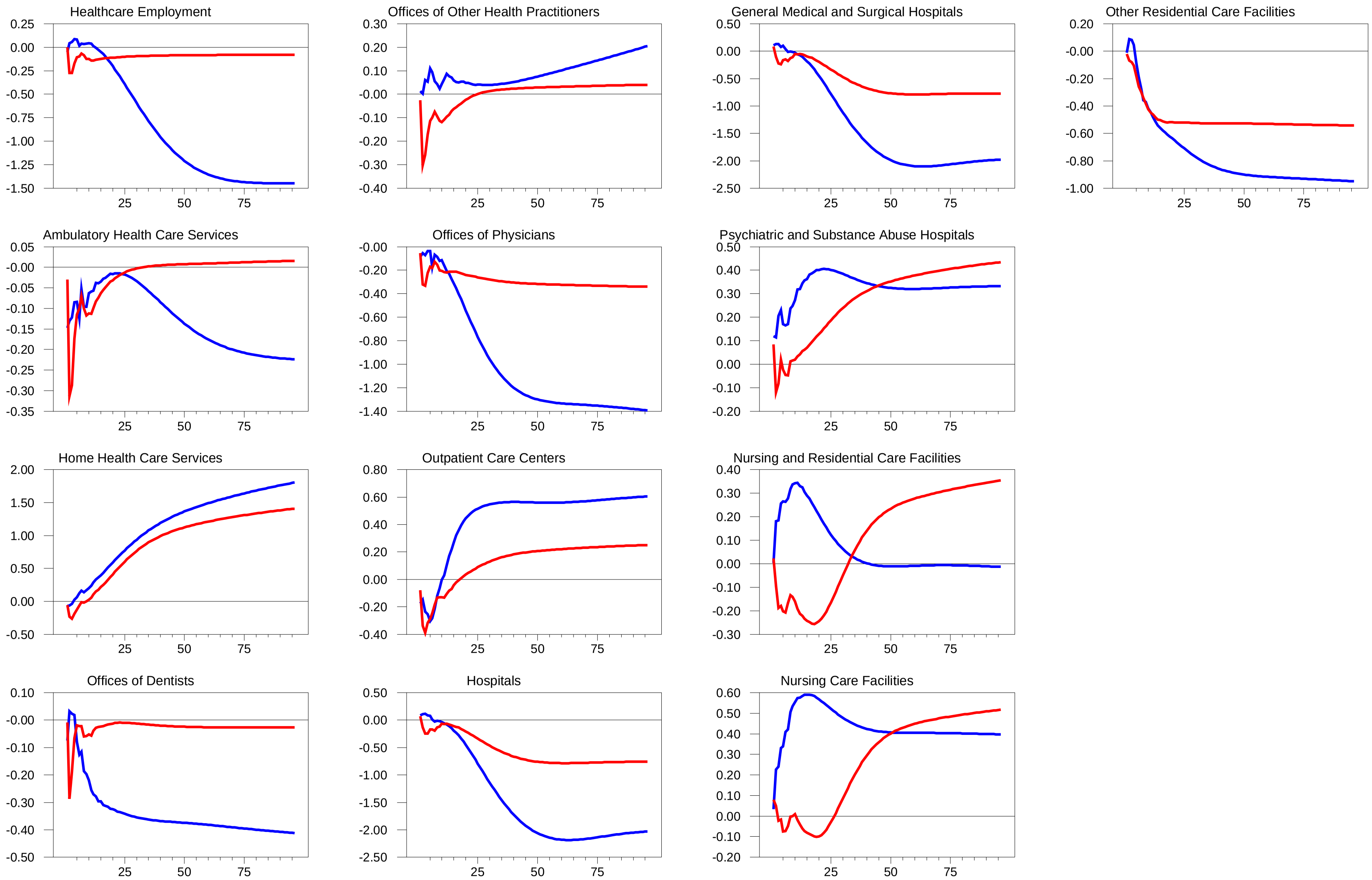

*Notes*: This figure presents the accumulated impulse responses of variables/factors to a one standard deviation negative aggregate supply shock using sign restrictions. The sample period is 1990-2021. The three lines are 16% quantile, the median and the 16% quantile of the posterior distribution. The vertical axis reports quantitative magnitude of the response (in %), while the horizontal scale reports months.

**Figure 6. Differential Response of Employment in Healthcare Industry to Negative Supply Shock**



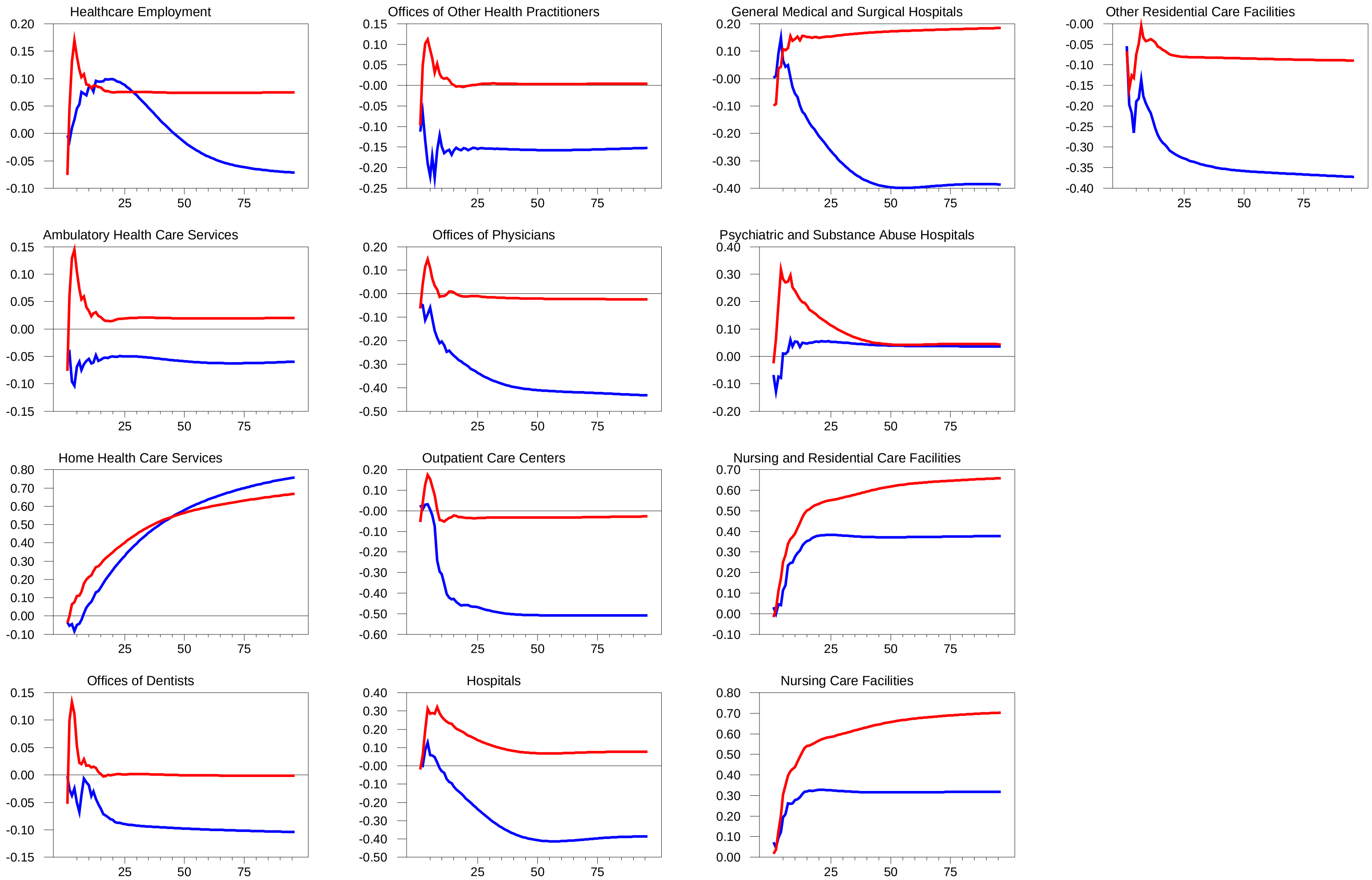

*Notes*: This figure presents the accumulated impulse responses of employment in the different healthcare sectors to a one standard deviation negative aggregate supply shock using sign restrictions. The sample period is 1990-2021. The three lines are 16% quantile, the median and the 16% quantile of the posterior distribution. The vertical axis reports quantitative magnitude of the response (in %), while the horizontal scale reports months.

## Figure 7. Responses of Healthcare Employment to Negative Demand Shock: 1990-2019 vs. 1990-2021



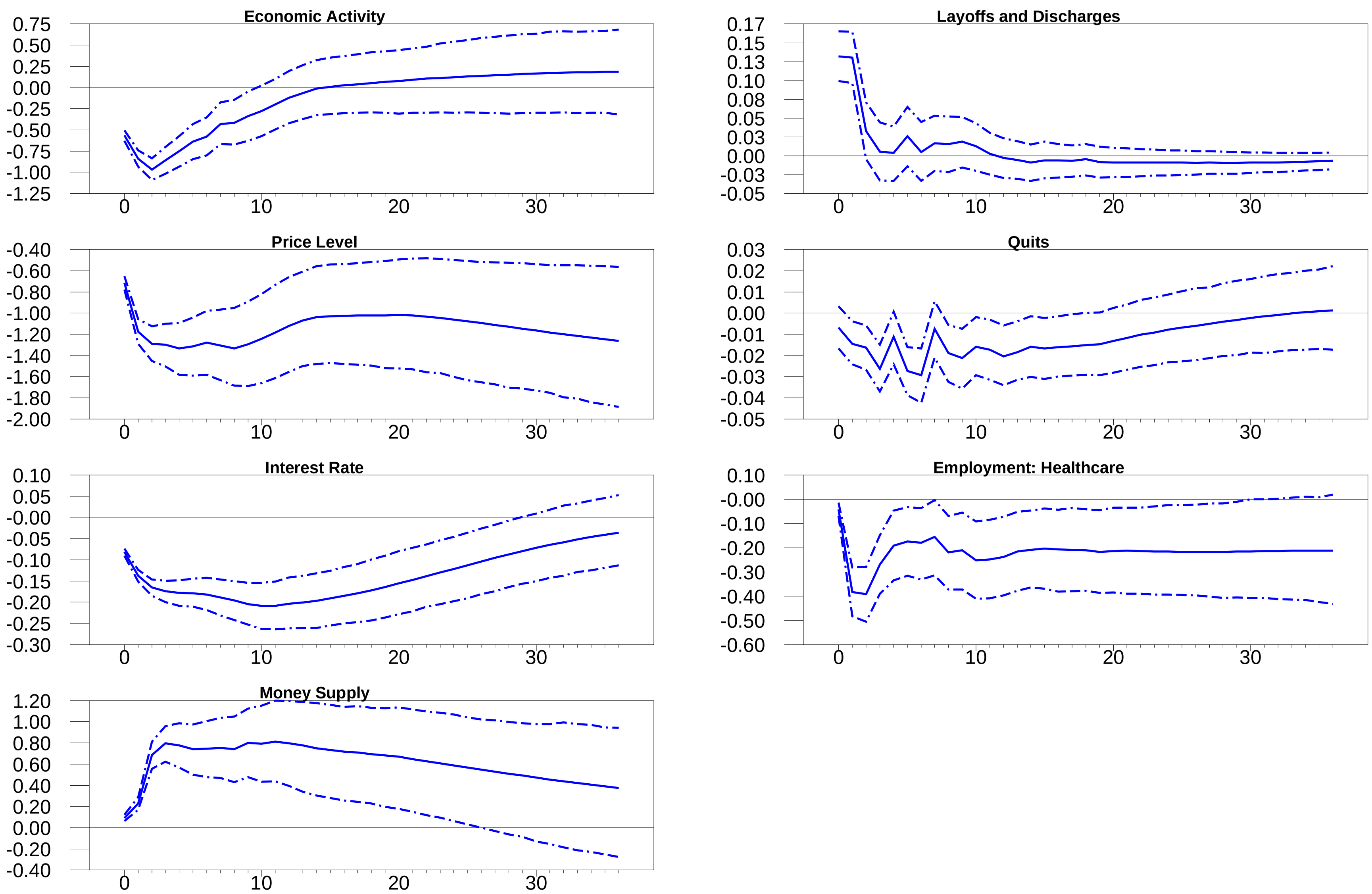

*Notes*: This figure compares the differential responses of employment in healthcare industry to a one standard deviation negative aggregate demand shock using data over two sample periods: 1990-2019 vs. 1990-2021. The red line reports the responses using 1990-2021 data, while the blue line reports the responses using 1990-2019 data. The vertical axis reports quantitative magnitude of the response (in %), while the horizontal scale reports months.

**Figure 8. Responses of Healthcare Employment to Negative Supply Shock: 1990-2019 vs. 1990-2021**



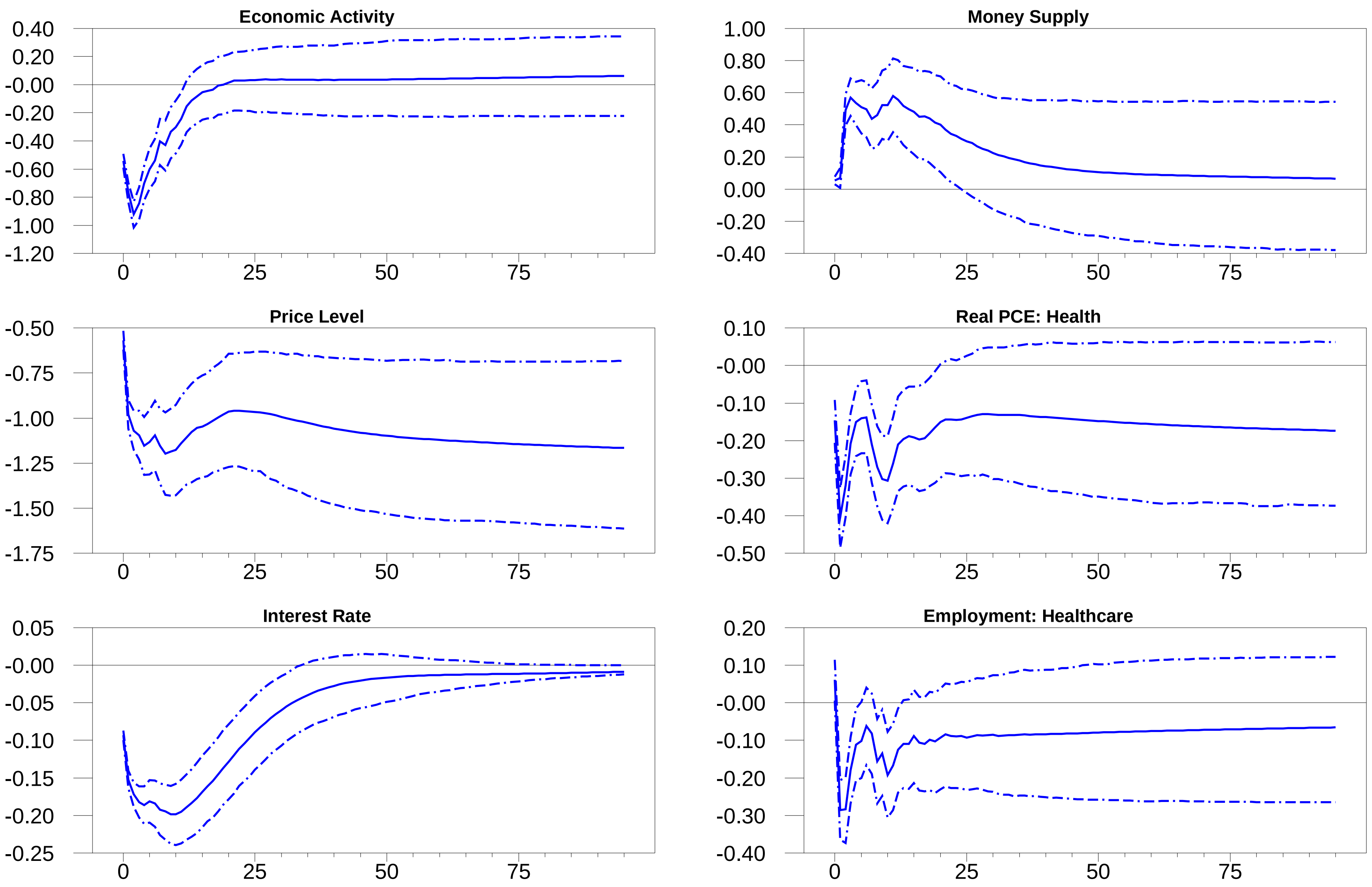

*Notes*: This figure compares the differential responses of employment in healthcare industry to a one standard deviation negative aggregate supply shock using data over two sample periods: 1990-2019 vs. 1990-2021. The red line reports the responses using 1990-2021 data, while the blue line reports the responses using 1990-2019 data. The vertical axis reports quantitative magnitude of the response (in %), while the horizontal scale reports months.

## Figure 9. Mechanism: Negative Demand Shock and Job Separations



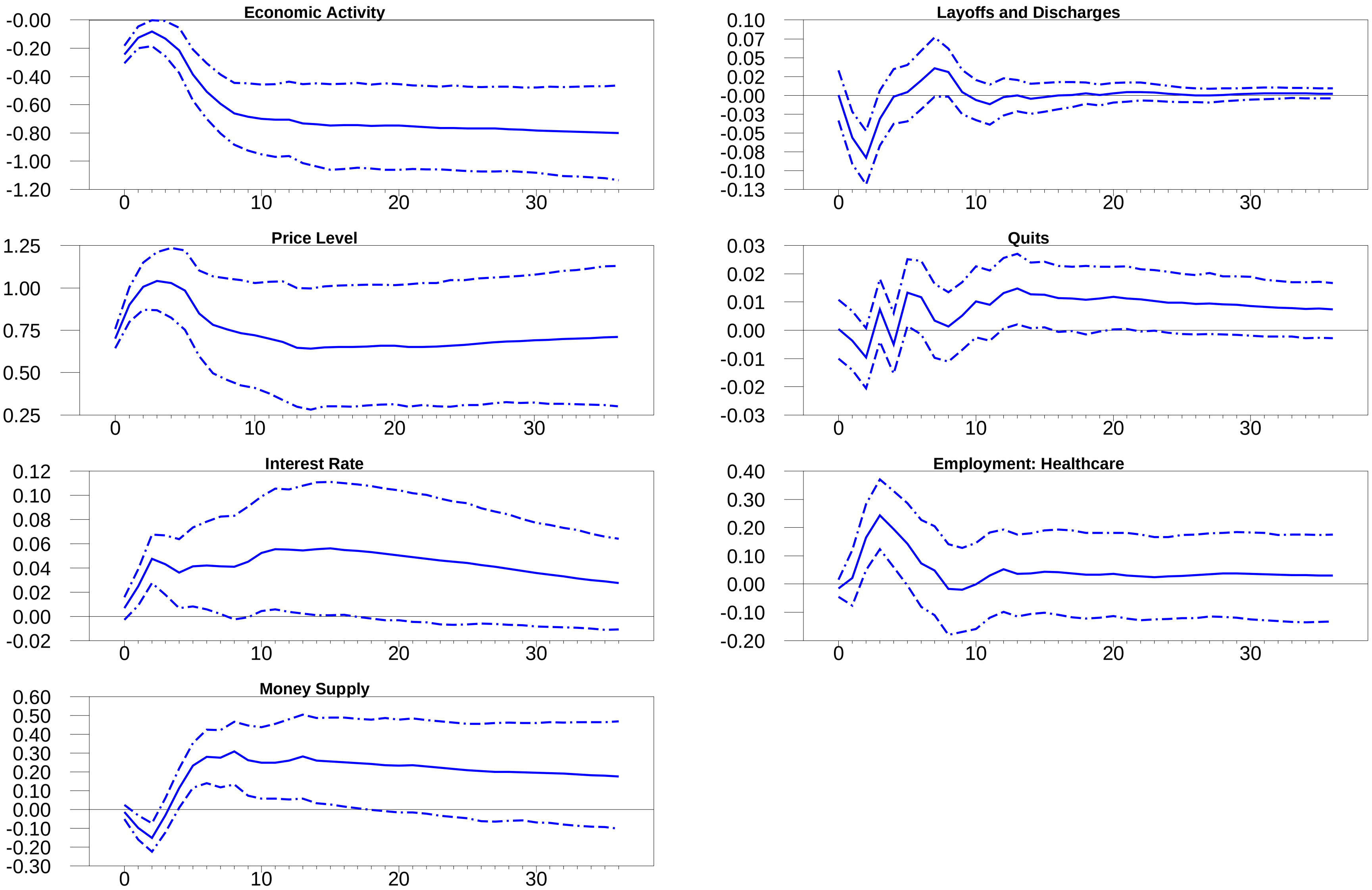

*Notes*: This figure presents the accumulated impulse responses of the variables/factors to a one standard deviation negative aggregate demand shock using sign restrictions. The sample period is 2001-2021. The three lines are 16% quantile, the median and the 16% quantile of the posterior distribution. The vertical axis reports quantitative magnitude of the response (in %), while the horizontal scale reports months.

**Figure 10. Mechanism: Negative Demand Shock and Personal Healthcare Expenditures**



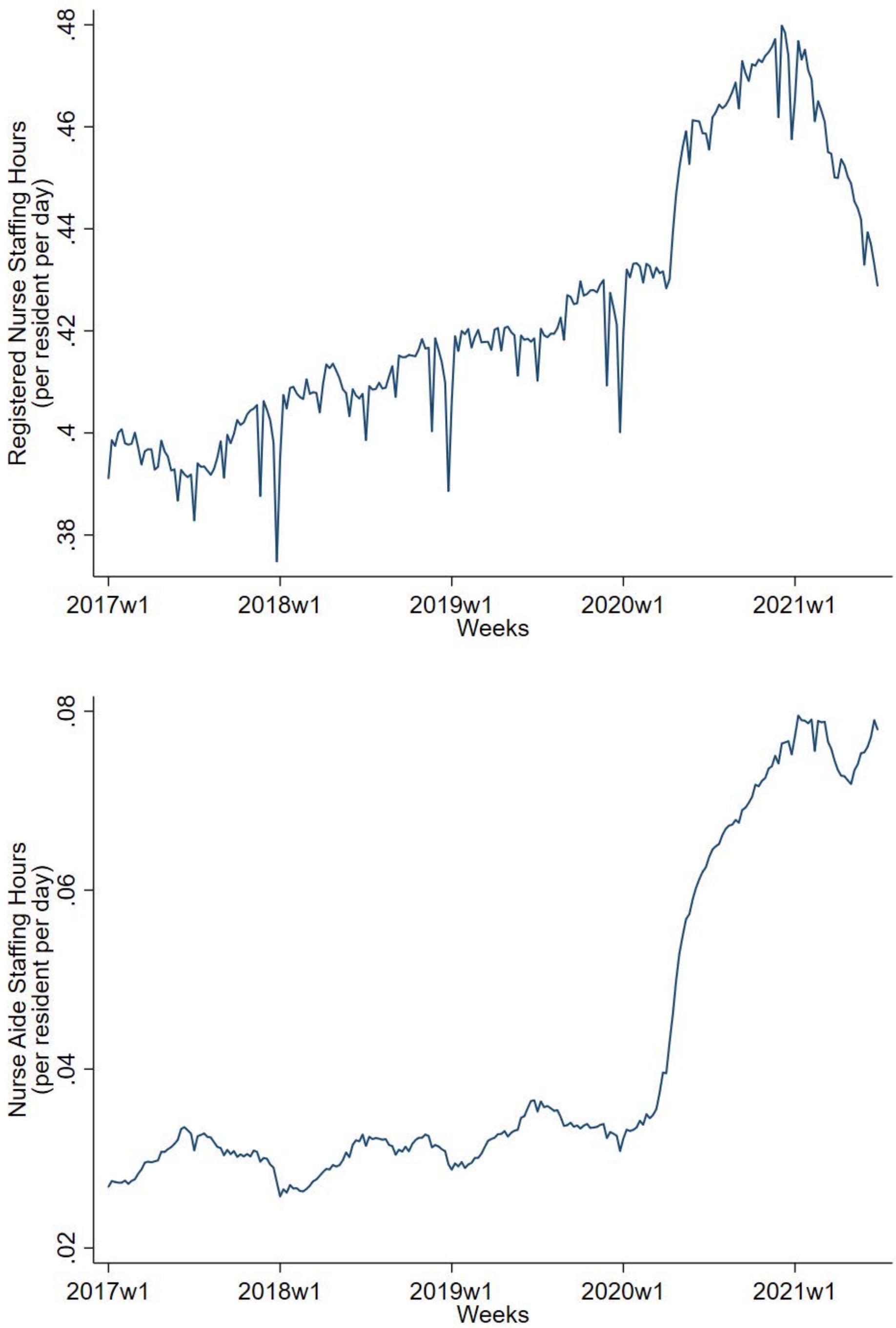

*Notes*: This figure presents the accumulated impulse responses of the variables/factors to a one standard deviation negative aggregate demand shock using sign restrictions. The sample period is 1990-2021. The three lines are 16% quantile, the median and the 16% quantile of the posterior distribution. The vertical axis reports quantitative magnitude of the response (in %), while the horizontal scale reports months.

**Figure 11. Mechanism: Negative Supply Shock**




*Notes*: This figure presents the accumulated impulse responses of variables/factors to a one standard deviation negative aggregate supply shock using sign restrictions. The sample period is 2001-2021. The three lines are 16% quantile, the median and the 16% quantile of the posterior distribution. The vertical axis reports quantitative magnitude of the response (in %), while the horizontal scale reports months.

**Figure 12. Payroll-Based Nurse Staffing Hours**

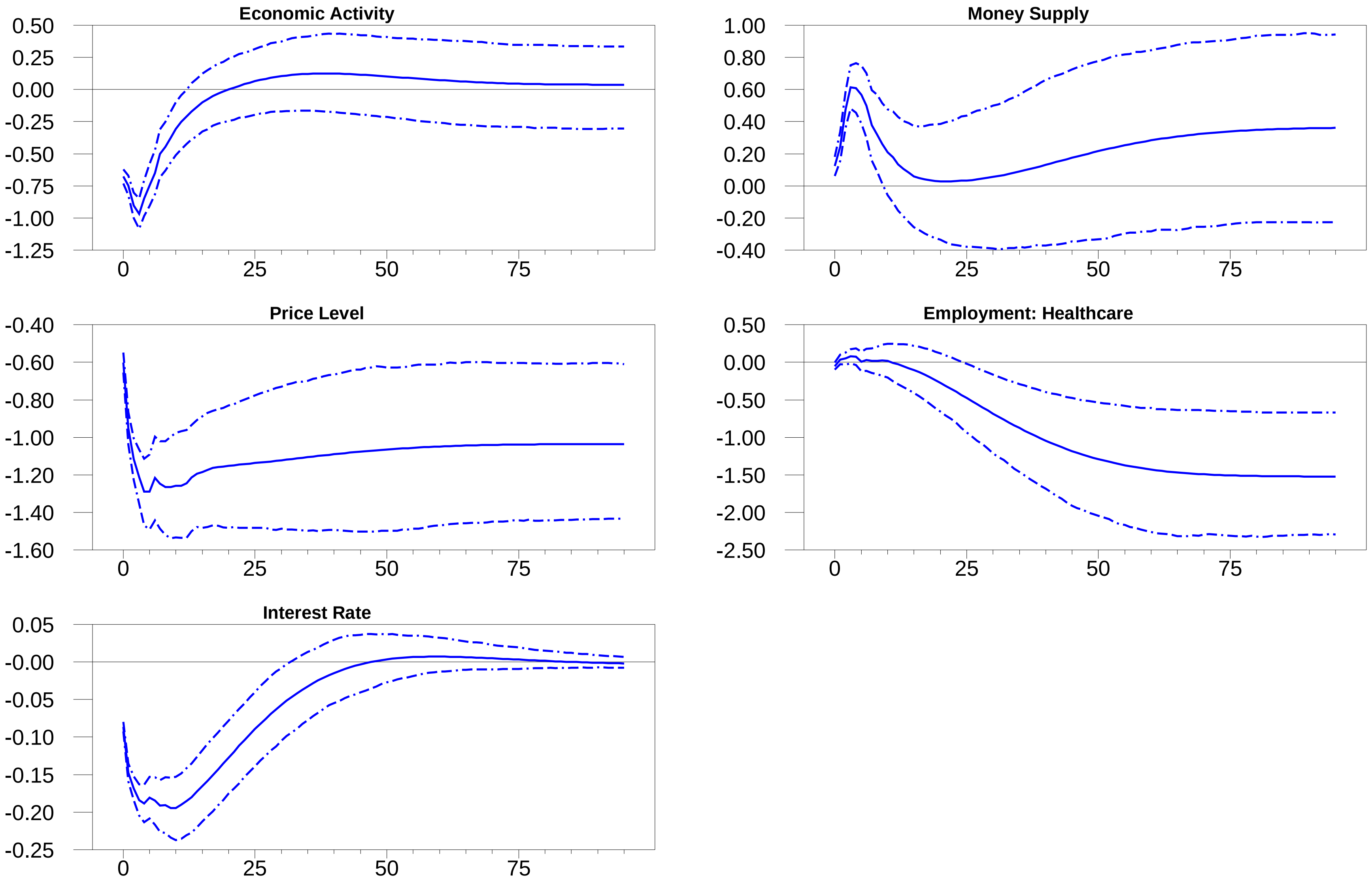



*Notes*: This figure shows staffing hours per resident day for registered nurses and nursing aides. The daily facility-level data for payroll-based number of hours are aggregated to obtain weekly national estimates. The data come from the Payroll-Based Journal of the Centers for Medicare & Medicaid Services.

# For Online Publication: Appendix

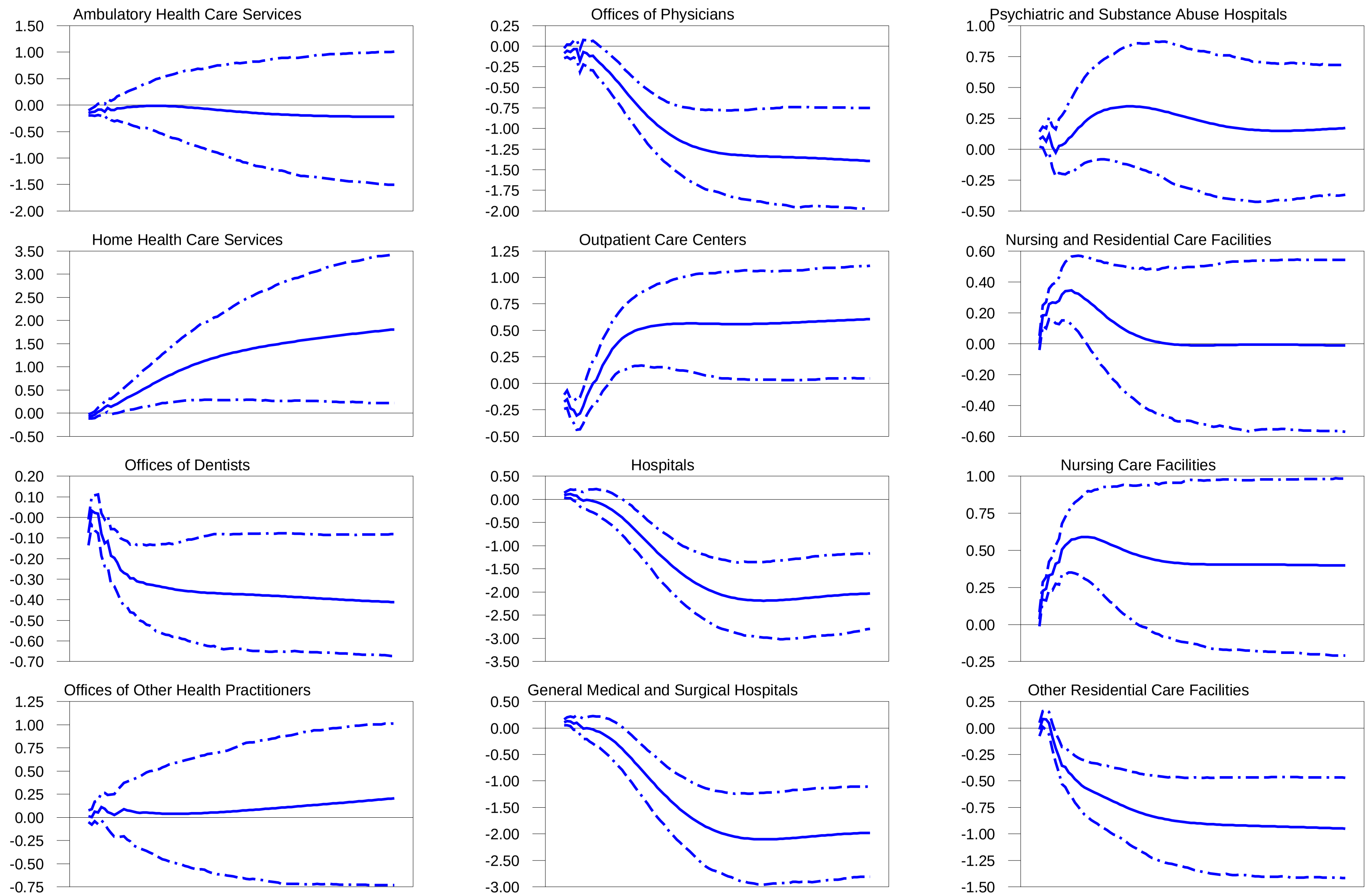
## Appendix A. Figures

**Figure A1. IRFs of Health Care Employment to Negative Demand Shock**



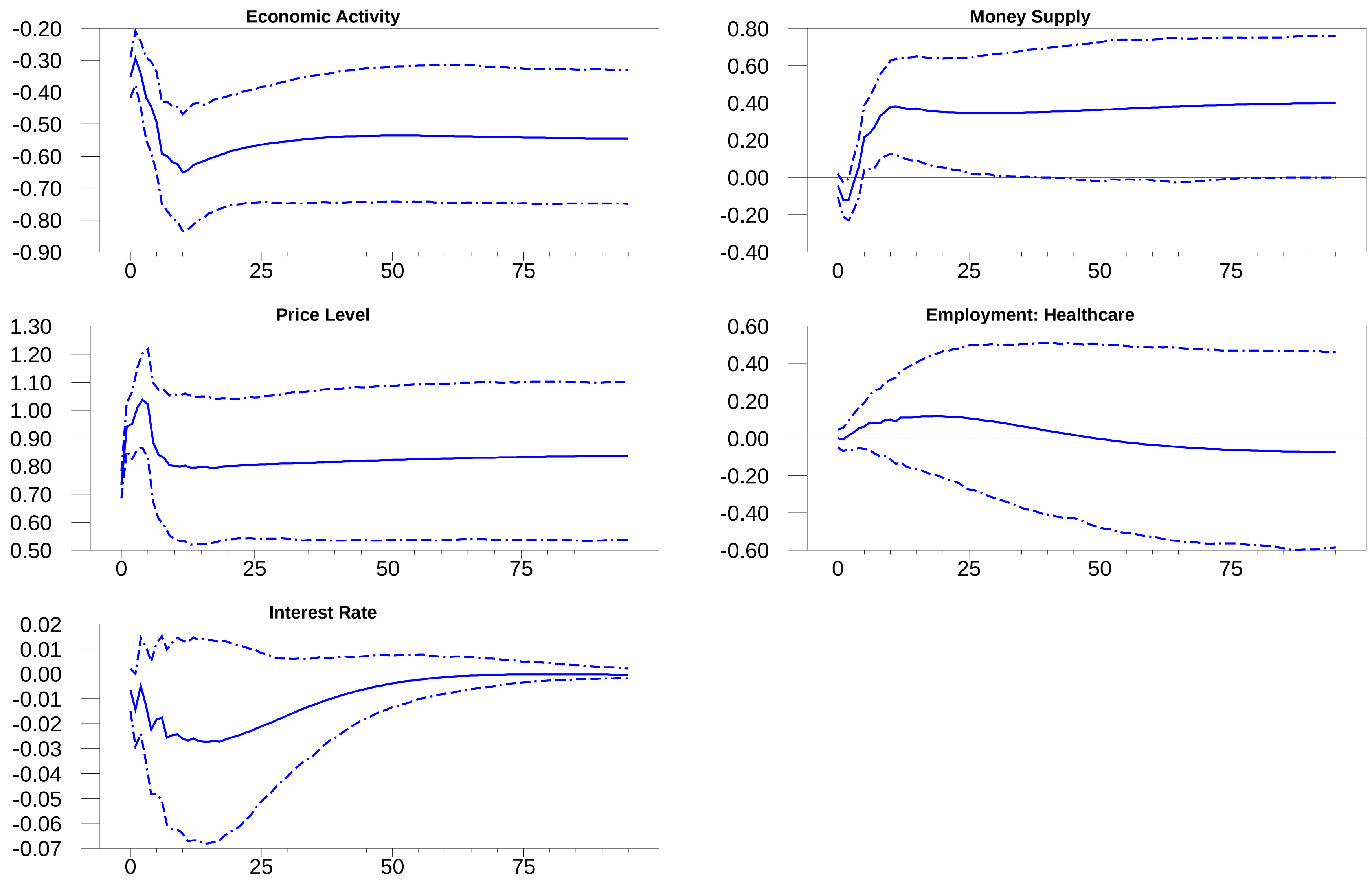

*Notes*: This figure presents the accumulated impulse responses of the variables/factors to a one standard deviation negative aggregate demand shock using sign restrictions. The sample period is 1990-2019. The three lines are 16% quantile, the median and the 16% quantile of the posterior distribution. The vertical axis reports quantitative magnitude of the response (in %), while the horizontal scale reports months.

## Figure A2. Differential Response of Employment in Healthcare Industry to Negative Demand Shock



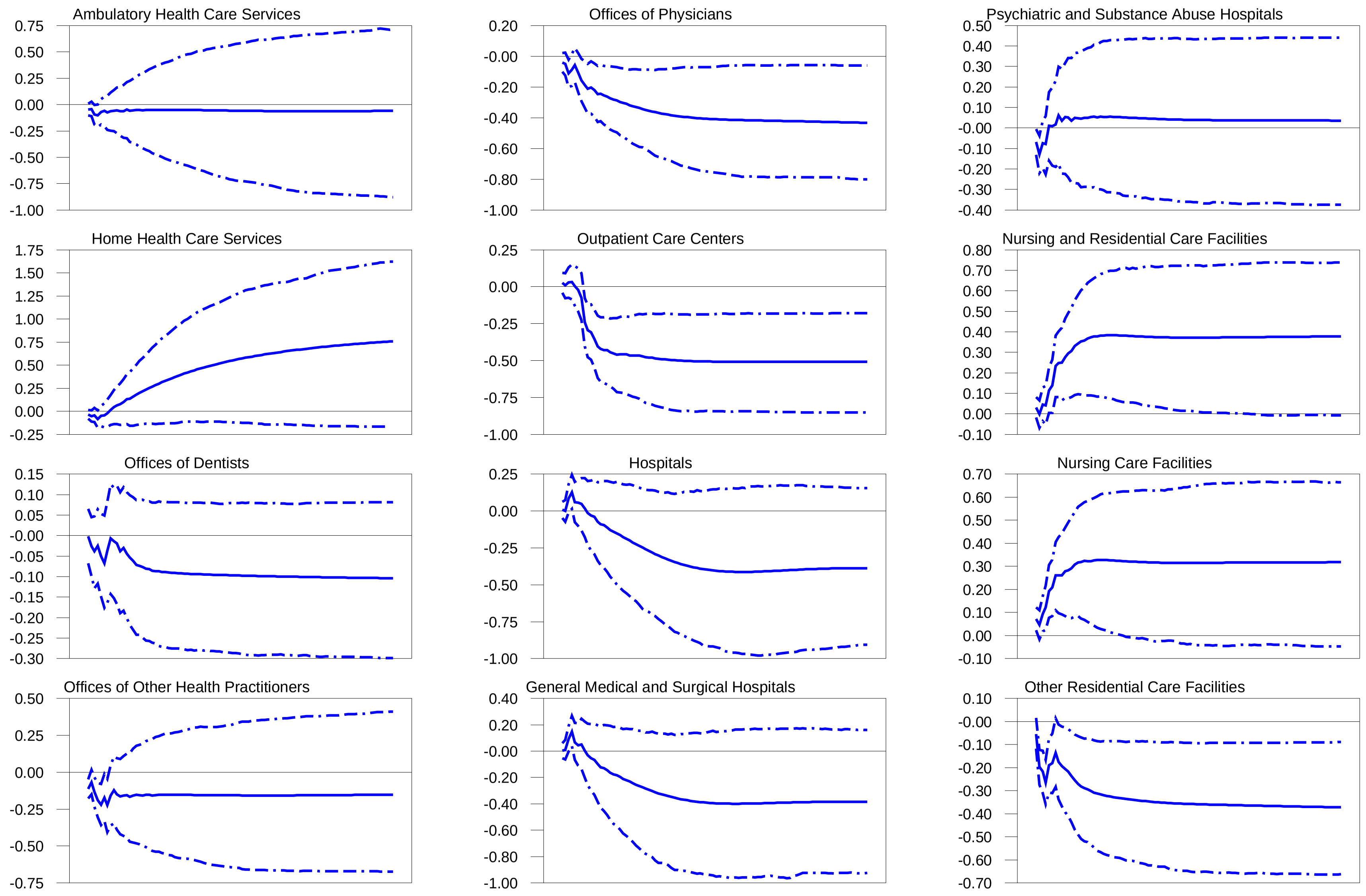

*Notes*: This figure presents the accumulated impulse responses of employment in the different healthcare sectors to a one standard deviation negative aggregate demand shock using sign restrictions. The sample period is 1990-2019. The three lines are 16% quantile, the median and the 16% quantile of the posterior distribution. The vertical axis reports quantitative magnitude of the response (in %), while the horizontal scale reports months.

**Figure A3. IRFs of Health Care Employment to Negative Supply Shock**




*Notes*: This figure presents the accumulated impulse responses of employment in the different healthcare sectors to a one standard deviation negative aggregate supply shock using sign restrictions. The sample period is 1990-2019. The three lines are 16% quantile, the median and the 16% quantile of the posterior distribution. The vertical axis reports quantitative magnitude of the response (in %), while the horizontal scale reports months.

## Figure A4. Differential Response of Employment in Healthcare Industry to Negative Supply Shock




*Notes*: This figure presents the accumulated impulse responses of employment in the different healthcare sectors to a one standard deviation negative aggregate supply shock using sign restrictions. The sample period is 1990-2019. The three lines are 16% quantile, the median and the 16% quantile of the posterior distribution. The vertical axis reports quantitative magnitude of the response (in %), while the horizontal scale reports months.

**Supplementary Tables**

Data Sources: Federal Reserve Economic Database (FRED) of the St. Louis Fed, IMF International Financial Statistics, and Institute of Supply Management.

**Table A1. U.S. Economic Activity Factor and Factor Loading**

| No. | Variables Constructing U.S. Economic Activity Factor | Transformation Code | Description | Factor Loading ($\lambda$) |
|---|---|---|---|---|
| 1 | INDPRO | 2 | Industrial Production Index, Index 2012=100, SA | 0.1886 |
| 2 | IPFINAL | 2 | Industrial Production: Final Products (Market Group), Index 2012=100, SA | 0.1907 |
| 3 | IPCONGD | 2 | Industrial Production: Consumer Goods, Index 2012=100, SA | 0.1930 |
| 4 | IPDCONGD | 2 | Industrial Production: Durable Consumer Goods, Index 2012=100, SA | 0.1879 |
| 5 | IPNCONGD | 2 | Industrial Production: Nondurable Consumer Goods, Index 2012=100, SA | 0.1945 |
| 6 | IPMAT | 2 | Industrial Production: Materials, Index 2012=100, SA | 0.1856 |
| 7 | IPDMAT | 2 | Industrial Production: Durable Materials, Index 2012=100, SA | 0.1809 |
| 8 | IPNMAT | 2 | Industrial Production: Nondurable Materials, Index 2012=100, SA | 0.1956 |
| 9 | IPMANSICS | 2 | Industrial Production: Manufacturing (SIC), Index 2012=100, SA | 0.1893 |
| 10 | IPBUSEQ | 2 | Industrial Production: Business Equipment, Index 2012=100, SA | 0.1835 |
| 11 | IPB53820S | 2 | Industrial Production: Non-energy materials for intermediate goods producers, Index 2012=100, SA | 0.1935 |

| | | | | |
|---|---|---|---|---|
| 12 | IPB562A3CS | 2 | Industrial Production: Primary and semifinished processing, Index 2012=100, SA | 0.1889 |
| 13 | IPDMAN | 2 | Industrial Production: Durable Manufacturing (NAICS), Index 2012=100, SA | 0.1830 |
| 14 | IPNMAN | 2 | Industrial Production: Nondurable Manufacturing (NAICS), Index 2012=100, SA | 0.1947 |
| 15 | IPMINE | 2 | Industrial Production: Mining, Index 2012=100, SA | 0.1894 |
| 16 | IPG22111S | 2 | Industrial Production: Utilities: Electric power generation, Index 2012=100, SA | 0.1919 |
| 17 | CAPUTLGMFNS | 1 | Capacity Utilization: Nondurable manufacturing, Percent of Capacity, SA | 3.3118 |
| 18 | CAPUTLGMFDS | 1 | Capacity Utilization: Durable manufacturing, Percent of Capacity, SA | 3.2003 |
| 19 | CUMFNS | 1 | Capacity Utilization: Manufacturing (SIC), Percent of Capacity, SA | 3.2491 |
| 20 | ISMMANPMI | 1 | ISM Manufacturing: PMI Composite Index, SA (in percent) | 2.2171 |
| 21 | ISMMANPROD | 1 | ISM Manufacturing: Production Index, SA (in percent) | 2.3395 |
| 22 | ISMMANNEWORDERS | 1 | ISM Manufacturing: New Order Index, SA (in percent) | 2.3380 |
| 23 | ISMMANEMPL | 1 | ISM Manufacturing: Employment Index, SA (in percent) | 2.0920 |
| 24 | ISMMANDELIV | 1 | ISM Manufacturing: Supplies Delivery Index, SA (in percent) | 2.2735 |
| 25 | ISMMANINVENT | 1 | ISM Manufacturing: Inventories Index, SA (in percent) | 1.9562 |

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|---|---|---|---|---|
| 26 | RPI | 2 | Real Personal Income, Billions of Chained 2012 Dollars, SAAR | 0.3953 |
| 27 | W875RX1 | 2 | Real personal income excluding current transfer receipts, Billions of Chained 2012 Dollars, SAAR | 0.3883 |
| 28 | DPCERA3M086SBEA | 2 | Real Personal Consumption Expenditures, Index 2012=100, SA | 0.1872 |
| 29 | DDURRA3M086SBEA | 2 | Real personal consumption expenditures: Durable goods (chain-type quantity index), Index 2012=100, SA | 0.1823 |
| 30 | DNDGRA3M086SBEA | 2 | Real personal consumption expenditures: Nondurable goods (chain-type quantity index), Index 2012=100, SA | 0.1896 |
| 31 | DSERRA3M086SBEA | 2 | Real Personal Consumption Expenditures: Services, Index 2012=100, SA | 0.1875 |
| 32 | DPCCRA3M086SBEA | 2 | Real Personal Consumption Expenditures Excluding Food and Energy, Index 2012=100, SA | 0.1864 |
| 33 | UMCSENT | 2 | University of Michigan: Consumer Sentiment, Index 1966:Q1=100, NSA | 0.1880 |
| 34 | CSCICP03USM665S | 2 | Consumer Opinion Surveys: Confidence Indicators: Composite Indicators: OECD Indicator for the United States, Normalised (Normal=100), SA | 0.1941 |
| 35 | CE16OV | 2 | Civilian Employment Level, Thousands of Persons, SA | 0.4985 |
| 36 | LNS12035019 | 2 | Employment Level: Nonagricultural Industries, Thousands of Persons, SA | 0.4977 |

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|---|---|---|---|---|
| 37 | LNS12034560 | 2 | Employment Level: Agriculture and Related Industries, Thousands of Persons, SA | 0.3308 |
| 38 | UNRATE | 1 | Civilian Unemployment Rate, Percent, SA | -0.2482 |
| 39 | UEMPMEAN | 2 | Average (Mean) Duration of Unemployment, Weeks, SA | -0.1265 |
| 40 | UEMPLT5 | 2 | Number of Civilians Unemployed for Less Than 5 Weeks, Thousands of Persons, SA | -0.3326 |
| 41 | UEMP5TO14 | 2 | Number of Civilians Unemployed for 5 to 14 Weeks, Thousands of Persons, SA | -0.3279 |
| 42 | UEMP15OV | 2 | Number of Civilians Unemployed for 15 Weeks and Over, Thousands of Persons, SA | -0.3373 |
| 43 | UEMP15T26 | 2 | Number of Civilians Unemployed for 15 to 26 Weeks, Thousands of Persons, SA | -0.2996 |
| 44 | UEMP27OV | 2 | Number of Civilians Unemployed for 27 Weeks and Over, Thousands of Persons, SA | -0.3139 |
| 45 | USPRIV | 2 | All Employees: Total Private, Thousands of Persons, SA | 0.4887 |
| 46 | PAYEMS | 2 | All Employees: Total Nonfarm, Thousands of Persons, SA | 0.4962 |
| 47 | USGOOD | 2 | All Employees: Goods-producing, Thousands of Persons, SA | 0.4202 |
| 48 | USMINE | 2 | All Employees: Mining and Logging, Thousands of Persons, SA | 0.2751 |
| 49 | USCONS | 2 | All Employees: Construction, Thousands of Persons, SA | 0.3681 |
| 50 | MANEMP | 2 | All Employees: Manufacturing, Thousands of Persons, SA | 0.4033 |

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|---|---|---|---|---|
| 51 | DMANEMP | 2 | All Employees: Durable Goods, Thousands of Persons, SA | 0.3831 |
| 52 | NDMANEMP | 2 | All Employees: Non durable Goods, Thousands of Persons, SA | 0.3626 |
| 53 | SRVPRD | 2 | All Employees: Service Providing, Thousands of Persons, SA | 0.4885 |
| 54 | USTPU | 2 | All Employees: Trade, Transportation, and Utilities, Thousands of Persons, SA | 0.4271 |
| 55 | USWTRADE | 2 | All Employees: Wholesale Trade, Thousands of Persons, SA | 0.3636 |
| 56 | USTRADE | 2 | All Employees: Retail Trade, Thousands of Persons, SA | 0.4043 |
| 57 | USFIRE | 2 | All Employees: Financial Activities, Thousands of Persons, SA | 0.3773 |
| 58 | USSERV | 2 | All Employees: Other Services, Thousands of Persons, SA | 0.3602 |
| 59 | USGOVT | 2 | All Employees: Government, Thousands of Persons, SA | 0.4194 |
| 60 | CIVPART | 2 | Civilian Labor Force Participation Rate, Percent, SA | 2.7474 |
| 61 | UNEMPLOY | 2 | Unemployment Level, Thousands of Persons, SA | -0.3802 |
| 62 | AWHMAN | 2 | Average Weekly Hours of Production and Nonsupervisory Employees: Manufacturing, Hours, SA | 0.1567 |
| 63 | AWOTMAN | 2 | Average Weekly Overtime Hours of Production and Nonsupervisory Employees: Manufacturing, Hours, SA | 0.0613 |
| 64 | CES2000000008 | 2 | Average Hourly Earnings of Production and Nonsupervisory Employees: Construction, 1982-84 Dollars, SA | 0.1258 |

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| 65 | CES3000000008 | 2 | Average Hourly Earnings of Production and Nonsupervisory Employees: Manufacturing, 1982-84 Dollars, SA | 0.1171 |
| 66 | AHETPI | 2 | Average Hourly Earnings of Production and Nonsupervisory Employees: Total Private, 1982-84 Dollars, SA | 0.1171 |
| 67 | CES0600000008 | 2 | Average Hourly Earnings of Production and Nonsupervisory Employees: Goods-producing, 1982-84 Dollars, SA | 0.1203 |
| 68 | CES0800000008 | 2 | Average Hourly Earnings of Production and Nonsupervisory Employees: Private Service-providing, 1982-84 Dollars, SA | 0.1161 |
| 69 | HOUST | 2 | Housing Starts: Total: New Privately Owned Housing Units Started, Thousands of Units, SAAR | 0.3004 |
| 70 | HOUSTMW | 2 | Housing Starts in Midwest Census Region, Thousands of Units, SAAR | 0.2276 |
| 71 | HOUSTNE | 2 | Housing Starts in Northeast Census Region, Thousands of Units, SAAR | 0.2024 |
| 72 | HOUSTS | 2 | Housing Starts in South Census Region, Thousands of Units, SAAR | 0.2690 |
| 73 | HOUSTW | 2 | Housing Starts in West Census Region, Thousands of Units, SAAR | 0.2404 |
| 74 | PERMIT | 2 | New Private Housing Units Authorized by Building Permits, Thousands of Units, SAAR | 0.3010 |

Data Sources: Federal Reserve Economic Database (FRED) of the St. Louis Fed, IMF International Financial Statistics, Bureau of Labour Statistics, and Institute of Supply Management.

**Table A2. U.S. Price Factor and Factor Loading**

| No. | Variables Constructing U.S. Price Factor | Transformation Code | Description | Factor Loading ($\zeta$) |
|---|---|---|---|---|
| 1 | WPS141 | 2 | Producer Price Index by Commodity for Transportation Equipment: Motor Vehicles and Equipment, Index 1982=100, SA | 0.9764 |
| 2 | WPSFD4111 | 2 | Producer Price Index by Commodity for Final Demand: Finished Consumer Foods, Index 1982=100, SA | 1.0121 |
| 3 | WPSFD49207 | 2 | Producer Price Index by Commodity for Final Demand: Finished Goods, Index 1982=100, SA | 1.0078 |
| 4 | WPSID62 | 2 | Producer Price Index by Commodity for Intermediate Demand by Commodity Type: Unprocessed Goods for Intermediate Demand, Index 1982=100, SA | 1.0022 |
| 5 | WPSID61 | 2 | Producer Price Index by Commodity for Intermediate Demand by Commodity Type: Processed Goods for Intermediate Demand, Index 1982=100, SA | 1.0024 |
| 6 | WPSID69111 | 2 | Producer Price Index by Commodity for Intermediate Demand by Commodity Type: Processed Materials Less Foods and Feed, Index 1982=100, SA | 1.0029 |

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|---|---|---|---|---|
| 7 | WPSID69211 | 2 | Producer Price Index by Commodity for Intermediate Demand by Commodity Type: Unprocessed Materials Less Agricultural Products, Index 1982=100, SA | 1.0118 |
| 8 | PPIACO | 2 | Producer Price Index for All Commodities, Index 1982=100, NSA | 1.0053 |
| 9 | PPIACO | 2 | Producer Price Index for All Commodities, Index 1982=100, NSA | 0.7357 |
| 10 | CPIAPPSL | 2 | Consumer Price Index for All Urban Consumers: Apparel, Index 1982-1984=100, SA | 0.9599 |
| 11 | CPITRNSL | 2 | Consumer Price Index for All Urban Consumers: Transportation, Index 1982-1984=100, SA | 1.0212 |
| 12 | CPIMEDSL | 2 | Consumer Price Index for All Urban Consumers: Medical Care, Index 1982-1984=100, SA | 1.1464 |
| 13 | CUSR0000SAC | 2 | Consumer Price Index for All Urban Consumers: Commodities, Index 1982-1984=100, SA | 1.0082 |
| 14 | CUSR0000SAD | 2 | Consumer Price Index for All Urban Consumers: Durables, Index 1982-1984=100, SA | 0.9433 |
| 15 | CUSR0000SAS | 2 | Consumer Price Index for All Urban Consumers: Durables, Index 1982-1984=100, SA | 1.0787 |
| 16 | CPIULFSL | 2 | Consumer Price Index for All Urban Consumers: All Items Less Food, Index 1982-1984=100, SA | 1.0471 |
| 17 | CUSR0000SA0L2 | 2 | Consumer Price Index for All Urban Consumers: All items less shelter, Index 1982-1984=100, SA | 1.0377 |

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|---|---|---|---|---|
| 18 | CPILFESL | 2 | Consumer Price Index for All Urban Consumers: All Items Less Food and Energy, Index 1982-1984=100, SA | 1.0536 |
| 19 | CUSR0000SA0L5 | 2 | Consumer Price Index for All Urban Consumers: All Items Less Medical Care, Index 1982-1984=100, SA | 1.0402 |
| 20 | CPIENGSL | 2 | Consumer Price Index for All Urban Consumers: Energy, Index 1982-1984=100, SA | 1.0087 |
| 21 | CPILEGSL | 2 | Consumer Price Index for All Urban Consumers: All Items Less Energy, Index 1982-1984=100, SA | 1.0520 |
| 22 | CPIUFDSL | 2 | Consumer Price Index for All Urban Consumers: Food, Index 1982-1984=100, SA | 1.0466 |
| 23 | WTISPLC | 2 | Spot Crude Oil Prices: West Texas Intermediate (WTI) - Cushing, Oklahoma, Dollars per Barrel, NSA | 0.7357 |
| 24 | CPIAUCSL | 2 | Consumer Price Index for All Urban Consumers: All Items in U.S. City Average, SA | 1.0470 |
| 25 | CSUSHPISA | 2 | S&P/Case-Shiller U.S. National Home Price Index, Index Jan 2000=100, SA | 1.0713 |
| 26 | CUSR0000SEHA | 2 | Consumer Price Index for All Urban Consumers: Rent of primary residence, Index 1982-1984=100, SA | 0.9695 |
| 27 | PXPIX | 2 | Export Price Index: All Commodities, Index, NSA | 0.9373 |
| 28 | PMPIX | 2 | Import Price Index: All Commodities, Index, NSA | 0.9373 |

Data Sources: Federal Reserve Economic Database (FRED) of the St. Louis Fed, IMF International Financial Statistics, Bureau of Labour Statistics, and Institute of Supply Management.

**Table A3. U.S. Interest Rate Factor and Factor Loading**

| No. | Variables Constructing the U.S. Interest Rate Factor | Transformation Code | Description | Factor Loadings ($\eta$) |
|---|---|---|---|---|
| 1 | FEDFUNDS | 1 | Effective Federal Funds Rate, Percent, NSA | 0.7852 |
| 2 | TB3MS | 1 | 3-Month Treasury Bill: Secondary Market Rate, Percent, NSA | 0.7337 |
| 3 | TB6MS | 1 | 6-Month Treasury Bill: Secondary Market Rate, Percent, NSA | 0.7529 |
| 4 | GS1 | 1 | 1-Year Treasury Constant Maturity Rate, Percent, NSA | 0.8094 |
| 5 | GS3 | 1 | 3-Year Treasury Constant Maturity Rate, Percent, NSA | 0.9087 |
| 6 | GS5 | 1 | 5-Year Treasury Constant Maturity Rate, Percent, NSA | 0.9723 |
| 7 | GS10 | 1 | 10-Year Treasury Constant Maturity Rate, Percent, NSA | 1.0531 |
| 8 | MPRIME | 1 | Bank Prime Loan Rate, Percent, NSA | 1.3629 |
| 9 | MORTGAGE30US | 1 | 30 year Mortgage Rate, Percent, NSA | 1.3731 |

Data Sources: Federal Reserve Economic Database (FRED) of the St. Louis Fed, IMF International Financial Statistics, Bureau of Labour Statistics, and Institute of Supply Management.

**Table A4. U.S. Monetary Aggregate Factor and Factor Loading**

| No. | Variables Constructing the U.S. Monetary Aggregate Factor | Transformation Code | Description | Factor Loading ($\gamma$) |
|---|---|---|---|---|
| 1 | M1SL | 2 | M1 Money Stock, Billions of Dollars, SA | 0.9474 |
| 2 | M2SL | 2 | M2 Money Stock, Billions of Dollars, SA | 1.1241 |
| 3 | NOM1M2 | 2 | Non-M1 Components of M2, Billions of Dollars, SA | 1.1025 |
| 4 | M2MSL | 2 | M2 Less Small Time Deposits, Billions of Dollars, SA | 1.0808 |
| 5 | BUSLOANS | 2 | Commercial and Industrial Loans, All Commercial Banks, Billions of U.S. Dollars, SA | 0.8979 |
| 6 | CONSUMER | 2 | Consumer Loans at All Commercial Banks, Billions of U.S. Dollars, SA | 0.8418 |
| 7 | TOTALSL | 2 | Total Consumer Credit Owned and Securitized, Outstanding, SA | 0.9698 |