Are transfer payments stimulative? - Sometimes*

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Abstract

This paper investigates the stimulative effects of transfer payments on macroeconomic aggregates using impulse response functions, forecast error variance decompositions, and spending multipliers in state-dependent time series econometric models. It is shown that under symmetric response assumptions, positive transfer payment impulses lead to positive effects on gross domestic product, personal income and personal consumption. However, when an asymmetry linked to economic conditions is used, it is found that transfer payment effects are asymmetric and have significant positive effects on macroeconomic variables during economic recessions but are not very stimulative during economic expansions. A deeper analysis shows that the stimulus effects during economic recessions results primarily from the recent special programs undertaken during the Great Recession and the COVID-19 recession. These results indicate that policy which uses transfer payments as economic stimulus for the economy during expansionary economic conditions will not see much benefit. Furthermore, transfer payment policy expansions during recessionary economic conditions do not offer much stimulus except when the programs are unusually large as seen during the Great Recession and the COVID recession. Results for forecast error variance decompositions and spending multipliers reinforce these findings. Transfer payment programs are often motivated by both the benefits to recipients, and the stimulative benefit to the economy. These results show that, outside of the periods where extraordinary transfer payment expansions occur, the economic stimulus effects of transfer payment programs are small and that transfer payments should only be motivated by the benefits to the recipients.

JEL Codes: E21, E62, H55

Keywords: Transfer payments, local projection, state-dependent time series econometric model

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1 Introduction

U.S. government transfer payments are a significant federal expenditure, making up about 40 percent of total spending. Most transfer payment programs are motivated by their benefits to the recipients of the payments, but their effects on the aggregate economy are typically argued to be stimulative for Gross Domestic Product (GDP) and other macroeconomic variables. A considerable body of research has focused on how total government spending affects the economy.[1] More recently, the effects of transfer payments in isolation have garnered attention.[2] Despite the recent focus, there are still important gaps in the literature. For instance, it is unclear whether different types of transfer payments have the same impact on economic activities. This paper addresses this gap by examining the disaggregated data of transfer payments.[3] Here, we study the impact of transfer payments on the aggregate economy using modern time series econometric methods to tease out the macroeconomic consequences of transfer payment impulses. We further investigate whether there are asymmetric effects of transfer payments where the asymmetry depends on the state of the business cycle. We apply these methods to several subseries of the transfer payment series to isolate the origin of the transfer payment macroeconomic effects. Examining these subcomponents is crucial, as it enables policymakers to distinguish the impact of measures such as unemployment insurance benefits from other types of aid provided during times of crisis, such as during the financial crisis and COVID-19 pandemic. This knowledge can better inform policymakers as they make decisions on economic policies.

Using time series econometric methods on broadly defined Total Transfers data, we do find stimulative effects from these payments. However, when these time series methods are further refined to introduce an asymmetry associated with the business cycle, the stimulative effects are concentrated in economic recessions. Further analysis of the Total Transfers subseries shows that most of these stimulative effects during economic recessions are due to special programs in

[1] These effects were central to the older Keynesian models. More recent New Classical models questioned these effects, and modern time series econometric methods have sought to resolve these differences. Notable recent contributions include Blanchard and Perotti (2002), Perotti (2007), Mountford and Uhlig (2009), Barro and Redlick (2011), Ramey (2011a,b), Auerbach and Gorodnichenko (2012a,b, 2013), Leeper et al. (2017), Ramey and Zubairy (2018), Fotiou et al. (2020) and Auerbach et al. (2022).

[2] Romer and Romer (2016), and Rodríguez (2018) use a narrative approach to isolate transfer payment shocks and study the consequences of these shocks.

[3] Government social benefits are broken into six groups, Social Security, Medicare, Medicaid, Unemployment Insurance, Veterans' benefits and Other Transfers. In this paper we will capitalize these names to be clear that we are referring to the subseries data series rather than something more generic such as unemployment insurance. We will also use the capitalized term Total Transfers to refer to the government social benefits data series which is the sum of these six series.

the Unemployment Insurance and the Other Transfers subseries initiated during the two most recent economic downturns. Removing those subseries from the broad Total Transfer payment series, or focusing on sub-sample data, such as prior to the Great Recession, shows that the positive transfer payment impulses have much smaller positive effects and are not as asymmetric over the course of the business cycle. Transfer payment programs are typically motivated by both the benefits to recipients and the stimulative benefit to the economy. These findings show that, outside of the periods where extraordinary transfer payment programs occur, the economic stimulus effects of transfer payments are small, which leads us to conclude that transfer payment programs should only be motivated by the benefits to the recipients.

To provide some background and insight for understanding these results, Figure 1 plots several of the series studied in this paper, including Total Transfer receipts, which is the total amount of transfer payments, Other Transfer receipts, which is a subseries of Total Transfer receipts and is a catch-all residual category that includes transfer payment programs that do not fit into one of the main categories, and Unemployment Insurance.[4] Prior to the 2008 Great Recession, these series had fairly stable trends. However, significant transfer payment expansionary programs were implemented during the Great Recession and the COVID-19 recession. These programs included the American Recovery and Reinvestment Act (ARRA) of 2009, the Coronavirus Aid, Relief, and Economic Security (CARES) Act of 2020, and the Consolidated Appropriations Act of 2021, and can be seen as the large spikes in transfer payments during each of the economic downturns.[5] It is these spikes that largely account for the asymmetry in the macroeconomic effects of transfer payments. Since the spikes are recent phenomena, isolating the analysis to data prior to the fourth quarter of 2007 results in no asymmetry and no stimulus effects toward macroeconomic variables.

[4]These quarterly data series were obtained from the Federal Reserve Bank of St. Louis (FRED) data bank. The series names used in FRED are as follows: Total Transfer receipts has FRED data name PCTR; Other Transfer receipts has FRED data name PCTRO; Unemployment Insurance has FRED data name PCTRUNIN. These series are reported in nominal form which we adjusted to real form by dividing by the Gross Domestic Product deflator. The FRED data code for the Gross Domestic Product deflator is GDPDEF. Other subseries for Total Transfers that were not used in this study include: Personal current transfer receipts - Government social benefits to persons: Social Security which has FRED data name W823RC1, Personal current transfer receipts - Government social benefits to persons: Medicare which has FRED data name W824RC1, Personal current transfer receipts: Government social benefits to persons - Medicaid which has FRED data name W729RC1, and Personal current transfer receipts: Government social benefits to persons - Veterans' benefits which has FRED data name W826RC1. These four components exhibit smooth growth and were not included in Figure 1 to preserve clarity for the series of interest.

[5]Related work includes Chodorow-Reich et al. (2012) who study the impact of ARRA on state Medicaid programs and the implications for employment. Oh and Reis (2012) also focus on the Great Recession stimulus, but with a broader focus than just the US program and Kim (2021) focus on the Korean stimulus to these recent events.

Also notable in Figure 1 is that the spikes for Total Transfer are almost entirely due to the spikes in the two subseries Other Transfers and Unemployment Insurance, so subseries analysis proves to be useful for teasing out the source of the effects. Like the primary series, Total Transfers, the subseries Other Transfers and Unemployment Insurance produce strong asymmetric macroeconomic responses. However, subtracting the subseries Other Transfers and Unemployment Insurance from Total Transfers removes most of the spikes from the recessionary programs and running the analysis on that constructed subseries shows no asymmetry and only small stimulative effects.

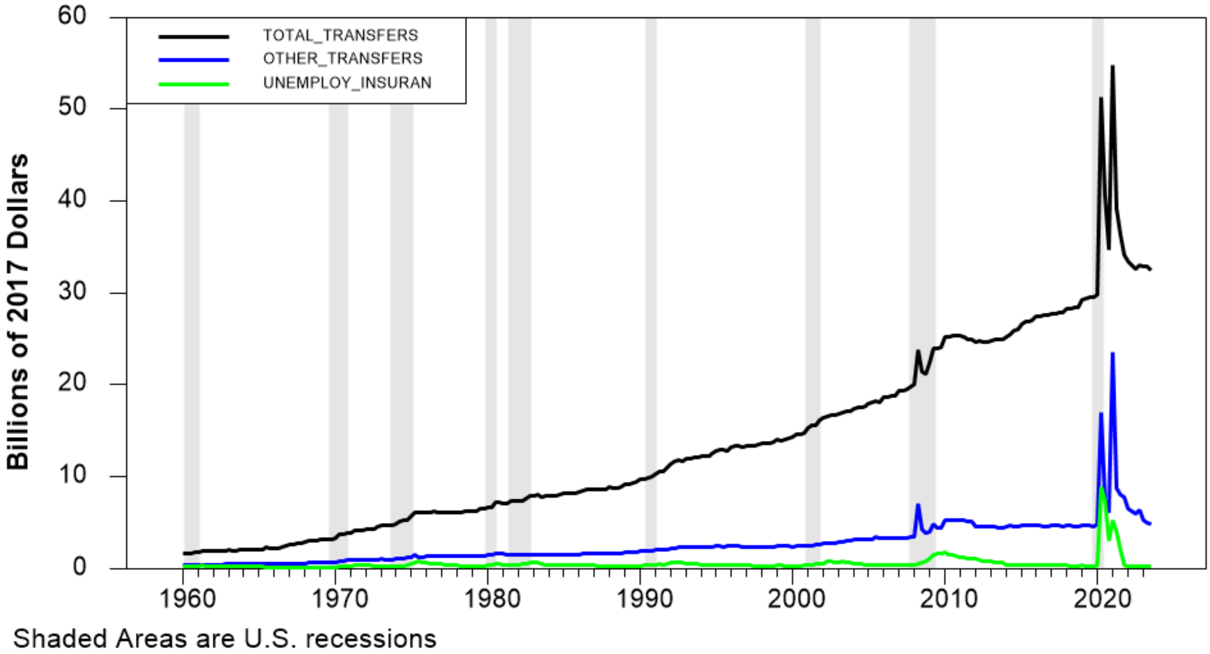

Figure 1: Total Transfers, Other Transfers and Unemployment Insurance

Our analysis uses modern time series econometric methods, including impulse response functions (IRF) and forecast error variance decompositions (FEVD). In addition, we use these estimated time series models to compute transfer payment multipliers, which are useful statistics used to assess the stimulative effects of government spending programs. We investigate both symmetric and asymmetric models. For the asymmetric models, we base the asymmetry on the National Bureau of Economic Research (NBER) business cycle economic series. Because of its flexibility for asymmetric model applications, we use the local projection method described in Jordà (2005) to compute these IRF and FEVD under different economic conditions. These methods are well suited for state-dependent time series models and have advantages over the traditional Vector Autoregression (VAR) methods, and have been applied in similar settings by Auerbach and Gorodnichenko (2012a,b, 2013, 2016), Ramey and Zubairy (2018), Owyang et al. (2013), Ahmed and Cassou (2016, 2021), Fotiou et al. (2020), and Ahmed et al. (2024).

There are several policy implications for these results. First, these results indicate that using transfer payments as an economic stimulus for the economy during expansionary economic conditions does not lead to large gains in macroeconomic variables. Second, the primary stimulative benefit to macroeconomic variables comes during recessionary economic conditions when unusually large special transfer payment programs are enacted, such as those enacted during the Great Recession and the COVID-19 recession. Taken altogether, the small stimulus from ordinary transfer payments should not be a significant motivation for transfer payment programs and the primary motive should remain the benefits to the recipients.

The paper is organized into several sections, each of which use related, but different analytical methods to first demonstrate the asymmetry in transfer payment stimuli and then to investigate the origins of the asymmetry. Section 2 begins by describing some of the empirical methods. Section 3 then presents the IRF results. This section begins by showing that the Total Transfer series exhibits an asymmetry linked to the business cycle and then undertakes a deeper analysis of the subseries and subsamples to determine the origin of the asymmetry. Section 4 continues the asymmetry analysis by using FEVD methods and then Section 5 turns to the computation of transfer payment multipliers to further reinforce the asymmetry findings. Section 6 discusses a few robustness exercises and Section 7 wraps up by summarizing the results.

2 Data and empirical methodology

The baseline empirical models use five variables, Real Gross Domestic Product (GDP), Real Personal Income (PI), Labor Supply (LS), Real Personal Consumption (PC), and Real Total Transfers (TT).[6] All the variables are in log levels. In our baseline sample, we use quarterly data from 1960:01 to 2023:03, but some subsample analysis described below used subsets of this sample. For ease of notation in describing the empirical methodology we denote the time t

[6]All data came from the FRED database. Information about Total Transfers and the various subseries was described in footnote 4 above. For GDP we obtained the FRED series of nominal gross domestic product (GDP), for PI we used FRED series Nominal Personal Income (PINCOME) and for PC we used Personal Consumption Expenditures (PCE). We convert the nominal series into real using the GDP deflator. For the Labor Supply we used the Civilian Labor Force Level with FRED series name CLF16OV.

vector of data by $x_t = [GDP_t \quad TT_t \quad PI_t \quad LS_t \quad PC_t]'$ where we use the parenthesis abbreviations for each data series noted above.

We consider two types of empirical models. The first is a simple linear or symmetric model with no threshold or switching behavior. Since a comparison between symmetric and asymmetric models is undertaken, we use the local projection method suggested by Jordà (2005) due to its ease of application for state-dependent time series models.[7] We begin by describing how to apply this method to a symmetric model and then later extend it to the threshold setting.

The local projection method produces IRFs by running a series of forecast models given by

$$x_{t+s} = \alpha^s + \sum_{i=1}^{p} B_i^{s+1} x_{t-i} + \gamma_1 t + \gamma_2 t^2 + u_{t+s}^s \qquad s = 0, 1, ..., h \tag{1}$$

where x_t is a vector of the model variables which we wish to forecast s steps ahead for h different forecast horizons using a forecasting model consisting of p lags of the variables in the system. The parameter notations in the model are commonly used, with α^s denoting a 5×1 vector of constants, and B_i^{s+1} denoting 5×5 square matrices of parameters corresponding to the ith lag, x_{t-i}, in the s step ahead forecasting model, and u_{t+s}^s is a moving average of the forecast errors from time t to time $t+s$. To account for potential linear and quadratic trends in the variables, we include the terms t and t^2.[8] [9]

The IRFs are defined as

$$\widehat{IR}(t, s, d_i) = B_1^s d_i \qquad s = 0, 1, ..., h \tag{2}$$

where $B_1^0 = I$, and d_i is an $n \times 1$ column vector that contains the mapping from the structural shock for the ith element of x_t to the experimental shocks.[10] We construct this mapping matrix following Jordà (2005), which closely adheres to techniques commonly employed in conventional VAR studies. The process begins with the estimation of a standard form VAR model, followed

[7]In discussing the IRF, we use the traditional interpretation that these represent how variables respond to one unit impulses in a structural shock. An alternative interpretation for the impulse response function under a Cholesky ordering is to note that it is the revision to the conditional forecast for a variable due to a one standard deviation impulse in one of the structural shocks. See Hamilton (1994) pages 318-23 for this approach. To avoid confusion, we stick to the traditional interpretation here.

[8]Owyang et al. (2013) also used quadratic trend terms to control for nonlinear trends.

[9]As noted by Jordà (2005), the local projection technique is robust to situations with nonstationary or cointegrated data, so this application, which uses level data, will have no issues. The issue of employing nonstationary data in VAR models was also addressed by Sims et al. (1990), who contend that VARs in log-levels yield consistent estimates of the IRFs even when co-integrating vectors are present.

[10]Here, we use Jordà's experimental shock terminology, but the terminology reduced form shock is also appropriate.

by the application of a Cholesky decomposition to the variance-covariance matrix. Within this framework, one defines d_i as a vector representing experimental shocks through the following formulation,

$$d_i = A_0^{-1}\Omega_\varepsilon \varphi_i, \tag{3}$$

where A_0 is a standard notation used for a coefficient matrix in the structural form VAR, while Ω_ε is the diagonal square root of the variance-covariance matrix associated with the structural shocks.[11]

For our baseline model, we use the ordering indicated in our vector x_t denoted above. Here it is assumed that GDP could contemporaneously affect all the other variables in the vector. In particular, GDP can affect transfer payments, but because transfer payments is listed second it cannot affect GDP contemporaneously. This ordering reflects the economic reality that transfer payments are typically adjusted in response to changes in economic conditions. For example, during a recession, GDP falls and unemployment rises, triggering automatic increases in transfer payments like unemployment benefits. An alternative assumption is to put transfer payments prior to GDP. This alternative assumption may be more appropriate in studies that investigate overall government spending as in Blanchard and Perotti (2002), where overall government spending is viewed as exogenous to the behavior of GDP. In the robustness section below, we investigate this alternative ordering and show that both orderings imply the same behavior. We also assumed that both GDP and transfer payments could contemporaneously affect personal income, labor supply and personal consumption. These later orderings reflect views that both GDP and transfer payments first have a direct impact on personal income, which then impacts decisions about working and finally consumption. It is also important to recognize that the Cholesky ordering assumptions dissipate within a few periods and the long run impulse responses almost entirely reflect the correlations in the data. Another identification strategy that has shown some promise, is to use sign restrictions, as in Faust (1998) and Uhlig (2005). The idea is that certain economic concepts are generally agreed upon and these concepts can aid identification using sign restrictions. In the robustness section, we also investigate this strategy for identification.

[11]Further details are provided in the Appendix where some of the notation, including A_0, Ω_ε and φ_i, are spelled out more completely. Jordà (2005) and Plagborg-Møller and Wolf (2021) show that IRFs generated by the local projections are equivalent to those calculated from VAR methods when the true data generating process (DGP) is a VAR, but that the IRFs for other DGPs that are not true VARs are better estimated using this local projection.

Next, using the local projection technique, one can compute confidence bands using estimates of the standard deviations for the impulses. One issue that needs to be recognized in doing this is that because the DGP is unknown, there could be serial correlation in the error term of (1) induced by the successive leads of the dependent variable. We address this issue by using Newey and West (1987) standard errors which correct for heteroskedasticity and autocorrelation (HAC). Letting $\widehat{\sum}_s$ be the estimated HAC corrected variance-covariance matrix of the coefficients $\widehat{B}_1^s$, a 68% (or a one standard deviation) confidence interval for each element of the IRF at horizon s can be constructed by $\widehat{IR}(t,s,d_i) \pm \sigma(d_i^{'}\widehat{\sum}_s d_i)$, where σ is a $n \times 1$ column vector of ones.

Our extension of the baseline model is to incorporate threshold behavior into the impulse response structure that allows the possibility that the IRF may differ depending on whether the economy is in a recession or not. We define our extension to (1) by

$$x_{t+s} = I_{t-1}\left[\alpha_R^s + \sum_{i=1}^{p} B_{i,R}^{s+1} x_{t-i}\right] + (1-I_{t-1})\left[\alpha_E^s + \sum_{i=1}^{p} B_{i,E}^{s+1} x_{t-i}\right] + \gamma_1 t + \gamma_2 t^2 + u_{T,t+s}^s \qquad s = 0,1,...,h \tag{4}$$

where most of the notation carries over from above, but subscripts of R or E have been added to the various parameters to indicate whether the economy is in a recession or an expansion, respectively. Here, we allow the coefficients of all variables, except the trend terms, to differ based on whether the economy is experiencing a recession or an expansion phases. We use a different notation of $u_{T,t+s}^s$ to denote the error process for this model where the added subscript indicates the error for the threshold model. The threshold dummy variable, denoted by I_t is based on the NBER business cycle indicator.[12] This is a zero and one time series, where values of zero correspond to expansionary phases of the business cycle and values of one correspond to recessionary phases of the business cycle.

By analogy to (4), we define the IRFs for the two states of the economy by

$$\widehat{IR}^j(t,s,d_i) = B_{1,j}^s d_i \qquad s = 0,1,...,h \text{ and } j \in (E,R) \tag{5}$$

with normalizations $B_{1,R}^0 = I$ and $B_{1,E}^0 = I$. The confidence bands for the impulse responses of the threshold model are simple extensions of the methodology discussed above.

[12]The FRED data series for the NBER based recession indicator for the United States has name USRECQM.

3 Impulse response function results

We discuss the IRF results in two subsections. In the first subsection, we show that there is an asymmetry in the responses to transfer payment impulses, while in the second subsection, we investigate several subseries and subsample models designed to establish the origin of the asymmetry. All models use two lags in the forecast equations to generate the IRFs, as this lag length was found optimal according to the Bayesian Information Criterion (BIC).

3.1 Asymmetric responses to transfer payment impulses

Since our interest is transfer payments' impact on other economic variables, we only present the responses to transfer payment impulses. Figure 2 shows the linear model and the threshold model IRFs in a side-by-side set of plots, with the linear model results on the left side and the threshold model on the right side. For the linear model, we plot several things in each subplot, including the actual impulse response indicated by a solid blue line, a sixty-eight percent standard error band, given by the two dashed blue lines closest to the impulse response line and a ninety percent standard error band given by the two dashed blue lines furthest from the impulse response line.[13] The vertical order of the subplots indicates the order used in the Cholesky decomposition. Here, GDP is ordered first, Total Transfers second, Personal Income third, Labor fourth and Personal Consumption fifth. Focusing on the second subplot on the left we see that a one unit impulse in Total Transfer payments is persistent, last roughly six quarters or one and a half years. This impulse leads to a significant rise in GDP, Personal Income and Personal Consumption, all of which last about four quarters. It also leads to a fall in the Labor supply for a similar four quarter duration, which likely arises due to an improved financial health of consumers from the transfer payments.

Next, focusing on the threshold model in the right panel, we see that the economic state becomes important. To interpret these plots, we have arranged them in the same order as in the linear model. Furthermore, for each subplot, the results for the expansionary economic state and the contractionary economic state, as governed by the NBER recession dates, are plotted. To distinguish between the two states, we use the convention of plotting the expansionary state using the same plotting conventions as the linear model, while for the contractionary state, we plot the IRFs using a solid red line and then the same two error bands are marked with shaded

[13] A popular convention is only to present the sixty-eight percent, or one standard error bands. Here we provide both a sixty-eight percent and a ninety percent confidence band.

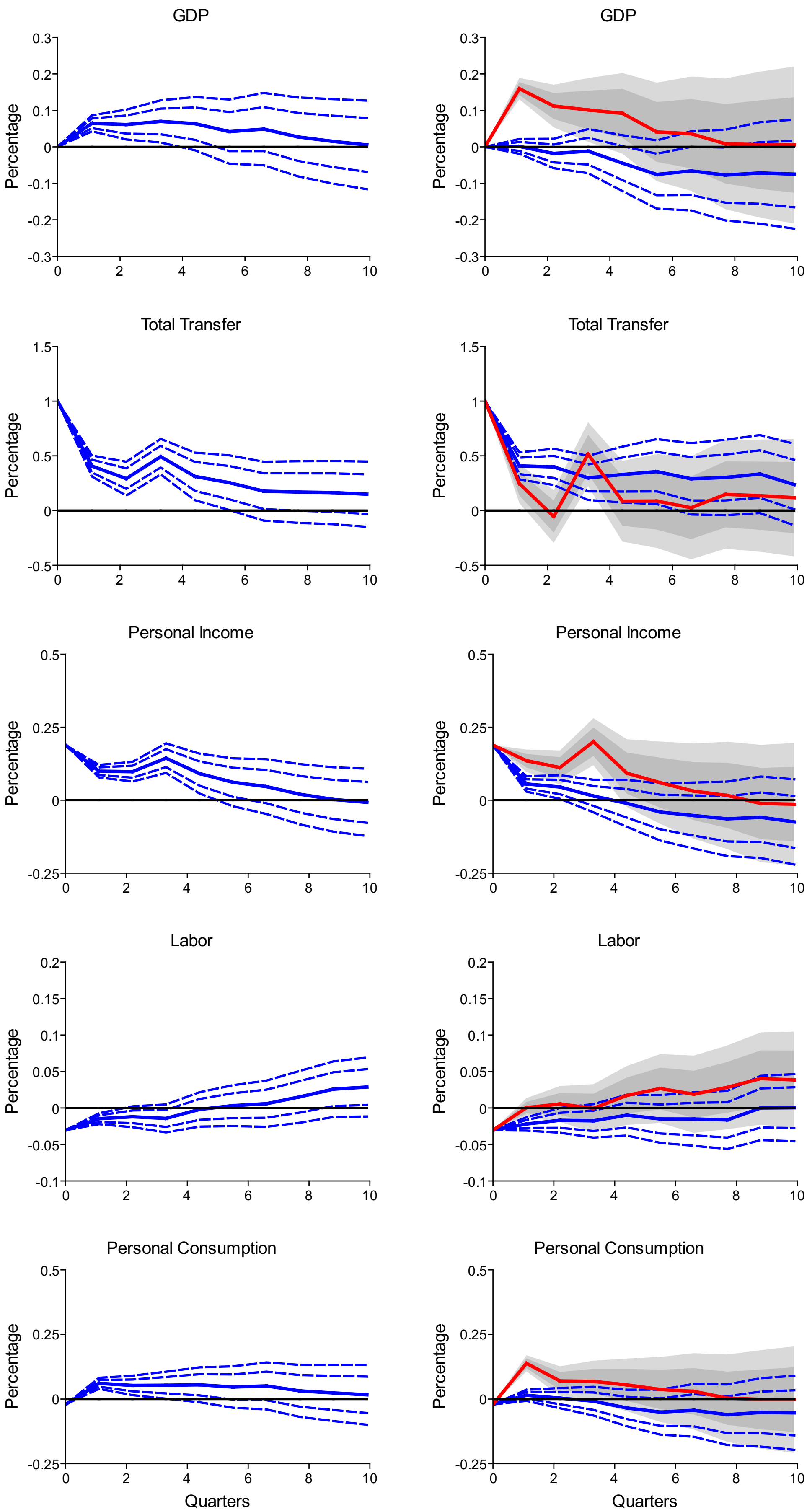

Figure 2: Response function to an impulse in Total Transfers

regions with the narrow, more darkly shaded region showing the sixty-eight percent band and the wider, more lightly shaded region showing the ninety percent band.

Starting with the second panel, we see that in both expansionary and contractionary state Total Transfers are persistent, but they are more uniformly persistent in the expansionary state. For the expansionary state, the IRF looks nearly the same as in the linear model, while in the contractionary state, the IRF is uneven and becomes momentarily insignificant after two quarters before rising and becoming significant for quarters three and four. Overall, the expansionary and contractionary state IRFs for Total Transfers largely overlap indicating they are statistically indistinguishable. Next, looking at the IRFs for GDP, Personal Income and Personal Consumption, we see there are significant differences between the two states. In the case of the expansionary state, the GDP and Personal Consumption IRFs are insignificant around zero, while Personal Income shows a brief one quarter significant positive effect before becoming insignificant around zero. On the other hand, the contractionary state IRFs for GDP, Personal Income and Personal Consumption all show significant positive effects lasting around four quarters. Furthermore, these effects are significantly different than the expansionary IRFs for most of this four quarter horizon. Finally, looking at the Labor Supply effects, we see that in both the expansionary and contractionary states, the two IRFs are largely the same as each other and the same as in the linear model. Overall, we can conclude that most of the significant positive IRF values for GDP, Personal Income and Personal Consumption seen in the linear model are due to the contractionary state. Similar state-dependent results were found by Auerbach et al. (2022) for Department of Defense spending during the Covid-19.

The degree to which the two states differ can also be understood using more traditional statistical measures. Table 1 provides p-values for hypothesis that there are no differences between the impulse responses for the contractionary state and the expansionary state. These p-values were computed using 10,000 bootstrap simulations of length equal to the data series minus two by randomly drawing from the observed errors with replacement.[14] The table is organized with five panels, one for each of the five variables in Figure 2. Each panel shows information on the impulse responses at the odd number horizons depicted in Figure 2. The value of the impulse response during the expansionary state and the contractionary state are given in columns 3 and 4 and their difference is given in column 5. Column 6 then reports the p-value for the null that

[14]The simulation process generates a new series equal to the length of the one used in the estimation, and because the model has two lags, the simulated series is smaller by two.

Table 1: Bootstrap Testing for Impulse Response Differences

Variable	Horizon	Regime: Expansionary	Regime: Contractionary	Difference	p-value
GDP	1	0.00126	0.15959	-0.15833	0.05080
	3	-0.01170	0.10120	-0.11289	0.07040
	5	-0.07571	0.04096	-0.11667	0.03180
	7	-0.07732	0.00831	-0.08563	0.10880
	9	-0.07476	0.00519	-0.07995	0.35620
Total Transfers	1	0.40820	0.24638	0.16182	0.33360
	3	0.29858	0.51522	-0.21663	0.85800
	5	0.35592	0.08678	0.26914	0.61300
	7	0.30209	0.14814	0.15395	0.18920
	9	0.23774	0.11801	0.11973	0.21580
Personal Income	1	0.05546	0.13515	-0.07968	0.50940
	3	0.01418	0.20025	-0.18606	0.11560
	5	-0.04083	0.05969	-0.10052	0.06600
	7	-0.06400	0.01621	-0.08021	0.40640
	9	-0.07451	-0.01383	0.06069	0.81220
Labor	1	-0.02196	0.00042	-0.02238	0.75080
	3	-0.01763	-0.00057	-0.01705	0.31220
	5	-0.01510	0.02667	-0.04177	0.53340
	7	-0.01637	0.02831	-0.04467	0.17340
	9	0.00038	0.03846	-0.03808	0.26560
Personal Consumption	1	0.01462	0.13828	-0.12366	0.13120
	3	-0.00811	0.06839	-0.07650	0.09460
	5	-0.05050	0.03717	-0.08767	0.04940
	7	-0.06051	0.00348	-0.06400	0.15800
	9	-0.05318	-0.00195	-0.05123	0.40640

the difference is not significantly different from zero. These p-values are for a two tailed test since some of the differences are negative and some are positive. One tailed p-values can be found by dividing these numbers by two.

Starting in the second panel of Table 1, we see that the p-values are large, indicating that the Total Transfer impulse responses are not significantly different from each other at most conventional levels of significance. Next, looking at the top panel of Table 1, we see that the impulses responses for GDP are significantly different from each other during the two states at the 10% level for the first five quarters and marginally insignificant at the 10% level at the seventh quarter. Furthermore, at the fifth quarter ahead horizon, the null is significant at the 5% level. Also, as noted above in the discussion of Figure 2, there are some statistical differences at some horizons for Personal Income and Personal Consumption impulse responses, but that is not the case for the Labor impulse responses which are always insignificant at conventional critical values.

3.2 The origin of the asymmetry

Having established that there is an asymmetry, this section turns to finding the source for the asymmetry. Here we break things into two parts. The first part shows that the asymmetry comes from the two subseries highlighted in Figure 1, while the second part restricts the analysis to subsamples to show that it is only recent programs captured by these subseries that generates the asymmetry as well as the stimulative effects of transfer payements. Without these recent programs, transfer payments do not produce stimulation for the macroeconomic aggregates.

3.2.1 Subseries analysis

The U.S. Bureau of Economic Analysis decomposes the Total Transfer series into six subseries. Refining the analysis to focus on these subseries can reveal much about the origin of the asymmetry seen in Figure 2. In Figure 1, we highlighted two subseries which also have rather pronounced spikes during recent recessionary periods. These include Other Transfers and Unemployment Insurance. Figures 3 - 5 show impulse responses to one percent impulses in three series, with Figure 3 showing the responses to Other Transfers, Figure 4 showing the response to Unemployment Insurance, and Figure 5 showing impulse responses to Total Transfers with the Other Transfers and Unemployment Insurance components removed. In these figures, we have adopted the same plotting conventions as in Figure 2.

Figures 3 and 4 show similar results as those seen in Figure 2 with both subseries showing significant short-run stimulus for GDP during economic contractions and no stimulus during economic expansions. The IRF for Personal Income and Personal Consumption show some similarities and some differences relative to Figure 2, with Other Transfers showing asymmetric similarities with Figure 2 for Personal Income, while Unemployment Insurance shows asymmetric similarities with Figure 2 for Personal Consumption. Both subseries show similar symmetric behavior for Labor Supply with Figure 2.

Table 2 also shows, among other things, the importance of the Other Transfers and Unemployment Insurance subseries for stimulating GDP. This table is similar to Table 1 in that it provides formal testing information regarding whether there are differences between the expansionary and contractionary state impulse responses, only here, just the results for the GDP impulse responses are reported. The table is organized into six panels, with each panel showing p-values for tests that the differences between the two states are significant for each of the GDP investigations undertaken in Figures 2 - 5, as well as two other GDP investigations undertaken below. The first two columns provide information about the figure for which a particular panel provides this supplementary information, and a short description of the focus of that particular investigation. The top panel repeats the information from the top panel of Table 1, and is included for orientation. That first panel shows the results from the Figure 2 investigation of the GDP responses to Total Transfers impulses, and the bootstrapped p-values. Those p-values show that under conventional critical values, one can reject the null that the expansionary and contractionary impulse responses are equal at horizons 1, 3 and 5. Next, focusing on the second and third panels, which focus first on the GDP responses to Other Transfers impulses and then the GDP responses to Unemployment Insurance impulses seen in Figures 3 and 4, we see that the p-values again show that there are significant differences between the expansionary state and contractionary state responses for some horizons.

Turning to Figure 5, which looks at the constructed series in which Unemployment Insurance and Other Transfers have been removed from Total Transfers, we see that most of the asymmetric differences disappear. There is a short-lived, one-quarter asymmetric response to GDP and some asymmetric behavior for Personal Income and Personal Consumption. But these later effects are not significantly different between contractions and expansions, nor from zero. The fourth panel of Table 2 reinforces this result, showing that at conventional levels of significance, there are no significant differences in the GDP impulse responses between the expansionary and contractionary states at all horizons.

Taken together, these three figures, and the results in Tables 2 show that the significant asymmetric stimulus effects seen in Figure 2 and Table 1 are due to the subseries of Other Transfers and Unemployment Insurance.

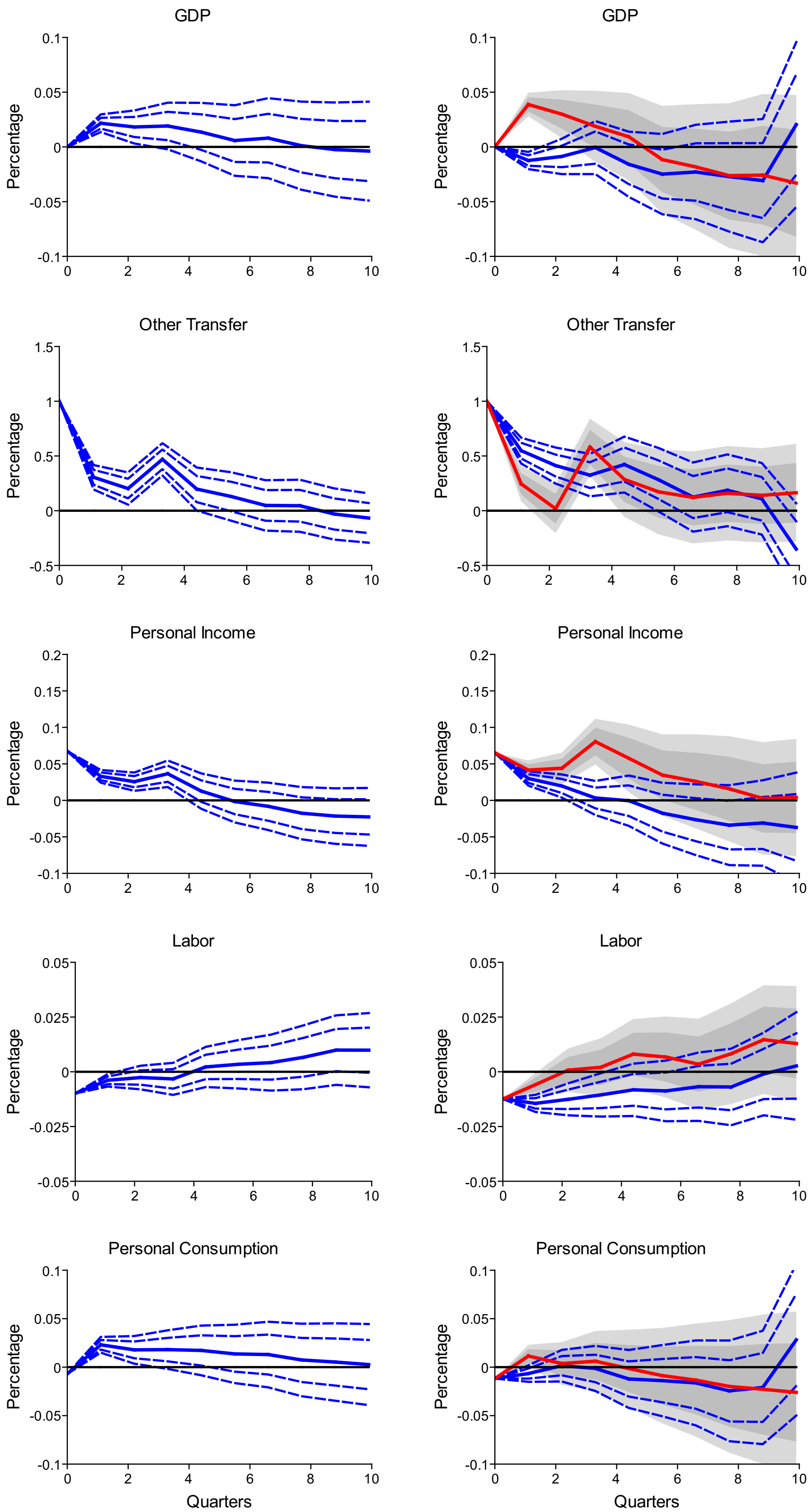

Figure 3: Response function to an impulse in Other Transfers

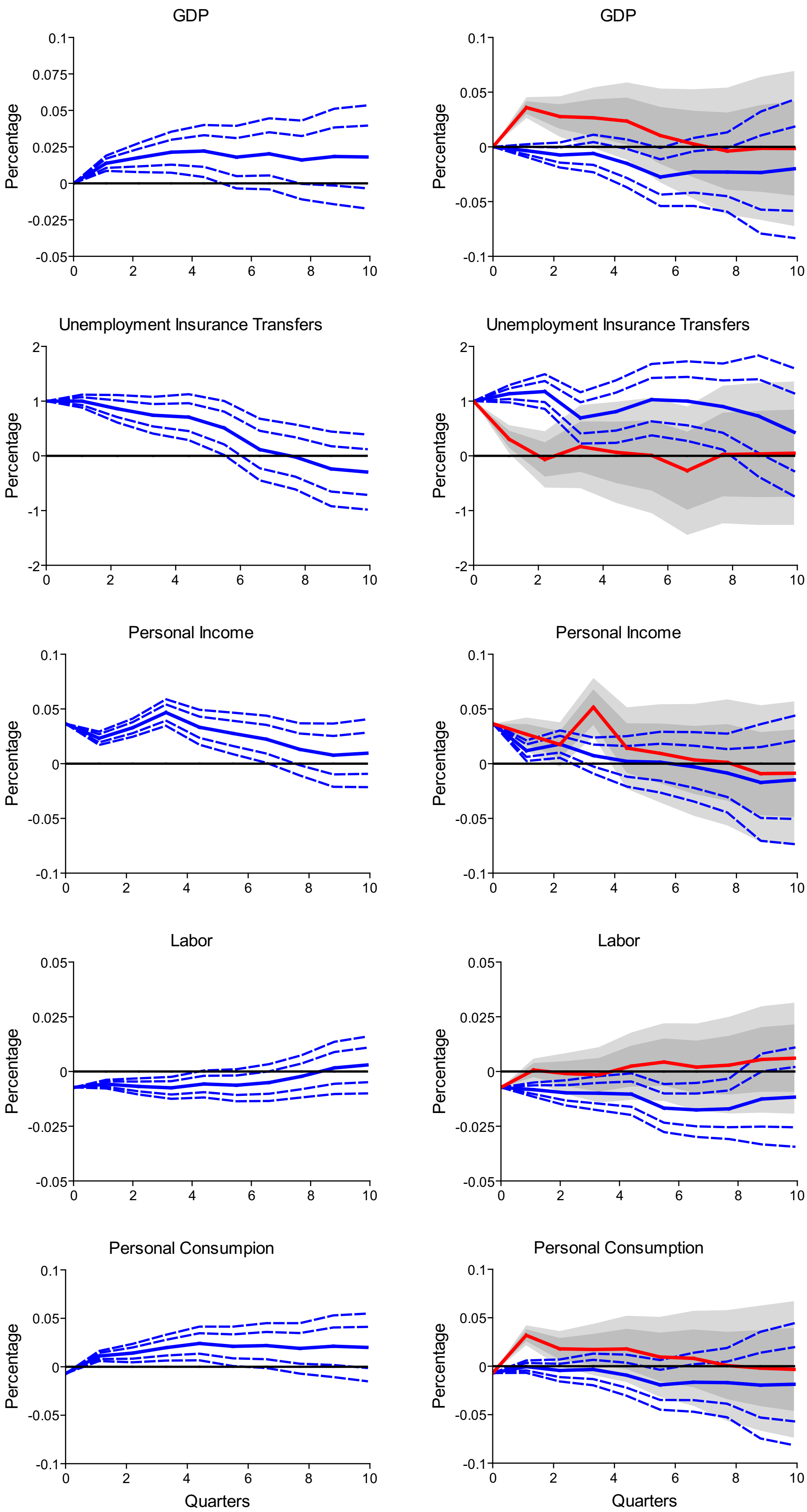

Figure 4: Response function to an impulse in Unemployment Insurance

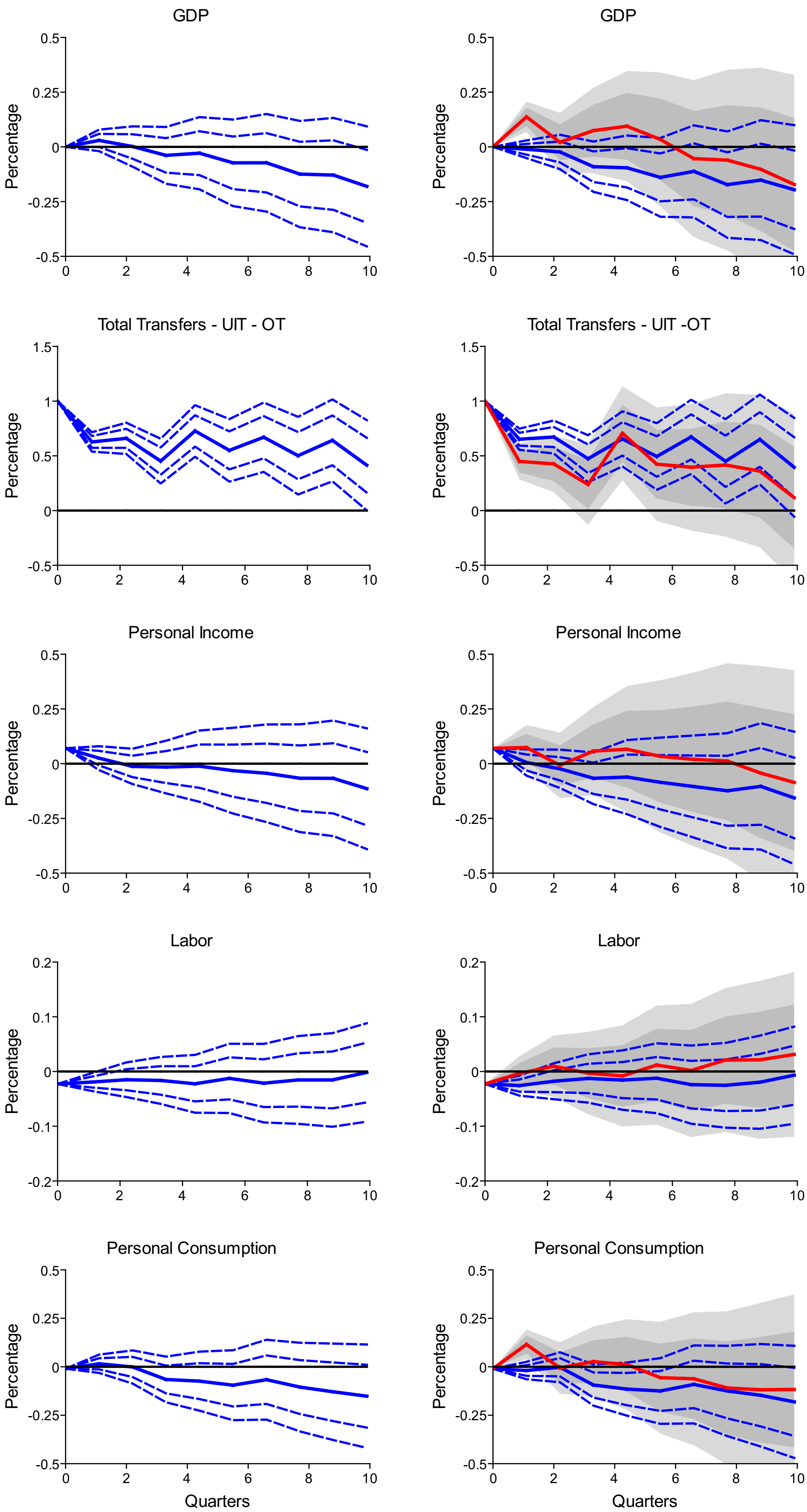

Figure 5: Response function to an impulse in Total Transfers excluding Other Transfers and Unemployment Insurance

Table 2: Bootstrap Testing for Impulse Response Differences
Focusing on GDP Responses to Impulses in Figures 2-7

Figure	Short Description	Horizon	Regime		Difference	p-value
			Expansionary	Contractionary		
Figure 2	Total Transfers (TT)	1	0.00126	0.15959	-0.15833	0.05080
	Impulse	3	-0.01170	0.10120	-0.11289	0.07040
	Full Sample	5	-0.07571	0.04096	-0.11667	0.03180
		7	-0.07732	0.00831	-0.08563	0.10880
		9	-0.07476	0.00519	-0.07995	0.35620
Figure 3	Other Transfers (OT)	1	0.00181	0.05555	-0.05374	0.01620
	Impulse	3	0.00091	0.03090	-0.02999	0.40420
	Full Sample	5	-0.02418	0.00779	-0.03197	0.23920
		7	-0.02676	-0.00952	-0.01724	0.30760
		9	-0.03180	-0.01381	-0.01799	0.46980
Figure 4	Unemployment	1	-0.00348	0.03588	-0.03936	0.01860
	Insurance Transfers (UIT)	3	-0.00605	0.02657	-0.03262	0.04900
	Impulse	5	-0.02752	0.01037	-0.03789	0.00340
	Full Sample	7	-0.02301	-0.00387	-0.01914	0.02680
		9	-0.02002	-0.00152	-0.01850	0.24600
Figure 5	TT Excluding	1	-0.01093	0.13701	-0.14794	0.62840
	OT and UIT	3	-0.09052	0.07420	-0.16472	0.74140
	Impulse	5	-0.13944	0.03398	-0.17342	0.45580
	Full Sample	7	-0.17245	-0.06060	-0.11185	0.35380
		9	-0.19581	-0.17180	-0.02401	0.36280
Figure 6	Other Transfers	1	-0.00352	0.03884	-0.04237	0.21640
	Pre-2008	3	0.01754	0.06109	-0.04355	0.39480
	Sample	5	0.05243	0.01184	0.04059	0.28100
		7	-0.00010	-0.00275	0.00264	0.56980
		9	-0.15687	0.00734	-0.16421	0.48820
Figure 7	Unemployment	1	-0.00352	0.03884	-0.04237	0.21640
	Insurance Transfers	3	0.01754	0.06109	-0.04355	0.39480
	Pre-COVID-19	5	0.05243	0.01184	0.04059	0.28100
	Sample	7	-0.00010	-0.00275	0.00264	0.56980
		9	-0.15687	0.00734	-0.16421	0.48820

3.2.2 Subsample results for Other Transfers and Unemployment Insurance

Finally, we undertake another exercise to show that the special programs undertaken during the 2008-09 and 2020 recessions are the source of the asymmetric responses. To do this, we focus on a subsample that excludes these recent recessions. Figures 6 and 7 show the same set of impulse response exercises as in Figures 3 and 4 respectively, over the two shorter subsamples. For the Other Transfers series, we choose the interval of 1960:1 to 2007:4 which stops just prior to the Great Recession in which very large transfer payment injections were implemented to combat the recession. For the Unemployment Insurance series, we choose the interval 1960:1 to 2019:4 which stops just prior to the COVID-19 recession. We did investigate the same shorter interval as used for Other Transfers, but as it turns out, the expansions in Unemployment Insurance during the Great Recession, as seen in Figure 1, while large, were not large enough to produce the asymmetric response. It was only the exceptionally generous unemployment insurance expansions during the COVID-19 recession where the asymmetry arose.

Both of these figures show that the asymmetry has largely gone away and thus indicate that it is only the recent special programs implemented during the two recent recessions that are contained in the Total Transfers series that generate the asymmetric responses. Without these recent programs, either by removing the Other Transfers and Unemployment Insurance series as in Figures 5, or by constraining the series to only use data prior to the large expansionary programs during the Great Recession or COVID-19, transfer payments are not stimulative in either an expansionary period or a contractionary period. These results are also confirmed in the fifth and sixth panels of Table 2, which show that both of these truncated series do not exhibit significant GDP impulse response differences between the expansionary and contractionary states at all forecast horizons.

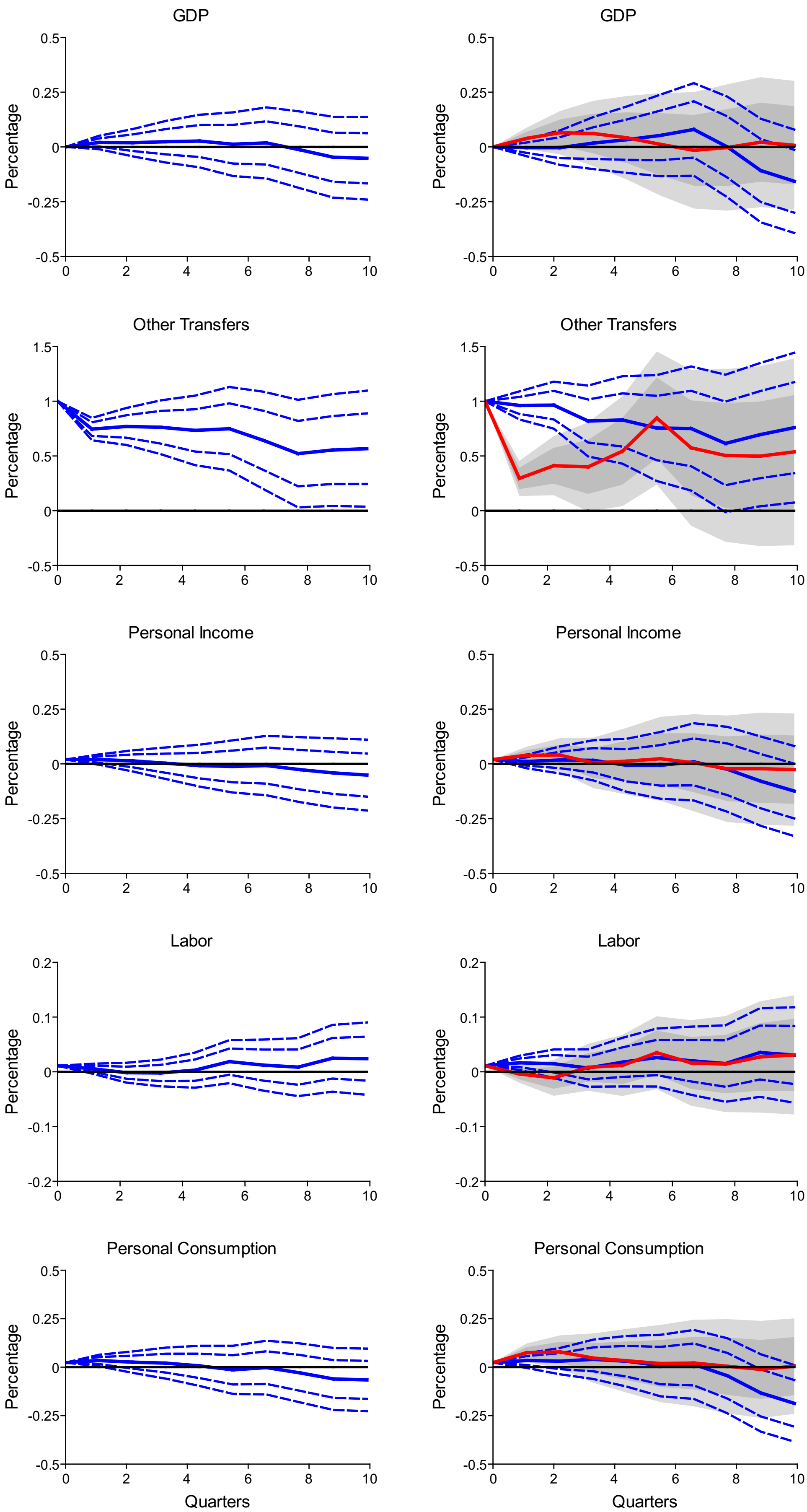

Figure 6: Response function to an impulse in Other Transfers - 1960:1 to 2007:4 (Before the financial crisis)

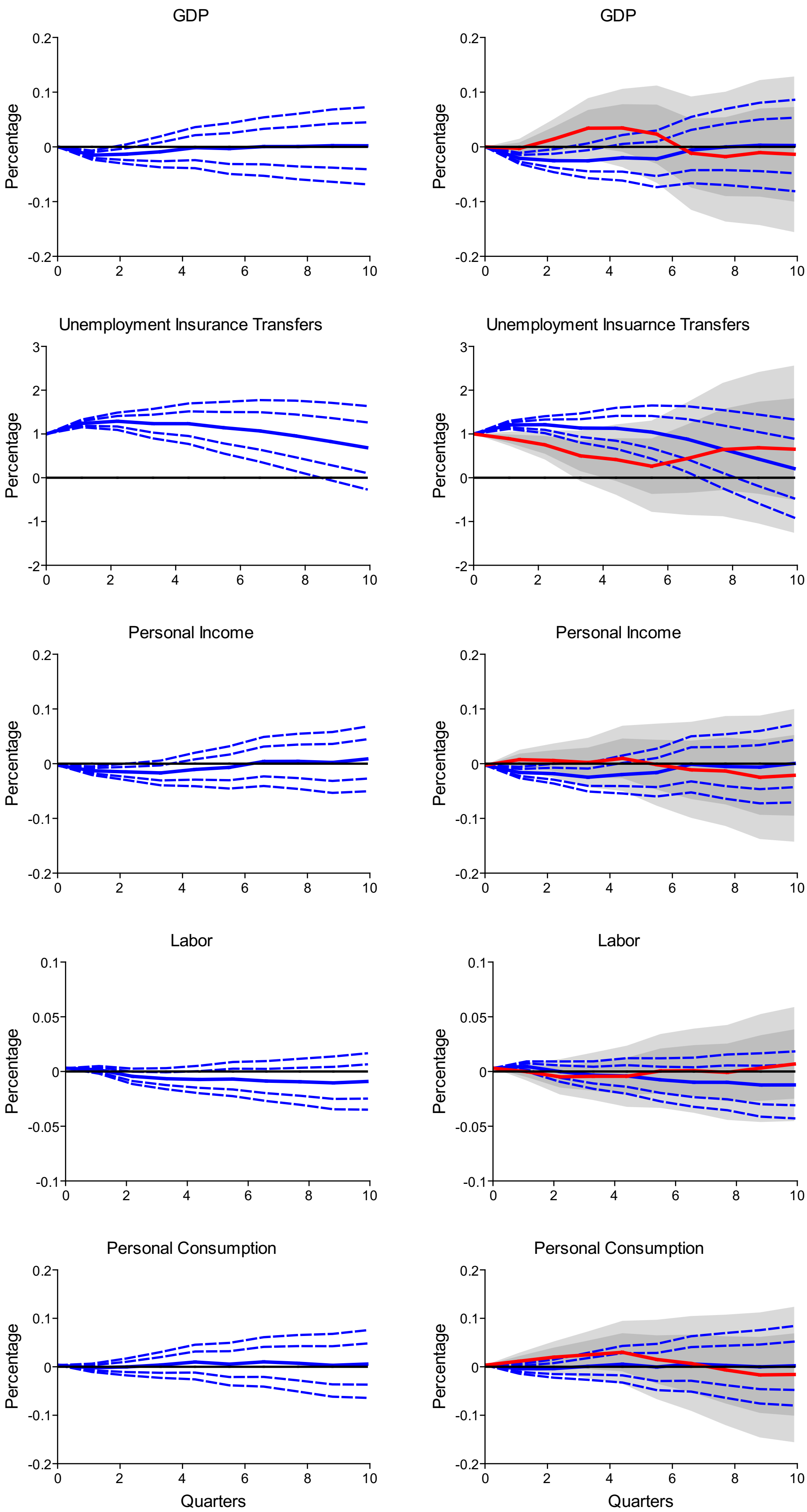

Figure 7: Response function to an impulse in Unemployment Insurance - 1960:1 to 2019:4 (Before COVID-19)

4 Forecast error variance decomposition results

Another useful time series econometric tool for revealing data patterns is the FEVD. In this section, we begin by providing a brief explanation on how to compute FEVDs when using the local projection time series structure described in Section 2. We then apply these methods to our data and demonstrate that the asymmetry in transfer payment stimulus is again a characteristic of the data and that when focusing on subseries and subsamples the origin of the stimulus and asymmetry is again the special programs initiated during the Great Recession and the COVID-19 recession.[15]

To understand the FEVD computations, it is useful to note that the mean squared error of the forecast error in (1) is defined as:

$$MSE_u(E(x_{t+s}|X_t)) = E(u^s_{t+s}u^{s'}_{t+s}) \qquad s = 0, 1, ..., h. \tag{6}$$

This can be estimated by using $\widehat{\sum}_{u^s} = \frac{1}{T}\sum_{t=1}^{T} \widehat{u}^s_{t+s}\widehat{u}^{s'}_{t+s}$, where $\widehat{u}^s_{t+s} = x_{t+s} - \widehat{\alpha}^s - \sum_{i=1}^{p} \widehat{B}^{s+1}_i x_{t-i} - \widehat{\gamma}_1 t - \widehat{\gamma}_2 t^2$. Here, the diagonal elements represent the variance of the s-step ahead forecast errors for each element in x_t. Next, we define the $n \times n$ experimental choice matrix D using the columns d_i from the mapping described in (3). Renormalizing MSE_u by the choice matrix D yields:

$$MSE(E(x_{t+s}|X_t)) = D^{-1}E(u^s_{t+s}u^{s'}_{t+s})D^{-1'} \qquad s = 0, 1, ..., h. \tag{7}$$

Using the interpretation that d_i is a vector representing experimental shocks arising from a one standard deviation structural shock in the ith variable, we see that D has columns representing experimental shocks arising form structural shocks and thus D^{-1} shows the inverse of this mapping, thus showing the mapping back from experimental shocks to structural shocks. This means that equation (7) shows a matrix in which the element in row j, column i shows the variance in variable j due to a one unit shock in variable i. This information can then be normalized by the total variance in j to obtain the variance decomposition for variable j; that is the percentage of the total variation in j due to variable i. Extending this calculation to threshold models involves a straightforward extension of the vector x_t by incorporating $I_{t-1}x_t$ terms in the upper half and $(1 - I_{t-1})x_t$ terms in the lower half of the new vector (Ahmed et al., 2024; Ahmed and Cassou, 2021).

[15] For more theoretical detail, we refer readers to Jordà (2005).

Tables 3a and 3b show FEVD results for each of the models run earlier in Section 3. In particular, these tables display six panels, with the upper left panel of Table 3a showing the FEVD values for the model used to compute Figure 2, the upper right panel of Table 3a showing the FEVD values for the model used to compute Figure 3, and this pattern continues on through the remaining panels of Table 3a and onto Table 3b. Since our objective is to study the impact of transfer payments, only the percentage of a variable's variance due to transfer payments is reported in the tables and we ignore the percentage of the variance due to other variables. Each panel consists of five columns, with each column showing the percentage of the variance for a particular variable due to the transfer payment series used for that model at various forecast horizons.

Focusing on the upper left panel, we see five columns, GDP, Total Transfers, Personal Income, Labor and Personal Consumption and then running down the rows of the table, we see FEVD information computed at one-quarter ahead, four-quarter ahead, and ten-quarter ahead horizons. For each horizon, three rows are provided with the first row showing the portion of the forecast variance for the variable listed at the column head that is due to transfer payments at the particular horizon in the linear model. Then, the next two rows show the portion of the forecast error variance for the variable listed at the column head that is due to transfer payments at the particular horizon in the asymmetric model for both the contractionary and expansionary states.

At the one-quarter horizon, the linear model shows that Total Transfers explains 66.69% of the forecast error variance for Personal Income, 13.86% of the forecast error variance for Labor, and 1.01% of the forecast error variance for Personal Consumption. In addition, we see that of the variation in Total Transfers explained by itself is 87.15% and the percentage of the variation in GDP is equal to zero, which is because it is ordered first in the Cholesky decomposition. Without noting the specific numbers, the next two rows show that Total Transfers explains a large percentage of the forecast error variance for Personal Income and smaller amounts for Labor and almost none for Personal Consumption and the distinction between contractionary and expansionary phases of the business cycle are small.

Table 3a: FEVD of transfer payment shocks

Full Sample										
	Total Transfers					Other Transfers				
States	GDP	Total Transfers	Personal Income	Labor	Personal Consumption	GDP	Other Transfers	Personal Income	Labor	Personal Consumption
Forecast horizon one-quarter ahead										
Linear	0.00	87.15	66.69	13.86	1.01	0.00	90.87	64.13	11.11	0.88
Contractionary	0.00	86.95	77.73	18.88	0.97	0.00	88.48	62.98	12.20	0.68
Expansionary	0.00	91.04	61.50	11.85	1.24	0.00	93.68	60.72	9.64	1.09
Forecast horizon four-quarter ahead										
Linear	7.03	59.22	42.14	7.06	6.05	5.67	75.06	34.35	4.11	4.66
Contractionary	32.42	63.00	52.60	7.51	23.50	23.32	64.42	34.00	5.73	15.13
Expansionary	0.22	79.53	20.61	8.02	0.40	0.09	86.64	22.76	4.55	0.46
Forecast horizon ten-quarter ahead										
Linear	6.68	38.26	31.39	6.79	6.08	4.15	58.54	22.65	11.26	3.12
Contractionary	24.13	47.39	38.18	26.07	13.40	18.24	49.99	25.20	18.61	9.66
Expansionary	3.53	49.11	9.62	3.31	2.26	3.55	62.04	14.47	2.67	3.55

	Unemployment Insurance Transfers (UIT)					Total Transfer - Other Transfers (OT) - Unemployment Insurance Transfers (UIT)				
	GDP	UIT	Personal Income	Labor	Personal Consumption	GDP	Total Transfers - OT -UIT	Personal Income	Labor	Personal Consumption
Forecast horizon one-quarter ahead										
Linear	0.00	60.66	41.02	13.58	2.09	0.00	99.73	1.76	1.56	0.05
Contractionary	0.00	61.74	57.75	19.54	2.14	0.00	99.59	1.42	1.5901	0.03
Expansionary	0.00	69.93	36.01	11.52	2.58	0.00	99.85	1.88	1.5923	0.07
Forecast horizon four-quarter ahead										
Linear	9.16	43.61	45.43	14.47	8.23	0.28	94.39	0.66	1.30	0.63
Contractionary	33.90	37.33	48.28	7.86	25.59	2.40	77.71	0.92	0.76	1.62
Expansionary	0.83	56.02	17.89	17.66	0.76	1.06	96.40	1.36	1.54	1.36
Forecast horizon ten-quarter ahead										
Linear	14.74	32.68	39.14	10.47	15.96	5.16	84.17	2.10	1.18	5.28
Contractionary	22.63	20.76	29.80	13.34	14.17	4.38	73.67	1.30	1.80	2.93
Expansionary	5.82	41.09	7.81	19.83	4.05	4.68	86.77	3.89	0.92	4.97

Table 3b: FEVD of transfer payment shocks using sub-samples and subseries

	Other Transfers					Unemployment Insurance Transfers (UIT)				
	Subsample: 1960:Q1 - 2007:Q4					Subsample: 1960:Q1 - 2019:Q4				
States	GDP	Other Transfers	Personal Income	Labor	Personal Consumption	GDP	UIT	Personal Income	Labor	Personal Consumption
Forecast horizon one-quarter ahead										
Linear	0.00	99.17	0.96	1.16	0.98	0.00	88.26	0.11	0.67	0.15
Contractionary	0.00	99.54	2.49	3.38	1.95	0.00	88.28	0.15	1.59	0.15
Expansionary	0.00	98.72	0.58	0.64	0.63	0.00	86.36	0.08	0.45	0.13
Forecast horizon four-quarter ahead										
Linear	0.33	75.56	0.37	0.48	1.01	0.94	49.96	1.75	1.39	0.07
Contractionary	5.64	66.79	4.78	3.08	18.11	4.11	34.41	0.46	3.29	4.33
Expansionary	0.05	71.15	0.25	1.14	0.95	2.50	50.84	2.29	0.54	0.09
Forecast horizon ten-quarter ahead										
Linear	1.04	63.98	1.13	2.16	2.35	0.43	40.82	1.08	3.02	0.31
Contractionary	3.81	49.43	3.92	15.35	7.57	5.77	34.73	3.90	3.11	4.40
Expansionary	2.90	53.00	2.00	2.87	5.63	1.39	34.47	1.30	2.31	0.07

Moving on to the four-quarter forecast horizon, we see a few patterns emerge. First, Total Transfers begins to explain more of the variation in GDP and Personal Consumption than at the one-quarter horizon. Furthermore, and more important to this study, we see that the percentage of the variation in GDP, Personal Income and Personal Consumption are considerable larger during the contractionary phase of the business cycle than during the expansionary phase of the business cycle. In addition, there are no real differences between the contractionary and expansionary phase of the business cycle for explaining Total Transfers own variation or Labor. All of these results are consistent with the findings noted earlier in the discussion of Figure 2. Moving on to the ten-quarter ahead horizon, again it can be seen that a relatively larger percentage of the forecast error variance for GDP, Personal Income, Personal Consumption and now Labor is explained by Total Transfers during contractionary phases of the business cycle than during expansionary phases. Again, these ten-quarter results are consistent with the results in Figure 2.

Next, moving on to the panel in the upper right and the panel in the lower left of Table 3a, we see results that are both consistent with Figures 3 and 4 as well as the results in the upper left of Table 3a. In particular, the percentage of the forecast error variance for GDP, Personal Income and Personal Consumption explained by either Other Transfers or Unemployment Insurance is considerably larger during the contractionary phase of the business cycle than during the expansionary phase.

Finally, the lower right panel of Table 3a and the two panels of Table 3b show results consistent with Figures 5-7. In the lower right panel of Table 3a, the Other Transfers and Unemployment Insurance subseries have been removed from the Total Transfers series and now we see no important differences in the forecast error variance of GDP, Personal Income and Personal Consumption between the contractionary or expansionary phases of the business cycle at any of the forecast horizons. Similarly, both panels of Table 3b show results for the Other Transfers and Unemployment Insurance subseries for subsamples which exclude the large transfer payment programs of the two most recent recessions. Here the panel to the left in Table 3b focuses on the Other Transfers subseries during the pre Great Recession period while the panel to the right in Table 3b focuses on the Unemployment Insurance subseries during the pre-COVID-19 recession period. In both of these panels there are no important differences in the forecast error variance of GDP, Personal Income and Personal Consumption between the contractionary or expansionary phases of the business cycle at any of the forecast horizons.

Overall, the FEVD analysis confirms the results seen in the IRF analysis. The FEVD indicates an important asymmetry in the economic responses of GDP, Personal Income and Personal Consumption for Total Transfers, Other Transfers and Unemployment Insurance over the full sample over several forecast horizons. But when one either removes the Other Transfers and Unemployment Insurance subseries from Total Transfers, or one focuses on subsamples for the Other Transfers and Unemployment Insurance subseries, the asymmetry goes away, thus indicating that the stimulus seen in the IRF analysis is due to the unusually large programs implemented during the Great Recession or the COVID-19 recession. .

5 Transfer payment multiplier results

This section studies the multiplier effects of transfer payments. We compute the multipliers in two ways, both of which show the change in GDP arising from a one unit change in one of the transfer payment series. The two computation approaches include: 1) The total stimulus, or stimulus summation, for a four-quarter horizon; and 2), the total stimulus, or stimulus summation, for a ten-quarter horizon. Both multiplier computations were computed in local projection IRFs for models in levels, which allow direct computations of the multipliers that models in logs do not.

Table 4 summarizes the results of these calculations for the same six settings summarized in Figures 2-7 and Tables 1a and 1b. The table has been organized in a similar fashion to Tables 1a and 1b, with the upper left showing the multiplier effects from Total Transfers under the different multiplier computation approaches for the linear model and the two states of the asymmetric model, the upper right showing the multiplier effects from Other Transfers under the different multiplier computation approaches for the linear model and the two states of the asymmetric model, and this pattern continues on through the remaining panels of Table 4.

Looking at the first three panels, the upper left, the upper right, and the middle row left, we see the stimulus effects from Total Transfers, Other Transfers and Unemployment Insurance. The linear models show positive stimulus effects from Total Transfers and Other Transfers for both multiplier computation approaches while the Unemployment Insurance shows negative multipliers. The negative multipliers for Unemployment Insurance likely arises because these benefits have an automatic stabilizing nature which suppresses the rate at which workers

Table 4: Multiplier effects from transfer payment shocks

States	Four-quarter sum	Ten-quarter sum	Four-quarter sum	Ten-quarter sum
Full sample results				
	Total Transfers (TT)		Other Transfers (OT)	
Linear	0.58	2.07	0.74	2.24
Contractionary	1.66	3.07	3.29	-0.44
Expansionary	0.10	-0.71	0.20	-1.57
	Unemployment Insurance Transfers (UIT)		TT-OT-UIT	
Linear	-1.37	-1.64	0.57	-2.97
Contractionary	0.20	13.38	2.79	-2.19
Expansionary	-6.51	-9.42	-0.33	-4.47
Subsample results				
	OT:1960:Q1-2007:Q4		UIT:1960:Q1-2019:Q4	
Linear	-0.64	-1.83	-2.84	-2.92
Contractionary	1.78	2.10	-1.92	-0.84
Expansionary	-1.19	-2.78	-4.67	-6.86

Note: All multipliers are ratios of the sum of coefficients from the GDP IRF and the transfer payment IRF. The Four-quarter and Ten-quarter sums add the numerator and denominator prior to taking the ratio.

return to work and dampens the stimulus effect. Next, looking at the stimulus effects for these three series in the asymmetric model, we see that most of the stimulus occurs during the contractionary phase of the business cycle, with little or even negative stimulus arising during the expansionary phase. However, one notable exception is that Unemployment Insurance has a large ten-quarter multiplier, but when comparing this to the lower right panel we see this large multiplier was due to the very generous unemployment insurance programs during the COVID-19 economic downturn.

Next, moving on to the three situations given in the middle right and two lower panels of Table 4, we see that the stimulus effects in the linear model have largely gone away while in the asymmetric model that breaks things down by the two phases of the business cycle, there is some indication that the asymmetry is still present. However, as noted in Figures 5- 7 these asymmetric multipliers are not significantly different.

Overall, the multiplier results are largely consistent with those discussed in the IRF and FEVD analysis. Here, we find large stimulus effects from Total Transfer and Other Transfers in the linear model. However, when an asymmetry due to the phase of the business cycle is introduced, we see the stimulus effects are concentrated in the contractionary phase of the business cycle. Next, when evaluating the subseries that removes the Other Transfers and Unemployment Insurance subseries from Total Transfers, the stimulus only lasts for a short while before going away when using the full sample data. Furthermore, evaluating the multipliers in subsample periods in which the unusually large expansions in either Other Transfers or

Unemployment Insurance occurred, we see the stimulus also is diminished for Other Transfers and has gone away entirely for Unemployment Insurance. All together, we see that outside of the periods when there were large transfer payment expansions, transfer payments are not particularly stimulative.

6 Robustness

Several robustness checks were conducted. These include, altering the ordering in the baseline model, adding a monetary policy variable, and several modeling variations with personal consumption further disaggregated into nondurable and durable consumption. In the subsections below, we describe these investigations in further detail without providing any IRF plots. The IRF plots are available in an online appendix.

6.1 Model in which transfer payments is ordered first

In our baseline Cholesky ordering, we ordered GDP prior to transfer payments to reflect the automatic stabilizing structure of some transfer payment programs like unemployment insurance. However, a common, more traditional approach for modeling government policy regards policy as being exogenous. If one held this view, one might assume that transfer payments should be ordered prior to GDP. This was the ordering used in Blanchard and Perotti (2002) in their analysis which focused more on general government spending than on transfer payments. As a robustness exercise, we investigated an ordering in which Total Transfers is ordered first, GDP is ordered second, Personal Income third, Labor fourth and Personal Consumption last. The results of this ordering, shown in Figure A.1, show virtually identical impulse responses as those seen in Figure 2, indicating that the ordering does not impact the findings discussed in Section 3. This result is not too surprising since the effects of the Cholesky ordering dissipate quickly and has a limited impact on the response functions for longer horizons.

6.2 Model with monetary policy

The previous models only included fiscal policy. One could argue that an important missing variable is a monetary policy variable. So as another check, the Federal Funds Rate was added to the model.[16] To make things easy to run and display, the Federal Funds Rate was swapped

[16] We used the Wu-Xia shadow Federal Funds Rate series, FFR-WUXIA, downloaded from the Federal Reserve Bank of Atlanta for this analysis.

in and Labor Supply swapped out and we left the ordering the same only now the Federal Funds Rate was ordered fourth. This late ordering of the Federal Funds Rate follows a common practice in the macroeconomic literature, which is to order monetary policy late so that monetary policy could respond to other economic variables contemporaneously, but monetary policy could affects other economic variables with a lag. The IRFs of the extended model are provided in Figure A.2. This extended model again showed that there are important positive effects from the extended transfer payment series only during economic weakness.

6.3 Models with durable and nondurable consumption

We also considered various models with Personal Consumption disaggregated into its durable good and nondurable good components.[17] A number of different five variable models were investigated. All of these models swapped Personal Income and Personal Consumption out and replaced them with Durable Goods and Nondurable Goods. Several Cholesky orderings for the new set of variables were considered including: 1) Ordering Nondurable Goods fourth and Durable Goods fifth as seen in Figure A.3; 2) Ordering them second and third with Total Transfers first, GDP fourth and Labor Supply fifth as seen in Figure A.4; and, 3) ordering them second and third with GDP first, Total Transfer fourth and Labor fifth as seen in Figure A.5. All of these figures show that GDP and Nondurable goods respond asymmetrically to Total Transfers impulses, with the responses to Total Transfers being significantly positive during economic contractions and insignificant during economic expansions. In addition, the response of Durable goods shows some small short-lived positive responses to positive Total Transfer impulses, and they show insignificant asymmetries between economic expansions and contractions. Overall, these results are largely consistent with the findings shown earlier in Figure 2.

6.4 Model with an alternative identification strategy

In all of the previous models, we relied on the Cholesky decomposition with specific structural assumptions about the ordering of variables to disentangle exogenous shocks to transfer payments. Since transfer payments respond to changes in economic activities, we mostly ordered transfer payments after key macroeconomic indicators such as GDP.[18] This ordering ensures

[17]The FRED series name for durable good is "Personal Consumption Expenditures: Durable Goods" and it is denoted PCEDG while the nondurable good has FRED series name "Personal Consumption Expenditures: Nondurable Goods" and is denoted PCEND. These are nominal series, so they were deflated using GDPDEF.

[18]One exception was the first robustness exercise described in Section 6.1.

the correct accounting for their role as automatic stabilizers. In this subsection, we conducted a robustness check using an alternative identification strategy to validate our findings. A popular approach to identification, developed by Faust (1998) and Uhlig (2005), uses sign restrictions. The idea is that certain economic concepts are generally agreed upon. Since our interest is in transfer payment shocks, we imposed restrictions on how the variables in the model could respond following such a shock. For example, a positive transfer payment shock should not lead to a decrease in transfer payments and personal income, so we imposed positive restrictions on these variables. We imposed negative restrictions on labor supply, reflecting the labor-leisure substitution effect, where increased transfer payments might reduce the incentive to work. For instance, if unemployment benefits are higher, some people might decide to stay unemployed longer instead of taking a job that pays only slightly more than the benefits. We did not impose any restrictions on GDP and personal consumption, implying that the impulse responses of these variables could move in either direction in response to transfer payment shocks. To implement this identification approach, we drew 10,000 models to obtain a set of IRFs that satisfy the restrictions. Figure A.6 displays the results. Overall, the consistency of IRFs using the sign restrictions supports the reliability of our Cholesky ordering approach.

7 Conclusion

This paper investigated the stimulative effects of transfer payments on GDP, Personal Income, Labor and Personal Consumption using impulse response functions, forecast error variance decompositions and spending multiplier approaches. It is shown that under symmetric response assumptions, positive transfer payment impulses lead to positive stimulative effects for GDP, Personal Income and Personal Consumption lasting about four quarters. The origin of this result was investigated using asymmetric models and exploring the subseries of the Total Transfer payment series and exploring subsample periods. It was found that the stimulative effects were asymmetric lasting up to four quarters during times of economic weakness. However, during economic strength, the stimulus was small, and short-lived. Breaking transfer payments into its subseries showed that much of the asymmetry is due to the special programs of the Great Recession and the COVID-19 recession. Removing the special programs from the transfer payment data shows a reduced asymmetry. Furthermore, focusing on data prior to these recent recessions shows much smaller stimulative effects and no asymmetry in the responses.

These results indicate that using transfer payments as an economic stimulus for the economy during expansionary economic conditions does not lead to large gains in major macroeconomic variables. A policy intended to stimulate GDP, Personal Income and Personal Consumption through transfer payment increases will have its greatest impact during contractionary economic conditions and through special programs such as those enacted during the Great Recession and the COVID-19 recession. Because transfer payment programs are often motivated by both the benefits to recipients and the stimulative benefit to the economy, our results show that, outside of the periods where large extraordinary expansions occur, the stimulative effects from transfer payment programs are small, and that transfer payments should only be motivated by the benefits to the recipients.

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Appendix

This appendix provides further detail on the construction of the shock process and is intended to be published with the paper.

As suggested in Jordà (2005), the mapping from the structural shocks to the experimental shocks uses the traditional VAR approach described in Sims (1980) which makes use of the Cholesky decomposition. This approach begins with what is called a structural form VAR given by

$$A_0 x_t = \sum_{i=1}^{p} A_i x_{t-i} + \varepsilon_t \tag{8}$$

where in our application A_i for $i = 0, ...p$ are 5×5 matrices, p is the lag length for the model and ε_t is a 5×1 vector of structural shocks and we have left out the vector of constant terms to keep things simple.[19] The structural form VAR is not directly estimable without making identification assumptions, so the traditional VAR approach recasts it as a reduced form VAR given by

$$x_t = \sum_{i=1}^{p} A_0^{-1} A_i x_{t-i} + u_t \tag{9}$$

where $u_t = A_0^{-1}\varepsilon_t$ is a 5×1 vector of experimental (or reduced form) shocks. Here, we use the same notation for the experimental (or reduced form) shocks, u_t, as was used in the local projection formulation to emphasize that this is how those shocks are modeled in their connection to the structural shocks. Because the reduced form model has fewer parameters than the structural form model, if one wishes to consider structural model implications, identifying restrictions need to be imposed on the structural parameters and the original suggestion in Sims (1980) was to use the Cholesky decomposition which requires that A_0 be lower triangular and this structure implies a contemporaneous causal ordering among the variables, with the variable listed at the top of the vector x_t potentially having contemporaneous causal effects on the remaining variables, the variable listed second from the top potentially having contemporaneous causal effects on all the variables except the first and so on down the list. So to use this approach, one must a decision about how the variables are ordered. As noted in the paper, we chose $x_t = [GDP_t \quad TT_t \quad PI_t \quad LS_t \quad PC_t]'$ which implies that GDP can contemporaneously cause all the other variables, Total Transfers can contemporaneously cause all the other variables except GDP and on down the list.

With these decisions in hand, we can now describe the construction of the d_i vectors used in the impulse response calculations. First note that $u_t = A_0^{-1}\varepsilon_t$ implies that the experimental shock variance is given by

$$u_t u_t' = A_0^{-1}\varepsilon_t\varepsilon_t'(A_0^{-1})' = A_0^{-1}\Omega_\varepsilon^2(A_0^{-1})' \tag{10}$$

where Ω_ε^2 and A_0 are given by

$$\Omega_\varepsilon^2 = \begin{bmatrix} \sigma_{GDP}^2 & 0 & 0 & 0 & 0 \\ 0 & \sigma_{TT}^2 & 0 & 0 & 0 \\ 0 & 0 & \sigma_{PI}^2 & 0 & 0 \\ 0 & 0 & 0 & \sigma_{LS}^2 & 0 \\ 0 & 0 & 0 & 0 & \sigma_{PC}^2 \end{bmatrix} \quad \text{and} \quad A_0 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 & 0 \\ a_{31} & a_{32} & 1 & 0 & 0 \\ a_{41} & a_{42} & a_{43} & 1 & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & 1 \end{bmatrix} \tag{11}$$

Next note that $u_t = A_0^{-1}\varepsilon_t$ can also be interpreted as showing the mapping from an arbitrary vector of structural shocks given by ε_t into a vector of experimental shocks given by u_t and that

[19] The notation here follows Enders (2015).

A_0^{-1} provides this mapping. Now, if we define d_i by

$$d_i = A_0^{-1}\Omega_\varepsilon \varphi_i \tag{12}$$

where φ_i is a column vector with a one in the ith position and zeros elsewhere, then d_i has a special interpretation. First note that the term $\Omega_\epsilon \varphi_i$ gives a vector with a one standard error shock for the ith variable in only the ith positon, with zeros elsewhere. So, by multiplying by A_0^{-1}, d_i can be interpreted as a vector of experimental shocks that arise from a one standard deviation structural shock in the ith variable. This means that the impulse response functions show how the vector of variables x_t respond to a one standard deviation shock in the ith structural variable at various forecast horizons.

Appendices

This appendix is a supplement to the paper, but is not intended to be published with the paper. Instead it is intend as an online supplement, either on the journal's server or on the author's personal web pages.

A Robustness exercises - Some alternative models

Here, Impulse Response Functions for the robustness exercises described in the paper are provided. These exercise where described in the paper, so here, they are provided without description other than a title for the exercise.

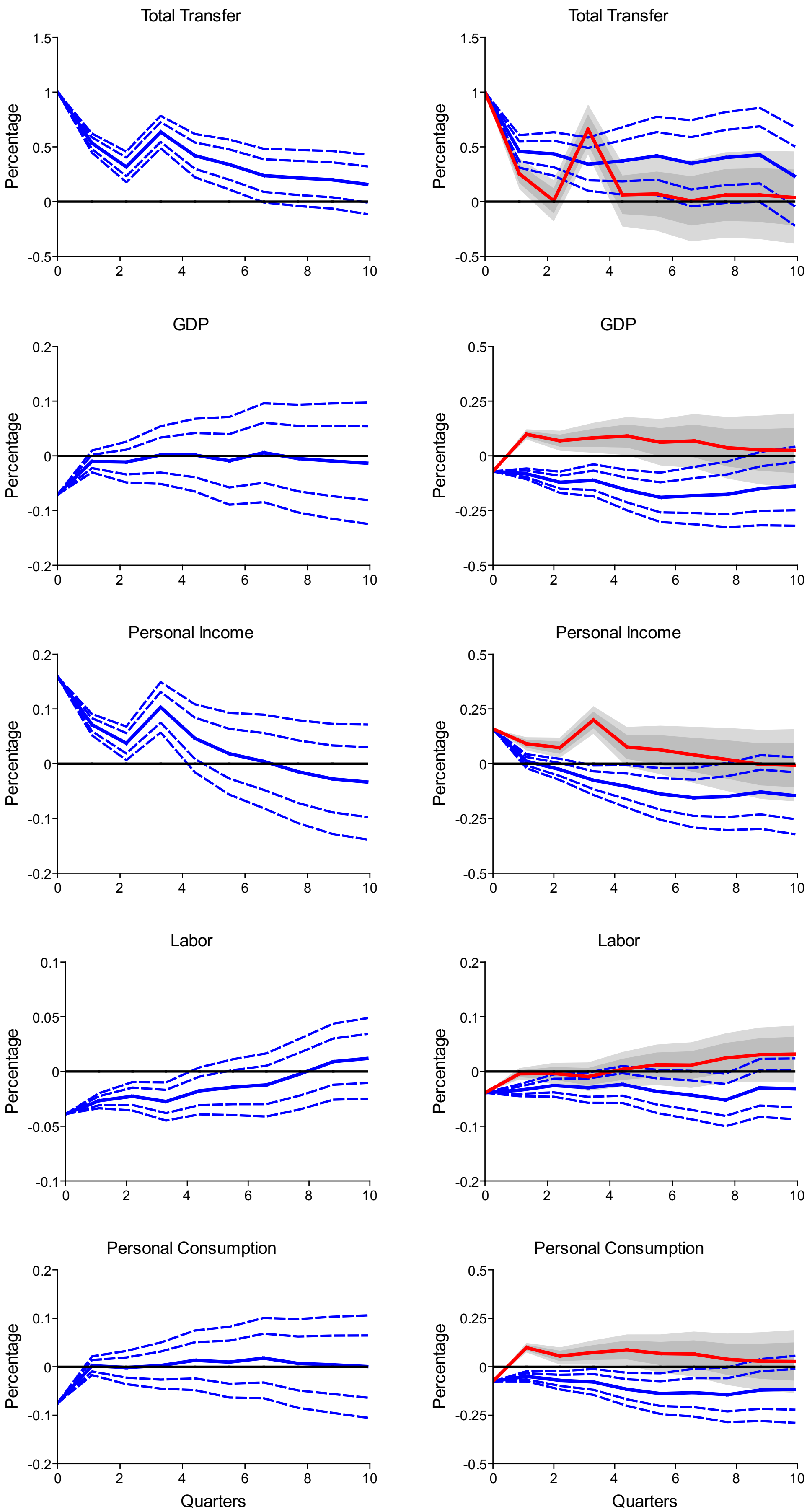

Figure A.1: Response function to an impulse in Total Transfers in a model with alternative ordering, putting Total Transfers first in the Cholesky order

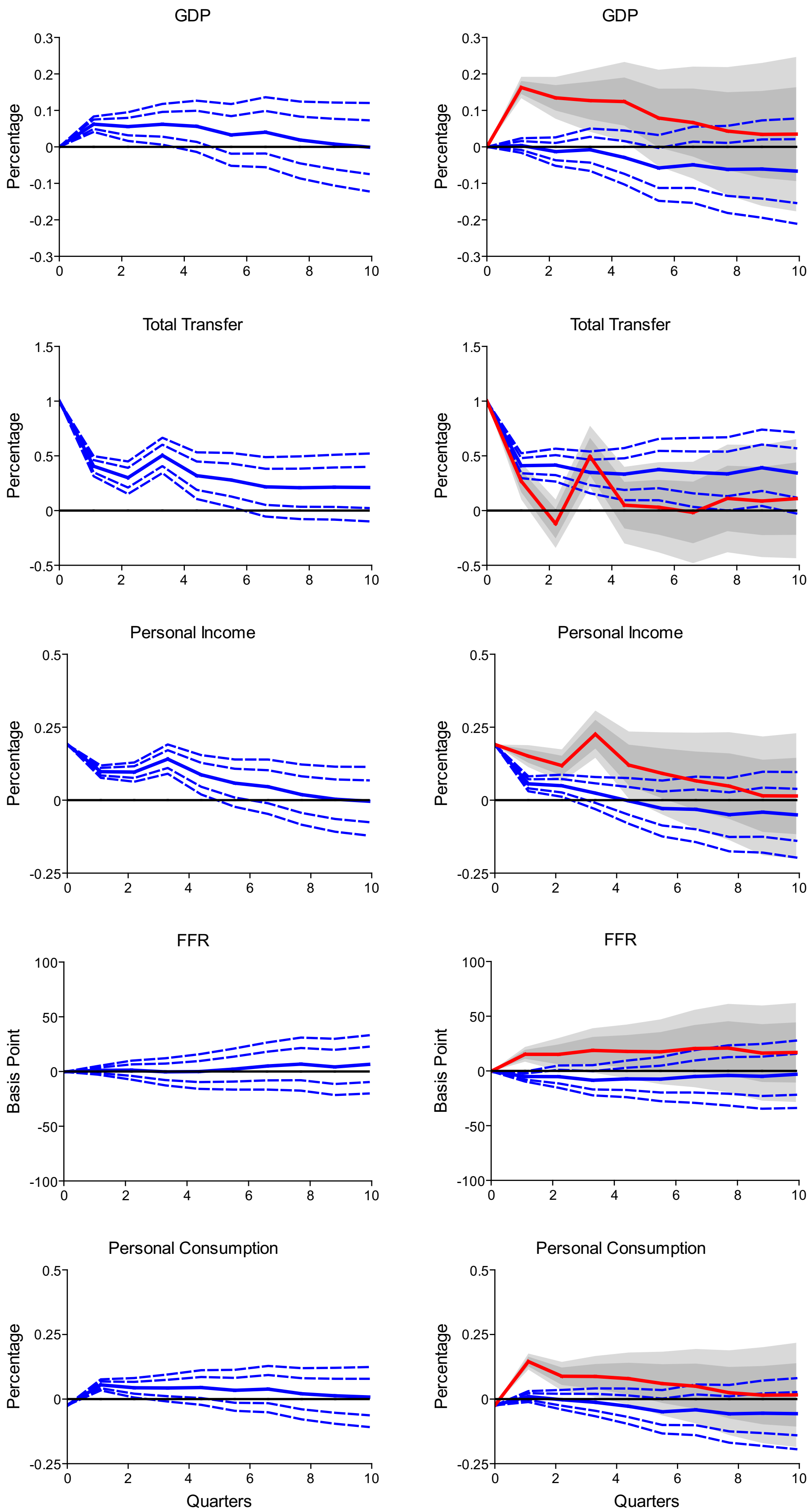

Figure A.2: Response function to an impulse in Total Transfers in model with monetary policy variable

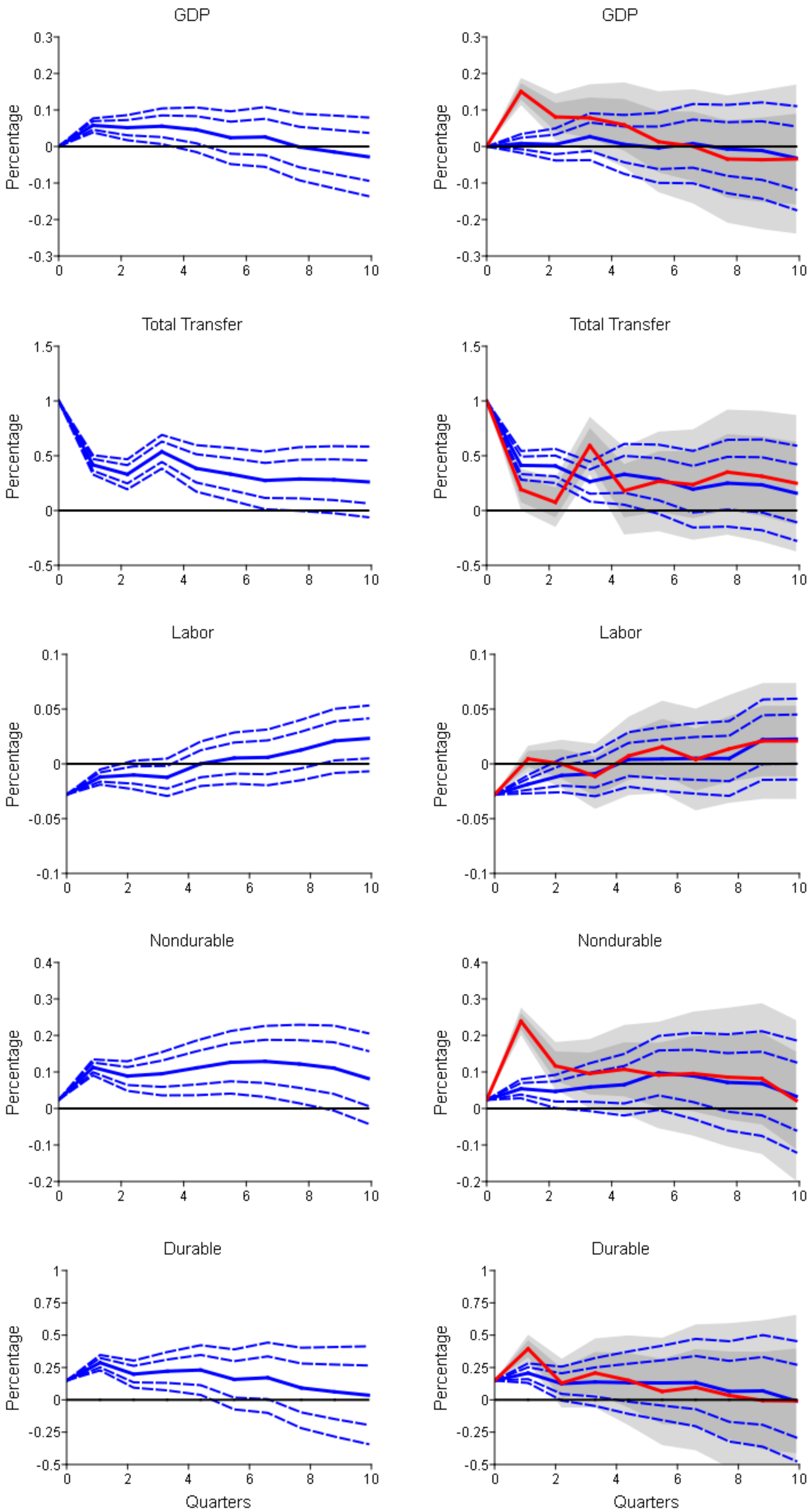

Figure A.3: Response function to an impulse in Total Transfers in model with durable and nondurable consumption

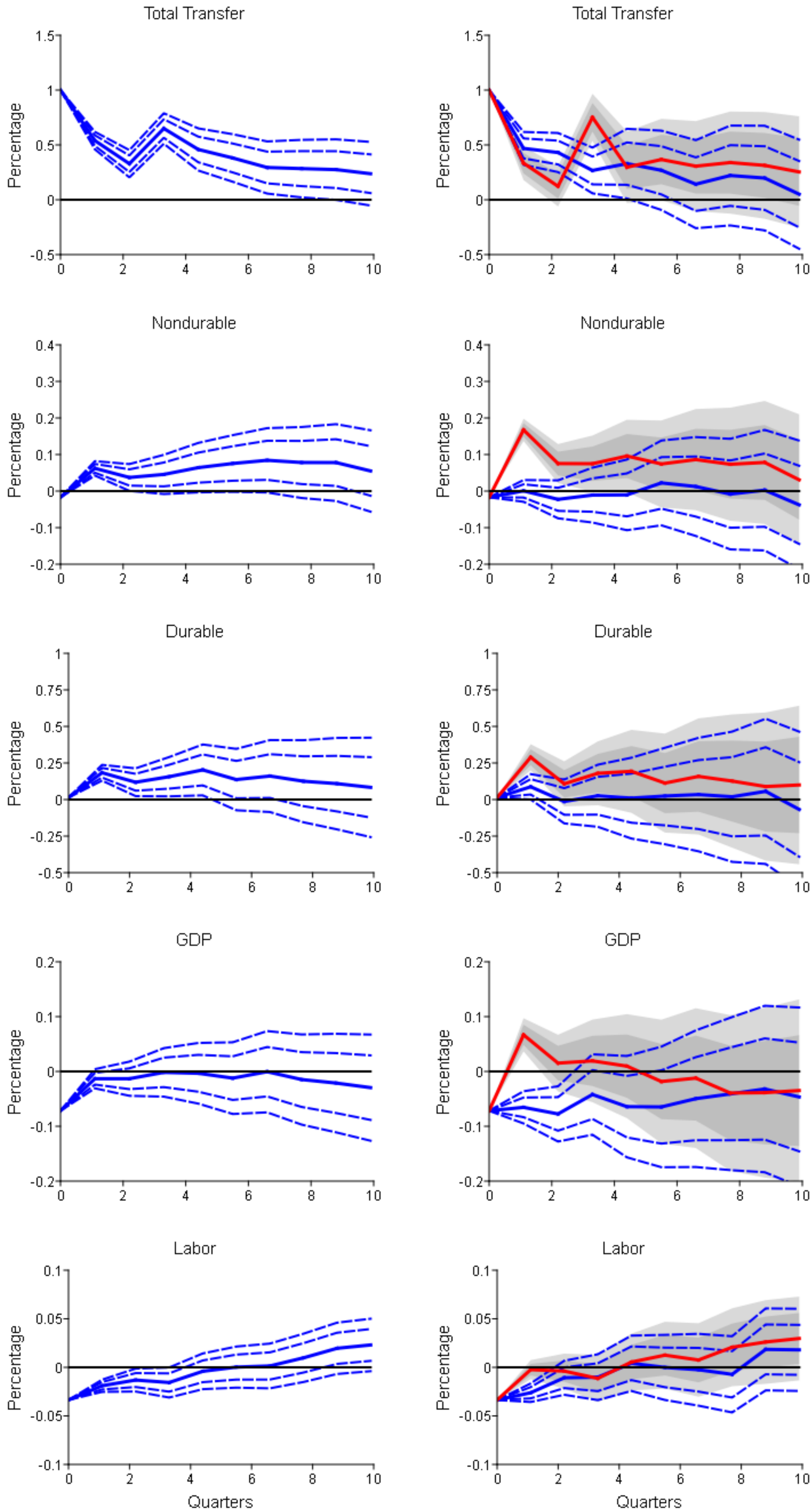

Figure A.4: Response function to an impulse in Total Transfers in model with durable and nondurable consumption putting total transfer before nondurable and durable goods

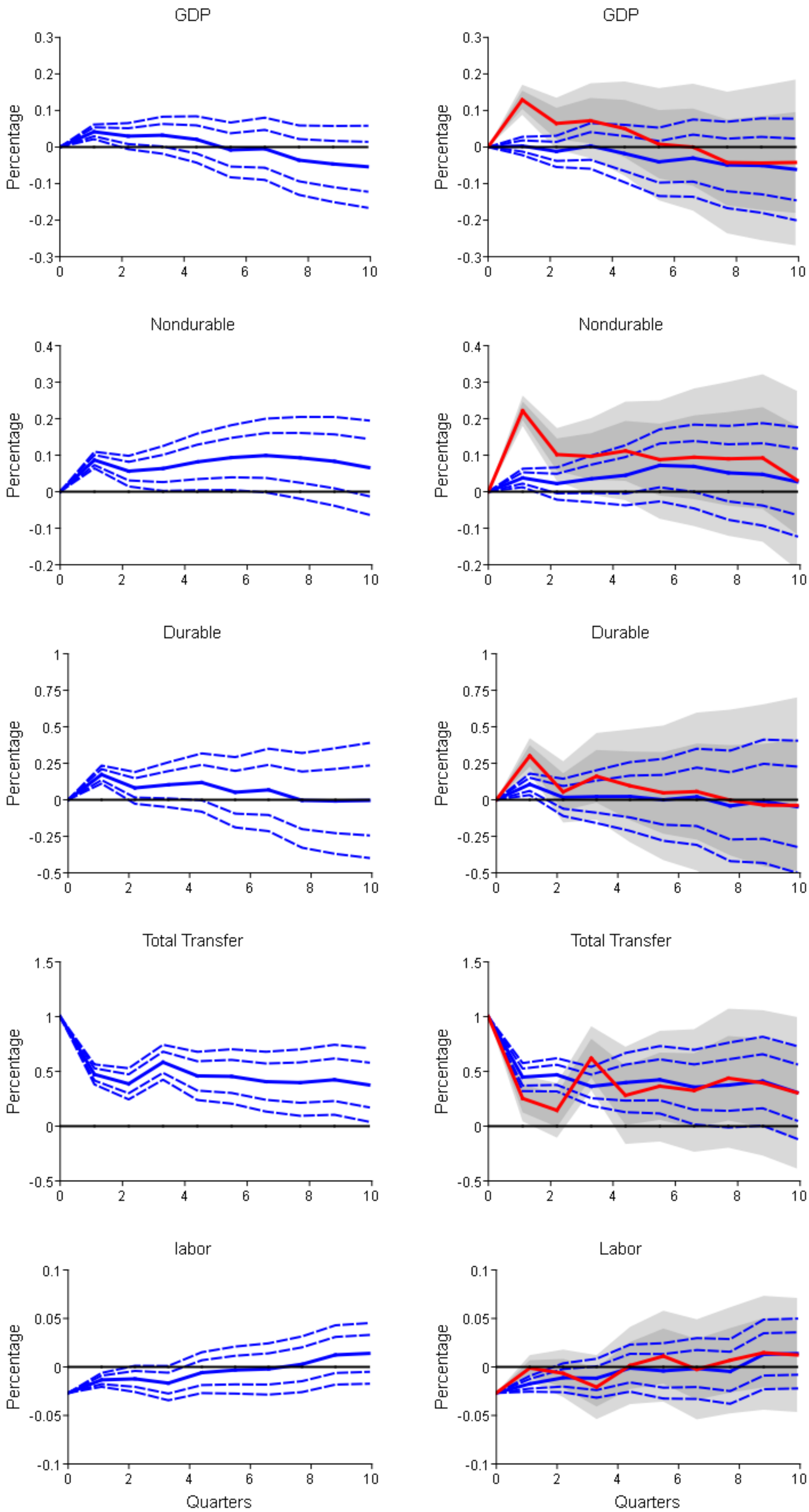

Figure A.5: Response function to an impulse in Total Transfers in model with durable and nondurable consumption putting total transfer after nondurable and durable goods

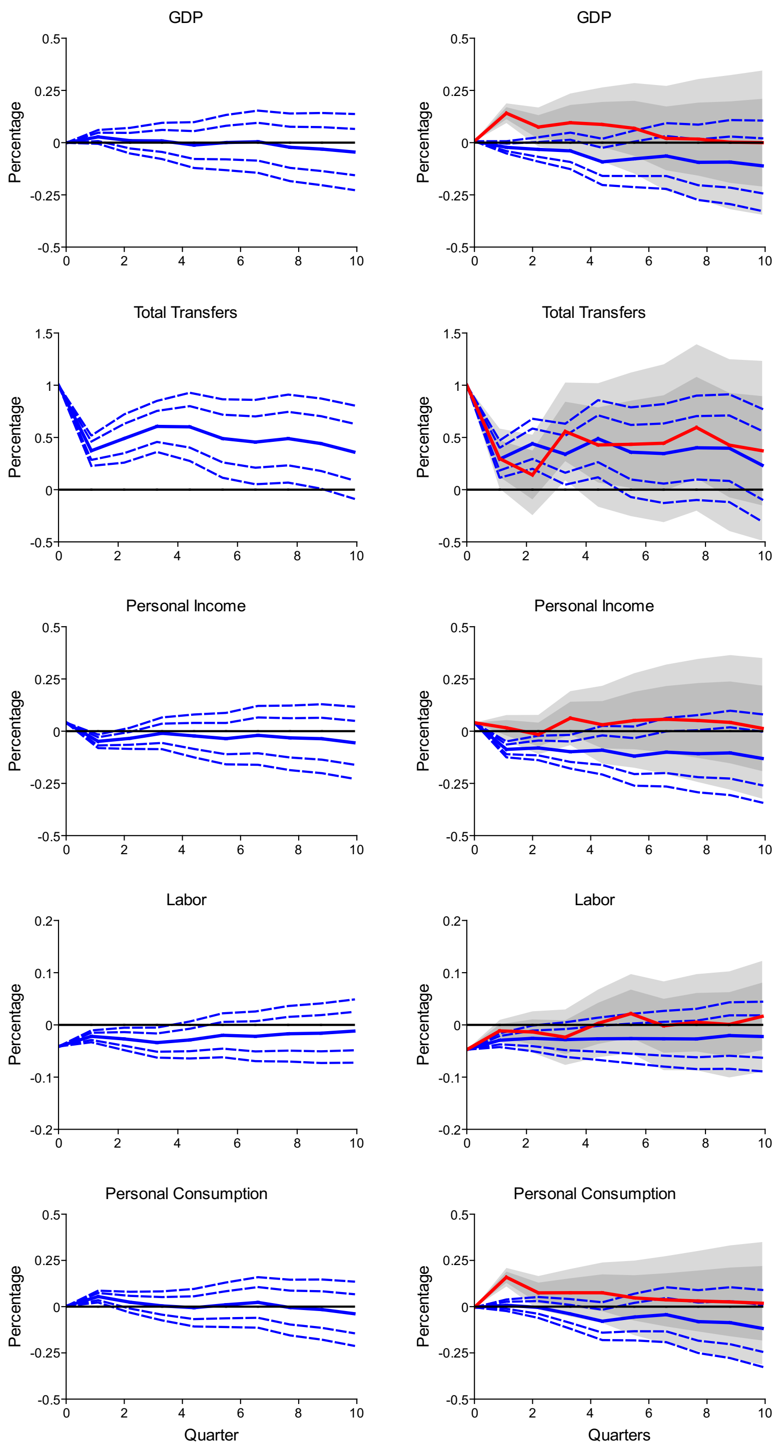

Figure A.6: Response function to an impulse in Total Transfers in a model using a combination of zero and sign restrictions